Dissertation

Essays on the Relationship Between Compensation and Productivity–A Regional Analysis

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Abstract

Essays on the Relationship Between Compensation and Productivity–A Regional Analysis

This dissertation is divided into three chapters–with the present abstract summarizing each. Across the three chapters, I seek to better describe the sectoral and regional characteristics of the relationship between compensation and productivity for the average worker in the United States. My results demonstrate the importance of disaggregating the economy into more than two or three sectors or regional units. Furthermore, regressions performed on a panel dataset of US states from 2005–2014 (or a subset of those years) across fifteen sectors highlight the disparate impacts that state policies–such as sales tax rates, income tax rates, and minimum wage laws–can have on the average worker of different sectors. These results are presented in Table 3.8 on page 156. Altogether, these papers quantify the tradeoffs for which policymakers should account as they craft state-level policy.

Data for all three chapters largely comes from government sources such as the Bureau of Economic Analysis, the Bureau of Labor Statistics, and the US Census Bureau. The dataset used is comprised of compensation and productivity estimates in tandem with a variety of state-level characteristic measures such as educational attainment and demographic information.

In Chapter 1, I estimate and report the labor share of output for workers within each US state, in each year from 2005-2014, across fifteen sectors of the private, non-farm economy. For simplicity, I refer to the US state, year, and sector collectively as "the three dimensions of the analysis." I thoroughly discuss the regional and sectoral differences in this labor share estimate and note that even within sectors, there are significant regional differences

in the labor share. This result is particularly interesting considering that, within some sectors, workers would intuitively be equally important in production regardless of location–Retail and Accommodation and Food Services, for example. Yet, despite this thought, results suggest that within a give sector, US states feature wildly different labor shares. This provides evidence of the importance of both a sectoral and regional analysis in future chapters.

The chapter itself is couched in terms of previous theories of labor share determinants. Economists from the time period of Smith (1817) to the present have analyzed and discussed labor shares and what drives their values. Labor shares are widely discussed due to the fact that labor shares are often considered a key measure of the distribution of income accruing to workers. As such, this chapter contributes to an already prevalent literature in a meaningful way. It adds greater regional and sectoral dimensions to the discussion and serves as a test of the applicability of a variety of theories to a disaggregated view of labor shares.

In Chapter 2, I use the previously calculated labor shares to estimate real compensation and productivity for the average worker across the three dimensions of the analysis. I discuss the regional and sectoral trends of compensation and productivity independently, as well as combined in the form of the Compensation-Productivity Difference–defined as the difference between compensation and productivity. Using maps to visualize compensation, productivity, and the comparison between the two, a clear pattern emerges. States in the Midwest tend to compensate workers at a level above productivity while the opposite is true in coastal states. Previous literature argues that this outcome is likely due to the presence of amenities or disamenities in regions. That same literature, however, argues that price differences should generally capture these amenities. Because I use real compensation and productivity estimates, my results suggest that current price measurements may not be capturing all amenities at the state-level.

This paper represents a contribution to existing literature via a significantly more detailed discussion of whether or not workers receive appropriate remuneration for their work-related endeavors. This makes for a very topical discussion as studies have routinely suggested a growing gap between compensation and productivity. In addition, there is a prevalence of workers that feel they are significantly underpaid. This chapter highlights that when looking at the economy in aggregate, results would suggest this to be the case. To the contrary, when the economy is disaggregated by sector or region, there is far greater variance in the relationship between compensation and productivity. With this result, I argue that over-aggregation misses a key component of the story.

In Chapter 3, I focus on the Compensation-Productivity Difference and seek to assess the extent to which workers view state-level policies as amenities or disamenities that either draw them to, or push them from, a given state. A supply and demand model of a labor market is used to predict the impact of state policies on the Compensation-Productivity Difference. I then run a set of regressions for each of the fifteen sectors using the Compensation-Productivity Difference as the dependent variable and a variety of state-level control variables and policy measures as the independent variables. The collection of control variables represent state characteristics such as educational attainment and demographic information. The results suggest that state-level policy changes can predictably impact the relationship between compensation and productivity in some cases. As an example, an increase in certain taxes would be viewed as a disamenity to prospective workers in a state labor market. This will tend to drive compensation up relative to productivity as a result of diminished labor supply due to the presence of a disamenity. While there is similar evidence for other policies–both amenities and disamenities–these effects differ across sectors. The chapter concludes with a detailed discussion of these results and the tradeoffs policymakers should consider before undertaking any policy change.

Combined, these chapters contribute to previous work in the amenity and labor literatures through the addition of a greater emphasis on regional differences in labor market outcomes. The works also yield tractable results that could be used as a guide for policymakers looking to implement changes in their state. While each chapter is written to be a standalone project, each builds on previous chapters to form a unified research agenda.

Acknowledgements

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[1] Go Eagles.

Thank you to the Alleycat staff for always being light-hearted and brightening my day in the early stages of my data work and drafts. Special acknowledgments go to Aidan, Cassie, and Lindsay.

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This dissertation is typset in LaTeX using a document class designed by Leif Anderson.

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CHAPTER 1

An Analysis of the US Labor Share Through Time, Across Regions, and Across Sectors

The labor share is a key indicator for the distribution of income in a given region and is traditionally defined as the percentage of output or income that accrues to workers (Schneider, 2011). In particular, the labor share assesses the payment for workers' contribution to output relative to all other inputs used in production. Considering this definition of the labor share, it becomes easy to see why the labor share is often cited as proxy of worker well-being resulting from labor market participation. Studies and reports from economists and the Bureau of Labor Statistics (BLS) point to a declining labor share for the majority of workers in recent decades in the United States.[1] Evidence further suggests that sectoral composition could be driving this result (Elsby et al., 2013). This paper argues that labor share disaggregation along only one or two dimensions–temporal, sectoral, and regional–does not fully capture the dynamics of this key income distribution measure. To fully understand the labor share, further disaggregation is needed.

Many recent studies have discussed labor shares along temporal and sectoral dimensions (Gomme and Rupert, 2004, Elsby et al., 2013, Armenter, 2015, Baker, 2016). While informative, this paper adds to the current literature through a more thorough inclusion of spatial characteristics of the labor share, in addition to temporal and sectoral discussions.[2] Using a dataset from 2005 to 2014, I discuss the temporal, regional, and sectoral differences in the US labor share over that time period. Most notably these estimates show distinct spatial and sectoral differences in the labor share. My labor share estimates and subsequent spatial

[1]See Armenter (2015) and Baker (2016), for recent examples.

[2]Collectively, I will refer to the dimensions of time, space, and sector as the "three dimensions of the analysis."

tests clearly demonstrate the necessity of including all three dimensions in any analysis of income distribution. Furthermore, the results highlight the need for a better understanding of what determines the observed labor share values in a given region.

To this end, I use previous literature to motivate the collection of state-level variables that macroeconomists theorize impact labor shares. The primary research question is: can macroeconomic theory describe the observed regional differences in the labor share, in a given sector and year? The data are then used in spatial model regressions in an attempt to answer this question. Regression results provide strong evidence for a handful of labor share theories while only weakly supporting others. For example, educational attainment rates, unemployment rates, and measures of firm bargaining power appear to statistically impact labor shares–supporting the theories of Smith (1817), Marx (1867), and Kalecki (1938), respectively. There is weak evidence of that capital expenditures impact labor shares in the only sector for which data is sectoral data is available, providing weak evidence for Ricardo (1821). Furthermore, my results demonstrate the heterogeneous effects of state-level variables on the labor share of any given sector and advance the argument of this paper that over-aggregation ignores fundamental aspects of the economy.

The analysis is divided into sections as follows. Section 1.1 discusses the theoretical debate surrounding how best to assess the labor share and Section 1.2 summarizes the labor share estimates across the three dimensions of the analysis. Section 1.3 describes the previous work of those studying the labor share and their findings, emphasizing primary variables through which the labor share may change. Sections 1.4 and 1.5 introduces the methodological framework employed to describe changes in the labor share and the data used in the statistical analysis. Finally, Section 1.6 discusses the regression results and evaluates the theories discussed in Section 1.3. Section 1.7 provides some key takeaways of the analysis and motivates future research.

1.1. Calculation of the Labor Share

While the notion of the labor share is intuitive–the percentage of compensation to total output–there are many contemporary debates about how best to undertake its estimation. As a result, it makes sense to first elucidate the arguments over how the labor share should be estimated prior to discussing the actual estimates. Most labor share measures face a myriad of potential criticisms and, as such, the literature is rich with discussions of how best to describe the allocation of income to labor. Historically, many have operated on the assumption that the labor share is constant. In discussing how best to estimate the labor share, I highlight how different assumptions may bias labor shares and challenge the notion of labor share constancy.

Kravis (1959) spurs a branch of the literature that focuses on the numerator of the labor share measure. To that point, the numerator had traditionally included only wages and salaries of employees. For Kravis (1959), a key issue is how best to allocate the income accruing to proprietors. More specifically, he questions whether proprietor income should be counted as part of wages and salaries or not. In the most simplistic example, entrepreneurs receive income from both the capital they control as well as their individual labor efforts. As a result, simply allocating entrepreneurial income to wages and salaries in the context of the labor share would tend to overstate the impact of workers in production, particularly in industries characterized by high levels of entrepreneurship (Gomme and Rupert, 2004). As Gomme and Rupert (2004) relevantly add, the structure of the National Income and Product Accounts (NIPA) can bias labor shares due to their method of calculation. Notably, no capital income is granted to the government and no labor income is allocated to the housing sector. This would bias the labor shares of these sectors higher and lower, respectively. The importance of appropriately handling proprietor income, then, cannot be understated.

