Macroeconomic Essays on Technological Change

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(Abstract)

In chapter 1, I find that wages in U.S. regions have been diverging instead of converging from 1975 onward. This coincides with the period of accelerating skill-biased technological change. A decomposition of the divergence rate indicates three channels underlying the divergence: (1) an ever-widening wage gap between college graduates and high school graduates, (2) an increasing within-education-group wage differential across regions, and (3) a concentration of skill composition across local labor markets. I then developed an endogenous skill-biased technology-adoption model in which firms invest capital more intensively in regions with higher employment share of college graduates, explaining these three channels jointly. Finally I quantitatively assess the model by separately calibrating the regional aggregate production function; the results show that the relative skilled-labor efficiency has been persistently higher in skill-abundant regions, nevertheless the country-wide skill-biased technological change, is the main force making divergence happening.

Chapter 2 studies energy-saving technological change in U.S. manufacturing sector, whose intensive margin and extensive margins are identified. I find that energy and capital are mostly complementary to each other, while labor is substitutive to energy-capital composite. However, a Cobb-Douglas nesting of labor is rejected. Quantitative exercise shows that in the post-crisis period, within in industry energy-saving technological change accounts for the largest proportion of the aggregate sectoral energy efficiency promotion in the long run. In contrast, in the short run, factor adjustment combined with sectoral shift accounts for the largest proportion of energy intensity reduction. Lastly, I provide evidence that structural change has

taken place around the oil crisis in 1970s, which is consistent with the existing literature.

In chapter 3, I documented the increasing dispersion of skill composition across different areas in the U.S. Meanwhile, the U.S. Housing Market has experienced a dramatic increase in the housing price, as well as a similarly increase in its dispersion across metropolitan areas. A set of related stylized facts are documented in this paper. First, the real wage goes similarly as real housing prices, but quantitatively different. Second, the rents and housing prices have not been going in the exactly same way, in terms of first two moments. Third, we find that local income inequality is positively correlated to the local housing price level. Based on these observations, we build a model where a dispersed skill-biased technology change can account for all the phenomena at the same time.

To Lu and Our Parents

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CHAPTER 1

Endogenous Skill-Biased Technological Change as a Cause of Change in Regional Convergence

1. Introduction

Economic convergence among U.S. states has been widely accepted (e.g. Barro and Sala-I-Martin [1991]), despite the fact that the unconditional convergence among countries has always been questioned. In a recent study, Ganong and Shoeg [2013] show that convergence among U.S. states has been slowing down. A back-of-the-envelope calculation shows that in terms of the average wage, from 1980 to 2010 states diverged instead of slowing down their convergence (see section 2). This period coincides with the period of rapid introduction of computers. The question of why states began to diverge is addressed in this chapter.

A rigorous decomposition of the divergence rate reveals channels underlying the divergence. First, the widening wage gap between skilled labor (college graduates) and unskilled labor (non-college graduates)(see Katz and Murphy [1992], Acemoglu [2002]) combined with the fact that the labor composition is different across states, creates a benefit states to with a higher share of college graduates. Second, college graduates earn disproportionately more in some places. Third, in a dynamic perspective, if unskilled labor migrates in a way that the distribution of skill composition across states equalizes, then convergence is promoted. If opposite, then divergence is promited.

In this paper, I show that all three of these channels are accelerating the divergence among states. I find that distribution of skilled labor was not even, and has been rapidly becoming more concentrated for at least three decades. States with a initially higher share of college graduates experience a higher increase. For instance, Massachusetts with 25% share of college graduates in 1980 experienced a 19% increase of the share, while Wyoming which had less than 20% share just experienced a 6% increase.

Surprisingly, I find a positive correlation between local skilled labor supply and the relative wage of college graduates compared to high school graduates. The correlation was not statistically significant in 1980 but became fairly significant three decades later. In Connecticut, the skill premium was 1.65 ($\exp\{0.5\}$) in 1980, but became 2.0 ($\exp\{0.7\}$) in 2000. In contrast, South Carolina which initially had relatively a low share of college graduates, merely experienced an increase of skill premium from 1.55 ($\exp\{0.44\}$) to 1.73 ($\exp\{0.55\}$). This evidence contradicts canonical demand-supply ideas as well as a simple endogenous technology adoption model (Beaudry, Doms, and Lewis [2010]), which predicts that skill premium should not be higher in skill-abundant states.

Based on these observations, I argue that the production method should be different for different places, in other words, the technological process is not identical for states; it should be more skill-biased in places with abundant skill supply. This point is supported by another piece of evidence. Ciccone and Peri [2005] estimate the state level production function allowing it to be factor-augmenting. I regress their skill-augmenting estimates on the college graduate share, finding that they are positively correlated. Parallel with this, capital-skill complementarity, another expression of skill-biased technology predicts that higher skill-biased technological change comes with greater level of skill-complementary capital. This prediction is confirmed by our evidence in section 2, which shows that states with higher proportion of college graduates attracted more capital, and hence the dispersion of capital per capita across states increases from 1975 to 2000.

With this evidence in hand, I then build a model featuring endogenous skill-biased technology adoption, migration cost, and inelastic local housing supply. The endogenous skill-biased technology adoption is the driving force behind the results in my model. It causes technology embedded capital to be adopted first in places with higher share of skilled labor. In a dynamic context, migration cost may prevent skilled labor from flowing into places with higher marginal productivity of skilled labor, which happen to be places with a higher share of skilled labor. Therefore, under certain conditions, places with higher rates of SBTC, may enjoy persistently higher skill premiums than others. Finally, an inelastic housing supply prevents all skilled labor from being concentrated in one place.

Although the model does a good job in explaining the divergence, it also predicts that divergence among states will not exist forever. Two typical scenarios cause the end of divergence. First, once the share of skilled labor reaches a threshold, the return to investing in higher-share states will drop, which direct the investment to lower share states. Thus the low productivity states will catch up. Second, when local housing prices have become too high, skilled labor will flow out of the states even though the productivity is higher there. Therefore, convergence is going to take place for this reason as well. [1]

1.1. Related Literature. The first literature related to my paper is on directed technological change, which has recently attracted a lot of attention. Acemoglu and Zilibotti [2001] (AZ01, hereafter) construct a powerful framework and discussed outcomes under different trade conditions and Intellectual Property Rights (IPR) regimes. Based on AZ01, Gancia, Müller, and Zilibotti [2011] develop a structural framework that permits an empirical cross-country development accounting exercise. My model is a within-country analog to these models, with the adjustment of assumptions on free trade, full IPR protection, and labor mobility. To the best of my knowledge, this chapter is the first to use the idea of endogenous skill-biased technology to investigate regional convergence, or divergence.

There are studies of directed technical change across different areas within a single country. Beaudry, Doms, and Lewis [2010] show that firms adopt technology differently, according to the local skill endowment (skill mix), even within narrowly defined industries. Lewis [2011] offers a quite similar result: in a skill-abundant place, firms are more likely to investment in technologies that complement skill.

[1]As Goldin and Katz [2007, 2008] argued, definition os skilled labor has changed for several times. A now unskilled labor was skilled labor one century ago. In the history, many types of manufacturing workers were supposed to be skilled labor. When employment in manufacturing became dominant, the convergence took place.

These studies are more qualitative than quantitative and do not study the consequent impact on either the wage inequality across areas or the average skill premium. Moreover, the prediction by Beaudry, Doms, and Lewis [2010] is slightly different from the one in this paper. As they show, the skill premium should decrease in the local skilled labor supply, and hence regional convergence is implicitly indicated.

My preliminary empirical study has some results similar to those in labor economics. Moretti [2011, 2013] shows that regional differences in the proportion of college graduates are highly persistent, and the housing rent increase is higher in areas with higher proportions of college graduate. The higher rent is one of the factors that guarantee a continuing high proportion of high skill workers and hence persistent productivity advantage in areas with initial advantage.

This paper is also related to the cross-country technology diffusion literature, though the geographic units are different. Recently, Comin and Hobijn [2010] show that a significant lag in technology adoption exists around the world, they obtain structural estimates of parameters of diffusion curves. Based on the estimates, they show that the lag of technology can account for a large fraction (one fourth) of cross-country income difference. My model is similar to theirs in that there is a time gap of technology adoption between different states, and also using structural estimates, I replicate the regional divergence and show the sources of regional convergence through quantitative analysis.

The rest of the paper is organized as follows: section 2 discusses the descriptive facts that motivated the present paper; I model a simple economy in sections 3 and 4; section 5 briefly describes the data I employed, section 6 quantitatively assesses the differential of skill-biased technological change, section 7 discusses three alternative hypothesis, and section 8 concludes.

2. Motivating Facts

In this section I document several empirical facts that motivate the present study, focusing on skilled labor supply, skill premium, skill-biased technological change and their relations at the U.S. state level. Since skill-biased technological change mostly took place after the mid 1970s, I focus on the period from 1980 onward. I compare these findings with previous studies in the literature, showing not only that some of them can be explained by the existing theory, but also which of the facts cannot be explained. Finally, I describe a potential theory that can help reconcile the facts with existing theories.

2.1. Dispersed Skilled Labor. First and foremost, there existed a significant variation in the share of workers who were college graduates across U.S. states. Meanwhile, this college graduate differential increased rather than decreased from 1980 to 2010. The upper panel of Figure 1-1 shows that this differential is fairly persistent. The states with higher initial level of college graduates share in 1980 would still have higher level in 2000. This fact holds if we extend the period to 2010. This fact is consistent with Lindley and Machin [2013], who confirm that this relation across space also holds if we use metropolitan areas instead of states.

In the lower panel of Figure 1-1, we find that places with higher initial college graduate shares experienced a greater increase of the same variable, which indicates that although the average level of college graduates share has been increasing throughout the period, it has been becoming more spatially concentrated. This result is comparable with Beaudry, Doms, and Lewis [2010] as well as Lindley and Machin [2013], both of who show quite similar result for different definitions of regions.

2.2. Dispersed Skill Return. Along with the the dispersion of skilled labor share comes the dispersion of the wage gap between skilled labor and unskilled labor. In 1980, among contiguous states except District of Columbia, Wyoming had skill premium as low as 1.22 and Connecticut had one as high as 1.6. The difference was

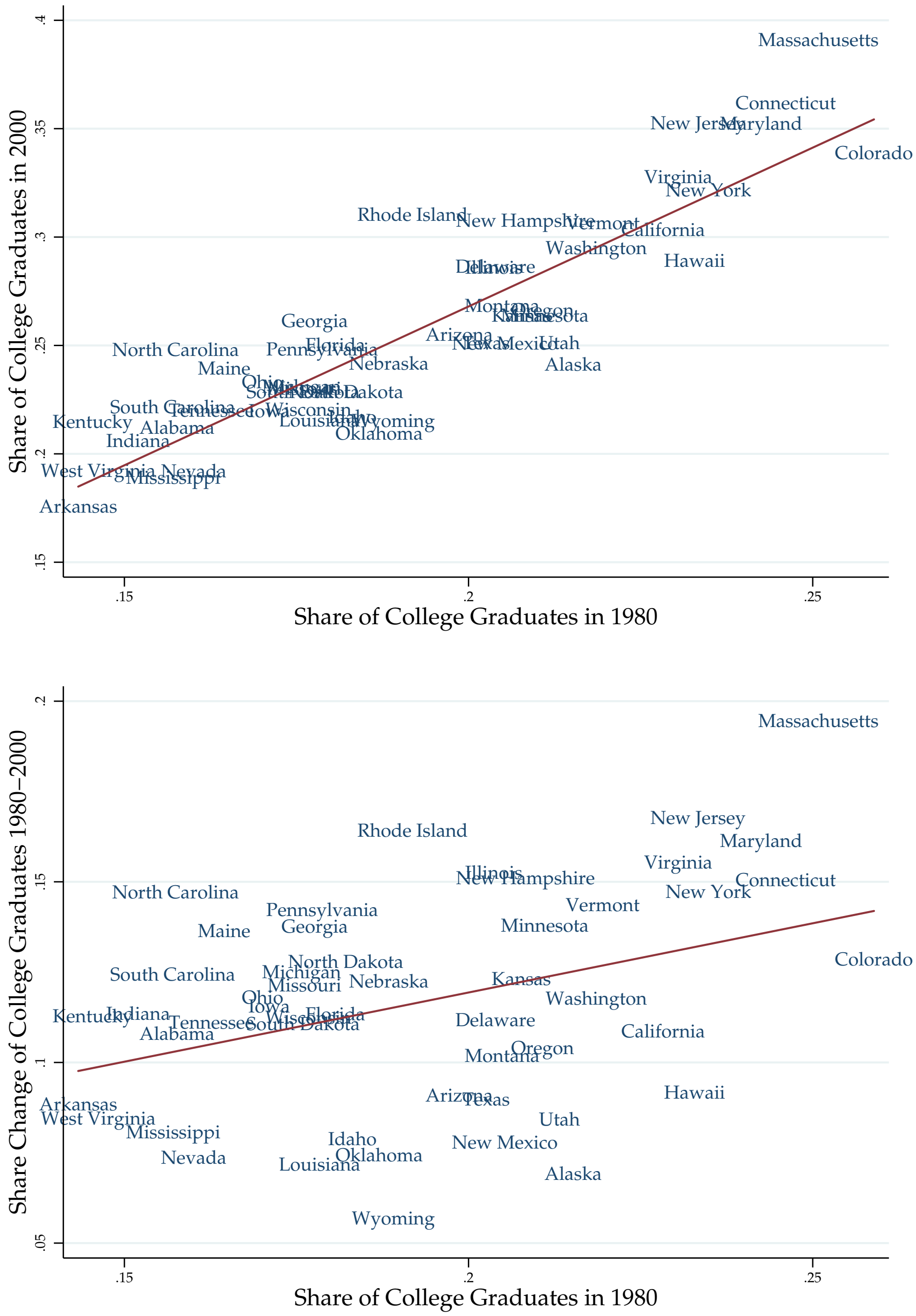


Figure 1-1: Concentrating Distribution of College Graduates: The upper panel shows the relation between share of college graduates out of employment in 2000 and that in 1980; The lower panel shows the change in the employment share of college graduates from 1980 to 2000 against its initial share in 1980. An OLS regression shows the slopes are significantly positive at 1% level, Note: The District of Columbia is dropped but the states of Hawaii and Alaska are included.

significant; in 2000, the difference became even greater, the lowest skill premium was around 1.5, while the highest was about 2.0 in Connecticut (see Figure 1-2).

According to standard demand-supply theory, the equilibrium wage usually decreases when the supply of labor shifts outward. Therefore if the same demand for labor prevail across states, then the return to skilled labor, i.e., the wage of college graduates, should decrease when its supply increases. Even with endogenous technology adoption taken into account, Beaudry, Doms, and Lewis [2010] predict that the skill premium will decrease when the supply of skilled labor increases. This prediction is not rejected by the data in 1980 and 1990 in our data set. In the upper panel of Figure 1-2, the relation between skill premium and skilled labor supply was slightly positive but not significant at 10% level (The p value is greater than 0.20). In 1990, this relation becomes negative but not significant. In 2000 and 2010, however, the situation changes. As shown in the lower panel of Figure 1-2, the skill premium is positively correlated with skilled labor supply, significant at 1% level.

This factor price inequality has also been tested by Bernard, Redding, and Schott [2013], who show that the ratio of the wage bill for skilled labor (nonproduction workers) to unskilled labor (production workers) has widened, from 1972 to 1992 and 2007. Their micro level results are fairly robust to different specification of the production function. Though their definition of regions is different from mine, my result is line with theirs. They also point to factor-biased productivity differentials as the cause of the inequality of relative wages across regions, within industries.

2.3. Dispersed Skill-biased Technological Change and Dispersed Capital Stock. In the previous two subsections, we were not able to identify places which have experienced greater increases in skilled labor efficiency. Based on a specific production function form, the parameter governing skilled-biased technical change is identified jointly with the elasticity of substitution. Ciccone and Peri [2005] estimate the skill-biased technological change for 48 contiguous U.S. states, based on a CES production function specification, with two labor inputs, i.e., skilled labor and unskilled labor.

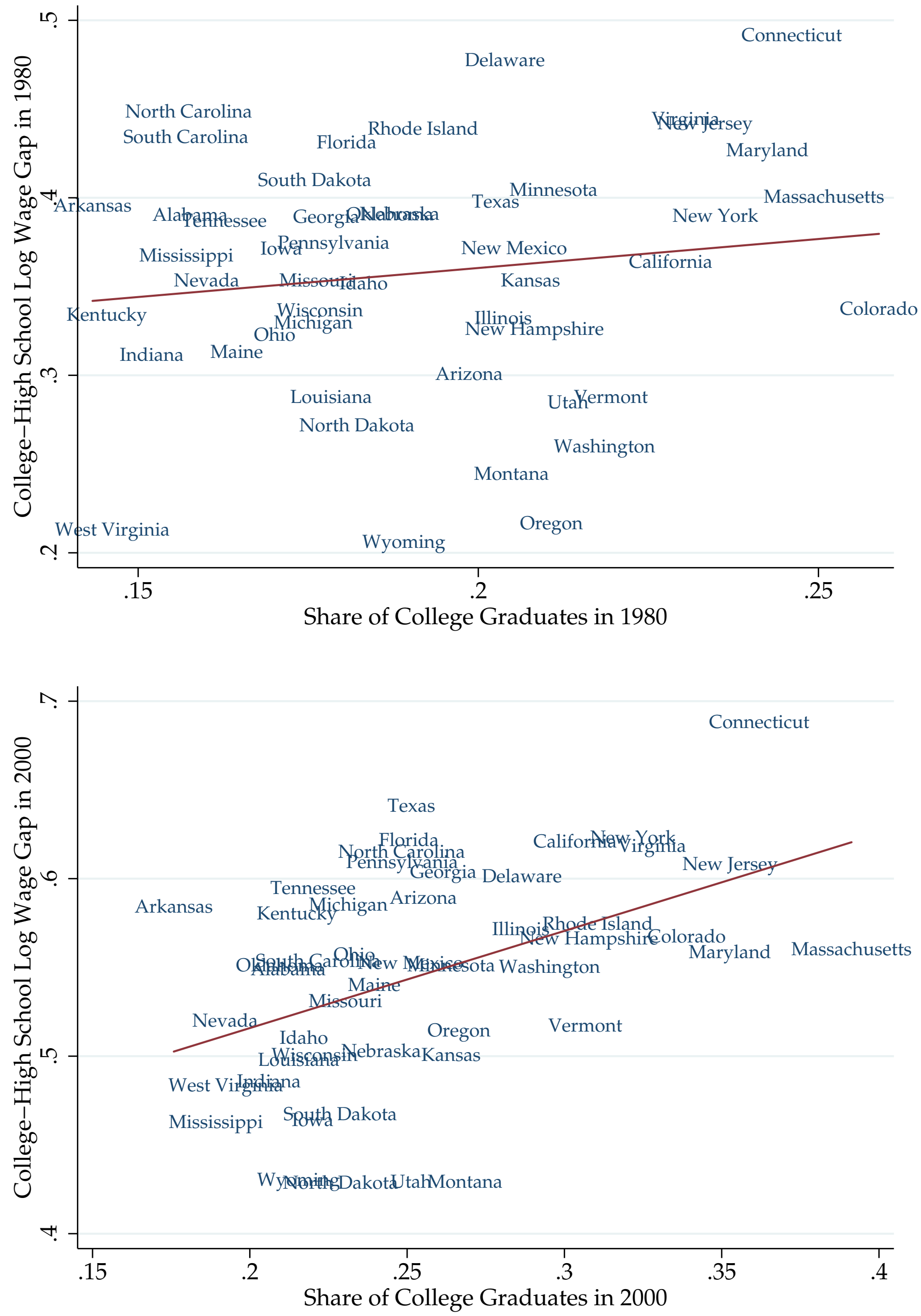


Figure 1-2: Persistence of Positive Supply-Wage Relationship for College Graduates: The upper panel shows the relation between Share of College gradates and log wage gap between college graduates and high school graduates in year 1980, the correlation was not significantly positive; The lower panel shows the same relation in year 2000, it is significant at 1% level. Note that observations for Alaska, Hawaii and District of Columbia are all dropped.

We use their estimates to show the patterns of skill-biased technological change (SBTC) across the whole country for the specific period.

Figure 1-3 shows that the skilled labor endowment in 1980 is positively correlated with the SBTC parameter value, which means that skill-biased technology is more abundant in skill abundant states. Ciccone and Peri [2005]'s data covers the period from 1950 to 1990. I do not intend to use result to fully support our theory, but their result at least partly indicates that skill-biased technology was adopted more intensively where the supply of skilled labor was relatively higher. Also, this result is consistent with Beaudry, Doms, and Lewis [2010], who show that skill biased technology, e.g. personal computers, should be more adopted in places with higher labor share of college graduates.

Capital-Skill complementarity is another form of skill biased technological change. According to this hypothesis capital should be more prevalent in places where share of skilled labor is higher. Using the data provided by Turner, Tamura, Schoellman, and Mulholland [2011], we find that places with a higher labor share of college graduates have a higher level of physical capital per capita. Furthermore, when we plot the time series of the coefficient of variation (CV) of total physical capital per capita across all contiguous states in bottom panel of Figure 1-3, it shows that the CV reaches the it trough around 1975, indicating that the capital per capita was converging before and diverging afterward. While the converging period coincides with a large part of structural transformation periods in Caselli and Coleman II [2001], the diverging period coincides with the period of accelerating skill biased technological change. It is important to note that here we include all physical capital in states; if we separately investigate capital in the manufacturing sector and the non-manufacturing sector, we can find that the CV of capital in the manufacturing sector declines dramatically throughout the period.[2] In contrast, the same series for the

[2]As Caselli and Coleman II [2001] note, labor productivity converge in manufacturing sector across U.S regions is driven by structural transformation. Although another side of structural transformation, i.e., the rising service sector, can explain the divergence after 1975, in this paper we focus on the

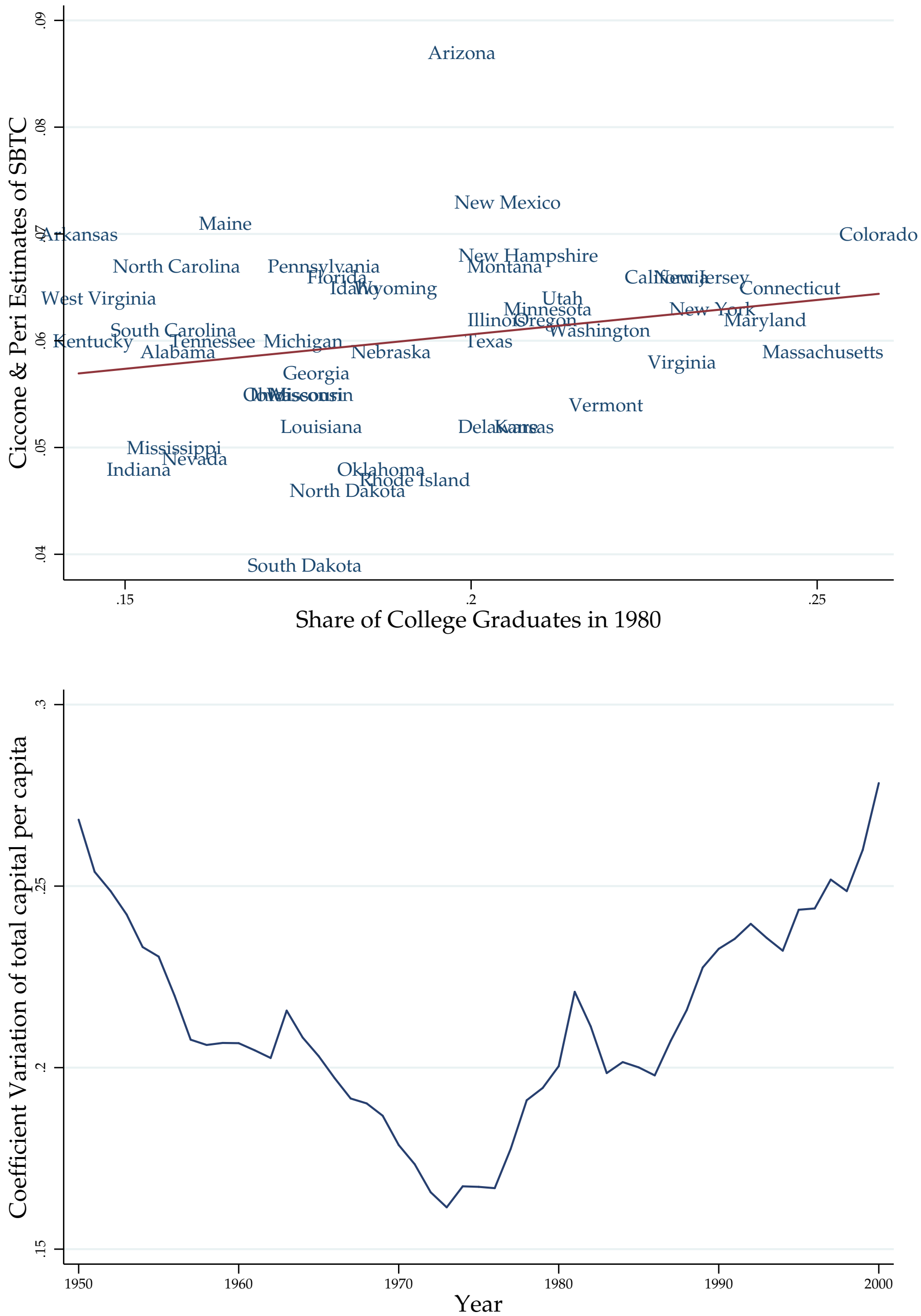


Figure 1-3: Capital, Skill-Biased Technological Change, and Initial Skilled Labor Distribution: Top panel plots Ciccone & Peri's Estimates of Skill Biased Technological Change against College Share in 1980. Arizona is potentially an outlier, an OLS regression including Arizona shows a positive correlation, with p value equals 0.11, Bottom panel plots the time series of coefficient variation of physical capital across states. Note that for both panels, only 48 contiguous U.S. states are included.

non-manufacturing sector exhibits a similar pattern to total physical capital. This information can be found in Appendix 1.A. According to a wide range of growth models, this evidence indicates entirely different pattern of convergence before and after 1975. We further study this issue in the next subsection.