Kravis (1959) proposes four methods for allocating proprietor income that range from granting all proprietor income to either capital or labor to some distribution of the income between the two. Through this distinction, he is able to show that the labor share had not been as constant as prevalently believed at the time. Elsby et al. (2013) follow up on the work of Kravis (1959) with a more updated discussion of the labor share in recent times. Like Kravis (1959), Elsby et al. (2013) use four separate estimates for the labor share that vary based on how much proprietor income is attributed to labor and do not find significant differences across measures of the labor share. However, they do find that the aggregated labor share changes may largely be driven by sectoral composition differences. Their work suggests that changes to the employment and income of individual sectors is largely driving the aggregate results observed in the economy. This result implies that breaking the economy into sectors when discussing the labor share is imperative. Gomme and Rupert (2004), Timmer et al. (2007), McKenzie and Brackfield (2008), and Arpaia et al. (2009) each support the importance of sectoral disaggregation in developed Western economies as well.

In addition, there is further debate about what should be included as part of the labor-related income accruing to workers in the numerator of the labor share, outside of the distribution of entrepreneurial income. Krueger (1999) is one of the first to bring up this point. Early labor share estimates used only wages and salaries–a relatively unambiguous measure–as the primary estimate of worker income. Krueger argues that, in modern times, this is no longer an appropriate measure. Stock options and employer contributions to insurance have become an increasingly important form of worker remuneration and this muddles the estimate of compensation that workers receive. From this critique, most now avoid using the narrow definition of wages and salaries as the estimate of worker remuneration in labor share estimates in favor of a broader term, often called "compensation." Section 1.5 elaborates on this distinction in my collected data, but this measure typically includes wages, salaries, as well as work-related benefits. Simply using wages and salaries would then bias labor shares lower and therefore understate the distribution of income to workers.

Another complicating factor in the calculation of the labor share is the denominator–or the estimate of value added/output–of the measure. Various studies have discussed the difficulties of successfully appropriating subsidies, taxes, governmental production, intangible assets, and the informal sector into the labor share, especially across countries. If these are omitted, they will generally bias labor shares higher as they would typically be included in the output measure. While most evidence points to a declining labor share in recent decades, omitting these components of output would suggest that the decline has been faster than previously thought. In fact, Corrado et al. (2013) attempt to incorporate the typically omitted intangible assets into output estimates for their study and do find evidence that there has been a greater decline in the labor share than indicated in previous studies.

The exclusion of informal economies in real output data could similarly bias any estimate of the labor share, through the denominator. As Jayadev (2007) points out, the nature of industries in the informal economy makes it unlikely that rigorous output data on these sectors is available, though in theory it should be included. The result is that the labor share may be underestimated in developing economies due to underreported income, in particular. This is especially important to note in international studies that compare various macro-economies, however the present analysis focuses on a single, developed economy over a relatively short time horizon. Because of this, the effects of the informal economy are not explicitly accounted for with the assumption that the relative size of the informal economy has not changed over the time period discussed (2005-2014). It is still worth noting that the informal economy should be considered in any income share estimate.

Considering these potential issues, I use an estimate of the labor share rooted in data from the Bureau of Economic Analysis (BEA). If α_{ijt} represents the labor share in sector i, state j, and time t, I estimate the labor share as:

$$\alpha_{ijt} = \frac{C_{ijt}}{N_{ijt}} \tag{1}$$

C_{ijt} represents the compensation of employees while N_{ijt} represents output, both in current dollars. Compensation of employees data comes from the BEA's series by the same name.[3] N_{ijt} comes from the BEA estimates of nominal output, by industry.

The BEA defines compensation as wages, salaries, and "supplements to wages and salaries." These supplements include firm contributions to insurance and pensions, as well as contributions to social insurance programs–on the logic that these ultimately end up in the hands of employees at a future date. Including these supplements avoids the potential understatement of the labor share that Krueger (1999) argues would happen if we were ignore that shifting demographic of worker compensation.

This only solves one potential issue, however. Because proprietors are often considered employees, my labor share estimates effectively allocate all proprietor income to labor. This should increase labor shares in all sectors, states, and years, but it should be noted that this bias will be higher in industries with higher levels of entrepreneurship as argued in Gomme and Rupert (2004). Furthermore, the output and compensation measures only

[3]Specifically, I use the SA6–Compensation of Employees measure.

account for formal sectors and so cannot account for the critiques of Jayadev (2007). My measure similarly cannot account for some unmeasured characteristics of the economy such as intangible assets Corrado et al. (2013). While there is certainly room for improvement, the remaining analysis relies on Equation 1 as the estimate of the labor share.

1.2. Labor Shares Across the Three Dimensions of the Analysis

Ignoring sectors and regions, my labor share estimates average 0.540 over the time period 2005-2014 with a low of 0.533 in 2013 and a high of 0.552 in 2008. In this section, I break down the labor share along the three dimensions of the analysis to better assess labor market outcomes in each sector, state, and year.

1.2.1. Labor Shares Through Time. Figure 1.1 shows the labor share estimate for the entire US economy from 1929-2016 using two potential measures of the labor share numerator–compensation and wages and salaries–that match viable BEA worker income measures.[4] Recessions are shaded to discuss the labor share's relationship to business cycles. In addition, my analysis focuses on 2005-2014, but more years are included to show greater time trends and match my measures to that of previous estimates referenced in Section 1.3.

Figure 1.1 shows that labor share time trends vary significantly depending on the measure for worker income. Most evident, there has been a significant divergence between wages and salaries and compensation since 1929. This supports the arguments of Krueger (1999) that work-related benefits have become an increasingly important aspect of worker remuneration. In particular, the divergence between the labor share, as estimated using each, grows significantly around 1970. To use wages and salaries exclusively may then artificially understate labor share values.

[4]Ultimately, compensation is used.

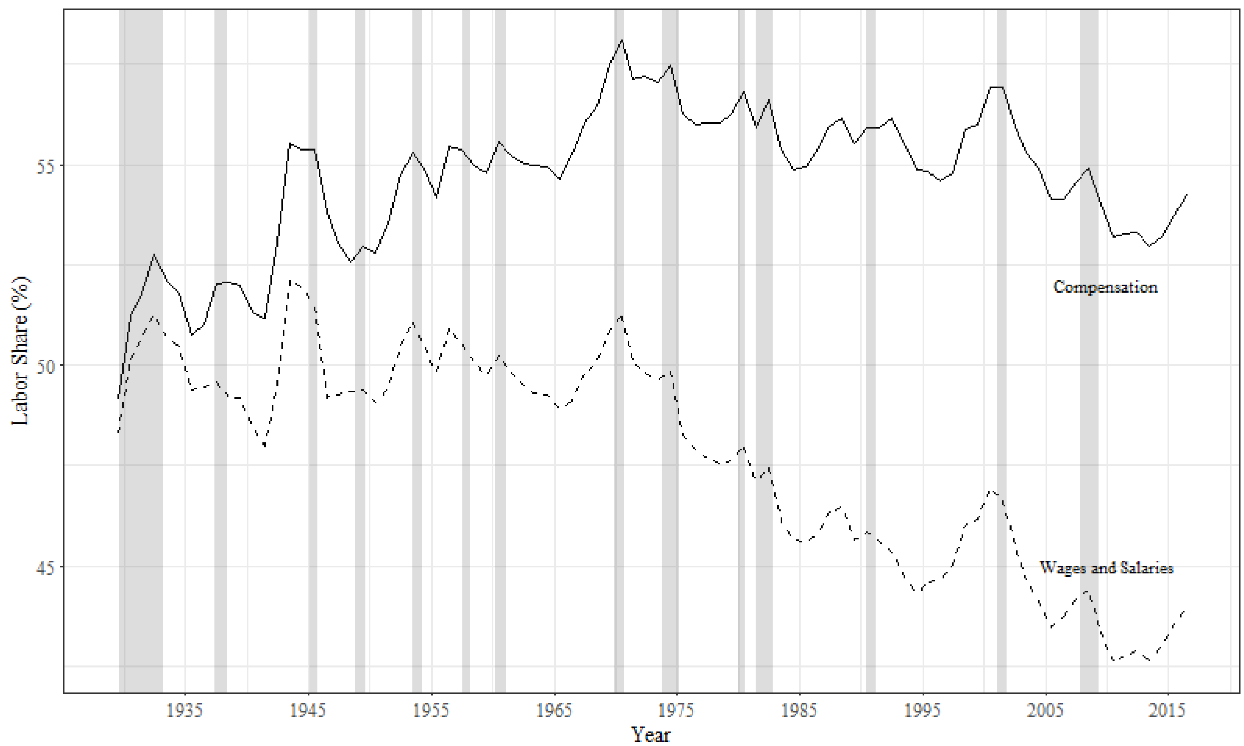


Figure 1.1. National US Labor Share, Single-Aggregated Sector for Two Different Labor Share Numerator Measures

The labor share using compensation, which includes wages and salaries in addition to work-related benefits, mimics the movements of the labor share of wages and salaries but appears far more stable through time. Indeed, over the entire time horizon of Figure 1.1 aggregate labor shares would appear to have fallen if using only wages and salaries while they would have grown using the more broad measure of compensation. Nevertheless, both labor share measures have witnessed a steady decline since 1970. This result matches that of more recent studies (BLS, 2017c, Lübker, 2007, Armenter, 2015, Baker, 2016).

In addition to general trends since 1929, there is a breadth of literature noting the countercyclical nature of the labor share. The pattern displayed in Figure 1.1 matches previous labor share theories with notable spikes in the labor share during recessions. McDonald and Solow (1981), Hansen and Prescott (2005), Choi and Rios-Rull (2009), and Rios-Rull and

Santaeulalia-Llopis (2010) each find evidence of the countercyclical behavior of the labor share.

Prevailing arguments to explain this phenomenon focus on labor market frictions that prevent wages from adjusting contemporaneously with business cycle shocks. In other words, output falls during recessions while worker income remains relatively sticky in the short run. Combined these factors would exert upward pressure on labor share values. To be more specific, Gomme and Greenwood (1995) and Boldrin (1995) use labor contracts as a measure of frictions in the labor market to explain labor share behavior. Young (2004) uses biased technical change of factor elasticities in production in his explanation of observed movements. While each of these studies employ varied explanations for labor share movements, their conclusions are unanimous–labor shares are countercyclical and can be volatile in the short-run.