2.4. Decomposing Regional Convergence or Divergence. In this subsection, we first check whether the regions in the U.S. are converging or diverging. It has been widely documented that the regions have been converging, at least in some time period in history, e.g. Barro and Sala-I-Martin [1991] and Caselli and Coleman II [2001]. As the latter showed, the U.S. states were significantly converging from 1870-1990. In 1980s, however, there was slight divergence between regions. To see whether that convergence between states might have changed both quantitatively and qualitatively, the subperiod of 1940-1970 and 1980-2010 are separately investigated. Moreover, we decompose the rate into different components to see which one is the largest contributor to the economic change.

To keep our study comparable to previous studies, we employ the method developed by Caselli and Coleman II [2001]. We divide the U.S. into two regions, a high skill endowment region, North N and a low skill endowment region, South S. The North region consists of states which are consistently in the top half in terms of college graduates share from 1980 through 2010, while the South region consists of states consistently among the bottom half.[3] We first define the relative wage gap between north and south:

$$\frac{w_{N,t} - w_{S,t}}{w_t} \tag{2.1}$$

endogenous skill biased technological change as our explanation, because of the facts displayed in previous subsections.

[3]North regions consists states: California, Colorado, Connecticut, Delaware, Illinois, Kansas, Maryland, Massachusetts, Minnesota, Montana, New Hampshire, New Jersey, New York, Oregon, Vermont, Virginia, Washington. South regions consists states: Alabama, Arkansas, Idaho, Indiana, Iowa, Kentucky, Louisiana, Michigan, Mississippi, Missouri, Nevada, North Dakota, Ohio, Oklahoma, South Carolina, South Dakota, Tennessee, West Virginia, Wisconsin. The geographical distribution of the states is shown in Figure 1-6 in Appendix 1.B

Table 1-1: Decomposition of Regional Convergence or Divergence in Subperiods

Period	Total (1)	Reallocation (2)	Between Group (3)	Within Group (4)
1940-1970	0.216	-0.017	0.007	0.225
	100%	-7.9%	3.2%	104.2%
1980-2010	-0.142	-0.038	-0.023	-0.082
	100%	26.8%	16.2%	57.7%

where w_t is the economy wide average wage including the North region, South region and the rest states in the country in period t, $w_{i,t}$ is the average wage in region $i \in \{N, S\}$. Based on this measure we can define the convergence rate between the North and the South by:

$$\frac{w_{S,t} - w_{N,t}}{w_t} - \frac{w_{S,t-1} - w_{N,t-1}}{w_{t-1}} \tag{2.2}$$

The convergence rate for period 1940 to 1970 was 0.216, and -0.142 for the period 1980 to 2010. Negative rate of convergence indicates that in the corresponding period, the regions were diverging rather than converging. Our finding is in line with Ganong and Shoeg [2013], but different in that they name the period from 1980 a slowing-down of convergence period. Moreover, we confirm Caselli and Coleman II [2001]'s result that for the period 1940 to 1970, a subperiod of 1940 to 1990, the regions were converging.

To further decompose the convergence rate, we rewrite the average wage of region $i \in \{N, S\}$ in year t as

$$w_{i,t} = w^H_{i,t} \cdot l^H_{i,t} + w^L_{i,t} \cdot (1 - l^H_{i,t}) \tag{2.3}$$

where $w_{i,t}$ stands for the average wage in region i in period t, $w^H_{i,t}$ is the average wage of skilled labor in region i at year t, $w^L_{i,t}$ the average wage of unskilled labor the same region, $l^H_{i,t}$ the share of skilled labor employed in region i. Combining this expression of $w_{i,t}$ with (2.3), the convergence rate is decomposed into three parts.

Appendix 1.B shows the detail of the decomposition procedure. In Table 1-1, we find that total convergence was almost mathched by within group convergence, that is, convergence of $w^H_{S,t}$ to $w^H_{N,t}$ and of $w^L_{S,t}$ to $w^L_{N,t}$. In contrast, convergence of w^L to w^H, contributed much less, which is because the wage gap between skilled labor and low skilled labor barely narrowed. Moreover, reallocation contributed negatively to the convergence, since low skilled labor was reallocating faster to high skilled labor sectors in the North that payed higher wages. As a matter of fact, this process reduced convergence.

In the subperiod of 1980 to 2010, all the three parts contributed negatively to convergence, or in other words, they contributed positively to the divergence between North and South. The within group component is still the most notable component, but in the opposite direction, which indicates that the wage gap between people has been widened even if they have the same skill level. As in the first subperiod, the reallocation component makes the regions diverge, but to a greater extent. Finally, the widening wage gap between skilled labor and unskilled labor contributed a significant part (16.2%) to the overall North-South divergence.

In summary, we find a strong pattern of convergence between North and South regions in the subperiod of 1940-1970, while other factors contribute to the convergence positively, the more concentrated distribution of skilled labor contributed negatively. Using the same method we find instead strong divergence between North and South regions in the sub period of 1980-2010, all three factors significantly contributed to the divergence.

3. Model

To simplify the analysis we assume there are two regions in the economy, namely the north (N) and the south (S), where the north has more skill endowment than the south at least initially. This setup is similar to Caselli and Coleman II [2001]. The firms and agents nevertheless do not make decisions simultaneously, instead they make decisions sequentially in every period. We first introduce the very basic model, then introduce the arrival of new technology that is skill biased to see what will happen in the new equilibrium.

3.1. Production. To keep the analysis simple and tractable, we assume there are three inputs in the production function, skilled labor H and unskilled labor L, as well as a technology-embedded capital K, which can possibly affect the efficiency of local skilled labor. However we do not model it here. We adopt a Constant Elasticity of Substitution (CES) production function in the spirit of Krusell, Ohanian, Ríos-Rull, and Violante [2000],

$$Y_{i,t} = F(L_{i,t}, H_{i,t}, K_{i,t}) = \left[\lambda_u \cdot L_{i,t}^{\sigma} + (1-\lambda_u) \cdot \left((1-\lambda_k) H_{i,t}^{\rho} + \lambda_k \cdot K_{i,t}^{\rho}\right)^{\frac{\sigma}{\rho}}\right]^{\frac{1}{\sigma}}. \quad (3.1)$$

Note that i specifies region, the parameter λ_u and λ_k govern the income shares, and are assumed to be constant across time, parameter $1/(1-\rho)$ governs the elasticity of substitution between skilled labor and capital, and $1/(1-\sigma)$ governs the elasticity of substitution between unskilled labor and the capital-skill composite. Moreover, we assume that $\rho < \sigma < 1$ which indicates capital is more complementary to skilled labor than unskilled labor.

We also assume that firms are identical within a given region, and the local markets are completely competitive, in the sense that the representative firm takes the local wages w_i^H and w_i^L, the supplies of labor, H_i and L_i as given. Then the representative firm's problem becomes

$$\max_{K_{i,t}} p_t \cdot Y_{i,t} - w_{i,t}^H \cdot H_{i,t} - w_{i,t}^L \cdot L_{i,t} - r_t \cdot K_{i,t}. \quad (3.2)$$

where p_t denotes the price of the tradable consumption good that can be produced in either of the regions and can be traded without any cost, and r_t denotes the capital rental cost, which also common over the country. Since the market is competitive, the profit for the firms are identically zero. The wages are given by the marginal productivity of each type of labor, and the skill premium can be defined as the ratio of these two wages,[4]

$$\kappa_{i,t} \equiv \frac{w_{i,t}^H}{w_{i,t}^L} = \frac{(1-\lambda_u)(1-\lambda_k)}{\lambda_u} \cdot \frac{\left[(1-\lambda_k)H_{i,t}^{\rho} + \lambda_k K_{i,t}^{\rho}\right]^{\frac{\sigma}{\rho}-1} H_{i,t}^{\rho-1}}{L_{i,t}^{\sigma-1}}, \quad \forall \rho \neq 0 \tag{3.3}$$

Apparently, given other factors unchanged, $\kappa_{i,t}$ increases in the capital-skill ratio $(K_{i,t}/H_{i,t})$, and decreases in skilled-unskilled ratio $(H_{i,t}/L_{i,t})$.[5] The local equilibrium level of the capital stock is then endogenously chosen by the local firms given local labor supply, wages, with the nationwide interest rate and depreciation rate. This mechanism is similar to Beaudry, Doms, and Lewis [2010] in the sense that the (technology embedded) capital is endogenously determined, but different in that in their model the firms decide whether or not to adopt the new technology-a discrete choice. Furthermore, we assume that the interest rate and depreciation rate are constant through time and that their sum equals the marginal product of capital.

In the literature of skill-biased technological change, authors usually distinguish it from capital-skill complementarity, which is reasonable if the parameters governing these two processes can be identified. However, we do not distinguish them, since in our model the technology is embedded in the new capital. Hence, an increase of capital per worker ratio is seen as skill biased technological change.

3.2. Households. Households consume final goods and local housing services to obtain utility. We set the instantaneous utility function as:

$$u_i^{\ell}(t) = \frac{[(c_{i,t}^{\ell})^{\alpha_c}(h_{i,t}^{\ell})^{\alpha_h}]^{1-\theta}}{1-\theta} \tag{3.4}$$

[4]As $\rho \to 0$, the skill premium is defined as:

$$\kappa_{i,t} \equiv \frac{w_{i,t}^H}{w_{i,t}^L} = \frac{(1-\lambda_u)(1-\lambda_k)}{\lambda_u} \cdot \left(\frac{K_{i,t}}{H_{i,t}}\right)^{\sigma\lambda_k} \cdot \left(\frac{H_{i,t}}{L_{i,t}}\right)^{\sigma-1}$$

[5]See Krusell, Ohanian, Ríos-Rull, and Violante [2000], Burstein, Cravino, and Vogel [2013] and Parro [2013] for the derivations.

where $c^{\ell}_{i,t}$ is the consumption of normal tradable goods for type $\ell \in \{H, L\}$ labor at time t, and $h^{\ell}_{i,t}$ is the consumption of housing services. We assume $\alpha_c + \alpha_h = 1$ for simplicity. This utility function is similar to Davis and Heathcote [2005], except that we do not contain leisure in the utility function since the labor supply is not our focus in this paper.[6] Finally, θ is the risk aversion coefficient. For every type of agent, her problem is to maximize the life time utility, that is,

$$\max_{\{c^{\ell}_{i,t}, h^{\ell}_{i,t}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \cdot \frac{[(c^{\ell}_{i,t})^{\alpha_c}(h^{\ell}_{i,t})^{\alpha_h}]^{1-\theta}}{1-\theta} \tag{3.5}$$

subject to

$$p_t \cdot c^{\ell}_{i,t} + q_{i,t} \cdot h^{\ell}_{i,t} = w^{\ell}_{i,t-1} \tag{3.6}$$

where β denotes the discount factor, $q_{i,t}$ denotes the housing rents at region i, $w^{\ell}_{i,t}$ denotes the wage in region i of a type ℓ agent who inelastically supplies one unit of labor in the market. Note that households take the wage in period $t-1$ as given when they decide which region to live in, as we introduced above. The first order conditions of this problem gives the following intratemporal equation:

$$\alpha_c \cdot w^{\ell}_{i,t-1} = p_t \cdot c^{\ell}_{i,t}, \tag{3.7}$$

$$(1-\alpha_c) \cdot w^{\ell}_{i,t-1} = q_{i,t} \cdot h^{\ell}_{i,t} \tag{3.8}$$

Moreover, we assume that the cost to move among regions is proportionate to the agent,s current income level, $\tau \cdot w^{\ell}_{i,t}$. The role of migration cost will be fully discussed in the sections below. However, if there is no migration cost, it is easy to check that skill premium $\kappa_{i,t}$ will be equalized across the two regions, that is, $\kappa_{N,t} = \kappa_{S,t}$. From

[6]This utility function also gives a unitary elasticity of housing expenditure. Recent study show that housing is an inferior good, hence the elasticity with respective to income is less than 1. See Black, Kolesnikova, and Taylor [2009] for a discussion, who also suggest that the income elasticity of housing expenditure is less than 1. However, this difference will not change our qualitative result in the model, and as Davis and Heathcote [2005] show the housing expenditure out of income is relatively constant, indicating that this.

(3.3) it is easy to find that, in the region with a higher $H_{i,t}$, the capital intensity is higher, consistent with the empirical facts in section 2.

3.3. Housing Service Production. In the literature, it is widely documented that the housing price difference across different areas has been increasing, which is partly due to regulation of the residential housing supply, and partly due to the fact that land close to cities is limited. Hence housing supply is usually not modeled elastically (e.g., Desmet and Rossi-Hansberg [2013]; Ganong and Shoeg [2013]; Van Nieuwerburgh and Weill [2010]). In line with these studies, we introduce the housing service supply curve to generate this difference so that we can introduce an implicit friction in labor markets and housing markets. The supply curve reads

$$h_{i,t} = (Y^h_{i,t})^\gamma \tag{3.9}$$

where $Y^h_{i,t}$ is what paid to the housing sector in i in the form of final goods locally produced; γ is the supply elasticity. When $\gamma = 0$, the housing service is supplied perfectly inelastically everywhere, in which case we can normalize it to one unit. If $\gamma = \infty$, the housing supply plays no role in agents migration decision; which would be ruled out in our analysis. Following a sizable literature, we assume $\gamma < 1$, which is reasonable and necessary to our analysis.

3.4. Equilibrium. The equilibrium consists of wages $\{w^\ell_{i,t}\}^{\ell=L,H}$ for $i = N, S$, housing service price $\{q_{i,t}\}_{i=N,S}$, and interest rate r_t, such that: (*1*) Given the wage and prices, the agents choose amount of normal goods, and housing services to maximize their temporary utility in (3.5), (*2*) Given the wage $\{w^\ell_i\}^{\ell=H,L}_{i=i,j}$, and the interest rate r_t, the local representative firm solve the problem in (3.2), (*3*) Labor market clears: $L_{N,t} + L_{S,t} = L_t$, $H_{N,t} + H_{S,t} = H_t$, (4) Housing market clears: $h^L_{i,t} + h^H_{i,t} = h_{i,t}$.

Since the production function in (3.1) is homogeneous of degree one, we can treat all the variables in per capita terms. Hence L_i and H_i corresponds to the fraction of unskilled and skilled labor, hence $L_i + H_i = 1$. Comparing the North and the South, $H_N > H_S$, hence the marginal productivity of H is higher in North than in South under any same level of capital K. Because of the exist of migration cost the utility of each type is not necessarily the same for both regions. However, this migration cost can generate skill premia differentials across regions in the equilibrium.

4. Arrival of New Skill-Biased Capital

In this section we describe how will the arrival of a new type of capital affects the equilibrium, especially the wages and the wage gap between the two regions. We assume that the newly developed technology features a higher level of $(1 - \lambda_u)$, or in other words a lower level of λ_u. To show intuitively the effect of the arrival of new technology, we first approximate the equation (3.3) as[7]

$$log(\kappa_{i,t}) \approx \lambda_k \frac{\sigma - \rho}{\rho} \left(\frac{K_{i,t}}{H_{i,t}}\right)^{\rho} + (1-\sigma) log\left(\frac{L_{i,t}}{H_{i,t}}\right). \tag{4.1}$$

Upon the arrival of new technology with a smaller λ_u, the new technology will demand more skilled labor under the same factor prices. By the equation above, it is easy to check that skill premium $\kappa_{i,t}$ will be driven up more quickly in the skill-scarce region. Hence the new technology is more likely to be adopted at the North, or neither of the regions will adopt the new technology. See the Appendix for the details.

Once the new technology is adopted, it will compete with old technology in the labor market for skilled labor, hence the ratio $L_{i,t}/H_{i,t}$ will increase, pushing up the local skill premium. Nevertheless, when $H_{i,t}$ is too high such that $L_{i,t}/H_{i,t} \to 0$, then despite the fact that the new skill-biased technology will be adopted, the skill

[7] Correspondingly, when $\rho \to 0$ it is defined as

$$log(\kappa_{i,t}) \approx \Xi_{i,t} + \sigma\lambda_k \cdot log\left(\frac{K_{i,t}}{H_{i,t}}\right) + (\sigma - 1) \cdot log\left(\frac{H_{i,t}}{L_{i,t}}\right).$$

where $\Xi_{i,t} = log(1 - \lambda_{u,i}) + log(1 - \lambda_u) + log(\lambda_{u,i})$ differs across regions.

premium may start to decline. In this case, the South region will catch up to the North region, hence convergence re-emerges.

5. Data

Several primary data sets will be employed in the empirical estimation, namely, Census of Population (CP), Current Population Survey, a regional data set from Bureau of Economic Analysis (BEA), and physical capital estimates from Turner, Tamura, Schoellman, and Mulholland [2011] (TTSM, hereafter).

BEA data provides employment, wage, and output at the state level. TTSM provides the estimates of physical capital for states at an annual frequency. Employing CP and CPS data, we will be able to construct the wages and the labor shares of skilled and unskilled labor, based on which we are also able to construct the wage bill ratio between these two groups. CP data is of decennial frequency, while CPS offers annual data. The former, however, covers a large percentage of the population, hence giving a more precise estimates of the variables we need. Nevertheless, both data set will be employed to estimate the model.

6. Quantitative Assessment

In this section, we first calibrate the aggregate production function for each region, North and South, like Caselli and Coleman II [2002, 2006] but in the spirit of León-Ledesma, McAdam, and Willman [2010], we do not estimate it directly. Moreover, we implement a couple of counterfactual experiments to show the factors that underly the divergence.

6.1. Calibration. The regional aggregate production function has two distinguishing features to be identified. In this subsection we use the data of yearly frequency from CPS. All introduction to the construction of variables can be found in the Appendix 1.A. We use the region instead of state because of the noisiness of a representative sample at state level in CPS data. To proceed, we first rewrite the production function described in section 3, as

$$y = \left[(\phi^l_{i,t}L_{i,t})^\sigma + \left((\phi^k_{i,t}K_{i,t})^\rho + (\phi^h_{i,t}H_{i,t})^\rho\right)^{\sigma/\rho}\right]^{1/\sigma} \tag{6.1}$$

We modify the production function in two ways. First, we introduce parameters governing the factor efficiencies, $\phi^l_{i,t}$, $\phi^h_{i,t}$ and $\phi^k_{i,t}$ indicating the efficiencies of unskilled labor, skilled labor and capital, respectively. Second, we drop the distributive parameters, since we cannot identify them jointly with the efficiency parameters. Our aim in this section is to back out the efficiency parameters. To do so, we use three equations. The first is the modified production function in (6.1). The other two are as follows:

$$\begin{aligned} r_t = &\left[(\phi^l_{i,t}L_{i,t})^\sigma + \left((\phi^k_{i,t}K_{i,t})^\rho + (\phi^h_{i,t}H_{i,t})^\rho\right)^{\sigma/\rho}\right]^{1/\sigma} \\ &\times \left((\phi^k_{i,t}K_{i,t})^\rho + (\phi^h_{i,t}H_{i,t})^\rho\right)^{\sigma/\rho-1}(\phi^k_{i,t}K_{i,t})^{\rho-1}\phi^k_{i,t} \end{aligned} \tag{6.2}$$

and

$$\frac{w^H_{i,t}}{w^L_{i,t}} = \frac{\left[(\phi^k_{i,t}K_{i,t})^\rho + (\phi^h_{i,t}H_{i,t})^\rho\right]^{\sigma/\rho-1} \cdot (\phi^h_{i,t}H_{i,t})^{\rho-1} \cdot \phi^l_{i,t}}{(\phi^l_{i,t}L_{i,t})^{\sigma-1} \cdot \phi^h_{i,t}}. \tag{6.3}$$

With ρ and σ known, based on these three equations, we can identify three unknowns.[8] However, before we estimate the efficiency parameters, we have to fix values for σ and ρ. We calibrate values from the literature. According to Caselli and Coleman II [2002], estimates of σ and ρ are 0.25 and 0.25 respectively. Solving the system of equations year by year yields the estimates of $\phi^\ell_{i,t}$ for each type of agent in each year. The results show that $log(\widehat{\phi}^L_{S,t})$ is persistently higher than $log(\widehat{\phi}^L_{N,t})$, which indicates that the South has a comparative advantage in unskilled labor efficiency, while $log(\widehat{\phi}^H_{N,t})$ is persistently higher than $log(\widehat{\phi}^H_{S,t})$, indicating that the North has a higher efficiency of skilled labor. Figure 1-4 plots the time series of $log(\widehat{\phi}^H_{i,t}/\widehat{\phi}^L_{i,t})$. Apparently, although the skill biased technological change is nationwide, in the North

[8] Caselli and Coleman II [2002, 2006] offer analytical solutions to this system of equations.

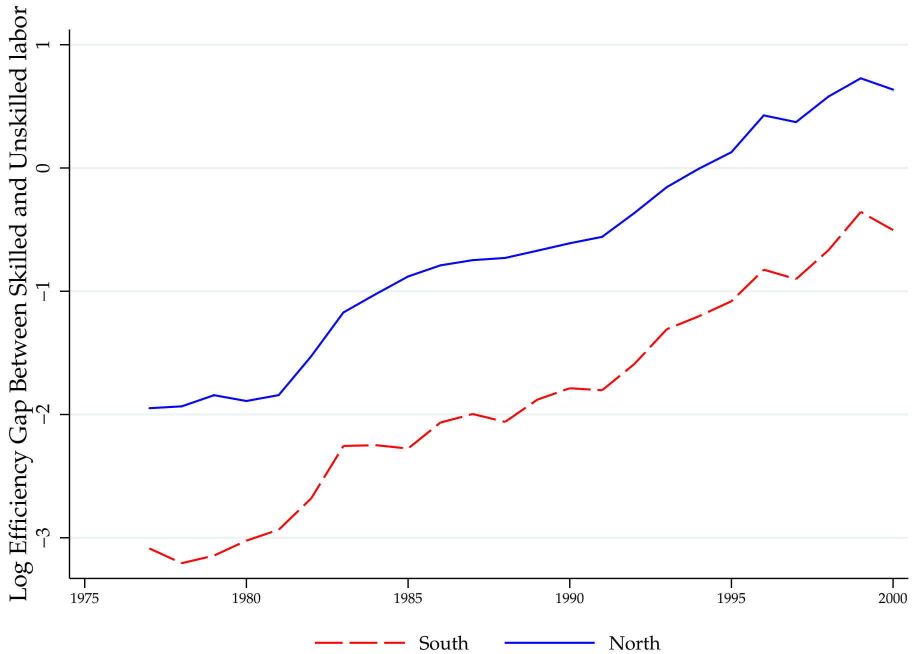


Figure 1-4: Time series of $log(\widehat{\phi}^{H}_{i,t}/\widehat{\phi}^{L}_{i,t})$. $\widehat{\phi}^{\ell}_{i,t}$ is the estimates of efficiency of type ℓ labor in region i. Blue solid line stands for the North region, red dashed line stands for the South region.

the relative efficiency of skilled labor is persistently higher throughout the period of interest.

6.2. Counterfactual. Based on the estimates of the function, we can now conduct a couple of counterfactual experiments to show the quantitative importance of underlying mechanisms.

6.2.1. *The Effect of The Labor Efficiency Differential.* First, we assess the quantitative effect of the labor efficiency differential on the divergence. In the years after 1977, we suppose that the labor composition never changed for both of the regions. Then we calculate the output level for both of the regions based on the given production function. Then we can calculate the variable described in (2.1). The result shows that divergence increased by 0.13, which is quite close to the numbers in Table 1-1, indicating that the nationwide technological change has favored the North, where skilled labor was relatively abundant in 1976.