The question becomes whether we see this same pattern across sectors. Despite the evident increase in the aggregate US labor share in 2008, Figure 1.1 demonstrates the notion that the labor share is relatively constant over the decade analyzed.[5] There is certainly some short-run volatility to the labor share from 2005-2014, however, the labor share remains within a 3% bound. Zuleta and Young (2007) argue that relatively stable long run shares mask the movements of industry specific labor shares. Perhaps a disaggregated economy would tell a different story.

In order to disaggregate the economy, I divide economic activity into sectors using the North American Industry Classification System (NAICS). I include most 2-digit industries, reflecting the fifteen largest, private, non-agricultural sectors in the United States. Table 1.1

[5]While this time span does not represent the "long-run," it does mirror the argument that labor shares tend to be relatively stable over longer time horizons.

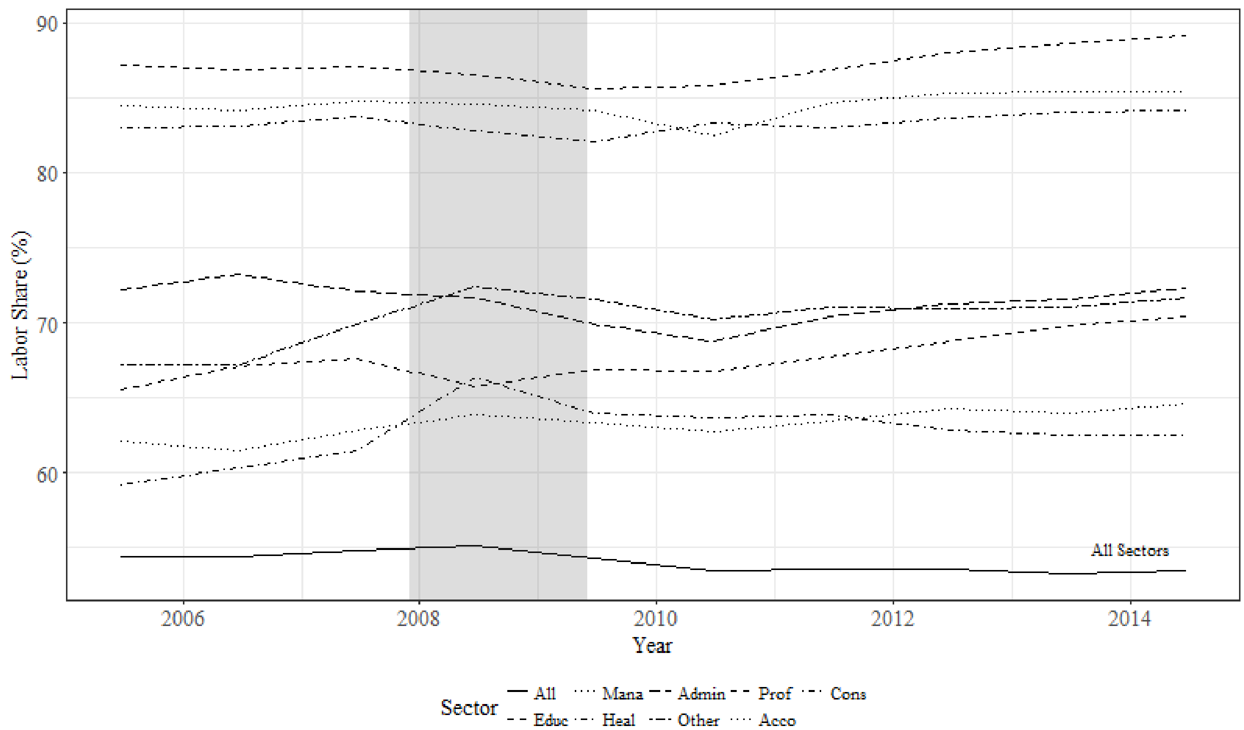
Table 1.1. Fifteen Sectors and Corresponding NAICS Codes

Sector Label	**Sector**	**NAICS Code(s)**
Acco	Accommodation/Food Services	72
Admin	Administrative/Support Services	56
Arts	Arts/Entertainment	71
Cons	Construction	23
Educ	Educational Services	61
FIRE	Finance/Insurance/Real Estate	52-53
Heal	Health Care/Social Services	62
Info	Information Services	51
Mana	Management of Companies	55
Manu	Manufacturing	31-33
Other	Other Services	81
Prof	Professional/Scientific Services	54
Ret	Retail Trade	44-45
Trans	Transportation/Warehousing	48-49
Whole	Wholesale Trade	42

displays these sectors, the abbreviation that is used in some figures to save space, as well as their corresponding codes in the NAICS system.

Figure 1.2 duplicates Figure 1.1 with two graphs featuring a subset of the sectors disaggregated. The top graph compares labor shares for those sectors with the highest labor shares while the lower graph looks at sectors with the lowest average labor shares. As with the previous, time-related graphs, the financial crisis is shaded to better visualize potential business cycle effects on the labor share of each sector. The sector labeled "All" represents the fully aggregated economy and matches the data presented in Figure 1.2.

At the sectoral level, some distinctly different patterns emerge when compared to the analysis of the US labor share for a single sector. Visually, the Arts and Entertainment, Construction, and Retail labor shares mirror the time trend of the aggregated economy with countercyclical movements and a noticeable increase in labor shares around 2008 and 2009. Simple regressions of the US labor share on a binary variable indicating a recession year suggest that the labor share is biased statistically upwards during the recession for these



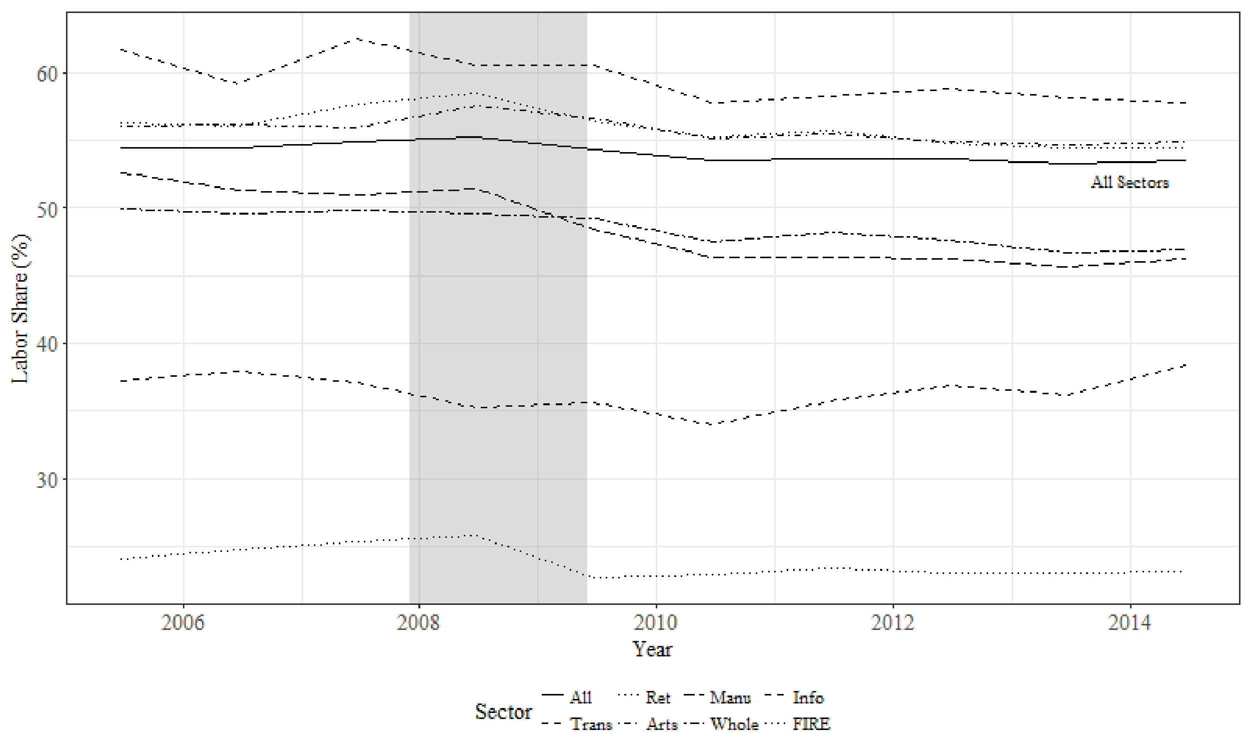


Figure 1.2. National US Labor Share (2005-2014), Subset of Disaggregated Sectors: High Labor Share (Above) and Low Labor Share (Below)

three sectors.[6] To the contrary, the other twelve sectors shown do not demonstrate this trend–indeed they remain relatively constant over the decade shown with no statistically significant countercyclical nature.

The fact that business cycles appear most associated with these three sectors should come as no surprise (Bukszpan, 2012). The financial crisis impacted the Construction industry, in particular, as the housing market collapsed. In 2008, Construction unemployment rose 43.2% from the previous year–the most of any sector and well above the 26.2% increase in unemployment for the economy overall (BLS, 2017a). This relationship between unemployment rates and the labor share in Construction would seem to support the arguments of Zuleta and Young (2007)–sectoral changes in the labor share impact the observed labor share of the aggregated economy. On the other hand, Arts and Entertainment and Retail each suffered unemployment rate increases closer to the national average. Unlike Construction, these two industries each saw significant declines in output as consumers "tightened their belts" and cut back on discretionary spending.

1.2.2. Labor Shares Across Sectors. It does appear, then, that sectors must be taken into account when discussing labor share values. Figure 1.2 shows the heterogeneous nature of labor share values across industries. Over the time period 2005-2014, the national labor share reached a high of 0.891 in Educational Services in 2014 and a low of 0.227 in Finance, Insurance, and Real Estate in 2009. Workers are not equally important to the production of goods and services in various industries, so intuitively there should be differences in the labor share between sectors. Table 1.2 shows some summary statistics of the labor share between 2005-2014.