6.2.2. *Composition effects.* We now check what would happen if the North had the same labor composition as the South. To do so, we replace the college graduates share in North by the number from South in each year. We find that there will be still divergence from 1977 to 2000, though quantitatively small: the number is 0.03. This result indicates that even if both of the regions have exactly the same labor force composition, income still diverges. The small amount may come from the fact that the technology lagged but diffused quickly to the South. Another way around, that is, replacing the college graduates share in South by the number from North, yields the same number, 0.03.

7. Alternative Explanations

7.1. Knowledge Spillover. One competing explanation to endogenous skill-biased technology adoption is knowledge spillover and agglomeration. Agglomeration has been evidenced to exist and to bring productivity advantage to states (Ciccone and Hall [1996]). Moreover, the knowledge spillover effect is higher for skilled labor (see Glaeser and Maré [2001]). However, college graduates existed before 1975. Under the hypothesis of knowledge spillover, both the economic divergence and the dispersion of physical capital should have existed even before 1975. We are not totally ruling out spillover effect, instead we are assuming that the spillover effect may exist at the city level, but not state or regional level.

7.2. Capital Taxation differential. A second possible explanation for the dispersion in skilled labor ratio and in physical capital per worker is the capital tax rate differential.[9] For instance, in the state of Delaware, the capital tax rate is far below the average, which attracts many companies to establish plants there, capital intensive firms in particular. A higher level of capital can increase labor productivity,

[9]Thanks to Nic Tideman for leading me to this possible explanation.

which whereafter attracts more labor into the state. As a matter of fact, we find in the data that Delaware has one of the highest capital-labor ratios among all the U.S states.

In a more dynamic way, this capital tax rate differential has difficult explaining why the capital per worker ratio dispersed after 1975, since Delaware has been corporate-friendly for more than one hundred years. If the this explanation is to work for the period after 1975, it must be combined with the change in the nature of capital around 1975. Therefore, the capital tax differential cannot be the sole explanation for the divergence after 1975.

7.3. Structural Transformation. As in Caselli and Coleman II [2001], structural transformation is the driving force for regional convergence before 1980. Two mechanisms underly this explanation. The first mechanism is that low-paid workers in the agricultural sector were reallocated to the highly-paid manufacturing sector, which drove down the wage differential between the two sectors. The Southern region's catchup to the Northern region's manufacturing sector was the other driving force. As Caselli and Coleman II [2001] find, the first reason is robust even if we take into account the skill composition in each sector.

Since 1975 or even earlier, a new version of structural transformation emerged. The sectoral composition was changing notably, generating the relative decline of the manufacturing sector, and rise of the service sector. As documented above and in the Appendix, capital intensity in the non-manufacturing sector has dispersed rather than equalized. With the hypothesis that the service sector is more skill intensive than the manufacturing and agricultural sectors, the new version of structural transformation can be a proper explanation of divergence.

The question of what has been driving the dispersion of the service sector is then important. For example, technological change may be more skill-biased or skill-complementary in the service sector. Buera and Kaboski [2012] document a coincidence of a rising skill premium and a rise of the service sector, and they provide a channel to link them. However, the timing of skill premium in their study is not consistent with what others have found.[10] However, we cannot separately identify these two mechanisms based on our theory and data set. Still, the combination of structural transformation and endogenous skill-biased technological change is a promising explanation for the divergence among U.S. states after 1975.

8. Concluding remark

In this paper I document that U.S. states have been diverging for the last three decades. The decomposition analysis of divergence strongly suggests an endogenous skill biased technological change. Three channels through which the divergence works are supported by our empirical evidence. Empirically, we find that first, the skilled labor distribution has become concentrated; second, both the wages and skill premia are higher in states with higher skilled labor supply; third both the within-skill-group wage gap and labor share differential have widened.

Motivated by these facts, I build an endogenous skill biased technological change model to explain the combination of these facts. The model shows that the new technology will be first adopted in states with the highest skilled labor supply and hence increase the skill premium most there. Moreover, the migration cost may lead to a utility differential and hence relative wage differential. Therefore, in the transition of the economy, the skill premium is higher in the skill abundant states. Finally, our model predicts that the economy will eventually converge provided the share of skilled labor is converging to some limit.

Quantitative assessment is carried out to see what source is the most important. I find that the relative efficiency of skilled labor is persistently higher in the skilled labor abundant region from 1977 onwards. The counterfactual experiment then shows that the endogenous skill biased technological change is the main driving force of

[10]Both Krusell, Ohanian, Ríos-Rull, and Violante [2000] and Katz and Murphy [1992] show that skill premium started to increase after 1970.

regional divergence from 1977 to 2000. The skill composition differential plays a significant but quantitatively smaller role in driving regional divergence.

1.A. Data

Individual and household data. The Current Population Survey (CPS) provides detailed information on the individual and household level. Based on it we construct labor inputs and prices at the state level from 1963 to 2011. CPS data provides information on earnings and weeks worked in the calendar years preceding the survey year. To calculate the hourly wage, I use the usual hours in a typical week in the last year (*uhsweek*) and intervalled weeks worked last year (*wkswork*2). Since the CPS only provides the exact number of weeks worked (*wkswork*1) last year after 1976, to obtain longer time series data for each state, I use the mean of weeks worked (*wksweek*1) from 1976 to 2011 to proxy the weeks worked from 1963 to 1975.[11] Using this variable, we can then compute the hourly wage by dividing wage income of last year by the total hours worked last year.

$$l_{i,t-1} = h_{it} wk_{i,t-1} \tag{1.A.1}$$

$$w_{i,t-1} = \frac{y_{i,t-1}}{l_{i,t-1}} \tag{1.A.2}$$

where $wk_{i,t-1}$ is the weeks worked in year $t-1$ by person i, $w_{i,t-1}$ is the hourly wage, $l_{i,t-1}$ is the totally hours worked by person i in year $t-1$, $h_{i,t}$ is the usual hours worked per week las year. The labor input for each state or region is then computed by the following two equations:

$$L^j_{m,t-1} = \frac{\sum_{i\in m} l_{i,t-1} \cdot \lambda_{it} \cdot \chi_{\{i\in j\}}}{\sum_{i\in m} \lambda_{it} \cdot \chi_{\{i\in j\}}} \tag{1.A.3}$$

$$w^j_{m,t-1} = \frac{\sum_{i\in m} w_{i,t-1} \lambda_{it} \cdot \chi_{\{i\in j\}}}{\sum_{i\in m} \lambda_{it} \cdot \chi_{\{i\in j\}}} \tag{1.A.4}$$

$L^j_{m,t-1}$ stands for the average hours worked by skill group j in year $t-1$ in state m, where as $w^l_{m,t-1}$ is the hourly wage rate. $\chi_{\{\cdot\}}$ is an indicator function. $\lambda_{i,t}$ is the sampling weight provided by CPS, here I use "*earnwt*" as suggested by CPS, moreover,

[11] As a matter of fact, the distribution of weeks worked in each interval is rather persistent, both the means and standard deviations within each interval change very slightly for different periods.

I use "*incwage*" for yearly wage. The methods we employ here is fairly similar to those used in the literature, e.g., Katz and Murphy [1992], Krusell, Ohanian, Ríos-Rull, and Violante [2000], Davis, Fisher, and Whited [2010], etc.

For the decennial Census data from 1940 to 2000, 5% samples are employed. Since these samples have equal weights to all the observations, it is not necessary to use *earnwt* or *perwt* to calculate the state representative variables. For the year 2010, since 5% sample is not yet available, we use the 3% American Community Survey (ACS) sample instead, and I follow the same procedure as employed for the CPS data.

Data on Capital. The data on capital of the state level is taken from Turner, Tamura, Schoellman, and Mulholland [2011]. Interested readers should refer to their paper for the estimation procedure and the much more detailed micro level data. In Figure 1-5, we plot the the time series of CV of capital per capita for the manufacturing and non-manufacturing sectors. Note that total capital excludes land and non-manufacturing capital excludes capital from the agricultural sector. The persistent convergence of manufacturing is consistent with the explanation of U.S. regional convergence by Caselli and Coleman II [2001] in terms of structural transformation. Moreover, the pattern of unconditional convergence in the manufacturing sector and divergence in the non-manufacturing sector is consistent with Rodrik [2013] in a context across countries. However, this pattern within a single country across regions is little documented. One thing worth mentioning is that the size of manufacturing is quantitatively small, with the highest percentage of total capital below 17%, while the non-manufacturing sector excluding agricultural has its lowest percentage of total capital above 73%. Therefore, the diverging force of the non-manufacturing sector dominates through the period from 1980 to 2000.

Figure 1-5: Time Series of Coefficient of Variation of Capital Across States: The top panel is for manufacturing sector and the bottom panel is non-manufacturing sector. Data Source: Turner, Tamura, Schoellman, and Mulholland [2011]. Only contiguous states are included.

1.B. Decomposing Regional Convergence

The average wage in region i in year t and be rewritten as:

$$w_{i,t} = (w_{i,t}^H - w_t^H)l_{i,t}^H + (w_{i,t}^L - w_t^L)l_{i,t}^L + w_t^H l_{i,t}^H + w_t^L l_{i,t}^L. \tag{1.B.1}$$

Based on (1.B.1), the wage gap between two regions can then be rewritten as:

$$\begin{aligned}\frac{w_{S,t} - w_{N,t}}{w_t} = & \frac{w_{S,t}^H - w_t^H}{w_t} \cdot l_{S,t}^H + \frac{w_{S,t}^L - w_t^L}{w_t} \cdot l_{S,t}^L \\ & - \frac{w_{N,t}^H - w_t^H}{w_t} \cdot l_{N,t}^H - \frac{w_{N,t}^L - w_t^L}{w_t} \cdot l_{N,t}^L \\ & + \frac{w_t^L - w_t^H}{w_t} \cdot (l_{S,t}^L - l_{N,t}^L).\end{aligned} \tag{1.B.2}$$

Denote $\delta_{i,t}^j = (w_{i,t}^j - w_t^j)/w_t$ for $i \in \{N, S\}$ and $j \in \{H, L\}$. Moreover, denote $\delta_{i,t} = (w_{i,t}^L - w_{i,t}^H)/w_t$ and $\delta_t = (w_t^L - w_t^H)/w_t$. Then the first differences of wage gap between North and south can be written as:

$$\frac{w_{S,t} - w_{N,t}}{w_t} - \frac{w_{S,t-1} - w_{N,t-1}}{w_{t-1}} = \underbrace{\Delta\delta_{S,t}^L \cdot \bar{l}_{S,t}^L + \Delta\delta_{S,t}^H \cdot \bar{l}_{S,t}^H - \Delta\delta_{N,t}^L \cdot \bar{l}_{N,t}^L - \Delta\delta_{N,t}^H \cdot \bar{l}_{N,t}^H}_{\text{Within Group}} \tag{1.B.3}$$

$$+ \underbrace{\bar{\delta}_{S,t} \cdot \Delta l_{S,t}^L - \bar{\delta}_{N,t} \cdot \Delta l_{N,t}^L}_{\text{Labor Reallocation}} + \underbrace{\Delta\delta_t \cdot (\bar{l}_{S,t}^L - \bar{l}_{N,t}^L)}_{\text{Between Group}} \tag{1.B.4}$$

where Δ denotes the first differences for the corresponding variables, top bar denotes the mean of corresponding variables across two period.

1.C. Proofs

Capital increase upon the new technology. To show the effect of the arrival of new technology, we begin with an extreme case, in which the North is fully occupied by skilled labor while the South is fully occupied by unskilled labor. The production function in North is then

$$Y_{N,t} = \left[(1-\lambda_u)\cdot\left((1-\lambda_k)+\lambda_k\cdot K_{N,t}^{\rho}\right)^{\frac{\sigma}{\rho}}\right]^{\frac{1}{\sigma}}. \tag{1.C.1}$$

and the production function in the South is

$$Y_{S,t} = \left[\lambda_u + (1-\lambda_u)\cdot\left(\lambda_k\cdot K_{S,t}^{\rho}\right)^{\frac{\sigma}{\rho}}\right]^{\frac{1}{\sigma}}. \tag{1.C.2}$$

Once the new technology arrives with a smaller λ_u, the marginal product of capital in the North becomes

$$\frac{\partial\tilde{Y}_{N,t}}{\partial K_{N,t}} = \left(\frac{1-\tilde{\lambda}_u}{1-\lambda_u}\right)^{\frac{1}{\sigma}}\cdot\frac{\partial Y_{N,t}}{\partial K_{N,t}} \tag{1.C.3}$$

Therefore, if capital stock per capita in the North does not change, marginal product of capital will increase by $\frac{1}{\sigma}\cdot\Delta\log(1-\lambda_u)$. However, in the South,

$$\tilde{Y}_{S,t} = (1-\tilde{\lambda}_u)^{\frac{1}{\sigma}}\cdot\left[\frac{\tilde{\lambda}_u}{1-\tilde{\lambda}_u}+\left(\lambda_k\cdot K_{S,t}^{\rho}\right)^{\frac{\sigma}{\rho}}\right]^{\frac{1}{\sigma}} \leq (1-\tilde{\lambda}_u)^{\frac{1}{\sigma}}\cdot\left[\frac{\lambda_u}{1-\lambda_u}+\left(\lambda_k\cdot K_{S,t}^{\rho}\right)^{\frac{\sigma}{\rho}}\right]^{\frac{1}{\sigma}}$$

hence

$$\frac{\partial\tilde{Y}_{S,t}}{\partial K_{S,t}} \leq \left(\frac{1-\tilde{\lambda}_u}{1-\lambda_u}\right)^{\frac{1}{\sigma}}\cdot\frac{\partial Y_{S,t}}{\partial K_{S,t}} \tag{1.C.4}$$

Compare (1.C.3) with (1.C.4), it is easy to find that upon the arrival of new technology, if the capital stock does not change, the marginal product of capital increase in the North increase disproportionately more, indicating a disproportionately more increase in capital stock after the firms make decision.

Change in Skill Premium. By (3.3) and (4.1), without migration, both increases in $K_{i,t}$ and $(1-\lambda_u)$ lead to an increase in $\kappa_{i,t}$. So if both regions adopt the new technology, skill premiums are going to increase in both. Nevertheless, since $K_{N,t}$ increase disproportionately more than $K_{S,t}$, and hence $K_{N,t}/H_{N,t}$ than $K_{S,t}/H_{S,t}$, $\kappa_{N,t}$ increases more than $\kappa_{S,t}$. Note that under $\sigma > \rho$, either $\rho \geq 0$ or $\rho < 0$ will lead to this result, that is, we do not need either type of labor is complementary to capital but L is more substitutable than H with capital. In conclusion, skill premium increases more in the North than in the South, consistent with Beaudry, Doms, and Lewis [2010].

Migration and relation between local supply of skilled labor and skill premium. First, we check that if there is no migration cost, skill premium is equalized between North and South. To see this, we first check the utility function in (3.4) and derived intratemporal equations in (3.7) and (3.8). Combining these equations, and rearranging it yields

$$\kappa_{i,t-1} = \frac{w^H_{i,t-1}}{w^L_{i,t-1}} = \left(\frac{u^H_{i,t}}{u^L_{i,t}}\right)^{\frac{1}{1-\theta}}$$

suppose $\kappa_{N,t-1} > \kappa_{S,t-1}$, then we have either $u^H_{N,t} \geq u^H_{S,t}$ or $u^L_{N,t} \leq u^L_{S,t}$, or both. Having migration cost absent, at least one type of labor will (partly) migrate to the other region, and will not stop until the skill premium is equalized.

However, in the presence of migration cost, skill premium differential exists. As shown above, skill premium increase disproportionately higher in the North, skilled labor will move from the South to North only if

$$\sum_{t=0}^{\infty} \beta^t u(w^H_{S,t}; p_t, q_{S,t}) \leq \sum_{t=0}^{\infty} \beta^t u(\tilde{w}^H_{N,t}; p_t, q_{N,t})$$

where $\{\tilde{w}^L_{N,t}\}_{t=0}^{\infty}$ is subject to the constraint

$$\sum_{t=0}^{\infty} \frac{\tilde{w}^H_{N,t}}{R_t} + \tau \cdot w^H_{S,t} \leq \sum_{t=0}^{\infty} \frac{w^H_{N,t}}{R_t} \tag{1.C.5}$$

For simplicity we assume that $R_t = (1+r)^t$, $\tilde{w}^H_{N,t} = \tilde{w}^H_N$, and $w^H_{N,t} = w^H_N$, then (1.C.5) can be simplified to

$$\tilde{w}^H_N + r\tau \cdot w^H_S \leq w^H_N$$

which indicates the existence of skill premium differential. Moreover, even when the wage gap between skilled labor in two regions is larger than the 'discounted' migration cost, $r\tau \cdot w^N_S$. It is not necessary for the skilled labor to move. This is because the living costs in two regions are not equalized. Since the housing price

$q_{N,t}$ is likely to be higher in the North, the real wage gap for the skilled labor between two regions, is smaller than the nominal one. Therefore, skilled labor will not move until the nominal wage gap becomes even larger. And divergence will be taking place. This result is different new in the literature.

1.D. Distribution of North and South States

Figure 1-6 below shows the geographical distribution of the 'North' states and the 'South' states. As shown in text, the 'North' region consists states: California, Colorado, Connecticut, Delaware, Illinois, Kansas, Maryland, Massachusetts, Minnesota, Montana, New Hampshire, New Jersey, New York, Oregon, Vermont, Virginia, Washington; The 'South' region consists states: Alabama, Arkansas, Idaho, Indiana, Iowa, Kentucky, Louisiana, Michigan, Mississippi, Missouri, Nevada, North Dakota, Ohio, Oklahoma, South Carolina, South Dakota, Tennessee, West Virginia, Wisconsin.

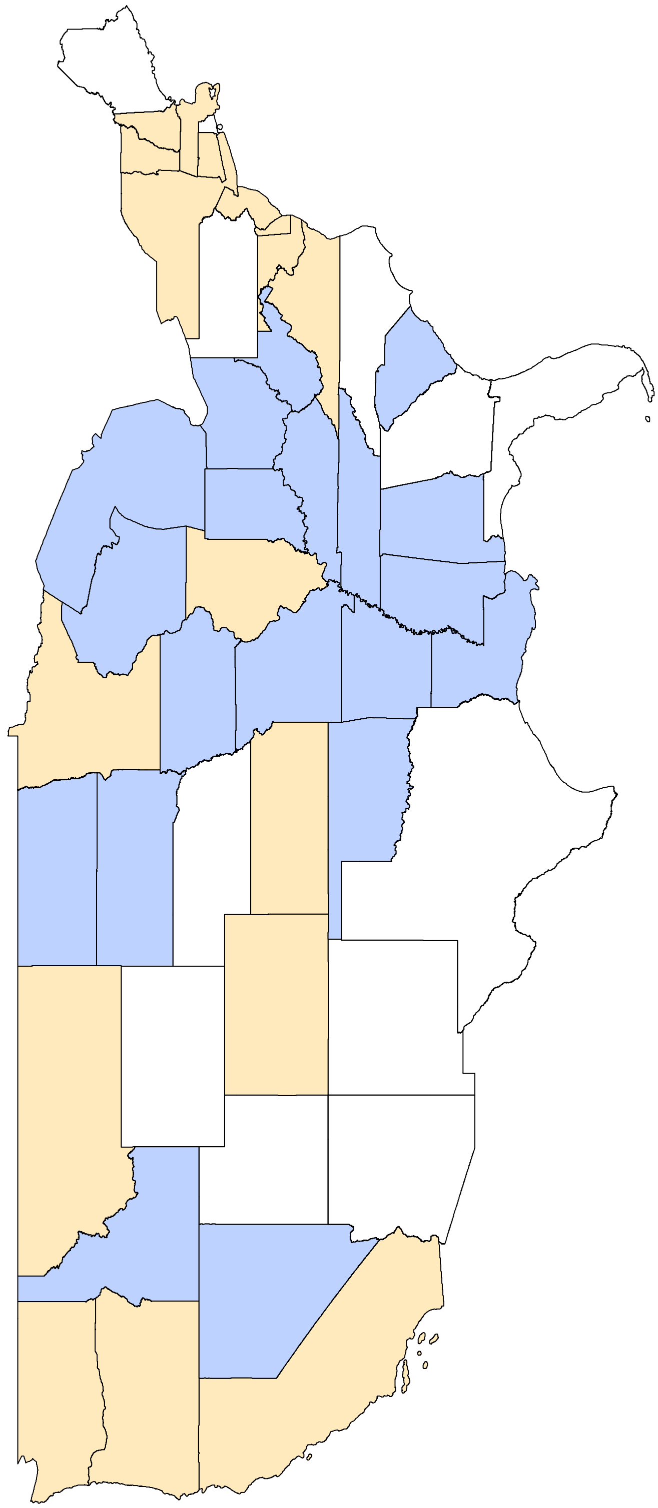


Figure 1-6: Geographical Distribution of 'North' and 'South' States: the states in blue are in the 'South' while the states in yellow color are in the 'North'. States in white are in neither of these categories.

CHAPTER 2

Energy Saving Technological Change: Intensive Margin Versus Extensive Margin

1. Motivation and Question

Because of its scarcity and inevitability in a modern economy, energy has been a popular topic recently, especially when it is argued that energy consumption, and therefore carbon emission, is responsible for global warming. The question of how efficiently we are using energy is critical for predicting the future carbon emissions as well as the climate. Despite its importance, few studies are found on this topic. Hassler, Krusell, and Olovsson [2012] is one of exceptions. They estimate the energy-saving technological change parameter jointly with the elasticity of substitution between a capital-labor composition and energy, and propose a directed technological change model to predict a 'peak oil' and a constant energy share. However, different mechanisms can underlie the aggregate energy efficiency improvement.

Figure 2-1 below shows the dynamics of the mean of the (log) energy-capital ratio for the whole U.S. manufacturing sector. It clearly shows that the energy intensity increased before the first oil crises and decreased afterward. Moreover, a back-of-the-envelope calculation shows that industry composition has changed substantially from 1970 to 2005. For instance, the share of Semiconductors and Related Devices industry of value added increased from less than 0.4% in 1970 to more than 2.8% in 2005. Maintaining the initial difference in capital-energy ratios across industries, a composition change can result in the change in the aggregate capital-energy ratio, and hence very likely a change in energy intensity. We refer to this mechanism as the first extensive margin of energy efficiency improvement.

In addition to the composition effect, changes in the (relative) energy price will lead to changes in the capital-energy ratio. The extent to which capital-energy responds to a change of the energy price depends on the elasticity of substitution between these two inputs. In industries with a greater elasticity of substitution, firms adjust by investing more in capital or other inputs as a response to an increase of relative price of energy. In contrast, firms in industries with lower elasticities of substitution are more likely to use more energy efficient technology rather than adjust their capital-energy ratios. Other things being equal, heterogeneous elasticities will generate a greater dispersion of capital-energy ratios after a price shock than homogeneous ones. This effect is categorized as the second extensive margin.

'Pure' energy efficiency improvement is another, probably the most important, channel through which the observed aggregate energy-saving technical change occurs. This channel, unlike in an aggregate model, can differ across industries. Unlike the adjustment of the capital-energy ratio in industries with a high elasticity of substitution, this effect is more a long run than a short run phenomenon. A challenge is to identify the energy efficiency from elasticities of substitution, and other technological changes for each industry. The first task of this paper is to jointly identify these parameters, and thereby decompose the aggregate energy efficiency improvement into three components, i.e., an intensive margin and two extensive margins. Their respective contributions are then quantitatively assessed.

Even if the capital-energy ratio is fixed, another production factor, labor, can affect the energy-output ratio. The labor cost share has been believed to be constant over time, which is referred to as Kaldor fact. In this case, the effect of labor is not of first order importance in affecting the energy-output ratio. However, recently this fact has been questioned (see Karabarbounis and Neiman [2014]). A widely recognized fact is that the labor cost share has been declining, across both countries and industries. If this is true, then the energy-output ratio cannot be solely accounted for by the capital-energy ratio. In this chapter, the effect of labor on the energy-value added ratio is quantitatively assessed.

The technology process is, however, not necessarily exogenous. A descriptive regression shows that industries with higher initial energy intensity in 1970 tend to experience higher reductions of energy intensity. This result is similar to the one obtained by Alpanda and Peralta-Alva [2010]. It indicates that the technological change has been directed toward energy saving by an increased relative energy price.

This mechanism is similar to that proposed Hassler, Krusell, and Olovsson [2012], in the sense that once the energy price increases, R&D on energy saving technology becomes more profitable, but differ from theirs in that more flexible sectors adjust by installing more capital, rather than by adopting more energy-efficient technology.