[6]The binary variable takes on a value of one in the years 2008 and 2009 and is 0 otherwise.

Table 1.2. Summary Statistics of US Labor Shares by Sector, 2005-2014

Sector	**Mean**	**St. Dev.**	**95% Confidence Interval Lower Bound**	**95% Confidence Interval Upper Bound**
All Sectors	**0.540**	**0.0066**	**0.536**	**0.545**
Accommodation	0.633	0.0100	0.625	0.640
Administrative Services	0.713	0.0131	0.704	0.723
Arts and Entertainment	0.557	0.0090	0.551	0.563
Construction	0.627	0.0200	0.612	0.641
Educational Services	0.871	0.0113	0.863	0.880
Finance and Real Estate	0.238	0.0111	0.230	0.246
Health Care	0.833	0.0060	0.828	0.837
Information	0.364	0.0131	0.355	0.374
Management	0.845	0.0086	0.839	0.851
Manufacturing	0.485	0.0271	0.466	0.505
Other Services	0.703	0.0180	0.690	0.716
Professional Services	0.676	0.0160	0.665	0.688
Retail	0.559	0.0134	0.550	0.569
Transportation	0.595	0.0169	0.583	0.607
Wholesale	0.485	0.0128	0.476	0.494

In particular, Table 1.2 hints at the intuitively disparate nature of worker compensation as a result of labor efforts. It should also be noted that based on this decade-long time period, we can say that each of the fifteen sectors differs from the nationally observed labor share value, with 95% confidence. Furthermore, almost every single sector is statistically different from one another at the 5% significance level when all pairwise combinations are analyzed.[7] This result directly mirrors that of Gomme and Rupert (2004), Timmer et al. (2007), McKenzie and Brackfield (2008), and Arpaia et al. (2009), with the conclusion that sectors cannot be ignored when analyzing labor share values. Furthermore, if each sector's labor share behaves differently from that of the national labor share then researchers could arrive at erroneous conclusions about the distribution of income to workers in the United States in too aggregated an analysis.

[7]The exceptions to this are: Accommodation and Food Services/Construction, Administrative Services/Other Services, Arts and Entertainment/Retail, and Manufacturing/Wholesale Trade.

Of course, these results should come as no surprise. If workers are not equally valuable in the productive process, then the percentage of income accruing to them should also be different. For example, we expect a high degree of capital employed in production for a sector such as Manufacturing versus Retail. This should cause labor shares to be lower and higher in these sectors, respectively.

1.2.3. Labor Shares Across Space. Sections 1.2.1 and 1.2.2 support previous literature while arguing for the importance of time and sector. Indeed, my collected data demonstrates many of the same conclusions of others (i.e. the countercyclical nature of labor shares, significant variation in inter-sectoral labor shares). This paper explicitly goes one step further than previous studies and argues that in addition to these first two dimensions, space matters as well. Namely, the labor share even within a given sector varies significantly across US states and groups of states.

Ignoring time and sector, Figure 1.3 shows the average labor share for the aggregated economy of each state from 2005-2014. Wyoming clearly has the lowest labor share while Massachusetts has the highest. Accounting for just space, these results are easily explained. Section 1.2.2 shows that sectors each have a very unique distribution of income between the factors of production. Extending this, it is likely that each state has sectors of very different sizes, which would contribute to labor share differences of close to 17% across states. If only sectors matter, then when we generate a similar map for a single sector, we should see more equivalent labor share values across US states.

In fact, this does not happen. Across all fifteen sectors, there are significant spatial characteristics of observed labor share values in the US economy. As one such example, Figure 1.4 shows the average labor share values over 2005-2014 for just the Accommodation and Food Services sector. By employment, this sector is the third largest in the United

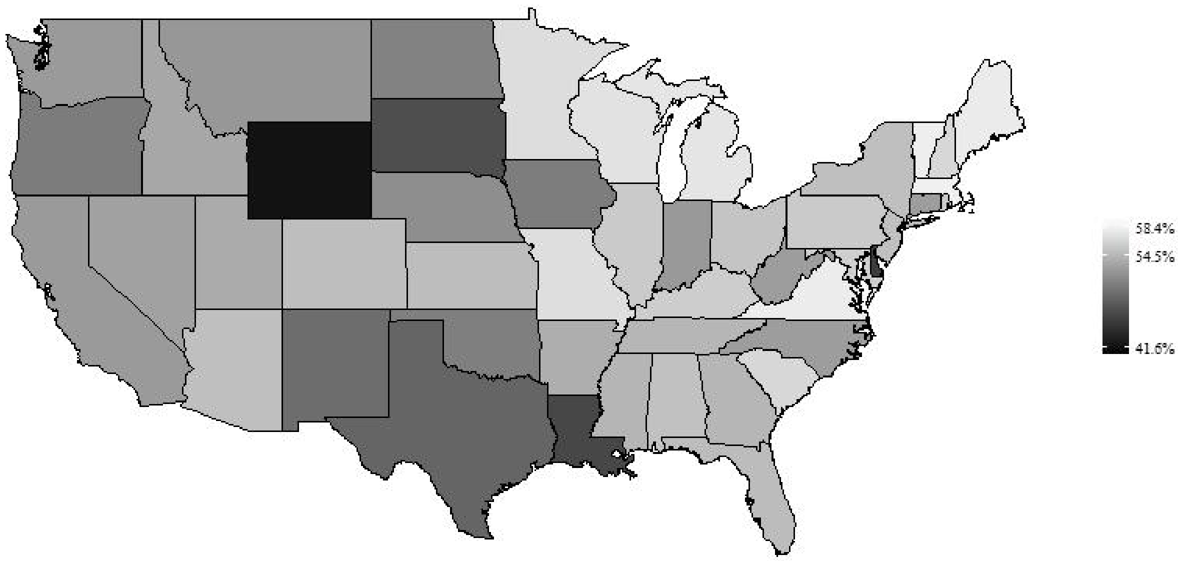


FIGURE 1.3. Labor Share by State–Aggregated Economy, Averaged 2005-2014

States (Census Bureau, 2017b). Here, the disparate nature of labor shares across space becomes evident. Even within a single sector, wherein workers should be relatively equal in importance, labor shares differ significantly across states.

This is not unique to the Accommodation and Food Services sector. Figures 1.5 and 1.6 show similar maps for Health Care, Retail, Manufacturing, and Administrative Services, respectively.[8] While these five sectors do not represent the entirety of the industries analyzed in this paper, they do paint a compelling picture. All three dimensions of the analysis matter and none should be ignored without losing important information about labor market outcomes for workers. Maps for the remaining ten sectors can be found, at the reader's convenience, in the Appendix, though the story remains the same.

[8]Sectors displayed in the body of the paper were chosen as they represent the five largest sectors in the economy, collectively accounting for about 57% of employment in the United States in 2015 (Census Bureau, 2017b). The rankings are: 1) Health Care and Social Assistance; 2) Retail; 3) Accommodation and Food Services; 4) Manufacturing; and 5) Administrative Services.

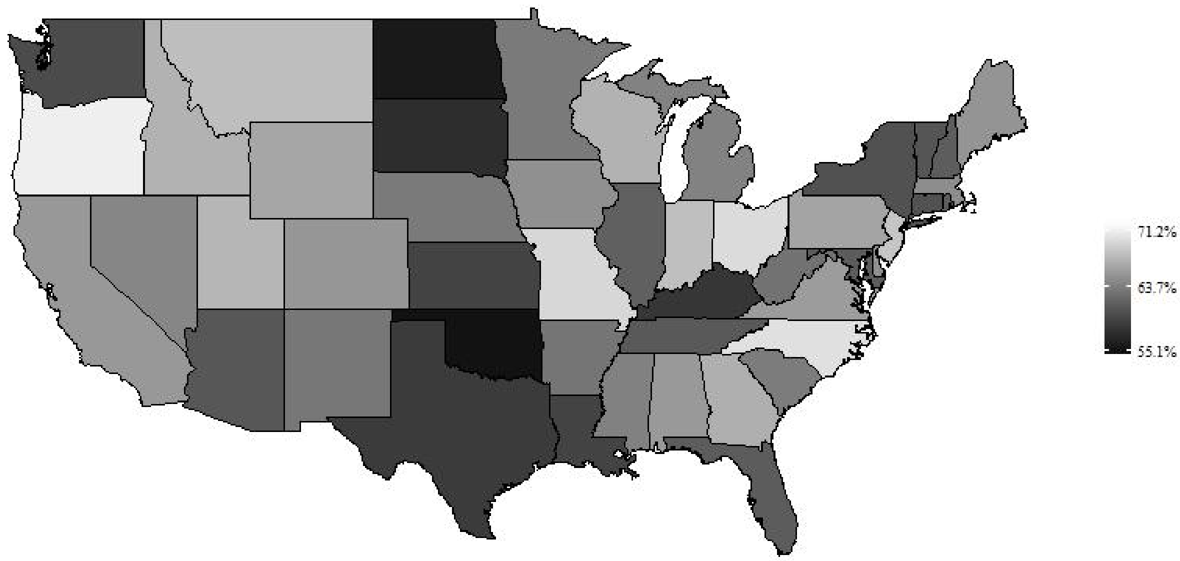
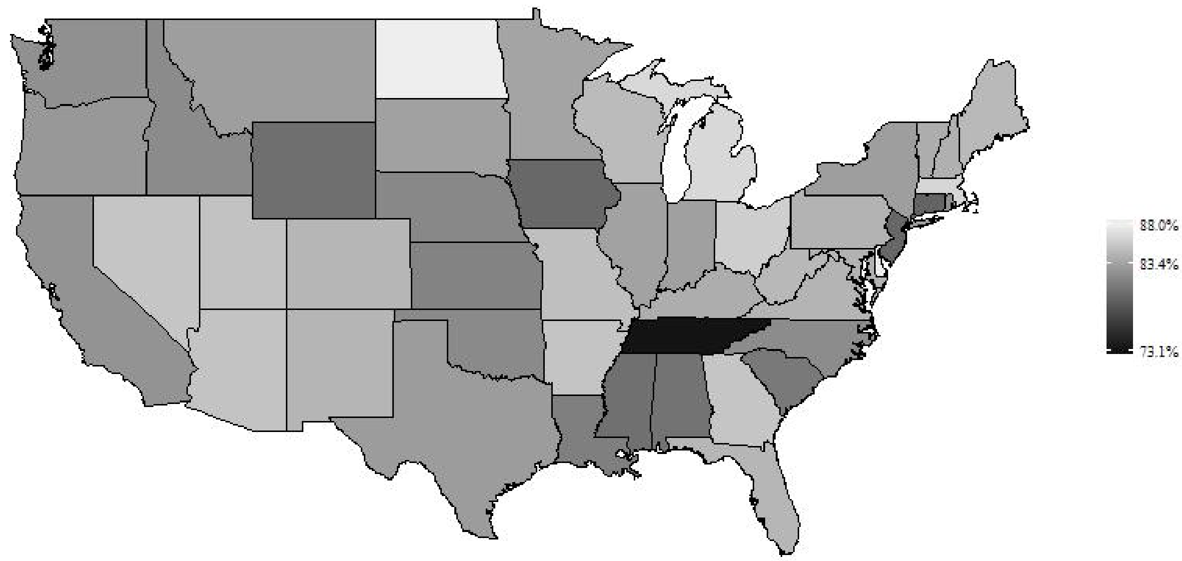


FIGURE 1.4. Labor Share by State–Accommodation and Food Services, Averaged 2005-2014

Adding to evidence that there are spatial characteristics to labor share values. I perform Moran Tests for spatial autocorrelation in labor share values within each sector (Moran, 1950). This test looks at the correlation between spatial observations of a variable and the distance between them.[9] The null hypothesis of this test is that no spatial autocorrelation exists with the alternative indicating evidence of spatial relationships in the data.

Each of these tests reject the null hypothesis that no spatial autocorrelation exists with greater than 99% confidence, regardless of whether the test is performed on the average labor share values over 2005-2014 or each year individually. This implies that a state's labor shares for a sector are jointly determined by the labor share value in a that state and that of its neighbors. Combined with the visual representations of labor shares in sector, these tests prove that omitting spatial dimensions of the labor share could be misleading.

[9]For more information about the test statistic, check the Chapter 1 Appendix on page 171 for more details.



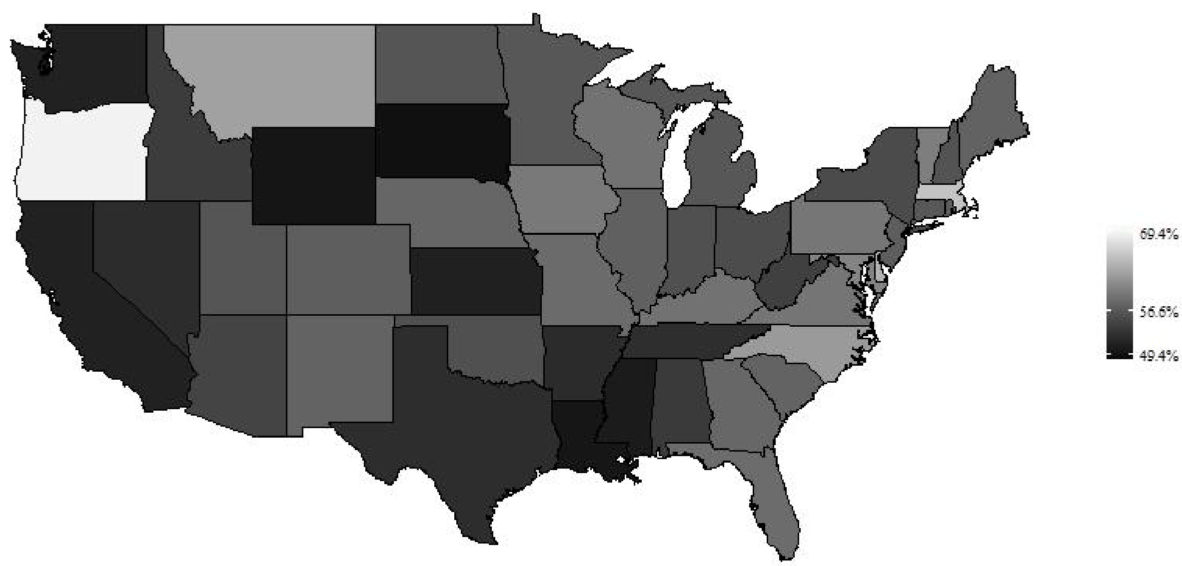


Figure 1.5. Labor Share by State–Health Care (Above) and Retail (Below), Averaged 2005-2014

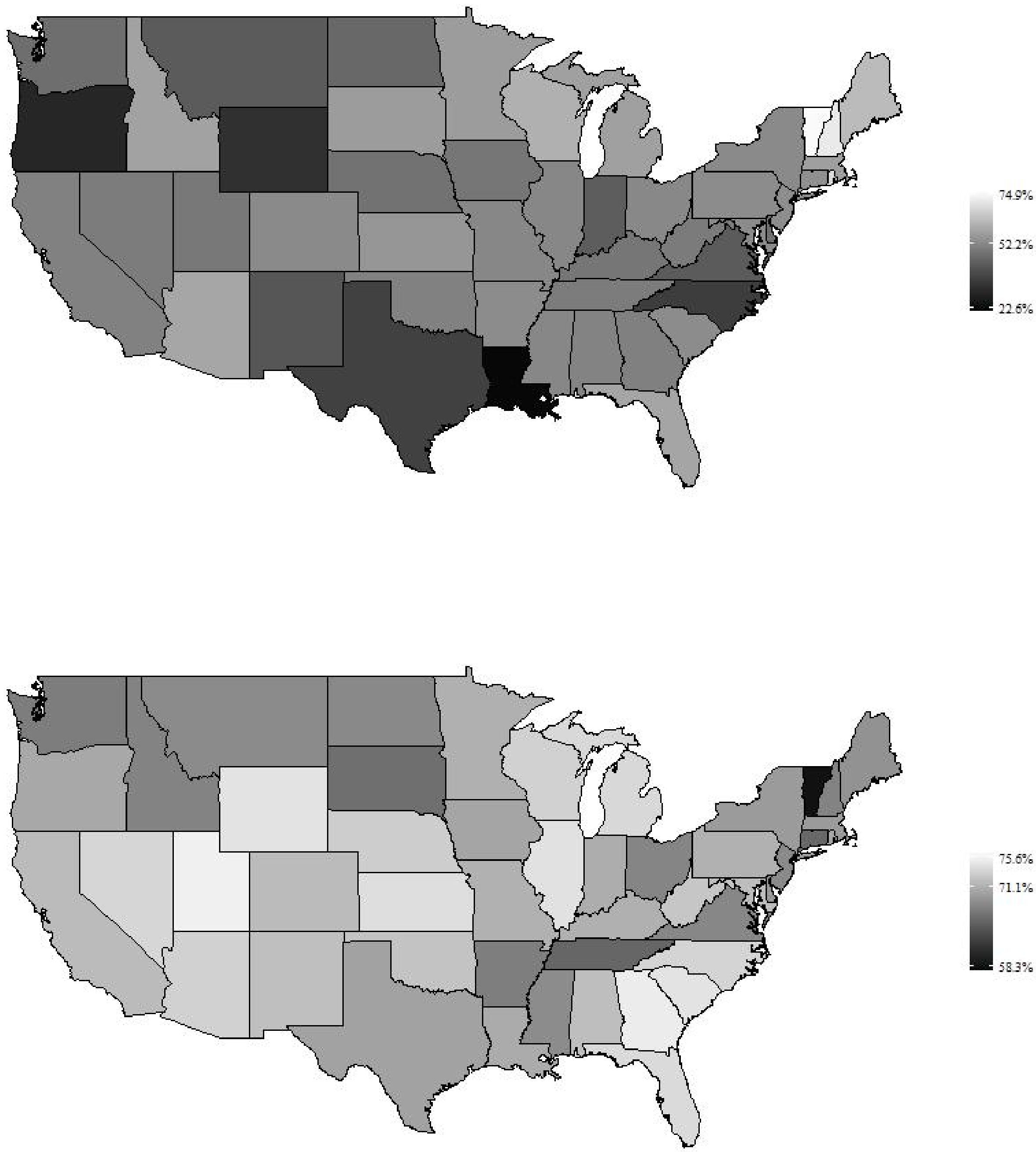


Figure 1.6. Labor Share by State–Manufacturing (Above) and Professional, Scientific, and Technical Services (Below), Averaged 2005-2014

1.3. Previous Discussions of the Labor Share

Time, sector, and space collectively impact the labor share. The remaining sections of this paper endeavor to elicit a better understanding of what drives the observed labor share values in a sector across space. Specifically, how can one explain such heterogeneity of the labor share across US states? I use previous literature and theory to motivate the assembly of state-level variables that researchers would argue impact labor shares and the distribution of income to workers.

The goal of such a discussion will be to both test existing labor share theories at a unique level of analysis and to garner a better sense of how a policymaker might impact the labor share should he or she have the goal to change the distribution of income in a sector or state. Ultimately, this will be accomplished through a series of regressions using the labor share as the dependent variable. This section is devoted to a discussion of previous literature on labor share determination in the hope of better selecting the explanatory variables for the regressions.