2. Motivating Facts

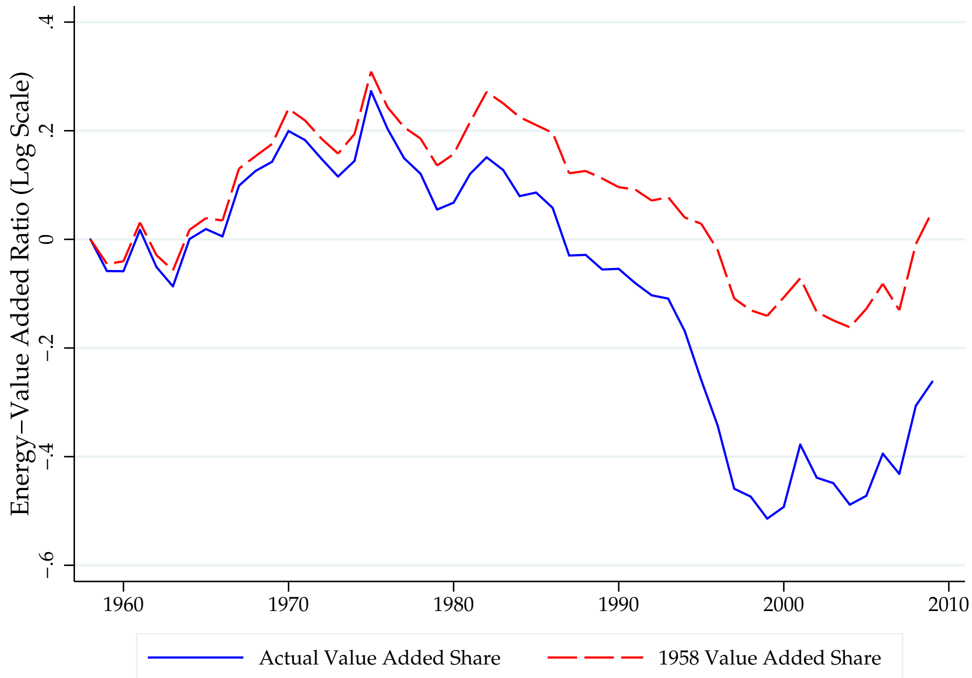
In this section, I describe several facts that motivate the present paper. I first implement a 'reduced-form' counterfactual experiment, holding either the input (capital) spending share or output share fixed at the initial year, 1958.

2.1. Reduced Form Decomposition. Figure Figure 2-1 (a) shows the effect of a time-varying value added share on the energy use of the whole manufacturing sector. Figure 2-1 (b) shows the effect on the energy-capital ratio. Roughly, energy intensity had been increasing from 1958 to the oil crisis, reaching its peak around 1974. Within this period, the composition effect plays little role in accounting for changes in aggregate manufacturing energy intensity. In the aftermath of the oil crisis, composition effects grew. During the 1990s in particular, the gap between the actual energy intensity and the counterfactual one deepened, reaching its historical peak around 2000. With industrial composition unchanged, the aggregate energy intensity would have fallen to less than 20 percent (log change) in the energy-value added case, and close to zero in the energy-capital case. In contrast, with the composition effect counted, the two variables decreased more than 40% and 20%, respectively.

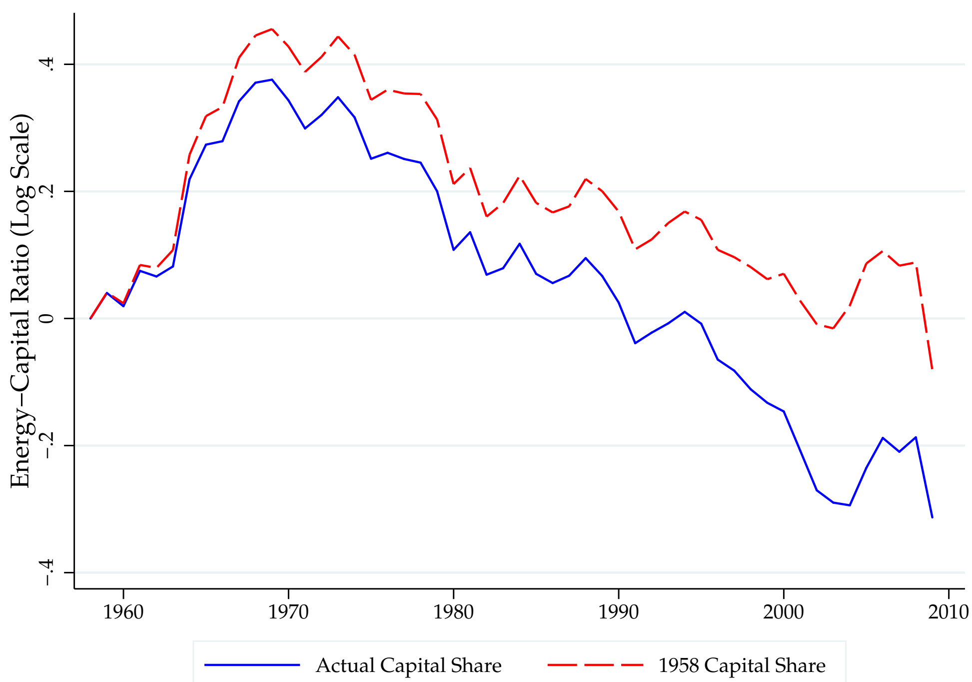
We then decompose the energy intensity into within-industry and between industry components by,

$$\Delta \log y_t = \underbrace{\sum_{j=1}^{J} \widehat{s}_{i,t} \cdot \Delta \log y_{i,t}}_{\text{Within Industry}} + \underbrace{\sum_{j=1}^{J} \widehat{\log(y_{i,t})} \cdot \Delta s_{i,t}}_{\text{Between Industry}}$$

Figure 2-2 shows the results. Figure 2-2 (a) shows the resulting decomposition using the NBER-CES data set. Compared to the compositional effect in the previous



(a) Energy-Value Added Ratio and Counterfactual with constant Value Added Share, 1958-2005



(b) Energy-Capital Ratio and Counterfactual with constant Real Capital Share, 1958-2005

Figure 2-1: The Impact of Composition Effect on Aggregate Energy Efficiency in the U.S. Manufacturing Sector. Data Source: NBER-CES Manufacturing Data Set.

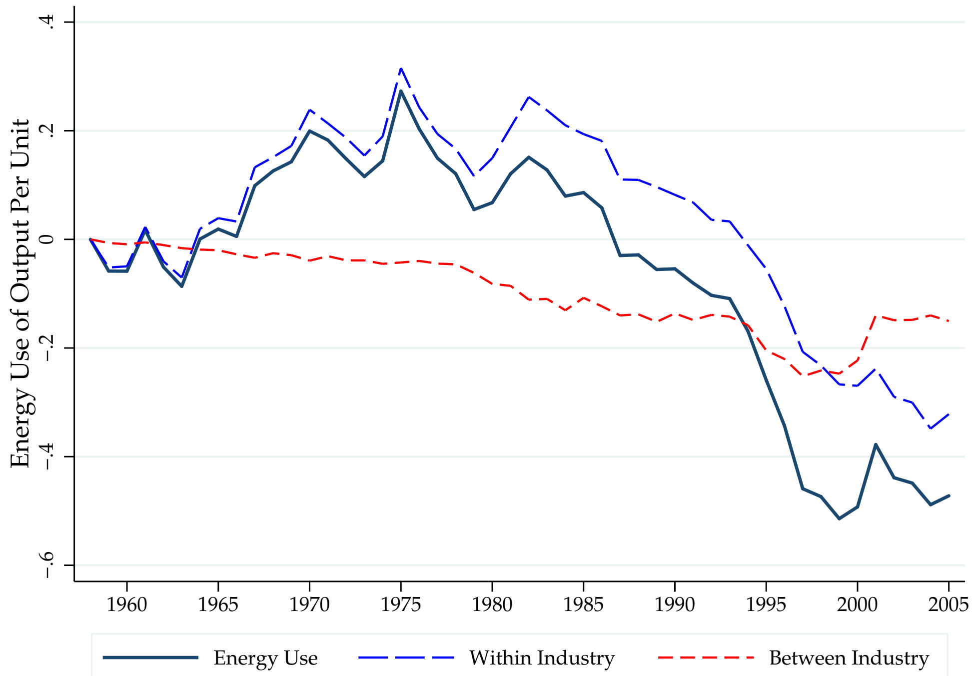
figure, the between-industry component is of great magnitude, contributing positively to energy use reduction even including the period before the oil crisis. The contribution, however, accelerated in early 1980s, leveled off around 2000, and then fell.

In contrast, the results from KLEMS data differ slightly. The within-industry variation dominates in the entire period, while the between-industry component contribute quantitatively less than it does in the NBER-CES data set, despite its significantly positive contribution. This descriptive evidence motivate studying the heterogeneity of energy across manufacturing industries as well as its impact on aggregate manufacturing technological changes, and energy-saving technological change in particular.

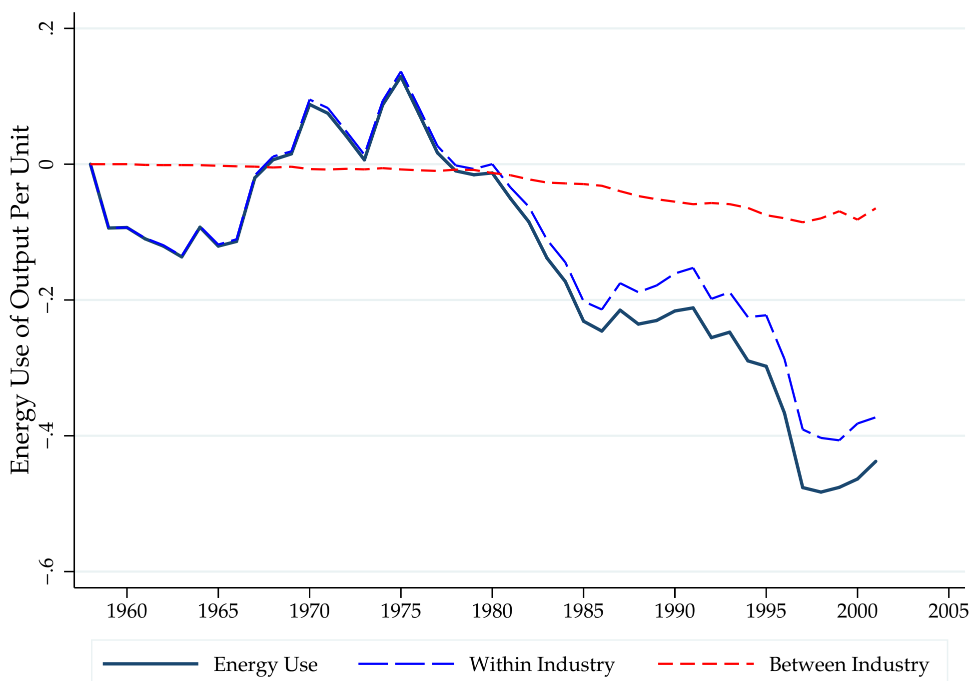
2.2. Periods Before and After the Oil Crisis of the 1970s. We have confirmed that time-varying heterogeneity contributes to the sectoral energy saving technological change. The heterogeneity, however, does not follow the same pattern all the time. An obvious regime switch occurred around the time of the oil crisis, as we will show below. Understanding the differential behavior of energy efficiency is helpful for predicting the direction in which it will go under certain policy regimes.

Before the oil crisis, there was convergence in energy use across manufacturing industries, meaning that industries with initially lower energy intensity experienced a higher growth rate of energy use (see Figure 2-3 (a)). Noting that the average energy intensity increased in this period, I prefer to interpret what happend as a catchup of industries with initially low energy intensity. Nevertheless, this pattern did not continue after the oil crisis. In Figure 2-3 (b) the relationship between the energy-capital ratio and its growth rate during the following 30 years is not significant. This indicates the energy-saving is not directed toward initially less energy-intensive industries.

This seems to contradict the documented composition effect. It does not, though. Figure 2-4 shows the energy-value added ratio instead of the energy-capital ratio.

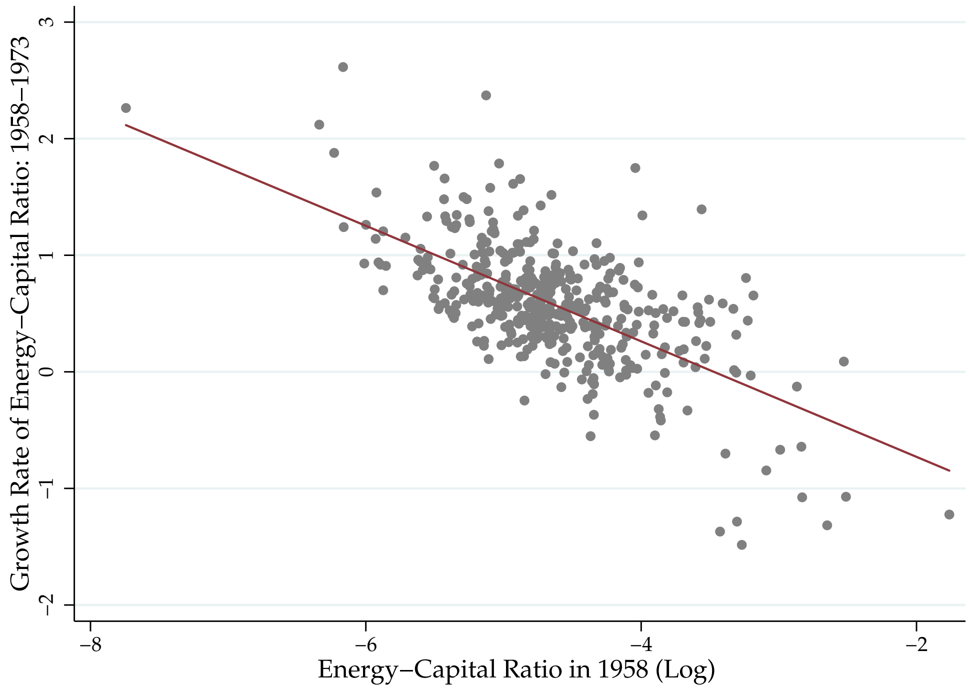


(a) NBER-CES 4 Digit Industry Decomposition.

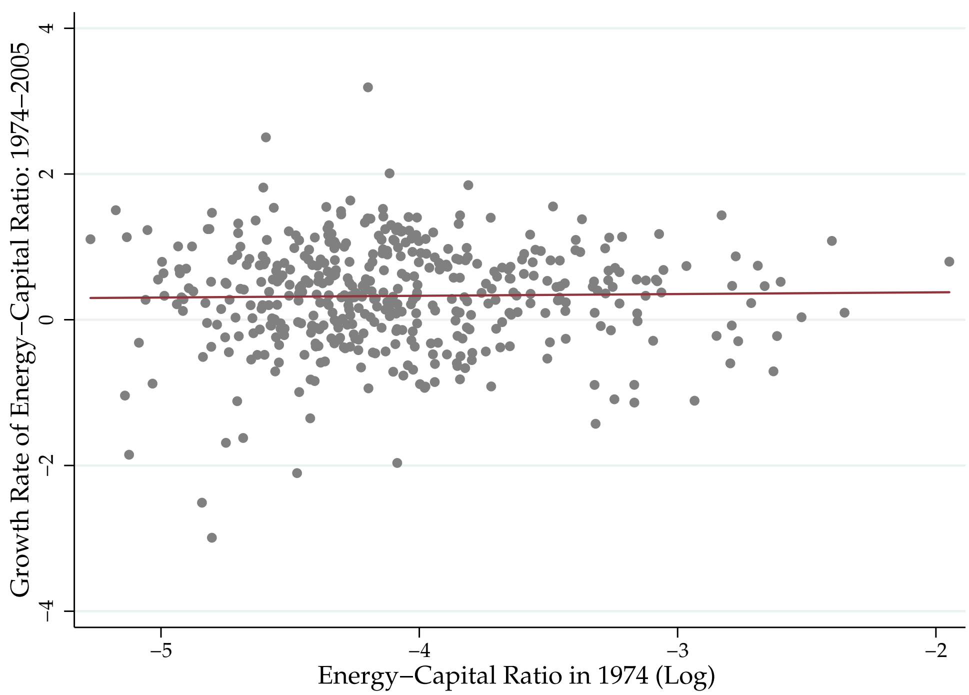


(b) KLEMS 2 Digit industry Decomposition

Figure 2-2: Within- and Between Industry Decomposition of Energy-Value Added. Data Source: NBER-CES data set and KLEMS provided by BEA.



(a) Before Oil Crisis



(b) After Oil Crisis

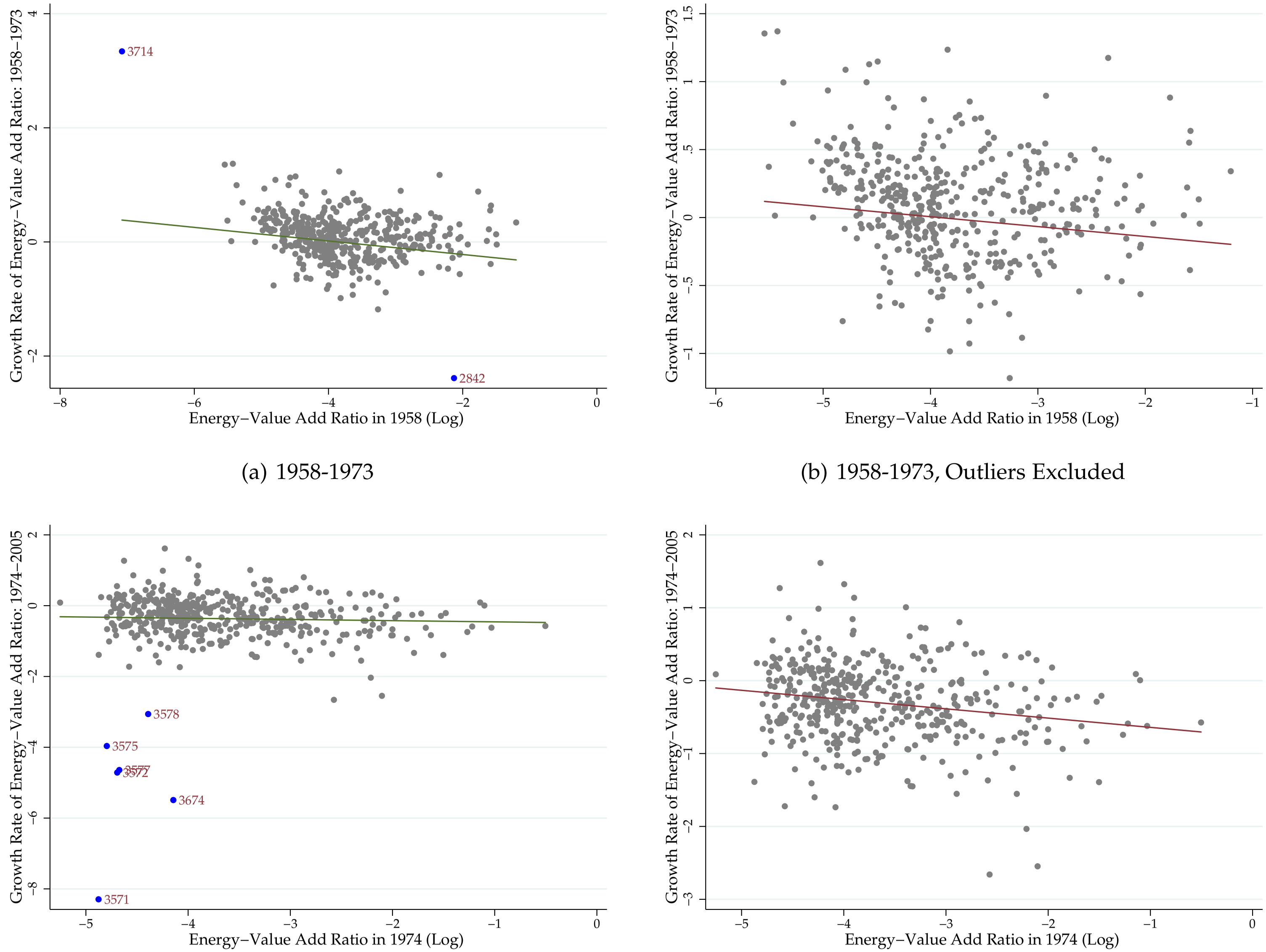
Figure 2-3: Regime Switch of Relation Between Changes in Energy-Capital Ratio and its Initial Level, Before and After the Oil Crisis.

Except for a few outlier industries, the relationship between the initial energy-value and its growth rate in the following 30 years is significantly negative. Moreover, consistent with a composition effect, Figure 2-5 shows a negative relationship between the growth rate of value-added and that of energy-value added ratio. These two effects hold for periods both before and after the oil crisis. Although the coefficients have the same sign, the magnitudes of the slope are very different for these two periods. To quantitatively asses which effect(s) is (are) dominating, we have to examine the data in a more rigorous framework.

3. Literature

The first branch of related literature is concerned with directed technological change. Newell, Jaffe, and Stavins [1999] test whether the direction of innovation is affected by the price of energy through the changes of consumption. They show that there is a price effect on the technological change, but it can be of different magnitudes, depending on other factors. However, their study only focus on three consumption models. More recently, macroeconomic studies of directed energy-saving technological change emerged, among which is Hassler, Krusell, and Olovsson [2012]. They show that the directed energy-saving technological change is quantitatively important for long run economic growth. Moreover, from the industrial organization perspective, Aghion, Dechezleprêtre, Hemous, Martin, and Reenen [2012] analyze the auto industry and shed light on the effect of possible policy and its welfare implications. Unlike these studies, my paper focuses on how quantitatively differently, and through what channels industries are responding to the increasing energy prices.

A second related branch of literature focuses on the complementarity (substitutability) between energy and capital. For instance, Polgreen and Silos [2009] estimate the elasticity of substitution based on de-trended variables, so their elasticity is



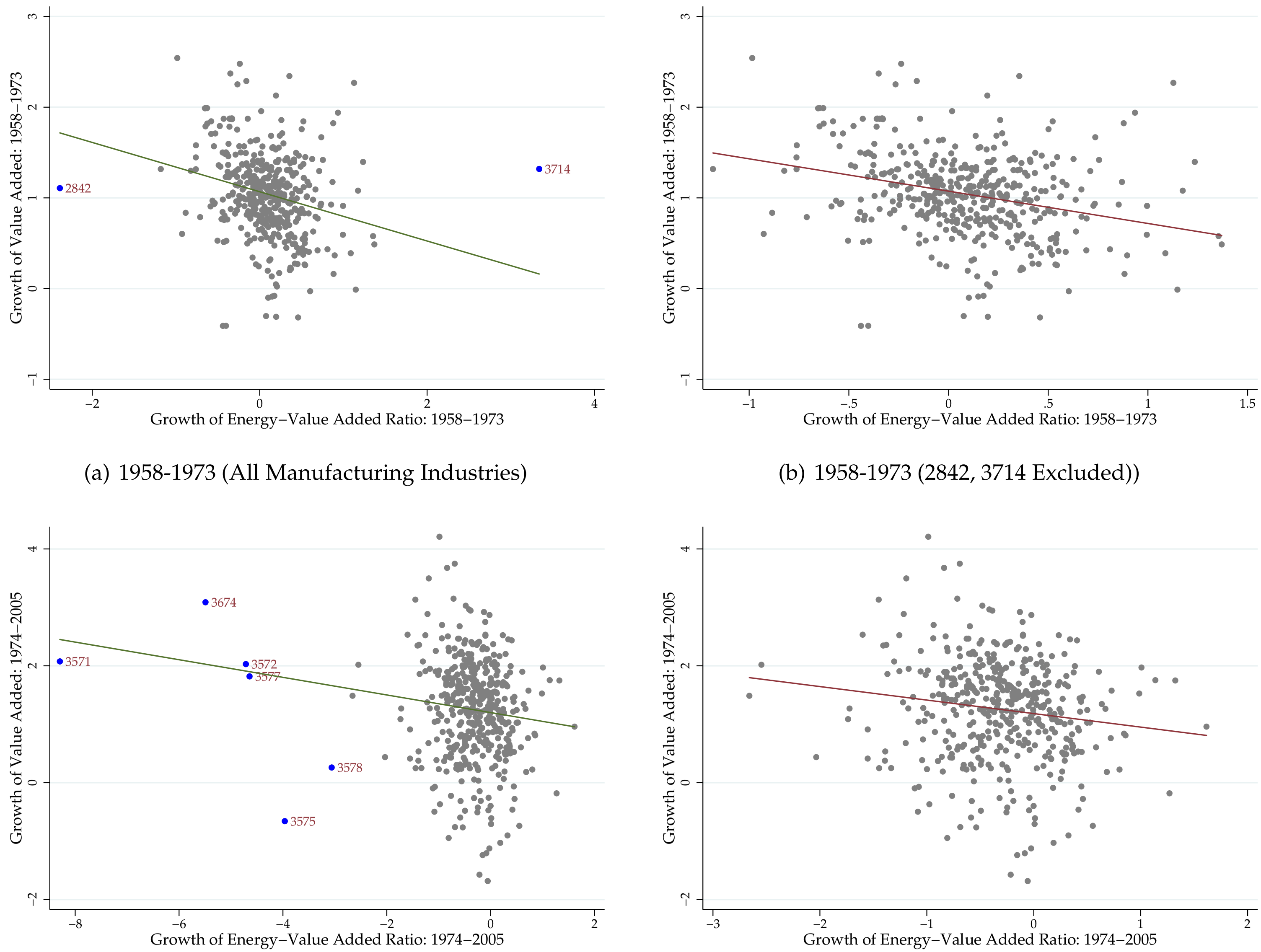
(a) 1958-1973

(b) 1958-1973, Outliers Excluded

(c) 1974-2005

(d) 1974-2005, Outliers Excluded

Figure 2-4: Directed Energy-Saving Effect.



(a) 1958-1973 (All Manufacturing Industries)

(b) 1958-1973 (2842, 3714 Excluded))

(c) 1974-2005 (All Manufacturing Industries)

(d) 1974-2005 (3751,3572,3575,3578,3674 Escluded)

Figure 2-5: Growth Rate of Energy-Capital Ratio against Growth of Value Added.

that between the 'residuals'. Moreover, like a large body of literature on energy economics, they do not identify the parameter capturing technical change.[1] Following a procedure proposed by León-Ledesma, McAdam, and Willman [2010], my model will be able to jointly identify the elasticity and the biased technical change, and will focus on long term rather than on the 'residuals'. Furthermore, my model can tell in which industries capital and energy are more complementary than in others. Finally, disaggregate variables can be aggregated to shed light on the effects on macroeconomic outcomes.

This paper is also related to putty-clay models of energy use, e.g., Atkeson and Kehoe [1999] and Alpanda and Peralta-Alva [2010], to name a few. This type of model is widely used to reconcile the cross-sectional substitution between energy and capital, and the time series complementarity between them. However, their putty-clay models assume restrictive capital-energy complementarity for each type of capital, hence changes in the aggregate capital-energy ratio come completely from the change in the distribution of capital types. This mechanism is similar to one operating on extensive margins. Putty-clay models are appealing for studies focusing on short run outcomes (e.g. business cycle). Most of them forgo technical change. My model nests an endogenous technological change in a 'putty-clay' model.

4. Model

To reasonably capture the heterogeneity in the macroeconomy, we assume that the firms are heterogeneous, in that firms are relatively homogeneous within the same industry though heterogeneous across industries. I model a firm's heterogeneity in this way for two reasons. First, according to Basu and Fernald [1997, 2002], heterogeneity within industries is not quantitatively important comparing to that between industries. Second, no data sets covering the whole population of firms in the U.S. is available. Most of the available data sets are only survey data, which may

[1] According to Diamond, McFadden, and Rodriguez [1978], in time series model, it is 'impossible' to jointly identify the elasticity and parameter of biased technical change.

entail extra measurement errors, and are not able to represent the whole manufacturing sector.

We assume a representative firm for each industry, and the firm maximizes its profit given the input prices and the output market condition. Production involves three inputs, capital, labor and energy, featuring factor-augmenting technological changes that differ across industries. The econometric model is based on estimation of a CES production function, which can be written as:

$$Y = \left[\gamma\left(\lambda(\Phi_k \cdot K)^\rho + (1-\lambda)(\Phi_e \cdot E)^\rho\right)^{\frac{\sigma}{\rho}} + (1-\gamma)(\Phi_l \cdot L)^\sigma\right]^{\frac{1}{\sigma}} \tag{4.1}$$

where the subscripts t for time and the subscripts i for industry are dropped. Φ_l denotes the labor-augmenting technological change, which increases at the rate of ϕ_l: $\Phi_{l,t} = \exp\{\phi_l \cdot t\}$. Note that in the base model we do not identify the contributing sources, e.g., increases inlabor quality and human capital embodied in labor. Φ_e denotes the energy saving technological change which grows at the rate of ϕ_e: $\Phi_{e,t} = \exp\{\phi_e \cdot t\}$. Φ_k denotes the energy saving technological change, which grows at the rate of ϕ_k: $\Phi_{k,t} = \exp\{\phi_k \cdot t\}$. $\{\rho, \sigma, \gamma, \lambda\}$ are other parameters to be identified, γ and λ are distributive parameters. ρ determines the elasticity of substitution between energy and capital, $1/(1-\rho)$, while σ governs the elasticity of substitution between labor and the capital-energy composite, $1/(1-\sigma)$. ρ and σ are restricted to $\rho < 1$ and $\sigma < 1$.

Hall [1988] and many who follow him (price/marginal cost ratio) estimate markups using industry level data, regressing changes in output per capital unit on labor share multiplied by changes in labor input per capital unit. We, however, are not able to identify markups by the same method for several reasons. First, since the technological change is likely to be labor-augmenting or energy saving, estimates of the coefficients already contain the effect of the these factor-biased technological changes. Without identifying these technological changes, we are not able to identify the markup. Second, De Loecker and Warzynski [2012] extend Hall [1988]'s framework to a generalized one, which allows the labor shares to vary across both firms and time periods and can be extended to cases featuring input biased technological change. Based on estimates of the output elasticity of output with respect to on inputs and those of input shares, markups can be backed out. These vary across both firms and time periods. Nevertheless, it is not suitable to apply this framework in our case. Because, first, De Loecker and Warzynski [2012]'s framework uses data for the real prices of inputs, while our prices of inputs are normalized to one in a specific year, so it is clueless if we use these price data to back out the markup and compare it across industries in a specific year. While changes in markups can be backed out in this way, the term Θ_t still captures the relevant dynamics. Therefore, we do not aim to identify markups in this study.[2] For simplicity, I assume that markets are competitive.

Our specification of the production function is also different from Hassler, Krusell, and Olovsson [2012], in that they nest in a CES production function energy and a capital-labor composite which is a Cobb-Douglas function of capital and labor, keeping the labor shares constant. According to Karabarbounis and Neiman [2014], however, labor shares have been declining 'globally' across a majority of countries and industries, because of a declining investment price and an elasticity of substitution between capital and labor greater than one. To avoid ruling out this possibility, we permit the possibility that the elasticity of substitution between capital and labor is different from one. Polgreen and Silos [2009] provide the most generalized version of a nested CES production function, allowing all elasticities of substitution to possibly be different from one, and the distributive parameters to be estimated within the model. Their model, however, studies short run fluctuations rather than the long run trend. As a matter of fact, their estimating model abstracts from technological

[2]Most firm level data with input prices can help to identify the markups and factor-augmenting technological change jointly.

changes. In contrast, our study focuses on the technological change. Therefore it nests factor-biased technological changes in the CES production.

Capital-Energy Composite. To understand the behavior of aggregate energy-saving technological change, we first investigate in individual industries. Assuming that markets are competitive, the energy price equals the marginal product of energy, and the price of capital service equals the marginal product of capital. However, we do not directly use the prices. Instead we focus on the ratio of payments for energy and capital services.

$$\frac{r_t \cdot K_t}{p_{e,t} \cdot E_t} = \frac{\lambda(\Phi_{k,t} \cdot K_t)^{\rho}}{(1-\lambda)(\Phi_{e,t} \cdot E_t)^{\rho}}. \tag{4.2}$$

Taking the first difference of logs of both side and rearranging yields

$$\Delta \log\left(\frac{E_t}{K_t}\right) = \frac{\rho}{\rho-1}(\phi_k - \phi_e) + \frac{1}{\rho-1}\Delta \log\left(\frac{p_{e,t}}{r_t}\right). \tag{4.3}$$

Equation 4.3 depicts the relationship between energy intensity relative to capital-augmenting technological change, as well as that of energy price relative to capital services price. The intuition behind (4.3) is straightforward. As $\rho \to 1$, energy and capital become perfect substitutive for each other, and energy use relative to capital use becomes very sensitive to the relative price, since theoretically the coefficient of the term $\Delta \log(p_{e,t}/r_t)$ approaches minus infinity. As the value of ρ falls toward 0, the elasticity become unitary, a 1% increase in the energy price relative to capital price shall lead to a 1% decrease in the energy-capital ratio. As ρ falls further, energy and capital become gross complements and the change in energy use becomes less sensitive to the relative price change, since the corresponding coefficient approaches zero. Besides relative price effects, factor-augmenting technological changes also affect energy use. Suppose capital and energy are gross complements, as suggested by a great number of papers,[3] i.e. $\rho < 0$, and capital-augmenting technological change grows faster than energy-augmenting technological change, that is $\phi_k >$

[3]See Hassler, Krusell, and Olovsson [2012], Alpanda and Peralta-Alva [2010] for instance.

ϕ_e. Then energy intensity will rise over time. Conversely, if capital-augmenting technological change grows less fast, then the energy intensity will fall over time.

Labor Share. In equation (4.1), the energy use or energy intensity does not depend only on the energy cost share of the energy-capital composite, but also on the fraction of cost paid to labor, which is time-varying since the production function is not a Cobb-Douglas production function, which allows the labor share to be non-constant over time. As above, we assume the labor market is competitive, and the wage equals to tje marginal product of labor. Then the payment to labor relative to capital can be written as:

$$\frac{w_t \cdot L_t}{r_t \cdot K_t} = \frac{(1-\gamma)}{\gamma \cdot \lambda} \left(\frac{\Phi_{l,t} \cdot L_t}{\Phi_{k,t} \cdot K_t} \right)^{\sigma} \left[\lambda + \lambda \left(\frac{r_t \cdot K_t}{p_{e,t} \cdot E_t} \right) \right]^{\frac{\rho - \sigma}{\rho}} . \tag{4.4}$$

Borrowing the results in (4.2) and denoting by $s_{L,t}$, $s_{E,t}$, $s_{K,t}$ the cost shares of labor, energy, capital respectively, we have

$$\Delta \log \left(\frac{s_{L,t}}{s_{K,t}} \right) = \sigma(\phi_l - \phi_k) + \sigma \Delta \log \left(\frac{L_t}{K_t} \right) + \frac{\rho - \sigma}{\rho} \Delta \log \left(1 + \frac{s_{K,t}}{s_{E,t}} \right), \tag{4.5}$$

which indicates that, given the cost of energy relative to capital and the technology level, if $\sigma > 0$, then an increase the in wage will lead to a decrease in the labor-capital ratio, and a decrease in price of capital relative to labor will lead to a decrease of the labor share relative to capital.[4] Moreover, other things equal, $\sigma > 0$, i.e., gross substitutability between labor and capital, indicates that labor-augmenting technological change is faster than the capital-augmenting technological change will result in a higher labor share. Conversely, $\sigma < 0$ indicates the opposite. Interestingly, a Cobb-Douglas production ($\sigma = 0$) indicates a time-invariant labor share, given a constant capital-energy cost share ratio. A time-varying capital-energy cost share ratio, however, will make the relative labor share time-varying, which is very likely

[4] As Karabarbounis and Neiman [2014] show $\sigma > 0$ is prevailing in a majority of countries, across a majority of industries. We allow the σ to be either positive or negative, depending on each industry's behavior.

the case in the short run. The sign of the effect within each industry depends on the value of ρ relative to σ and the sign of ρ. For instance, if energy and capital are gross complements ($\rho < 0$), capital and labor are gross substitutes ($\sigma > 0$), then a rising capital share relative to energy indicates a rising labor share, which results from a rising marginal productivity of labor relative to energy.

Total Output. Equation 4.1 involves many parameters to depict output growth. Using information from the capital-energy composite and the equation above describing the labor share, I can reduce the number of endogenous variables determining the output. Once the relative factor-augmenting technological parameters and the curvature parameters are known, there is only one factor-augmenting technological parameter we need to predict the total output for an industry. Nevertheless, since this chapter focuses on heterogeneity of elasticity and relative factor-augmenting technological change and their impacts on the aggregate energy efficiency, we are not going to depict how these factors affect the total output level. The assessment of impacts from these factors can be found below.

Once the estimates are obtained, we can figure out if there exists a relationship between A_i^e of industry i and its initial energy consumption share in the costs of inputs. By the conjecture of directed technical change, there might be a negative relationship.

5. Data

The NBER-CES Manufacturing Industry Database contains information on capital, labor, energy and material input for both 4-digit SIC manufacturing industries and 6-digit NAICS industries, from 1958 to 2005. The Bureau of Economic Analysis (BEA) provides KLEMS data from 1998 to 2011 at the NAICS industry level. Merging these two data sets allows us to have a large panel data set with more than 400 industries for a longer than 50 years period. Moreover, the Energy Information

Administration (EIA) also provides comprehensive information on the prices of different kinds of energy, e.g., electricity, fuel oil, natural gas, etc., so that we can either construct an energy composite or investigate separate kinds of energy as we want.

The Current Population Survey (CPS, hereafter) contains information on what industry is an employees are working in, along with the information on their education, wage, working hours, etc. So we can construct labor input variables at the industry level. Because of the information on the wage, the first order condition with respect to the labor input can help identify the parameters of labor efficiency.

6. Estimation

In this section, I calibrate the key parameters, including curvature parameters $\{\rho, \sigma\}$, the factor augmenting technological change parameters $\{\phi_l, \phi_k, \phi_e\}$. I first estimate $\{\rho, \sigma\}$ for each 2 digit SIC industry, since I allow industries be heterogeneous in all these dimensions so that we can assess the quantitative impact of these heterogeneities. Nevertheless, I allow the technological parameters to be different across 4 digit SIC industries. These parameters will be backed out after the curvature parameters have been estimated. Moreover, many studies show that there may have been structural change before and after the oil crisis in 1973,[5] I focus on the period 1974 to 2005.

Curvature Parameters. In this subsection, I estimate the curvature parameters, using the moments described in section 4. We first estimate ρ which determines the elasticity of substitution between capital and energy. Modifying equation (4.2) or (4.3), we have the following estimating equation

$$\Delta \log \left(\frac{s_E}{s_K}\right)_{ijt} = \underbrace{-\frac{\rho_i}{\rho_i - 1} \cdot \chi_{E,ij}}_{\equiv \mu_{ij}} + \frac{\rho_i}{\rho_i - 1} \Delta \log \left(\frac{p_e}{r}\right)_{ijt} + \varepsilon_{ijt} \tag{6.1}$$

[5] E.g., Ilmakunnas and Törmä [1989, 1994] show that the elasticity of substitution between energy and capital after the oil crisis is significantly different from the one before.

where $\chi_{E,ij} = \phi_{e,ij} - \phi_{k,ij}$, i stands for a 2 digit SIC industry and j stands for a 4 digit SIC industry, each belonging to a 2 digit SIC industry. An OLS regression identifies the parameters $\rho_i/(\rho_i - 1)$ as well as $\mu_{ij} \equiv -\rho_i \cdot \chi_{E,ij}/(\rho_i - 1)$, the fixed effect. Hence we have two values to pin down to parameters, ρ_i and $\chi_{E,ij}$. Note that $\phi_{k,ij}$ and $\phi_{l,ij}$ are not pinned down, and are not identified in this exercise. We will not estimate parameters ϕs. Rather, we will back out their values for every four digit SIC industry j. To further pin down the other curvature parameter, σ_i, I take the advantage of (4.5), running the following OLS regression,

$$\Delta \log \left(\frac{s_L}{s_K} \right)_{ijt} = \underbrace{\sigma_i \cdot \chi_{L,ij}}_{\kappa_{ij}} + \sigma_i \Delta \log \left(\frac{L}{K} \right)_{ijt} + \frac{\rho_i - \sigma_i}{\rho_i} \Delta \log \left(1 + \frac{s_K}{s_E} \right)_{ijt} + \nu_{ijt} \tag{6.2}$$

where $\chi_{L,ij} = \phi_{L,ij} - \phi_{K,ij}$ is the rate of labor-augmenting technological change relative to the capital-augmenting technological change. The coefficient estimate of $\Delta \log(L_{ijt}/K_{ijt})$ identifies σ_i, and $\sigma_i \cdot \chi_{L,ij}$ is identified as the fixed effect term. Note that by this regression, we can identify the term $(\rho_i - \sigma_i)/\rho_i$ as well.[6] However, the focus from this regression is on σ_i.

Factor-Augmenting Technological Change. In addition to the curvature parameters, factor-augmenting technological changes are important for understanding the relative factor shares in production functions, except in the Cobb-Douglas case, in which technological progress is not identifiable, and the factor shares are constant throughout the period. We can take advantage of the share of energy relative to labor to make a further relation among three technological parameters. We are not doing this, since this paper focuses on the relative quantity and share of energy. Depending on the relative factor-augmenting parameters, we are able to describe the dynamics of the relative energy quantity and cost share over time.

To back out the relative factor-augmenting parameters $\chi_{E,ijt}$ and $\chi_{L,ijt}$, we plug the estimates of ρ_i and σ_i into equations (6.1) and (6.2). Note that $\chi_{E,ijt}$ and $\chi_{L,ijt}$ vary

[6] Since the relative capital share varies in short run, the term can be well identified by this variation.

not only across 2 digit SIC industries, but also across 4 digit SIC industries and time periods. This large degree of freedom allows us to uncover the technology pattern across industries as well as across time periods. Also note that these estimates of the relative technology parameters contain information about random shocks, ε_{ijt} and ν_{ijt}.

7. Results

In this section we focus on the period 1974 through 2005. Table 2-1 presents the estimates, $\hat{\sigma}_i$ and $\hat{\rho}_i$, together with statistics on technology parameters. Estimates of $\hat{\rho}_i$ are negative for the whole manufacturing sector, separately for nondurable and durable goods sectors. Moreover, $\hat{\rho}_i$ are all negative, with the lowest being -7.627 for the 'paper and allied products' industry and highest being -1.770 for the 'Printing, Publishing and Allied Product' industry, indicating that capital and energy are grossly complementary in all 2 digit SIC industries. The result is qualitatively consistent with the majority of estimates in the literature (e.g. Alpanda and Peralta-Alva [2010]; Hassler, Krusell, and Olovsson [2012]), though quantitatively different.[7] Incomplete complementarity between energy and capital indicates that, other things unchanged, firms are likely to slightly substitute away from energy and toward capital, once the relative energy price increases or, in other words, once the relative capital price decreases. We show the estimation results for the pre-1973 period in Table 2-2 in the Appendix, where the gross complementarity between capital and energy is maintained, although the magnitude is slightly different. Despite the fact that capital and energy are complementary throughout the manufacturing sector, the heterogeneity of the elasticity of substitution is obvious. In particular, the elasticity ranges from 0.116 (SIC 26) to 0.361 (SIC 27) for the post-1973 period and from ≈ 0

[7] Hassler, Krusell, and Olovsson [2012] show that capital and energy are almost perfectly complementary, and Alpanda and Peralta-Alva [2010] obtain $\rho = -6$ in his calibration exercise and $\rho = -20$ in an earlier working paper version.

(SIC 36) to 0.437 (SIC 27) for the pre-1973 period.[8] Note that SIC 27 has the highest elasticity of substitution for both periods. Due to this heterogeneity in elasticity, industries are likely to respond differently when faced with a common energy price shock. We are going to show quantitative relevance of this in the following sections.

Compared to the complementarity between capital and energy, capital and labor are much more substitutable in each industry. The estimate of $\hat{\sigma}_i$ for the whole manufacturing sector is 0.146 for 1974 to 2005, and 0.331 (more than double) for 1958 to 1973 (see the Appendix). For the whole nondurable good sector, the estimate is 0.134, significantly different from 0. The lowest estimates of $\hat{\sigma}$ among 2 digit SIC industries is -0.025 for the industry 'Leather and Leather Products,' with a standard error of 0.076, which means it is virtually not significantly different from zero. All the rest of the $\hat{\sigma}_i$s are positive. The average indicated elasticity between labor and capital is 1.22, very close to Karabarbounis and Neiman [2014]. This result also suggests a time-varying labor share, and hence a time-varying relative energy quantity and energy cost share. Moreover, it indicates that energy price volatility is likely to affect the labor share in the short run. Nevertheless, the range of $\hat{\sigma}_i$ is wide, from a low of 0.98 to a high of 1.61, suggesting industrial heterogeneity once again. Heterogeneity in the elasticity is illustrative of the value of building a multi-sector growth model as in Ngai and Pissarides [2007].

We then compute relative factor-augmenting technology parameters based on the estimates of ρ_is and σ_is, using the following procedure. First, we back out $\chi_{E,ijt}$ and $\chi_{L,ijt}$, which vary across industries and years. Second, we then compute the average relative technological progress for each 4 digit SIC industry by $\widehat{\chi}_{E,ij} = \frac{1}{T}\sum_{t=1}^{T}\chi_{E,ijt}$ and $\widehat{\chi}_{L,ij} = \frac{1}{T}\sum_{t=1}^{T}\chi_{L,ijt}$. In Table 2-1, I report the means and the standard deviations of $\hat{\chi}_{E,ij}$ and $\hat{\chi}_{L,ij}$ for each 2 digit SIC industry. The first row shows the estimates

[8] Interestingly, SIC 27, 'Pringting, Publishing and Applied Product,' has the highest elasticity of substitution between energy and capital for both periods; The estimate of $\rho_i/(\rho_i-1)$ is greater than 1 for period 1958 to 1973, resulting in a mathematically negative elasticity. We, however, cannot reject the hypothesis that $\rho_i/(\rho_i-1)$ is significantly different from 1, which in turn indicate a Leontif nesting of capital and energy in the two level CES production function .

Table 2-1: Estimation Results: 1974-2005

Industry	SIC	(1) $\widehat{\rho_i/(\rho_i-1)}$	(2) $\hat{\rho}_i$	(3) $\hat{\sigma}_i$	(4) $\hat{\chi}_{E,ij}$	(5) $\hat{\chi}_{L,ij}$
Manufacturing		0.783	-3.612	0.146	0.018	-0.151
		(0.010)		(0.015)	(0.020)	(0.626)
Nondurable		0.790	-3.767	0.134	0.015	-.235
		(0.009)		(0.018)	(0.021)	(0.931)
Food and Kindred products	20	0.816	-4.445	0.019	0.010	-0.992
		(0.020)		(0.047)	(0.025)	(1.400)
Tobacco Products	21	0.748	-2.972	0.201	0.038	-0.386
		(0.050)		(0.092)	(0.007)	(0.114)
Textile Mill Products	22	0.796	-3.900	0.227	0.009	0.010
		(0.018)		(0.038)	(0.016)	(0.096)
Apparel, Finished Products	23	0.758	-3.136	0.178	0.027	-0.011
		(0.032)		(0.037)	(0.018)	(0.152)
Paper and Allied Products	26	0.884	-7.627	0.269	-0.001	0.021
		(0.027)		(0.066)	(0.012)	(0.069)
Printing, Publishing and Allied	27	0.639	-1.770	0.100	0.016	-0.096
		(0.058)		(0.059)	(0.016)	(0.136)
Chemicals and Allied Products	28	0.833	-4.984	0.137	0.018	-0.146
		(0.020)		(0.048)	(0.018)	(0.191)
Petroleum Refining and Related	29	0.784	-3.630	0.377	0.015	-0.047
		(0.046)		(0.121)	(0.018)	(0.054)
Rubber and Miscellaneous Plastic	30	0.684	-2.166	0.222	0.006	-0.012
		(0.026)		(0.045)	(0.016)	(0.089)
Leather and Leather Products	31	0.729	-2.691	-0.025	0.037	0.914
		(0.033)		(0.076)	(0.015)	(1.495)
Durable		0.778	-3.508	0.169	-0.089	-0.089
		(0.006)		(0.013)	(0.019)	(0.175)
Lumber and Wood Products,	24	0.738	-2.818	0.153	0.021	-0.020
Furniture		(0.028)		(0.048)	(0.019)	(0.143)
Furniture and Fixtures	25	0.674	-2.070	0.163	0.024	-0.141
		(0.029)		(0.045)	(0.012)	(0.116)
Stone, Clay, Glass and Concrete	32	0.729	-2.471	0.203	0.012	-0.049
		(0.018)		(0.036)	(0.017)	(0.102)
Primary Metal Industries	33	0.840	-5.252	0.256	0.007	-0.063
		(0.013)		(0.051)	(0.020)	(0.112)
Fabricated Metal	34	0.732	-2.727	0.060	0.015	-0.249
		(0.022)		(0.030)	(0.013)	(0.282)
Industrial, Commercial Machinery	35	0.842	-5.347	0.172	0.027	-0.044
Computer		(0.014)		(0.026)	(0.017)	(0.133)
Electronic, Electrical Equipment	36	0.763	-3.227	0.252	0.030	-0.023
		(0.017)		(0.030)	(0.015)	(0.104)
Transportation Equipment	37	0.799	-3.976	0.189	0.022	-0.086
		(0.019)		(0.045)	(0.015)	(0.142)
Instruments	38	0.667	-2.002	0.137	0.033	-0.107
		(0.036)		(0.052)	(0.021)	(0.163)
Miscellaneous Manufacturing	39	0.665	-1.990	0.152	0.027	-0.114
		(0.032)		(0.041)	(0.020)	(0.171)

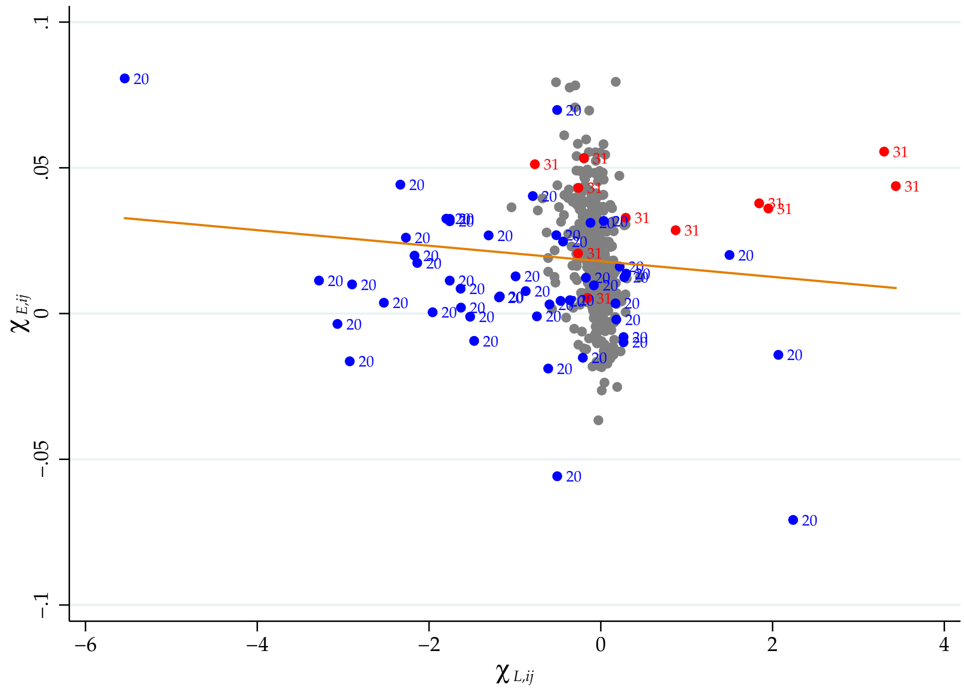
for the whole manufacturing sector, revealing a mean of $\hat{\chi}_{E,ij}$ that is positive while the mean of $\hat{\chi}_{L,ij}$ is negative. At the 2-digit industry level, the means of $\hat{\chi}_{E,ij}$ are all positive except the 'Paper and Allied Products' industry, while means of $\hat{\chi}_{L,ij}$ are mostly negative, reflecting a prevailingly (relative) capital-augmenting technological change in the manufacturing sector.[9] Finally, it is worthwhile to point out that the heterogeneity of relative labor-augmenting technological change is greater than that of energy-saving technological change.