Most early research cites the arguments of Ricardo (1821) to justify the importance of factor shares of income for economic outcomes.[10] It should come as no surprise, then, that many economists have attempted to generate methodological explanations for the movements in the labor share, using their respective frameworks. These theories are paramount in the present analysis as they shed light on how we can anticipate labor share movements through time. While Ricardo (1821) is one of the first cited for establishing the importance of the labor share, Smith (1817) is the first to discuss labor share dynamics. He does not believe that wages will tend to rise proportionally with productivity increases. While productivity increases would result in greater output, wages would not see the same growth and so the

[10] Ricardo (1821) famously argues that factor income distribution is the main problem of political economy.

wage share would fall in the long-run. For Smith (1817), labor productivity is the primary determinant of the labor share through time. Labor productivity and the share of income distributed to workers should be inversely related due to productivity increases' failure to manifest into proportional wage increases.

David Ricardo seemingly argues that the labor share will fall as well, though he emphasizes a different determinant of the labor share. Most interpret the work of Ricardo (1821) to mean that a stagnation of capital acquisition would analogously result in asthenic labor share growth, though not all view Ricardian theory in this manner.[11] In this prolific interpretation, Ricardo (1821) further argues that this is inevitable as diminishing returns to labor will ensure that profits are not sufficient for continued capital acquisition. Because the labor share of income depends on capital per worker, this stagnation would have the side effect of ensuring that the labor share of income will fall through time. Capital acquisition is then the primary driver of observed labor share values in a Ricardian framework and should be positively related to the labor share in a given year.

Karl Marx also discussed labor shares. In a Marxian framework, labor shares could theoretically be constant through time, but the conditions under which this would occur make this possibility unlikely. To see this, Marx argues that wages are pinned down to the subsistence level. The relatively elastic labor supply would always exceed demand for workers–resulting in a "reserve" pool of unemployed that would ensure wages remained low due to worker competition. With consistently low wages, the labor share will necessarily fall through time as output per worker increases via growth. Because the reserve pool of unemployed workers drives the elasticity of labor supply, unemployment rates should

[11]This interpretation of Ricardo's work has been common, though later interpretations of Ricardo's work show that this conclusion may be incorrect. From Krämer (2010), see Preiser (1953), Kalmbach (1971), and Johnson (1973) for more alternative interpretations.

determine labor shares in a Marxian perspective. Downward pressure on the labor share via unemployment could be countered with commensurate increases in worker bargaining power, though a Marxian would argue this is unlikely.[12]

Estimates of the labor share in the early 20th Century indicated a remarkable stability that became deeply rooted in Neoclassical assumptions–largely stemming from the work of Marshall (1927). In this book, he provides a theoretical argument that the marginal rate of substitution between factors of production determine the share of income that each factor receives. The notion is that factor prices and quantities employed are based on their respective marginal productivities. More contemporary Neoclassical economists such as Hicks (1932) and Allen (1938) formulate mathematical models of Marshall's theories. Through these models, the movement of the labor share can be predicted if one knows the elasticity of substitution between inputs and the price elasticity of demand for the final product. If, as an example, the demand for a product is elastic and firms increase their prices in response to an increase in wages, then the amount of labor used in production would fall more than the reduction in output; the labor share would correspondingly fall. As Kaldor (1955) notes, an observed constancy of labor shares would then be evidence of a unitary elastic relationship between the factors of production.

In a more empirical approach than Marshall (1927), Cobb and Douglas (1928) use their now colloquially self-titled functional form to similarly explain the constancy of their wage share estimates.[13] With a Cobb-Douglas production function and the assumption of constant economies of scale, profit maximization, and perfectly competitive markets, the wage share

[12]It should also be noted that Krämer (2010) argues that the question of how labor shares would change in Post-Marxian theory is less clear. Instead, the wage share would depend on the growth in the rate of surplus accruing to capitalists, but there is no consensus on how the rate of surplus changes in the long-run. Capturing the rate of surplus on a sectoral or state level is, to my knowledge, impossible with current data available and so this potential determinant of labor shares is left for a different work.

[13]Recall that early labor share estimates used the narrow definition of wages and salaries as the measure of worker income.

must be, by definition, constant.[14] Bowley (1937) echoes the self-fulfilling constancy of labor shares inherent in a Cobb-Douglas production function.

Kalecki (1938) builds on the marginal framework of the Neoclassical economists and develops a theory in which the elasticity of demand singularly determines the share of profits in output. If this is the case, then the degree of market power each firm enjoys will determine the share of labor. This theory is not without criticism as Kaldor (1955) argues that this is a tautological argument akin to the other Neoclassical arguments as they simply develop the theory to match the observed, empirical outcome.

The conclusions of Cobb and Douglas (1928) and Bowley (1937), with subsequent empirical studies from others, led to the prevailing belief that labor shares are constant. This conclusion is not without criticism. For example, one of the primary concerns in any discussion of early estimates and conclusions surrounding the labor share, is whether the data is reliable (Krämer, 1996). Changes to the way data was collected, in addition to significant margins of error, should generate a degree of skepticism regarding labor share calculations, particularly in times long past. Analogously, the perceived stability in the labor shares of the late 19th Century and early 20th Century should be approached with a degree of caution. For example, in a paper discussing labor share measures from 1919-1938, Kuznets (1941) notes that the margin for error in national income estimates (the denominator of the labor share calculation) may be as high as 20%, especially in wartime. There are also issues over long time horizons as historical studies often did not include salaries nor social contributions of the employer (Bowley, 1937). Kalecki (1939) empirically argued relatively stable wage shares in the US that ranged between 34.9% and 39.3% however these estimates failed to include those elements previously mentioned.

[14] For Cobb and Douglas (1928), around 0.75.

Despite the potential for measurement error and over-reliance on a Cobb-Douglas production function (which guarantees constancy of labor shares, by definition), the fact remains that most economists believed labor shares would not change until the mid-1950s. Kaldor (1955) is another of the first to empirically analyze labor share movements, also noting their constancy. He applies numerous economic approaches (including those of Smith, Ricardo, Marx, and Keynes) to intuit why labor shares remained remarkably stable in the US economy despite significant technological progress in the century preceding his writing. This application of numerous theories to describe constant labor shares would later contribute to the eponymous "stylized fact" that the labor share is relatively constant over long time horizons.

The theories of Smith, Ricardo, and Marx have been elucidated so I focus on Keynes here. Although John Maynard Keynes did not explicitly discuss labor share values and movements, Kaldor (1955) also attempts to couch constant labor shares from his theoretical perspective. Kaldor (1955) is able to show that if the marginal propensity to save for workers is zero, then the labor share will necessarily be constant. Even if workers save a portion of their wages at a rate greater than zero, there could be Keynesian case for the long-term stability of labor shares. Specifically, the downward inflexibility of both prices as a ratio of output and the real wage rate would imply a constant ratio of investment to output and, as Kaldor (1955) shows, manifest in a constant labor share.

The middle of the 20th Centure marked a turning point in thinking regarding the labor share. Rather than simply accept the observed constancy in labor share values, economists began to more explicitly question the outcome. Denison (1954), Solow (1958), and Kravis (1959) all posit that labor shares may not be constant. Specifically, they begin to argue that income shares on the industry level are not necessarily constant and shifts across shares may be driving the observed constancy of the labor share at the national level. A constant national labor share would then be happenstance and therefore may not continue. As a result, Solow (1958) argues that labor share discussions should disaggregated into industries.

Arrow et al. (1961) use a CES production function in an attempt to explain why the labor share in some US industries remains constant while there is an observed increase in the capital-labor-ratio and thus an increase in wages. Ultimately, they argue that a countervailing effect between the elasticity of substitution and neutral technical change generate a relatively constant labor share–showing that the same may not be true at the sectoral level. In a similar vein, Christensen et al. (1973) derive the translog production function and argue for a more detailed look at income distribution.

As more emphasis became placed on disaggregation, studies also began to note that labor shares may be falling (BLS, 2017c). In one recent example, Lübker (2007) summarizes declining labor shares since the 1970s across the world–largely due to globalization. He estimates that the labor share is between 50% and 58% in industrialized countries worldwide and falling. Indeed, my labor share estimates indicate the labor share for the aggregated national economy has fallen almost 1% from 2005-2014. At the sectoral level, on the other hand, a majority of sectors have exhibited increasing labor shares over that decade, while some have witnessed a decline. The Professional, Scientific, and Technical Services labor share increased by almost 4.9 percentage points while Manufacturing labor shares fell 4.3 percentage points. Table 1.3 displays the change in labor share values in a comparison between 2014 and 2005. Even with the relatively short time horizon, my data exhibits evidence of a declining overall labor share with significant sectoral variation.

For the United States specifically, the decline of the labor share over recent decades is well-documented and discussed. Armenter (2015) cites three possible explanations for the

Table 1.3. Percentage Point Labor Share Change for Each Sector Between 2005 and 2014

Sector	**Labor Share Change**
All Sectors	−0.91
Accommodation/Food Services	+2.56
Administrative/Support Services	+0.08
Arts/Entertainment	−1.19
Construction	+3.33
Educational Services	+1.91
Finance/Insurance/Real Estate	−0.99
Health Care/Social Services	+1.14
Information Services	+1.09
Management of Companies	+0.95
Manufacturing	−6.33
Other Services	+4.52
Professional/Scientific Services	+4.85
Retail Trade	−1.80
Transportation/Warehousing	−3.98
Wholesale Trade	−3.06

decline in the US labor share. In one example, capital deepening would redistribute income from labor to capital and decrease labor shares unless labor productivity growth matched this rate of capital deepening. Armenter (2015) also argues that inequality could be the cause of labor share declines. Technological advancements primarily impact highly-skilled workers while making low-skilled workers expendable. As employment and compensation become concentrated, the labor share will fall. Finally, Armenter (2015) posits that globalization may be the cause as labor intensive industries outsource to countries with cheaper labor. In doing so, the distribution of income in the United States will shift away from labor and to capital. Baker (2016) notes the fall of the labor share to around 56% since 2001 while echoing the arguments of Armenter (2015).

It seems then, that if the data from earlier time periods can be trusted, the labor share was mostly constant through the early portions of the 20th Century and have subsequently declined. Regardless, these previous studies do present some possible explanations for labor

Table 1.4. Theoretical Determinants of the Labor Share and Their Predicted Impact on Labor Share Values

Determinant	**Impact**	**Source**
Labor Productivity	(-)	Smith (1817)
Capital Acquisition	(+)	Ricardo (1821)
Unemployment Rates	(-)	Marx (1867)
Elasticity of Input Substitution	(-)	Marshall (1927), Hicks (1932), Allen (1938)
Firm Market Power	(-)	Kalecki (1938)
Marginal Propensity to Save	(+)	Kaldor (1955), based on Keynes
Entrepreneurship Rates	(+)	Gomme and Rupert (2004)

share movements. Table 1.3 summarizes previous theories discussed in this section with a list of potential determinants of the labor share. The table also includes the predicted impact these variables may have on labor share values.

1.4. Methodological Framework for Determinants of the Labor Share

There are some clear theoretical labor share determinants that employ a variety of schools of thought. This section outlines the methodology through which I will describe labor shares along the three dimensions of analysis. Because panel data can only have a cross-sectional and temporal element, I perform a series of regressions for each sector analyzed. Suppose we continue to denote the labor share as α_{ijt}, as in Equation 1. Per the initial notation, i indexes the fifteen sectors of Table 1.1, j indexes the forty-nine states analyzed, and t indexes the ten years from 2005-2014.[15] If we drop the indices for the sake of simplicity, the labor share for each sector across states and years, α, can be written in vector form as:

$$\alpha = \mathbf{X}\beta_1 + \epsilon_{\mathbf{1}} \tag{2}$$

β_1 represents the vector of slope coefficients and is the primary motivation for the model's estimation. **X** represents a matrix of regressors. It contains measures of labor productivity,

[15] Due to it's low population, Wyoming's compensation and output data for certain sectors are withheld due to privacy concerns. As a result, Wyoming had to be dropped due to incomplete data for multiple sectors.

capital acquisition, unemployment rates, firm market power, and entrepreneurship rates, in addition to control variables listed in Table A.1. $\boldsymbol{\epsilon_1}$ represents a vector of errors.

While intuitively simple, the spatial characteristics of labor share values muddles the choice of estimation technique. I discuss four popular models that could best reflect the relationships between the variables to attain a robust estimate of β. The first model would use Ordinary Least Squares (OLS) and compare specifications of pooled OLS (ignoring cross-sections), fixed effects (assuming the regressors and the error term are related via the cross-sections), and random effects (assuming the regressor values are independent from the error term). While these models may be informative, OLS often fails to adequately account for spatial components of relationships if observations across states cannot be treated as independent. This would bias the coefficients and standard errors of the model.

As a result, it is more likely that one of the remaining three models best captures the true relationship in the data. This section uses the notation of Zhukov (2010) for these specifications of spatial panel data models. The specification of models that incorporate spatial elements are first described by Luc Anselin. See Anselin (2013) for a recent update of this type of model.

One of the possible spatial models assumes that the residuals of a linear model are correlated (spatial autocorrelation). The Spatial Autoregressive Model (SAR Model) uses the Maximum Likelihood Estimator (MLE) to estimate an adaptation of Equation 2:

$$\alpha = \rho \mathbf{W} \alpha + \mathbf{X} \beta_2 + \boldsymbol{\epsilon_2} \tag{3}$$

This model assumes contemporaneous spatial autocorrelation with the dependent variable of one cross-sectional unit with neighboring cross-sectional units in the same time period. The matrix $\mathbf{W}$ represents a weighting matrix that defines the relationship between each cross-sectional unit. ρ is a scalar that must be less than unity and indicates the degree of spatial autocorrelation between cross-sectional units. Also note that β and ϵ have different subscripts to indicate that these estimates will differ across models.

A third specification of the model in Equation 2, the Spatial Error Model (SEM), attempts to minimize the effects of omitted variable bias and spatial heterogeneity. When unobserved variables are not incorporated in any model, they collapse into the error term, ϵ. In a spatial framework, it is likely that these omitted variables are at least partially determined by location. The key argument for this model, then, is that any present autocorrelation is attributable to missing spatial covariates in the data. To account for this, the SEM model can be expressed as:

$$\alpha = \mathbf{X}\beta_3 + \lambda\mathbf{Wu} + \epsilon_{\mathbf{3}} \tag{4}$$

Here, the spatial weights matrix, $\mathbf{W}$ weights the error term instead of dependent variables of neighboring areas. λ indicates the degree to which there is spatial dependence in the error terms. A positive λ coefficient could indicate a strong and positive spatial dependence in the error terms, depending on its significance. The SEM model can be estimated through Maximum Likelihood estimation techniques.

A fourth specification is the Spatial Autoregressive Model with Spatial Autoregressive Errors (SARAR). This model allows for both a spatial dependent variable lag as well as spatial lag in the error term. As a result, it can be thought of as a combination of the SAR and SEM models. The SARAR model can be expressed as:

$$\alpha = \rho\mathbf{W}\alpha + \mathbf{X}\beta_4 + \lambda\mathbf{Wu} + \epsilon_{\mathbf{4}} \tag{5}$$

The spatial weights matrix, $\mathbf{W}$ now adjusts both the error term and the dependent variables of neighboring areas. λ still indicates the degree to which there is spatial dependence in the error terms while ρ is the analogous relationship in the dependent variables. Because both effects are included, this model is primarily used to assess which effect–a spatial lag in dependent variables or error terms–is strongest. The SARAR model can be estimated through Maximum Likelihood estimation techniques.

β is of primary interest in this paper as this vector grants a better understanding of which macroeconomic theories of labor share movements are supported at the state-level for each sector. Because each sector will be behave differently–as the map visuals demonstrate–there will not be a single estimation method for Equation 2. Instead, I will perform a series of tests to determine the best possible models for each sector and present each of the above specifications to increase the robustness of the results. For each sector, I will select between Pooled Ordinary Least Squares, Fixed Effects, and Random Effects non-spatial models as well as the SAR, SEM, and SARAR spatial models. For these, the weighting matrix uses Euclidean distance between states to weight observations and account for spatial dependence. Euclidean distance is calculated using the central geographic point of each state based on longitude and latitude (Ink Plant, 2017).[16] Different weighting schemes, such as a binary indication of neighboring status are left for future work.

1.5. Description of the Data Used

The data used in this paper comes from a variety of governmental surveys and a select number of private sources. This section summarizes those sources and provides cursory summary statistics for important variables.

[16]The website uses zip code databases to assess the average latitude and longitude of zip codes within the state. This average generates an estimate for the central point within the state.

Labor share estimates are derived exclusively from BEA data, using Equation 1 on page 6. Compensation of employees, which includes wages, salaries, and supplements to wages and salaries, is used as the numerator of labor share estimates (BEA, 2017a). As noted previously, if proprietors are also considered employees, their work-related income would be counted as part of this measure. The denominator for the labor share comes from the BEA estimate of nominal output (BEA, 2017b). Both of these measures are broken into NAICS industries that align with the sectors listed in Table 1.1. The proportion of nominal employee compensation to nominal output serves as the dependent variable in the analysis of Section 1.6.

Table 1.3 motivates the data collected for the independent variables. To my knowledge, no data exists at the state-level for the elasticity of input substitution nor the marginal propensity to save. As a result, only labor productivity, capital acquisition, unemployment rates, firm market power, and entrepreneurship rates are used as the key predictor variables included in Equation 2. State-level educational attainment rates are used as a proxy for labor productivity. The data comes from the American Community Survey of the U.S. Census Bureau (Census Bureau, 2017a) and represents the percentage of the population within each state that has earned a high-school diploma, has some college experience, has a Bachelor's degree, or has attained a Graduate degree. I assume more educated workers are more productive, on average, and so increased educational attainment within a state should similarly raise average productivity across sectors.

Capital acquisition data only exists at the sectoral and state-levels for Manufacturing and select years in Construction. Due to the necessity of balanced panel datasets for use in Maximum Likelihood and Generalized Least Squares models, I only consider capital acquisition for the Manufacturing sector. Data comes from the County Business Patterns survey of the U.S. Census Bureau (Census Bureau, 2017b). The data represents the dollar value of capital-related expenditures by firms within the Manufacturing sector.

To best see how unemployment measures impact labor shares, I use two different specifications of the unemployment rate from the BLS. One data series represents the unemployment rate for the state as a whole, ignoring sectors. Data for this measure comes from the Local Area Unemployment Statistics of the BLS (BLS, 2017b). In sectors not dependent on low-skill workers, the reserve pool of unemployed workers that Marx (1867) would argue drive compensation rates lower could initially come from a variety of sectors. As a result, the overall health of the labor market in the state may be what matters most. As a robustness check, I also use sectoral unemployment rates from the BLS, based on the Current Population Survey (BLS, 2017a). These unemployment rates are for the nation as a whole, but may better reflect the reserve pool of workers in high-skilled industries within which labor groups are more finite.

As a proxy of firm market power, two potential measures are considered. The first uses average employees per establishment in a state's sector in a year to measure how much control firms in the industry may have within their respective markets. The number of establishments differs from the number of firms in the market, as one firm may have multiple establishments. This measure may be a decent proxy for firm market power if establishments with more employees are able to exercise greater control both over the compensation rates of their employees as well as the political institution within which they operate. Data for the number of employees and establishments for a given sector, state, and year comes from the U.S. Census Bureau's County Business Patterns dataset (Census Bureau, 2017b). The second possible proxy for firm market power is the percentage of employees represented by unions, which comes from the Union Affiliation Data provided by BLS (2017d).