I further examine the cross-sectional pattern of the technological change. Figure 2-6 plots $\hat{\chi}_{E,ij}$ against $\hat{\chi}_{L,ij}$. 2-digit industries 'Food and Kindred Products' and 'Leather and Leather Products' seem to be outliers in figure 2-6(a).[10] However, excluding these two industries does not affect the results. In both cases, $\hat{\chi}_{L,ij}$ and $\hat{\chi}_{L,ij}$ are negatively correlated, which is in line with Hassler, Krusell, and Olovsson [2012]. They document that there is a constraint on developing two different types of technology. An increase in one eliminates the other. The difference is that in their model the representative firm trades off between the two technologies, while my result shows that this trade-off is accomplished by different types of firms (industries).

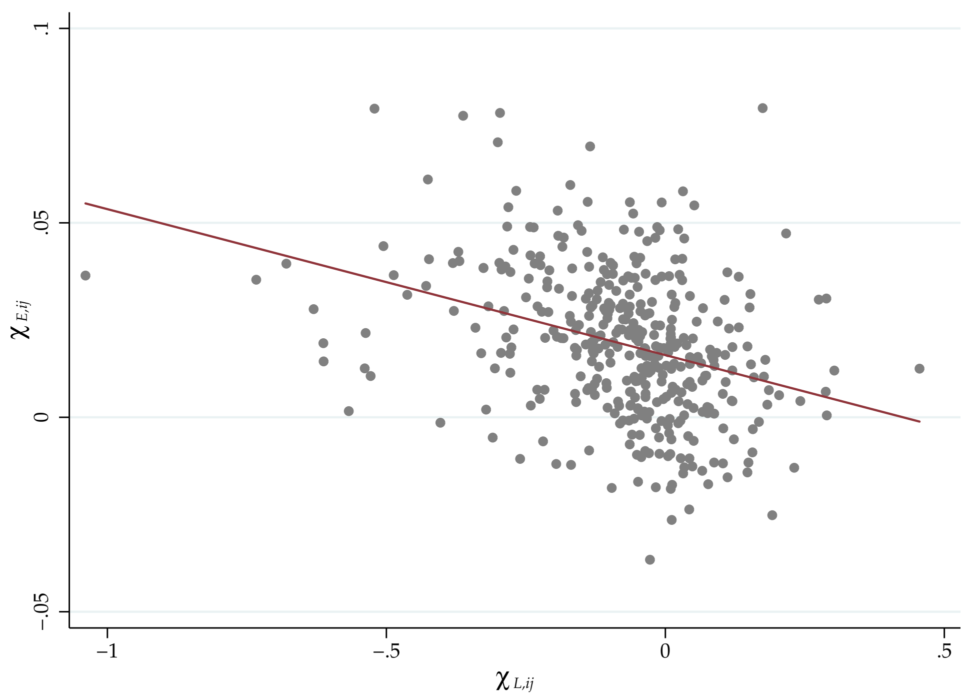
Before closing this section, a final remark to be made comparess the structural change in energy-saving technology before and after 1973. Comparing Table 2-1 with Table 2-2 in the Appendix, it is most evident that the whole manufacturing sector was energy-using before 1973 and became energy-saving afterward. Although consistent with the conclusion of Kander and Schön [2007], Hesse and Tarkka [1986], Ilmakunnas and Törmä [1989, 1994] that energy and capital became more substitutable after the crisis, in both period they are complementary. Nevertheless, the elasticities of substitution between capital and labor are generally greater than one

9 Seemingly unconvincing is the estimates for "Electronic, Electrical Equipment" industry. This is mainly due to the fact that we do not control for labor quality.

10 These two industries happen to σ_i not significantly different from zero, thus when we back out $\hat{\chi}_{L,ij}$, the ranges are greater.



(a) All 4 Digit SIC Industries



(b) SIC Industries 20, 31 Excluded

Figure 2-6: $\hat{\chi}_{E,ij}$ vs. $\hat{\chi}_{L,ij}$.

for both periods. Moreover, capital and labor are more substitutable in the pre-crisis period than in the post-crisis period. [11]

8. Counterfactuals

In this section we do several counter factual experiments to quantitatively assess the underlying mechanisms.

Composition Effect. In this subsection, I want to first highlight the composition effect. Figure 2-1 for the years 1973 to 2005 is replicated in Figure 2-7. It is evident that the composition effect accounted for very little of the reduction in the energy-capital ratio before the end of 1980s. However, the industrial composition evolved in an energy-reducing direction afterward. Throughout the period of interest, the composition effect accounts for about 30% of the energy-capital ratio reduction. This composition effect will be more or less the same in a scenario in which capital and energy are completely complementary (see Figure 2-9 in the Appendix). This is done by setting $\rho_i \to -\infty$.

What if there is no energy saving technological change ? In this scenario, I shut off the relative energy-saving technological change for each 4 digit industry. The energy-capital ratio fell by less than 17%, which indicates, first, that the pure composition effect with no within industry energy-saving technological change is relatively small (17% relative to 30%), second, that there is interaction between the composition effect and intensive energy-saving technological change. However, the intensive energy-saving technological change did not play an important role until the beginning of the 1980s. From 1974 to 1982, factor adjustment is the most important effect. This is reasonable since, during that period, the relative price of energy increased so steeply that, although capital and energy are very complementary,

[11] Ilmakunnas and Törmä [1989, 1994] compare the complementarity before and after the crisis, while Kander and Schön [2007] investigate the question in a much longer history, they found that there have been several structural change taken place from 1870 to 2000 and that the structural changes were stimulated by the changing relative price of energy to capital.

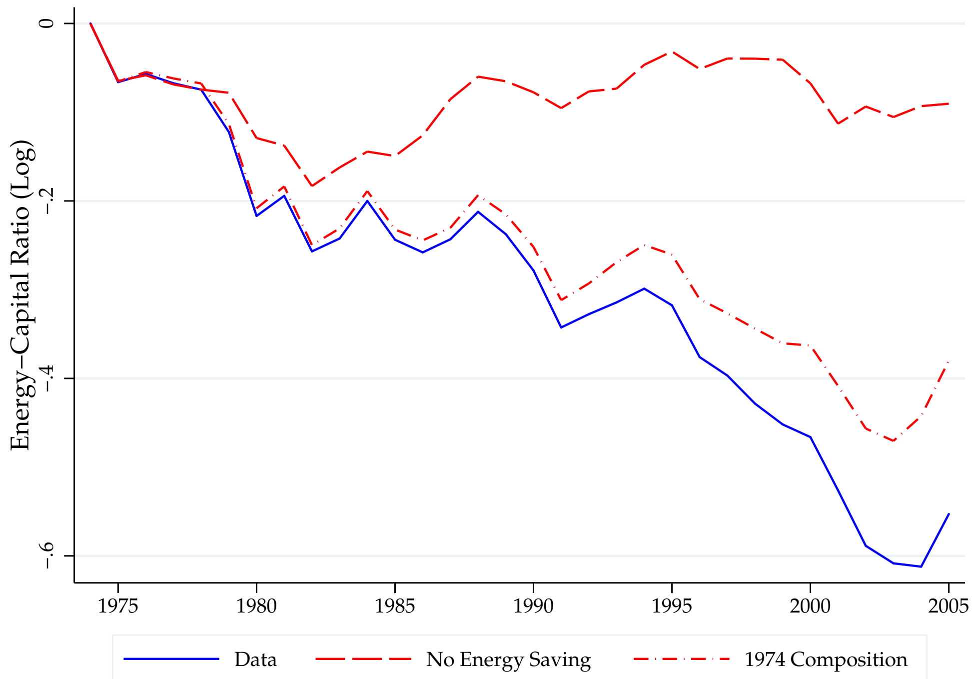


Figure 2-7: Counterfactual within Capital-Energy Composite: The blue line represents the aggregate (log) energy-capital ratio, the red dashed line represents the effect of composition effect combined with factor adjustment, the red dash-dotted line represents the counterfactual ratio with the industry proportions kept at their 1974 level.

businesses were willing to substitute a large amount of capital for a small amount of energy. This fact, however, is at odds with the directed technological change literature, since the skyrocketing energy price alone is the cause of the energy intensity reduction, without any technological change.

The effect of Labor. In the previous two counterfactuals, we only check the energy-saving technological change within the capital-energy composite. Nevertheless, labor is very likely to contribute to the reduction of energy intensity. There are two mechanisms underlying the effect of labor. The first is the substitution between labor and capital-energy composite, and the second is labor-augmenting technological change effect. Since the labor-augmenting technological change is not well identified for each industry, the second effect is not considered here. In Figure 2-8,

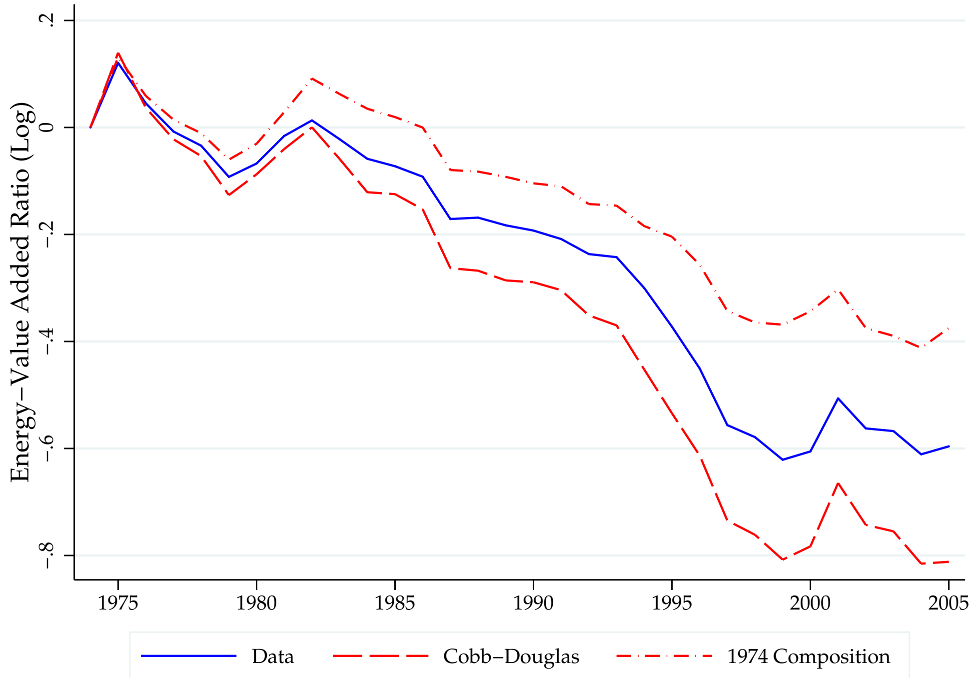


Figure 2-8: Counterfactual of Labor Effects.

once again the composition effect is replicated from Figure 2-1, which is captured by dash-dotted line.

The focus of this counterfactual is on the dashed line, where we assume that the elasticity of substitution between labor and capital-energy composite is unitary, i.e. $\sigma_i = 0$ for each industry. In Figure 2-8, this change will lead to a further approximately 30% reduction in the energy-value add ratio. In the model, the elasticity is greater than unitary, therefore a decrease in price of capital will lead to a decrease in the labor share. Consequently, energy use in the model is more intensive than in the counterfactual.

9. Conclusions and Implications

In this chapter, I estimate the production function for all 2 digit manufacturing industries, finding tremendous heterogeneity in the elasticity of substitution between factors, factor-augmenting technological changes, and output value shares. Based on these estimates, I find that to certain extant all these variables contribute to the reduction of energy use. Moreover, a representative firm model may be misleading, in the case of directed energy-saving technological change. The assumption that two factor-augmenting technological change is zero-sum is qualitatively true, but too simple to capture other variations that affect aggregate energy-saving technical change, such as, reallocation of factors across 4 digit industries and the substitution effect when s factor price skyrockets.

Aggregation of heterogeneous sectors is a difficult challenge faced by macroeconomist, since heterogeneity makes it a difficult time for simple adding-up. Nevertheless, recently Ngai and Pissarides [2007] built a model that features heterogeneous technology and heterogeneous elasticities of substitution between factors, and the identify conditions under which a balanced growth path exists.[12] Including international trade and input-output relation among sectors will be interesting extensions of such a model.

[12] Three sector models, e.g., Herrendorf, Rogerson, and Valentinyi [2013], are not suitable for the case, since they only assume that elasticity of substitution between labor and capital is unitary.

10. Appendix

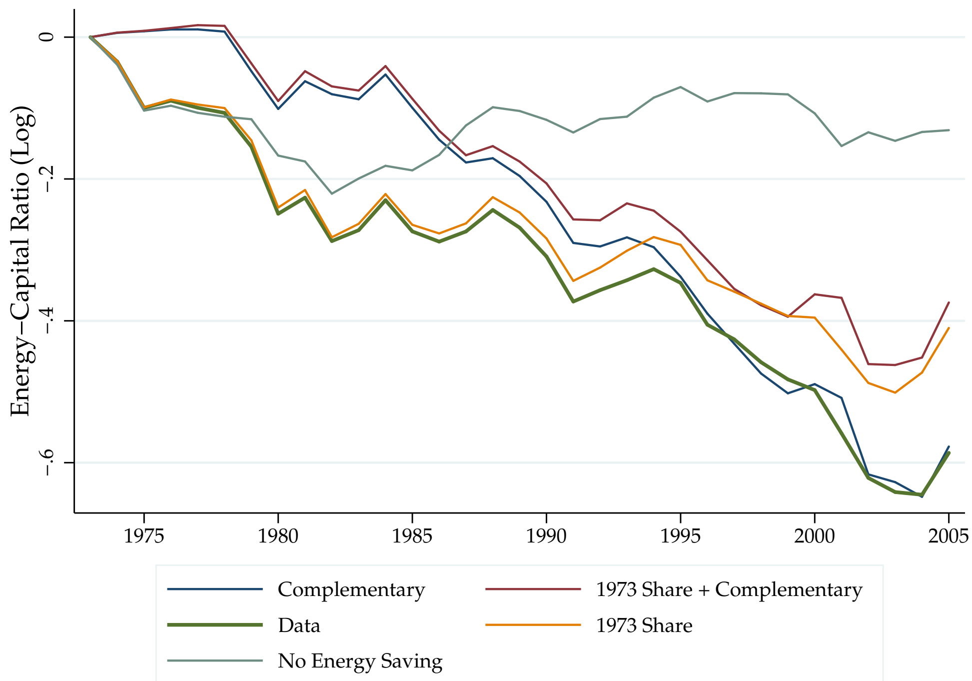


Figure 2-9: Counterfactual of Capital-Energy Composite.

10.1. Estimation for 1959-1973.

Table 2-2: Estimation Results: 1958-1973

Industry	SIC	(1) $\widehat{\rho_i/(\rho_i-1)}$	(2) $\hat{\rho}_i$	(3) $\hat{\sigma}_i$	(4) $\hat{\chi}_{E,ij}$	(5) $\hat{\chi}_{L,ij}$
Manufacturing		0.878	-7.212	0.331	0.010	-0.130
		(0.009)		(0.014)	(0.042)	(0.488)
Nondurable		0.820	-4.557	0.354	-0.006	-.060
		(0.011)		(0.019)	(0.043)	(0.157)
Food and Kindred products	20	0.871	-6.734	0.314	0.010	-0.044
		(0.020)		(0.038)	(0.056)	(0.136)
Tobacco Products	21	0.962	-25.35	0.616	0.004	0.067
		(0.061)		(0.098)	(0.016)	(0.029)
Textile Mill Products	22	0.822	-4.631	0.296	-0.017	-0.077
		(0.035)		(0.065)	(0.037)	(0.104)
Apparel, Finished Products	23	0.855	-5.883	0.378	-0.004	-0.019
		(0.028)		(0.055)	(0.036)	(0.093)
Paper and Allied Products	26	0.715	-2.513	0.114	-0.005	-0.163
		(0.040)		(0.056)	(0.031)	(0.274)
Printing, Publishing and Allied	27	0.562	-1.283	0.258	-0.028	0.015
		(0.072)		(0.047)	(0.034)	(0.146)
Chemicals and Allied Products	28	0.795	-3.869	0.453	-0.028	-0.006
		(0.033)		(0.048)	(0.051)	(0.123)
Petroleum Refining and Related	29	0.693	-2.259	0.404	-0.015	-0.114
		(0.055)		(0.111)	(0.020)	(0.101)
Rubber and Miscellaneous Plastic	30	0.727	-2.660	0.143	0.006	-0.260
		(0.040)		(0.050)	(0.017)	(0.105)
Leather and Leather Products	31	0.793	-3.828	0.359	-0.022	0.001
		(0.062)		(0.099)	(0.031)	(0.164)
Durable		0.911	-10.21	0.318	-0.014	-0.182
		(0.012)		(0.020)	(0.041)	(0.627)
Lumber and Wood Products,	24	0.996	-252.9	0.365	-0.026	-0.078
Furniture		(0.029)		(0.064)	(0.050)	(0.086)
Furniture and Fixtures	25	0.644	-1.806	0.073	-0.013	-0.301
		(0.059)		(0.060)	(0.033)	(0.458)
Stone, Clay, Glass and Concrete	32	0.945	-17.10	0.051	-0.024	-0.382
		(0.053)		(0.064)	(0.026)	(0.759)
Primary Metal Industries	33	0.911	-10.19	0.594	-0.024	-0.045
		(0.017)		(0.043)	(0.041)	(0.069)
Fabricated Metal	34	0.922	-11.81	0.525	-0.012	-0.055
		(0.029)		(0.048)	(0.042)	(0.081)
Industrial, Commercial Machinery	35	0.922	-11.77	0.629	-0.006	-0.084
Computer		(0.016)		(0.041)	(0.021)	(0.140)
Electronic, Electrical Equipment	36	1.015	–	0.450	-0.008	-0.035
		(0.024)		(0.032)	(0.037)	(0.071)
Transportation Equipment	37	0.879	-7.296	0.038	-0.035	-1.158
		(0.095)		(0.120)	(0.087)	(1.971)
Instruments	38	0.709	-3.771	0.394	-0.002	-0.071
		(0.033)		(0.046)	(0.031)	(0.087)
Miscellaneous Manufacturing	39	0.851	-5.726	0.200	-0.003	-0.138
		(0.047)		(0.062)	(0.034)	(0.178)

CHAPTER 3

Dispersed Skill-Biased Technology and Housing Price Dynamics in the U.S.

1. Introduction

For the past three decades, the U.S. housing market has experienced a dramatic increasing in average price, while the housing prices have been gradually diverging across Metropolitan Statistical Areas (MSAs). While the former has attracted plenty of attention, both in the media and in the academia, the latter has been studied by much less. Among the few who have been concerned with price divergence is Van Nieuwerburgh and Weill [2010]. As shown in Figure 3-1, the population weighted average local CPI-adjusted housing price increased by 56.55%. Following a somewhat similar pattern, the cross-sectional Coefficient of Variation increased by slightly more than 100%.[1]

A large part of the expenditure of a family goes to housing, either as a rental fee or to pay a mortgage. Therefore income is an important factor determining the local housing price. However, the personal income per capita did not diversify that much, according some growth literature. Despite this, Van Nieuwerburgh and Weill [2010] argue that the wages gradually diversify across MSAs, which is the key factor to account for the steep rise of housing price dispersion. It is a stylized fact as we will show in section 3 that when we exclude the effect of the local wage on the price of housing, the mean of Price-Wage ratio stays relatively constant from 1983 to 2000 before increasing steeply again from 2000 through 2006. On the other hand, the Coefficient of Variation of the same variable still has a shape fairly similar to that of the real price of housing, increasing from 0.2726 in 1980 to 0.4512 in 2007, an increase of more than 65%. This fact means that there must be factors beyond wage dispersion that affect it.

To identify the main determinant of the inequality of housing prices, we then check the income inequality across MSAs for specific percentiles. In section 3, we construct indices of income inequality across different MSAs for specific percentiles. We see that these indices evolved in different patterns. For high incomes, they were

[1]The figures for the balanced panel data set of 81 MSAs are respectively, 66.11% and 98.97%.

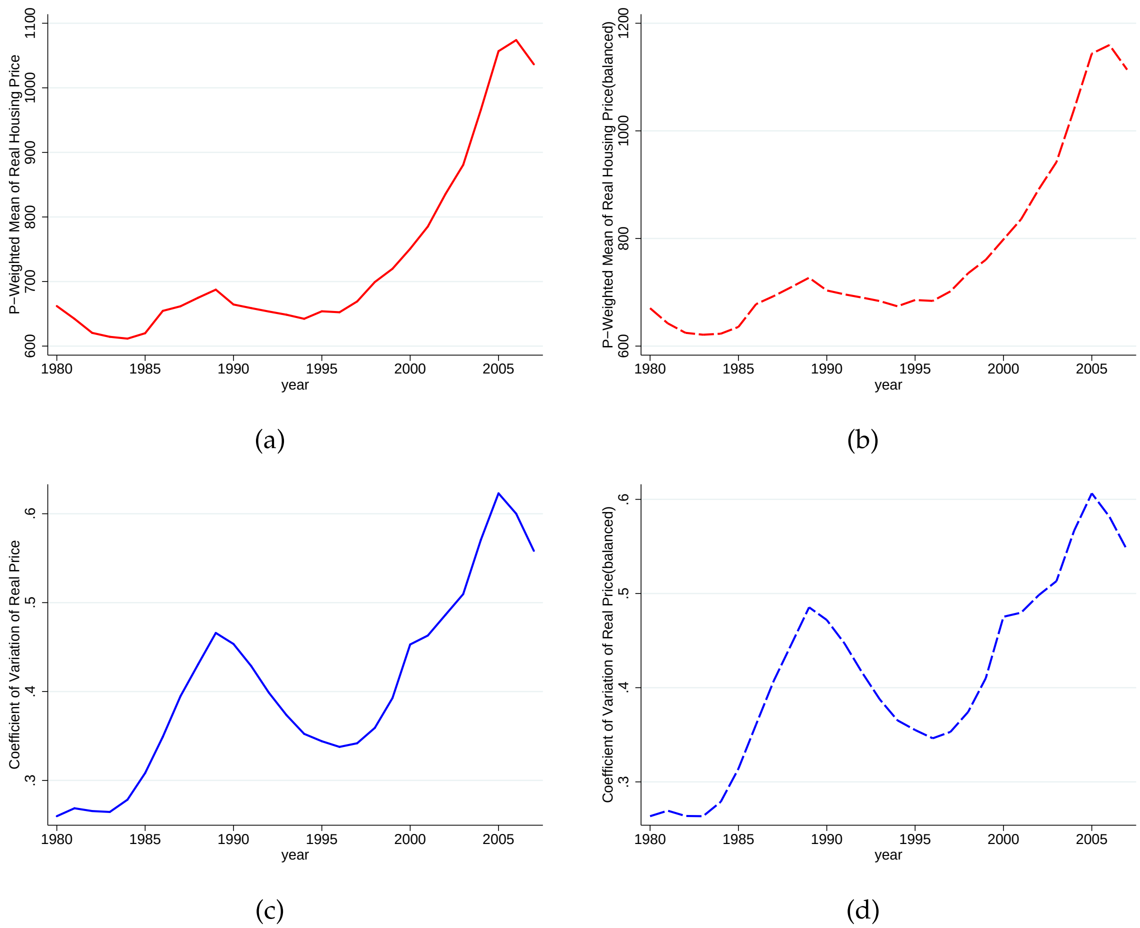


Figure 3-1: First and Second Moments of Housing Price: Red lines are the average real housing price across MSAs weighted by population, of which the solid line is shaped by the unbalanced panel and the dashed line is shaped by the balanced panel data; Blue lines are Coefficient of Variations of real housing price weighted by population, of which the solid line is shaped by unbalanced panel and the dashed line is shaped by the balanced panel.

becoming differently richer. In other words, the inequality of high incomes across MSAs rises; while for middle incomes and low incomes, the indices increased from 1980 to 1989, then decreased gradually. Occasionally, we find that 1989 is the year that the dispersion of housing price reached its first peak.

Understanding the reason why inequality indices for different percentiles follow different paths then becomes the key. In the present chapter, we seek the mechanisms that underlay the increasing cross-sectional dispersion of real housing price, and we find that dispersed skill biased technology change can contribute to a substantive variation of it. Skill premium has been well documented in the literature, Krusell, Ohanian, Ríos-Rull, and Violante [2000], for instance, show that the complementarity between capital equipment and skilled labor together with the technology change, accounts for a large fraction of income inequality. Moreover, like Hendricks [2011], I find and will show in section 3 that the difference of skill composition across MSAs increases gradually throughout the sample period. Because of skill biased technology change, the wage gap between skilled labor and unskilled labor has been widening for the past few decades. The effect of dispersed skill composition is two fold: first, the increasing income (and number) of skilled labor raised the demand of housing directly, while unskilled labor will still stay out of the housing market or still rent units rather than buying them; second, the increasing expected income of skilled labor makes it easier for them access to credit market.[2] Moreover, dispersion of skill composition offers other insights that the dispersion of productivity does not offer. I will show in section 3 that local housing prices are positively correlated with local income inequalities. Dispersed skill composition implies that this is the case under some reasonable assumption, and is supported by empirical evidence.[3]

The results in this chapter also shed light on the housing market. One of the most important thing in the asset pricing studies is the value of risk premia. However, it is not easy to perfectly distinguish risks from heterogeneity. Hizmo [2012] estimates the risk premia of income and housing price risks using a CAPM framework. However, if the heterogeneity is not controlled for, the result relied on pure CAPM framework will be biased. In other words, the risk premia will be either overestimated or underestimated. Our paper hopefully can help identify the risk premia. Moreover,

[2]According to Ortalo-Magné and Rady [2006], credit constraint plays a very important role in housing price dynamics.

[3]Määttäen and Terviö [2014] shows in an assignment model that the income inequality is negatively correlated with local housing prices, the result is different from mine. It is the full participation of the residents in housing market in their study that makes the result different. However, my result is supported by my empirical evidence.

like the effect of limited participation on asset prices in the finance literature (e.g. Brav, Constantinides, and Geczy [2002]), wage inequality results in heterogeneity of participation in housing markets, and has similar effect on equilibrium local housing prices. The rest of the chapter is organized as follows: section 2 discuss the relation between this paper and the existing literature; section 3 show a set of stylized facts that help us reach some conclusions.

2. Literature Review

2.1. Consumption. Our paper is related to theories of consumption. Krueger and Perri [2006], showed that in the U.S., an increase in income inequality does not necessarily lead to significant consumption inequality across regions. In a later paper, i.e., Krueger and Perri [2010], they found that in Italy low income households would not hold more real estate when their labor income increased, while high-income households prefer to hold more real estate when income increases. This chapter is different from those studies. First, I study how the income risks affect the housing prices in MSAs; Second, Krueger and Perri [2010] used micro-level data for both the U.S. and Italy, while we use MSA level data, which may avoid the problem of sample selection. Favara and Song [2014] claimed that households with the highest income growth ratio will be more optimistic and will buy more house. Our model is somewhat different from this. I will focus on the effect of income risk, rather than the expectation based on it on the local housing market demand. In the empirical part, I compute income inequalities within states, which is different from Favara and Song [2014] and Van Van Nieuwerburgh and Weill [2010]. The former compute income and wage inequality within MSAs, while the latter compute just wage inequality of the whole country. Actually, Van Nieuwerburgh and Weill [2010] accounted for the effect of wage inequality on the dispersion of housing prices, not the return in local market.

2.2. Borrowing Constraint and Down Payment. Recent work of Ortalo-Magné and Rady [2006] uses a rigorous dynamic general equilibrium model, incorporating borrowing constraint, income risks and a down payment for the first house, to study the effects of these factors on housing market dynamics. In a life cycle model, they find that the equilibrium price responds more to marginal buyers than tail income households. They also document the empirical evidence that young cohorts are a critical factor in the fluctuation of housing prices. At an earlier time, Stein [1995] studied the down payment effect on equilibrium prices at both the national level and the regional level. With the mechanism of an interaction between the down payment and the transaction amount in his static model, it is possible to generate a salient fluctuation of equilibrium housing prices. However, using a longer time series data than is used in Stein [1995], the empirical pattern of prices is predicted better by Ortalo-Magné and Rady [2006].

2.3. Limited Participation. This branch of literature is similar to that of credit constraints and down payments, with the difference that the limited participation literature focuses mostly on the stock market. However, this literature can help to explain the property of the housing market as an asset market. For instance, Brav, Constantinides, and Geczy [2002] argue and show empirically that a Stochastic Discount Factor (SDF), calculated as the weighted average of the individual household's marginal rate of substitution, can explain the equity premium puzzle. In our study, the limited participation of households or individuals in the local housing market can shed light on the local housing price dynamics.

2.4. Skill-Biased Technology and Income Inequality. There is a large body of literature on Skill-Biased Technological Change and income inequality, Acemoglu [2002] gives an excellent review of this area. Despite the fact that the cause of the technology change is not very clear, it is a stylized fact that the wage gap between skilled and unskilled labor is widening. Given this fact, skilled (or not) is an important heterogeneity for explaining the labor market, hence the housing market. In this paper, we put aside the cause of the technological change. Rather we take this as an exogenous process and study its effect on the price of housing.

Combining with the finding in Hendricks [2011] that the skill composition diversifies across cities in the U.S., the skill biased technology change can explain the housing price more precisely. The effect of this technology is two fold. First it makes the wage growth rate of skilled labor higher than that of unskilled labor. Second, since the composition of skilled labor increases faster in some MSAs, and the participation rate of high income persons is significantly higher than that of those with low income, the two effects make the dispersion of housing prices increases faster than predicted by just average wage in MSAs.

2.5. Urban Wage premium. In urban economics, it recently has been documented that the real wage in urban areas is highly correlated with the population size, as in Baum-Snow and Pavan [2012]. And Glaeser and Maré [2001] find that skill composition in cities can explain a substantial variation of the urban wage premium.[4] These studies use the local Consumer Price Index, which contains rent instead of a housing price, to explain the real wage. However, the disparity between the housing price and rent makes this index not completely suitable. At least, this index is accurate only for the agents who rent or are in places where the house price to rent ratio stays relatively constant.

2.6. Standard Asset Market Model. Housing is treated as a standard financial asset by many economists. Thus the housing market is treated as a financial market, e.g., Poterba [1984]. In his seminal work, Poterba [1984] treats housing as a standard asset. The price is determined jointly by the construction cost, expected income from rental fees, transactions costs and so on. Thus, the price-rent ratio is determined by some variables, that are not quite time varying. However, this theory has a hard

[4] Glaeser, Saiz, Burtless, and Strange [2004] give a thorough disucssion on this issue.

time explaining the housing price dynamics in the past two decades. Using different approaches, Stein [1995] and Favara and Song [2014] document the speculative behavior of agents in the housing markets. The former relates the trading volume to the volatility of the housing price, while the latter argues that heterogeneous expectations will affect the equilibrium housing price. Recently, Ortalo-Magné and Prat [2010] developed a spatial pricing model that implies that a CAPM model could be applied to predict the housing price. In their model, the spatial allocation is taken as an element of portfolio, so in the equilibrium, the marginal utility obtained from all the allocations are identical. Most recently, Hizmo [2012] similarly employs the CAPM framework, relating local incomes to housing prices to identify the risk factors.

Standard asset pricing model have difficulty explaining the equity premium puzzle, Piazzesi, Schneider, and Tuzel [2007] use a consumption-based asset pricing model to include housing services in and asset pricing framework, so that they can explain the equity premium puzzle to some extent.

2.7. Heterogeneity and Risk Shocks. Studies on this aspects of housing market are relatively rare. Exceptions are Han [2008, 2010], who by using a GARCH model, found that the the risk return relation has a salient variation across MSAs, and she then found that MSAs can be sorted into two groups according to the net immigration. Lustig and Nieuwerburgh [2010, 2005] explore the relation between housing collateral and regional risk sharing. However, they don't investigate risk-return relation in the housing market. Favara and Song [2014] show with empirical evidence that heterogeneous expectation conditional on the income shock will drive the housing price up. They also show that positive income shock and negative income shock can have asymmetric effect on the local equilibrium housing prices. Using a similar data set, we find that under the hypothesis of skill biased technology change, income inequality can be positively correlated to the mean price.

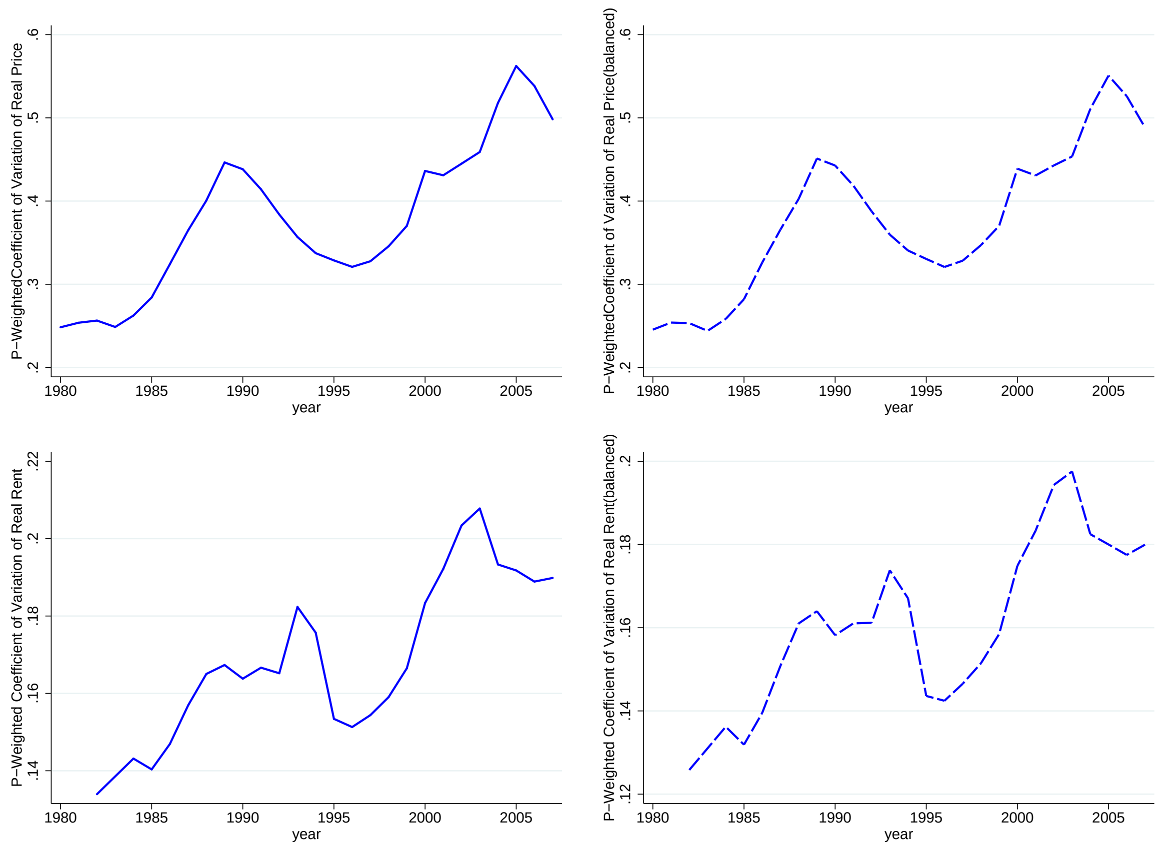


Figure 3-2: Coefficient of variation of real housing price and real rent: the upper panels show the real housing price with the left constructed by the unbalanced MSAs, the right constructed by balanced panel data for 81 MSAs. Lower panels are the real rent counterparts of the upper panels

3. Stylized Facts

In this section I present some stylized facts of dynamics of rent, wage, housing price and so on. Figure 3-7 in the Appendix shows the variation of four main variables that will be focused on in following subsections.

3.1. Increasing Dispersion of Housing Price Across MSAs. In Figure 3-2, I show the time trend of the dispersion of housing price and real rent across MSAs. It is a salient fact that these two indices have been displaying similar patterns. However, the indices for real housing price increased from 0.2484 to 0.4983, slightly more than that for real rents which increases from 0.1340 in 1983 to 0.1898 in 2007. If the housing markets are entirely asset markets, then as Poterba [1984] predicted, rent and the price should go in the same direction. It is true that they are roughly moving in the same direction, but the percentage changes are not the same.

In the top right panel of Figure 3-3, we can see that the dispersion of real wage increases roughly throughout the sample period, with exceptions of sudden increase and sudden decrease around 2000. As predicted by Van Nieuwerburgh and Weill [2010], CV of the real housing price and CV of the real wage go in the same direction. However, the variation of the real wage only accounts for a small fraction of that of real housing price. In the lower right panel we can see the CV of the price-wage ratio still increases, in a scale that is similar to the CV of real price, which is evidence that the dispersion of real wages across MSAs can only account for a small part of the dispersion of housing prices.

Moreover, in the bottom left panel of Figure 3-3 is the CV of the price-rent ratio.[5]Although there was a big decrease after 1990, the index increases from 1984 to 1990 and from 1994 to 2005 again. For the whole sample period, the CV of price-rent ratio increases by more than 80% from 0.1714 in 1984 to 0.3212 in 2007. Combining these facts, we find that the evidence is not completely in favor of Poterba [1984] and Van Nieuwerburgh and Weill [2010]'s theories. Furthermore, the first two moments for the Rent-Wage ratio as shown in Figure 3-4, provide additional evidence their theories may not be correct. Surprisingly, while the mean price-wage ratio increases over time, the rent-wage ratio decreases. This fact strengthen the finding that housing price and rent are not going in exactly the same way. In contrast with the steep increase of the dispersion of housing price, the CV of the rent-wage ratio has not increased so notably. Instead, it has fluctuated around some value, and the variation has been small: from 1980 to 2008 it increased less than 7%; the peak value was about 25% higher than the trough value.

[5]Himmelberg, Mayer, and Sinai [2005] studies the price-rent ratio fluctuation for the aggregate economy, similarly, they did not see a rather flat price-rent ratio.

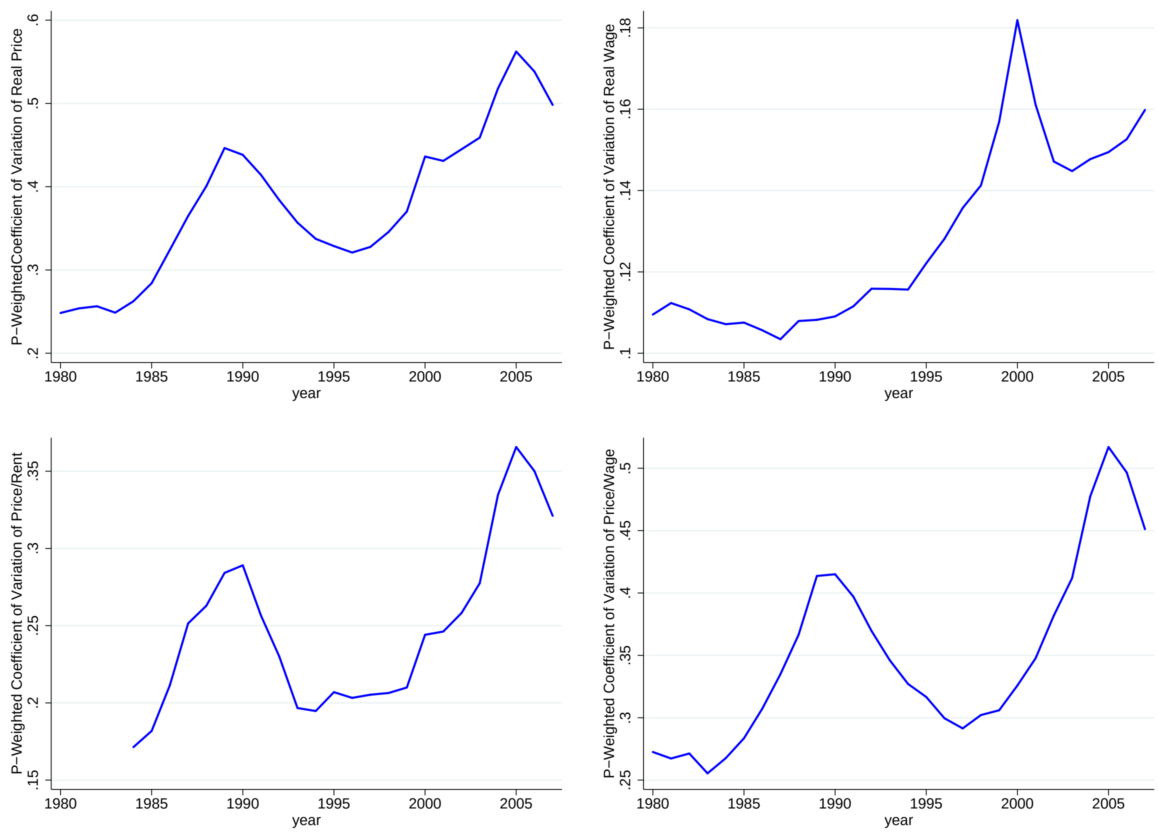


Figure 3-3: Dispersion Across MSAs. Top left panel is the Coefficient of Variation (CV) of real housing price; Top right panel is the CV of real wage; Bottom left panel is the CV of Price-Rent Ratio; Bottom right panel is the CV of Price-Wage Ratio.

3.2. Income Inequality in Detail. We then investigate the inequality within several groups. We first find the specific income for the 95th percentile in an MSA, then construct an inequality index across MSAs for this specific income. In the same way, we construct inequality indices for different percentile incomes. It is apparent that the trends of these indices are different for different groups. In Figure 3-5, we show the indices for top income, middle income and lower income groups. The inequality within top income group increases gradually, but those for the middle and lower income groups increased from 1980 to 1989, then decreased from 1989 through 2010. Although the amount is not particularly close to that for dispersion of housing prices, but still it can give us some hint on the issue. That is, the income or wages

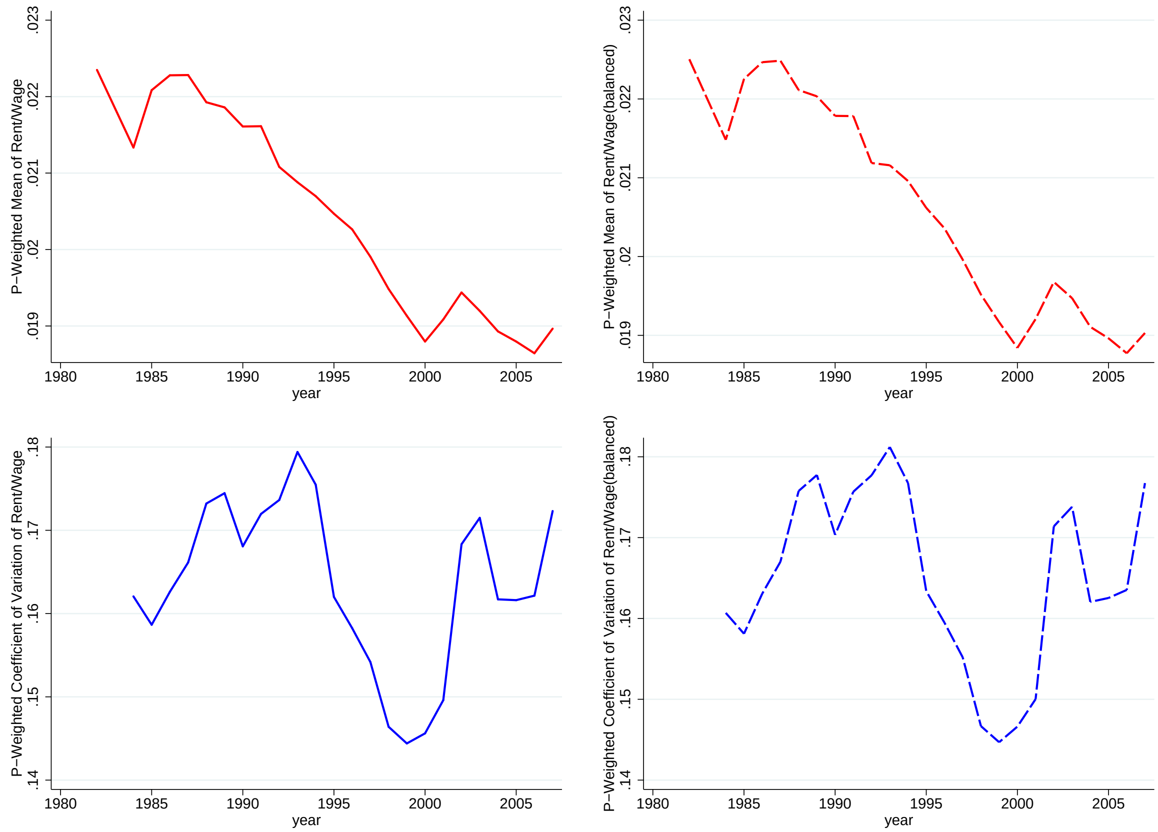


Figure 3-4: Coefficient of variation of Rent-Wage Ratio: Top left panel is the mean of Rent-Wage Ratio; Top right panel is population weighted mean of Rent-Wage Ratio; Bottom left panel is the CV of Price-Rent Ratio; Bottom right panel is the population weighted CV of Rent-Wage Ratio.

of some specific groups account for more of the dispersion of the housing price than other groups.

3.3. Increasing Dispersion of Skill Composition. Skill composition diperses increasingly across both the states and the MSAs.[6] Figure 3-6 displays the increasing dispersion of the skill composition across states. In both panels, the series increase strikingly, in particular, the population weighted series increased by more than 50%,

[6]The data for MSAs is more noisy than that for states though.

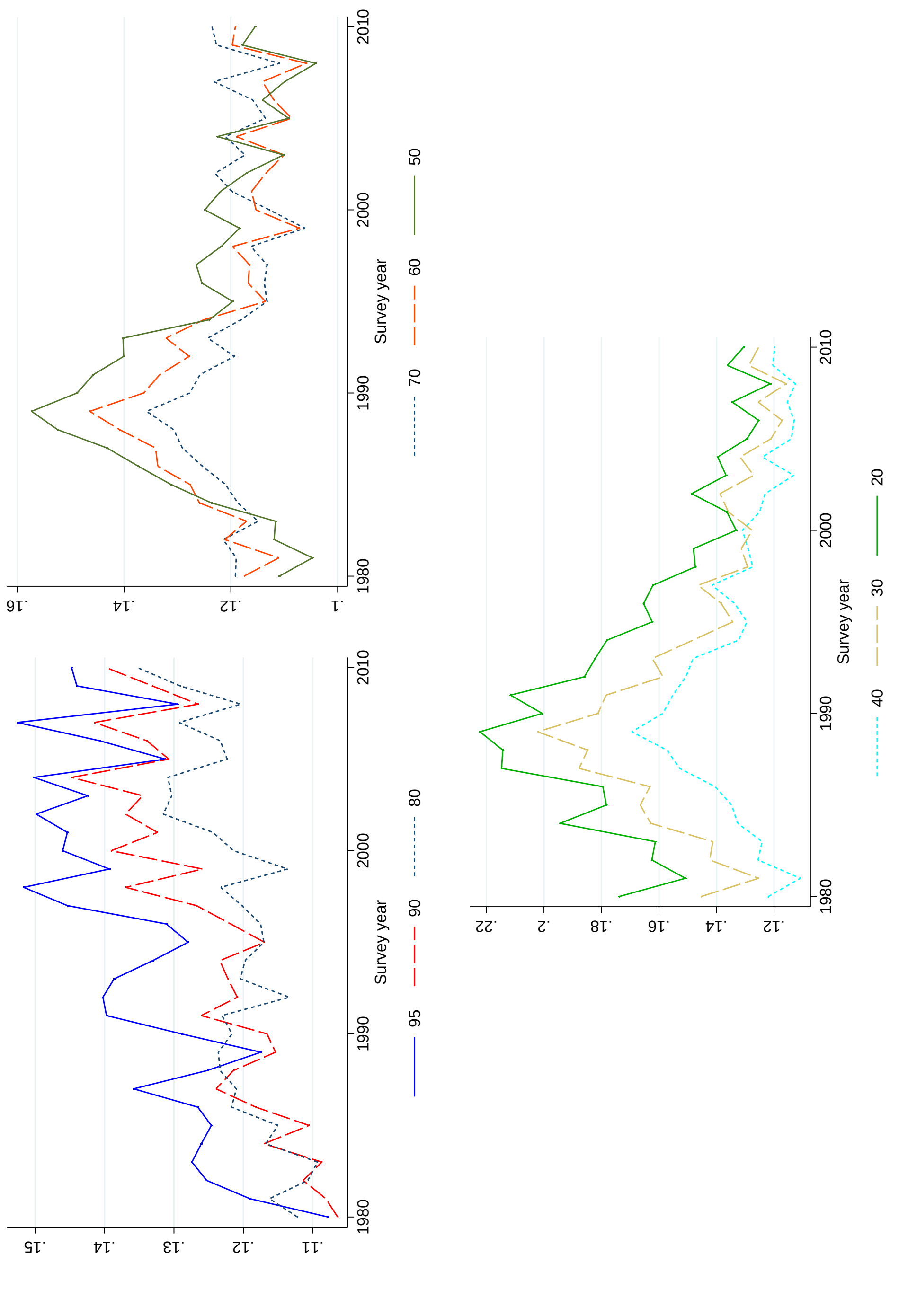


Figure 3-5: Income inequality across MSAs within same groups.

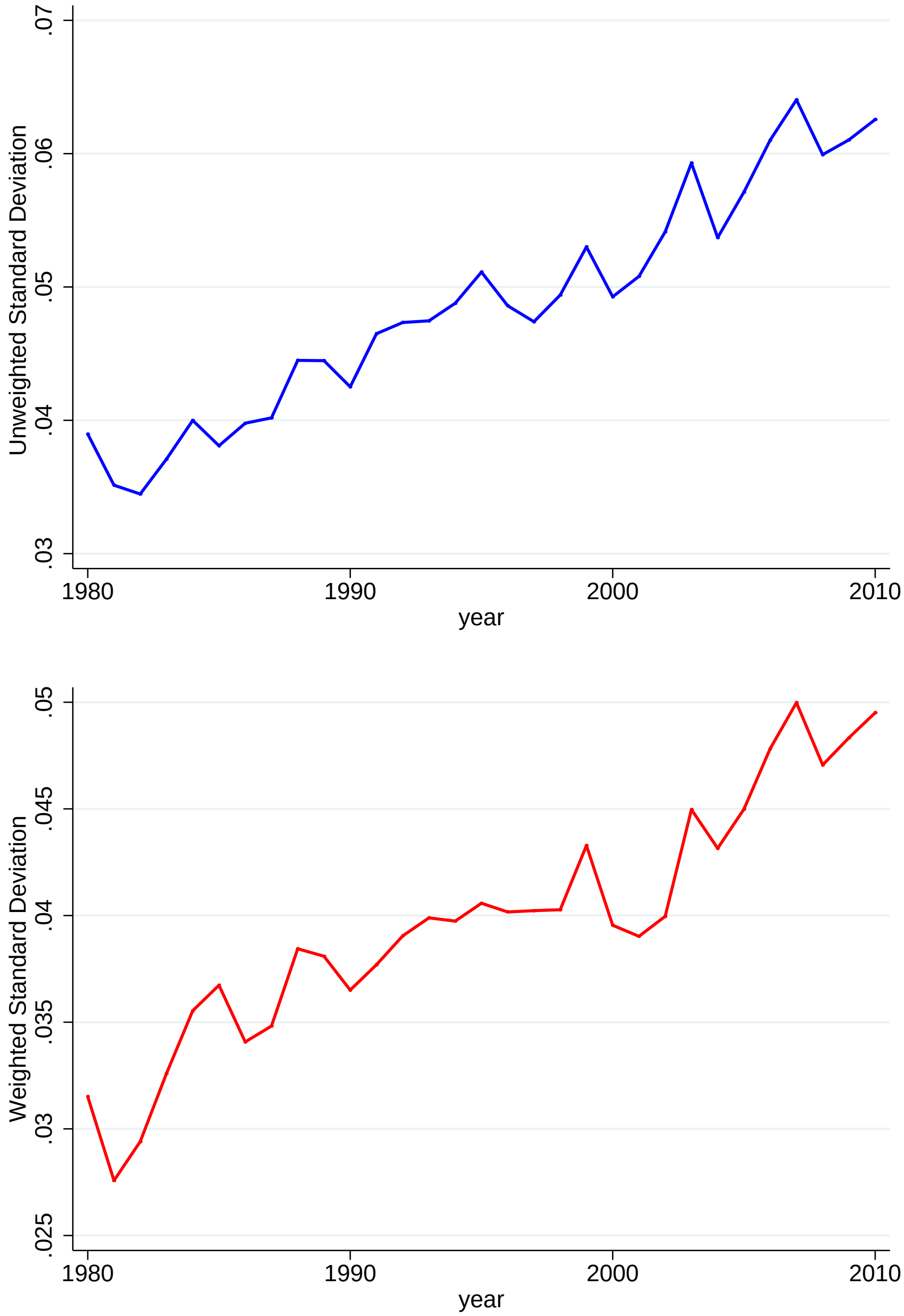


Figure 3-6: Increasing Dispersion of Skill Composition. The data comes from CPS. Standard Deviation instead of Coefficient of Variation is used to measure the dispersion of skill composition across states. The blue line on the left panel is for the series not weighted by population, while the red line on the right panel is the series weighted by population.

Table 3-1: Relation between local education wage and education share

Dependent Variable: $\log w_{it}^{CG}$				
Variables	(1)	(2)	(3)	(4)
$S_{i,t}^{CG}$	0.8402			
	(0.0877)			
$S_{i,t-1}^{CG}$		0.8906		
		(0.0902)		
$S_{i,t}^{HD}$			-0.1618	
			(0.0801)	
$S_{i,t-1}^{HD}$				-0.1681
				(0.0823)
Year dummy	yes	yes	yes	yes
Observations	1581	1530	1581	1530

from less than 0.035 to 0.05. This fact gives us a hint that the increased income inequality across space within the high income cohort may be caused by the dispersed skill composition.

3.4. The Relationship between The College Graduate share and their Wage. To examine whether the college graduate share is able to account for variations of the wage, we run the regression

$$\log w_{it}^{CG} = \beta S_{it}^{CG} + \alpha_i + \alpha_t + \varepsilon_{it}.$$

The results are shown in Table 3-1. It shows that the logarithm of wage is highly positively correlated to the college graduate share, and negatively correlated with the high school dropouts. The results show that the supply of skilled labor is not driving the demand for skills. Rather, causation is it is working in the opposite direction. When we add a lagged term of the dependent variable, and apply the method of Arellano and Bond [1991], the result still holds. The limitation is that the data is at the state level not the MSA level. Since the definition of MSAs in the CPS data is not fixed over time, panel data with a long time period is not available for

MSAs. Despite this fact, the state level can still describe the spatial evolution of the college graduate share of labor and their wage.

3.5. Local Income Inequality and Housing Price. The last thing that we want to check is the relationship between the local income inequality and local housing price. To do so, we first construct local income inequality index for every MSA, by calculating the population weighted Gini coefficient from the county level data. In Table 3-2, the results show that as local income inequality increases, the local housing price increases as well. This result is consistent with Favara and Song [2014], and in contrast with Määttäen and Terviö [2014], whose assignment model predicts that the mean housing price in an area should go down as the income inequality increases. The inequality index constructed using county data will lose some information about the real income inequality because of income inequality within counties. However, this index can roughly capture the inequality in the MSAs.[7]

[7]This phenomenon is not that obvious for the index constructed by wage and weighted by employment. This is probably because we use the county data rather than individual data. A good alternative is to use Census data with geocode, which offers detailed in formation on a representative sample. However, Census survey is not conducted every year, it can only give the data at the frequency of decade.

Table 3-2: Relation Between Housing Price and Income Inequality (MSA Level)

Panel A: MSA level data, Dependent Variable: $\log p_{i,t}$			
Variables	(1)	(2)	(3)
$\sigma^2_{i,t}$	1.009	0.435	0.422
	(0.154)	(0.142)	(0.143)
$\log y_{i,t}$		1.212	1.200
		(.142)	(0.067)
$\log Pop_{i,t}$			0.033
			(0.031)
Year dummy			
Observations	1511	1511	1511
Panel B: state level data, Dependent Variable: $\log p_{i,t}$			
Variables	(1)	(2)	(3)
$\sigma^2_{i,t}$	4.108	2.038	2.034
	(0.221)	(0.230)	(0.229)
$\log y_{i,t}$		0.194	0.157
		(.011)	(0.015)
$\log Pop_{i,t}$			0.179
			(0.048)
Year dummy			
Observations	1530	1530	1530

4. Data Sources

4.1. Current Population Survey. CPS March data is employed to construct the indices of regional economies, with the help of geo code.[8] However, before 1987, the geo codes are not widely recorded, especially for metropolitan areas, which makes the data more noisy before that.

[8]Geo code is a location label that CPS has been putting on some dates since 1987.

4.2. Nominal Housing Price. There are several data sources for nominal housing prices, either a housing index or nominal housing values. Since we focus on the evolution of the dispersion of housing price across time, we need housing prices that are comparable both across MSAs and across times. Therefore, an index which is normalized to be 1 for every MSA at a specific year is not appropriate. Therefore, we adopt the Freddie Mac Conventional Mortgage Home Price Index (CMHPI) from 1975 on, which is the same as in Van Nieuwerburgh and Weill [2010]. The CMHPI is a repeat-sale price index which pertains to single-family properties purchased or refinanced with a mortgage below the conforming loan limit. Thus, it is a constant-quality house price index.

Moreover, Davis and Heathcote [2007] provide a data set that includes, among other things, land price, structure capital cost and housing values, at both the aggregate level and the state level. In their paper, they provided a sophisticated method for constructing and estimating these variables.

4.3. MSA level data. Most of the MSA level data are from Bureau of Economic Analysis (BEA)'s web site, Table CA1-3 at `http://www.bea.gov/regional/reis/` provides the data in detail.

5. A Preliminary Model

Consider one region one period model, with two types of skilled labor, s and u, no uncertainty. Preferences can be described by the utility function:

$$U_i = \log(C_i) + \theta \log(H_i). \tag{5.1}$$

where C_i refers to non-housing consumption, and H_i is the housing service consumption, $i = u, s$, means unskilled and skilled labor respectively. The production side of the economy consists of two sectors, a normal good sector and a housing production sector. The normal good is produced following the function:

$$Y = f(N_s, N_u) = A\left[\lambda_s(\phi_s N_s)^{\frac{\sigma-1}{\sigma}} + \lambda_u(\phi_u N_u)^{(\frac{\sigma-1}{\sigma})}\right]^{\frac{\sigma}{\sigma-1}}. \tag{5.2}$$

where σ is the elasticity of substitution between the two types of labor; ϕ_s and ϕ_u are respectively the efficiency unit of s and u. In the present chapter, they stand for promoters of the technologies that use them. $\phi_s > \phi_u$ means the technology is more s-biased overall. Moreover, a unit of housing service is produced following the function:

$$H = (Y_h)^\gamma \text{ with } 0 < \gamma < 1.$$

For simplicity, we assume that there is only one input for the production of housing service, that is, housing is a normal good produced by labor.[9] Furthermore, since the housing supply is relatively inelastic, the assumption that $0 < \gamma < 1$ is reasonable. The equilibrium requires both of the markets clear, first the normal good market clears, so:

$$N_s C_s + N_u C_u + Y_h = Y$$

and then the housing market clears:

$$N_s H_s + N_u H_u = H.$$

The following lemmas and propositions deliver the main result of this model.

Lemma 5.1. Under the assumption $\sigma > 1$, we have:

$$\frac{\partial(w_s/w_u)}{\partial(\phi_s/\phi_u)} > 0.$$

which means that if there is s-biased technology change in the region, then the relative wage of s type increases and hence the wage inequality in the region increases as well.

[9]More realistically, land is the most important factor to account for housing price, but since there is no landlord in this simple model, this assumption is reasonable.

PROOF. The wage for each type of labor is the first order derivative of the normal good production function with respective to its quantity. Thus the wage ratio can be written as:

$$\frac{w_s}{w_u} = \frac{\lambda_s}{\lambda_u}\left(\frac{\phi_s}{\phi_u}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{N_s}{N_u}\right)^{-\frac{1}{\sigma}}.$$

Under the assumption that $\sigma > 1$, it is very easy to see that, as the ratio ϕ_s/ϕ_u increases the wage ratio increases as well, given other things unchanged. Moreover, the wage dispersion can be written as:

$$\delta = 2\frac{w_s - w_u}{w_s + w_u} = 2\left(1 - \frac{2}{w_s/w_u + 1}\right),$$

which increases in the skill premium w_s/w_u. By the inequality proved above, wage dispersion within a region increases in the ratio ϕ_s/ϕ_u. □

We then turn to investigate the effect of technological change on the real housing price. A salient fact is that housing ownership rate of high income persons is significantly higher than that of low income persons, i.e., the participation rate of high income persons is higher. Based on this observation, we use a similar mechanism in our model to show that if an s-biased technology process happens, there should be an increase in the housing price, assuming the average wage or income unchanged. This result is shown in Proposition 5.2.

PROPOSITION 5.2. If the u labor does not participate in the housing market, and its utility function is $U_u = \log(C_u)$, given the assumption in Lemma 5.1, $\gamma < 1$ and that the income in the region Y does not change, then

$$\frac{\partial(Q/P)}{\partial(\phi_s/\phi_u)} > 0$$

PROOF. The s types will maximize their utility function in (5.1), subject to the income constraint $P \cdot C_s + Q \cdot H_s = w_s$. According to the property of the functional forms, the optimal allocation is given by the first order condition:

$$P \cdot C_s = \frac{H_s \cdot Q}{\theta}.$$

Since only this type of labor participate in the housing market, the total demand of housing is

$$H = N_s \cdot H_s = \frac{N_s \cdot w_s}{(1+\theta)Q}.$$

For normal good, its consumption by s type is $N_s \cdot C_s = \theta \cdot N_s \cdot w_s/(P + \theta P)$. Meanwhile, the u types will only consume the normal good. Thus their consumption is $C_u = w_u/P$. To make the normal good market clear, we must have the following equilibrium condition:

$$\frac{N_u w_u}{P} + \frac{\theta N_s w_s}{(1+\theta)P} + \left[\frac{N_s w_s}{(1+\theta)Q}\right]^{\frac{1}{\gamma}} = Y. \tag{5.3}$$

To keep the average income level unchanged, we assume $Y = \bar{Y}$ to be constant. It is not difficult to see that the price P would not change, if we keep the real output unchanged, because

$$\frac{N_u w_u}{P} + \frac{\theta N_s w_s}{(1+\theta)P} + \frac{N_s w_s}{(1+\theta)P} = \bar{Y}.$$

To see how this change will lead to an increase in Q, we check the balance sheet in Equation 5.3, where the third term on the left hand has to satisfy

$$\left[\frac{N_s w_s}{(1+\theta)Q}\right]^{\frac{1}{\gamma}} = \frac{N_s w_s}{(1+\theta)P}.$$

Given w_s increases and P is fixed, to make the equation hold, Q must increases. Otherwise the left hand side will increase more than the right hand side. The result is driven by the assumption: $\gamma < 1$. □

6. Conclusion and Future Work

In this chapter, I examine the relation between the dispersion of skill composition across MSAs in the United States and that of the housing price for the recent decades. We find that Skill Biased Technology Change together with the dispersed skill composition can explain the dispersion of the housing price across areas. Mostly this chapter considers the effect of *ex ante* heterogeneity on the local housing market. Future work should include in the model *ex post* heterogeneity, i.e., the risks in the economy. In terms of methodology, Fernández-Villaverde and Rubio-Ramírez [2007] provide a very promising econometric method to estimate DSGE models with stochastic volatility, and Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe [2011] give an example of its application. My future work will go in this direction. Moreover, other data sets like the Census survey data can possibly be employed.

7. Appendix

7.1. Raw Data.

7.2. Dispersion of Different Education Level Shares.

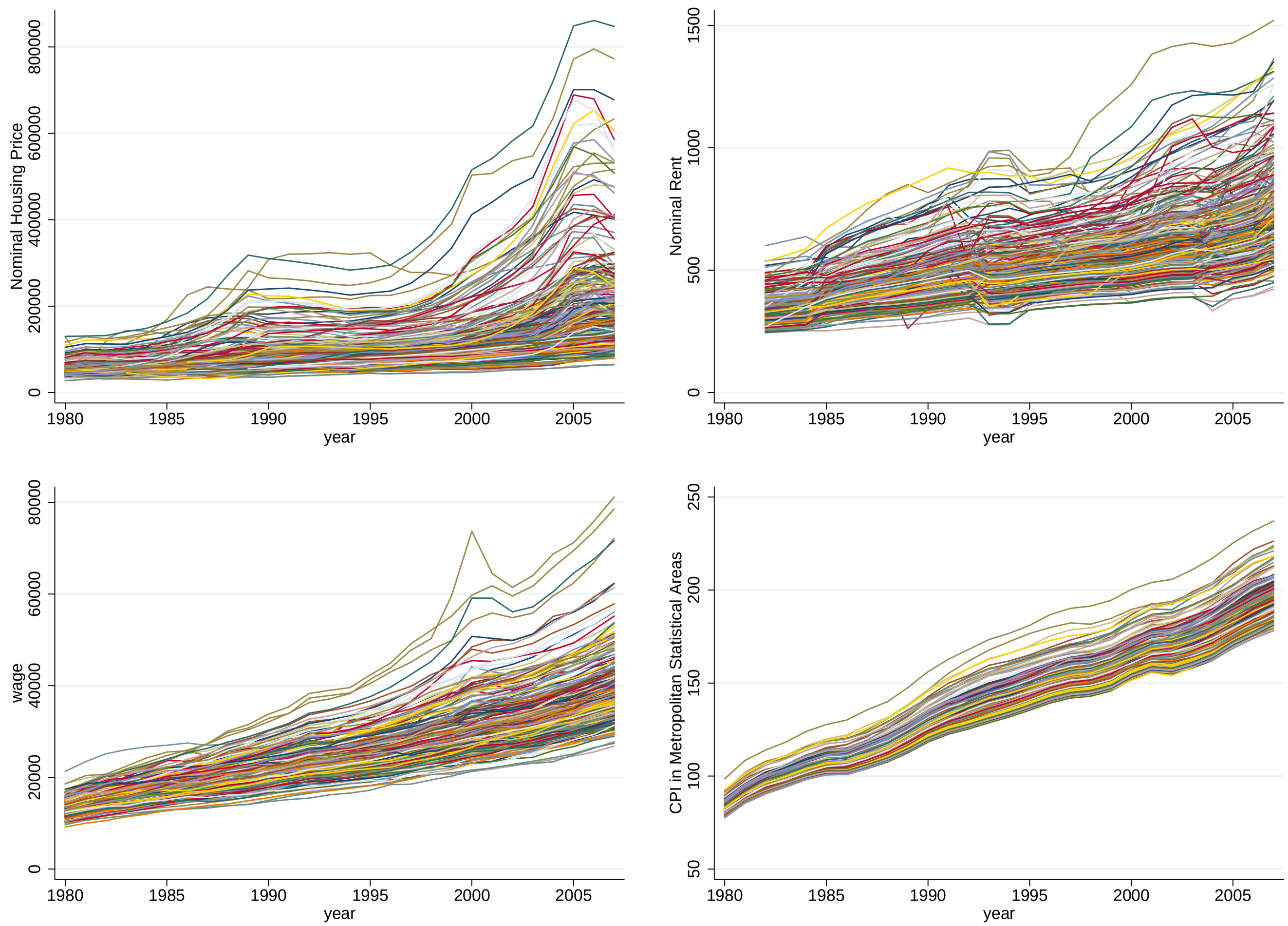


Figure 3-7: The Plot of Raw Data. The top left panel shows the nominal time series of housing price in each MSA; Top right panel shows that of nominal rent in each MSA; Bottom left panel shows the nominal wage in each MSA; Bottom right panel shows the Consumer Price Index in each MSA. Note that the data for rent start from 1983.

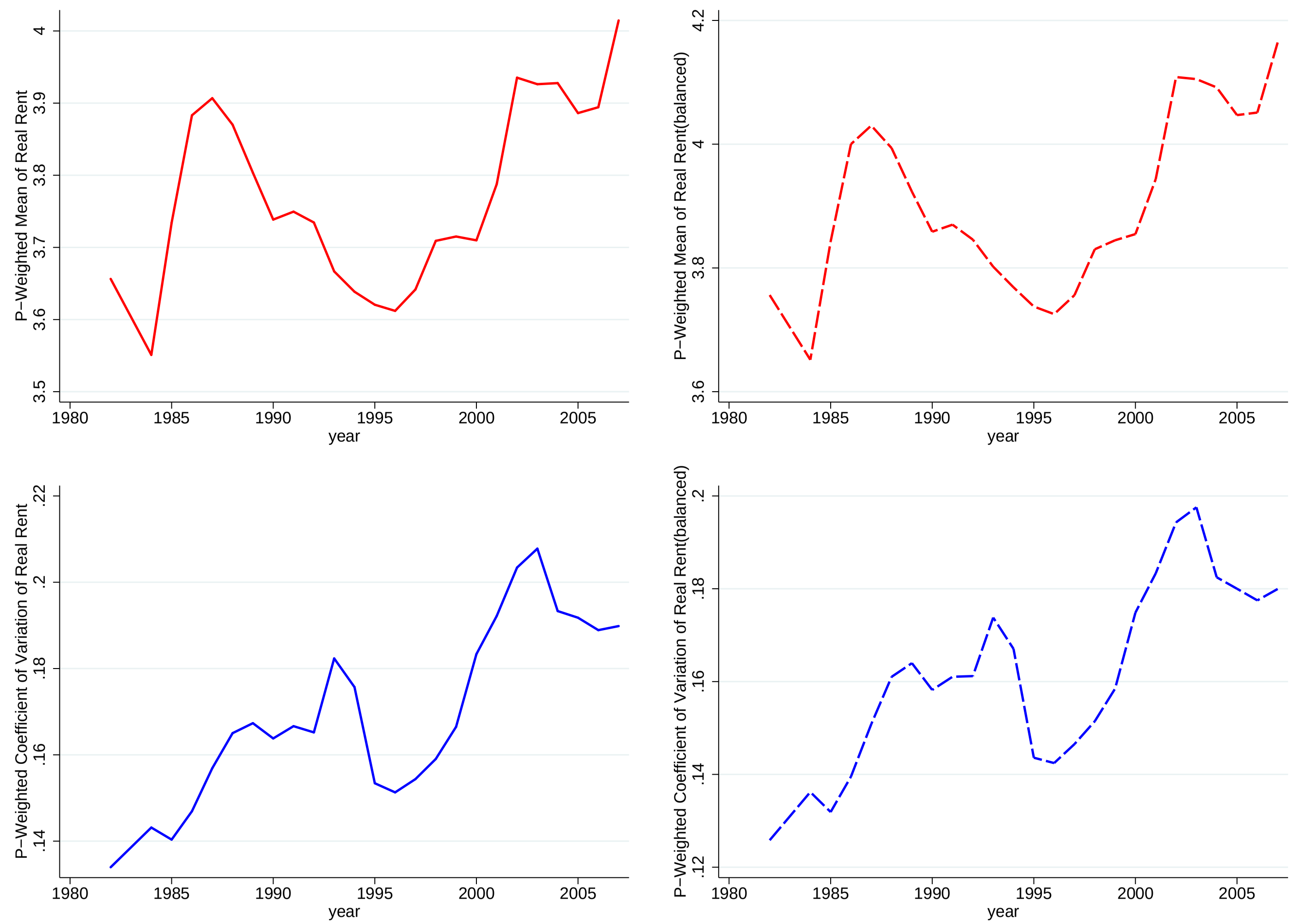


Figure 3-8: First two Moments of Real Rent. Top panels are respectively the mean of real rent across MSAs for unbalanced panel and that of the balanced one; The bottom panels are respectively the CV of real rents across MSAs for unbalanced panel and that of the balanced one.

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