Table 1.5. Summary Statistics of Key Variables Across States: 2015, Single Aggregated Sector

Variable	**Units**	**Count**	**Mean**	**St. Dev.**
Labor Share	Percentage	49	53.370	3.415
High School Attainment	Percentage	49	28.994	3.985
Some College Attainment	Percentage	49	30.122	3.614
Bachelor's Degree Attainment	Percentage	49	18.408	2.796
Graduate Degree Attainment	Percentage	49	10.884	2.652
Sectoral Unemployment	Percentage	49	6.200	0.000
State Unemployment	Percentage	49	5.773	1.241
Employees per Establishment	Count	49	15.577	1.800
Union Representation	Percentage	49	11.545	5.394
Self Employment	Percentage	49	6.055	1.310

Note: Capital Acquistion is not included as it is only used for Manufacturing and these data points represent information in a single, aggregated sector for the economy in 2015, across all states. For those interested, the mean for the Manufacturing Capital Expenditures is $3.06 billion with a standard deviation is $3.32 billion. This is also why there is no variation in sectoral unemployment as this represents the national unemployment rate.

For the last of the variables of interest, entrepreneurship rates, I use self-employment rates of the state. While not specific to a sector, I argue that states with higher self-employment rates are more prone to entrepreneurship in all sectors. Self-employment rates come from the American Community Survey of the U.S. Census Bureau (Census Bureau, 2017a).

The remaining variables are considered controls meant to capture the observable demographic characteristics of each state. Each of the controls are collected from the American Community Survey (Census Bureau, 2017a). These controls include the median age, percentage of the population that is male, household size, veteran rates, disabled rates, migration rates (both in-state and out-of-state), commuting times, and data on cash transfers to households.

Table 1.5 displays the summary statistics for the key, theory-based regressors for the forty-nine studied states in 2015. Table A.1 on page 170 provides similar summary statistics for the control variables in the Chapter 1 Appendix.

1.6. Labor Share Results and Discussions

With each sector undergoing a series of tests to ensure proper modeling, it seems fitting to devote a section to each of the fifteen sectors listed in Table 1.1. Each section will include a description of the tests results, noting any potential issues with spatial autocorrelation and heteroskedasticity, as well as a summary of the models used to describe the relationship between labor share determinants and the labor share.

Testing methodology and implementation relies heavily on the work of Breusch and Pagan (1979), Breusch and Pagan (1980), Pesaran (2004), Baltagi et al. (2007) and Millo and Piras (2012). Breusch and Pagan (1979) describe a method through which heteroskedasticity can be identified. Breusch and Pagan (1980) and Pesaran (2004) generate methods through which one can test and subsequently account for autocorrelation. Baltagi et al. (2007) combines and summarizes the work of spatial econometricians from the mid 1990s to 2007. While others have contributed to testing in specific circumstances since 2007, the tests of Baltagi et al. (2007) are still used.[17] Their main contribution in this paper is to generalize previous studies by deriving test statistics for models employing spatial panel data to discover serial autocorrelation in the remainder error term, ϵ. Millo and Piras (2012) generate a package in the statistical program R to implement spatial panel data models and perform the tests of Baltagi et al. (2007) and others.

1.6.1. Summary of Tests Performed for Non-Spatial Model.

Each of the sectors will have the results from a non-spatial panel model (pooled OLS, fixed effects, or random effects), an SAR spatial panel model, an SEM spatial panel model, and an SARAR spatial panel model. Based on the collective results of each test, I will argue which model I believe to be most representative of the labor share's relationship with its determinants.

[17]See Anselin (2012) for some recent updates.

For the choice of non-spatial model, we must first decide between a pooled OLS, fixed effects, or random effects model. An F-test is used to test whether time fixed effects would be needed. With these results, a subsequent F-test between a fixed effects model and pooled OLS indicates whether pooled OLS can be used.[18] A Breusch-Pagan test is used to choose between a random effects model and pooled OLS, again testing if pooled OLS is adequate. If pooled OLS is strictly rejected, then I choose between fixed effects and random effects models using the so-called Hausman test. Hausman (1978) and Hausman and Taylor (1981) outline this test statistic and the null and alternative hypotheses of random effects and fixed effects, respectively.

Choosing a general panel model structure is the first step. To ensure proper hypothesis testing of the coefficients, these models must account for any combination of heteroskedasticity or serial correlation in the idiosyncratic error, ϵ.[19] There are three proposed tests for serial correlation that I will employ for robustness. One is a Breusch-Pagan Lagrange Multiplier (LM) Test first described in Breusch and Pagan (1980). In this paper, they show that the LM test can be used to test for autocorrelation in panel models. Pesaran (2004) proposes a CD (Cross-section Dependence) test based on the average of all possible pairwise correlation coefficients of OLS residuals from individual regressions in a panel.[20] This specification is different from that of Breusch and Pagan (1980), who use the average of the squared pairwise correlation of the residuals as the basis for their LM test-statistic. The final test is the Breusch-Godfrey/Wooldridge test most recently outlined in Wooldridge (2015). This test forms an LM test statistic with the inclusion of lagged residuals and the same covariates in a model with current residuals as the dependent variable.

[18]The fixed effects model used in this comparison is either a two-way model (time and cross-sectional effects) or an individual model (cross-sectional effects only), depending on the results of the previous F-test.
[19]I use serial correlation, autocorrelation, and cross-sectional dependence interchangeably in this analysis.
[20]Pesaran (2015) provides an update to this test focused on large panels.

Heteroskedasticity could similarly cause issues with the hypothesis testing of the chosen non-spatial model. I use a Breusch-Pagan test from Breusch and Pagan (1979) to test for the presence of heteroskedasticity.

Once these tests have been performed, I apply the appropriate robust standard errors to each non-spatial regression. White (1980), White (1984), and Arellano (1987) are the first to generate robust covariance matrices in the presence of heteroskedasticity, autocorrelation, or both. Because there are significant cross-sectional effects to the analysis, standard errors will be clustered by group. If there is no evidence of heteroskedasticity or autocorrelation, the normal standard errors are reported.

1.6.2. Summary of Tests Performed for Spatial Models. Extending the analysis to a spatial framework, Moran Tests are used to assess the presence of spatial autocorrelation. In cases where spatial autocorrelation exist, the presented non-spatial model may be informative but will likely not accurately specify the true relationships between labor shares and determinants. As a robustness check, a spatial equivalent to the autocorrelation test of Pesaran (2004) is implemented (Millo, 2016).

If spatial autocorrelation is present, the remaining question is how best to incorporate spatial elements to capture this relationship. Spatial Hausman tests are used to determine whether fixed effects or random effects models are best suited for the analysis.[21] Results for each of the three spatial models discussed in Section 1.4 will be presented for each sector. As a reminder, these thee models can be summarized as: 1) Including a spatial lag of the dependent variable (SAR model); 2) Including a spatial lag of the error terms (SEM model); or 3) Including both. Tests from Baltagi et al. (2007) are used to find evidence of spatial

[21]When spatial autocorrelation exists, pooled OLS will be strictly rejected as the best model.

lags or spatial error correlation to ascertain which model may be best. Correspondingly, I suggest which model best represents the results.

1.6.3. Results by Sector. This section divides up the results of each sector into subsections. Within these subsections, I will briefly describe the results of the tests described in Sections 1.6.1 and 1.6.2. I then present and discuss the regression results for the four models and highlight which model is most likely accurate.

1.6.3.1. *Accommodation and Food Services.* In Accommodation and Food Services, tests indicate that time fixed effects matter and the fixed effects model would be best when compared to pooled OLS and a random effects model. There is also evidence of heteroskedasticity and autocorrelation. The OLS model in Table 1.6 is then a fixed effects model using clustered Arellano robust standard errors.

In this column, Sectoral Unemployment drops from he model as it collapses into the time fixed effect in the fixed effects specification. The significance on Bachelor's degree attainment indicates that labor productivity is an important determinant of labor share values across states, supporting the thoughts of Smith (1817). The coefficient implies that a 1% increase in those with Bachelor's degrees in the state is associated with an average decrease in the labor share of 1.18%. The implication is that increased productivity is manifesting in output increases in the sector across states with smaller gains to worker compensation.

The results do not support the significance of other variables meant to capture theory. Unemployment, bargaining power, and the percentage of self employment all appear to be insignificant in this OLS specification.

For the spatial models, a spatial Hausman test again affirms the use of a fixed effects framework. The spatial Pesaran test strongly suggests spatial autocorrelation which suggests that one of the spatial models will be better than OLS. Indeed, all versions of the tests

Table 1.6. Full Regression Results for Accommodation and Food Services

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
High School Attainment	0.260	0.372	0.486	0.462
	(0.324)	(0.252)	(0.269)	(0.269)
Some College Attainment	−0.150	0.224	0.330	0.309
	(0.359)	(0.227)	(0.241)	(0.244)
Bachelor's Attainment	−1.181**	−0.790*	−0.628	−0.665
	(0.450)	(0.341)	(0.353)	(0.359)
Graduate Attainment	0.072	0.726*	0.933*	0.880*
	(0.569)	(0.369)	(0.395)	(0.401)
Sectoral Unemployment		−0.275	−0.146	−0.182
		(0.153)	(0.196)	(0.191)
State Unemployment	0.059	0.106	0.134	0.130
	(0.249)	(0.147)	(0.151)	(0.151)
Employees per Est.	−0.345	−0.333*	−0.283	−0.288
	(0.189)	(0.168)	(0.170)	(0.170)
Self Employment	−0.346	−0.569	−0.500	−0.508
	(0.534)	(0.376)	(0.376)	(0.377)
Union Rep.	0.124	0.087	0.098	0.099
	(0.147)	(0.102)	(0.103)	(0.103)
Cash Percentage	0.197	0.222	0.214	0.222
	(0.462)	(0.348)	(0.359)	(0.359)
Median Age	−1.745***	−1.427***	−1.315***	−1.329***
	(0.0033)	(0.279)	(0.289)	(0.289)
Dif. House	−0.497*	−0.550***	−0.526***	−0.527***
	(0.199)	(0.148)	(0.154)	(0.153)
Commute Time	0.712	1.027***	1.151***	1.132***
	(0.473)	(0.309)	(0.324)	(0.325)
Male Proportion	−0.646	−0.553	−0.564	−0.554
	(0.780)	(0.674)	(0.678)	(0.680)
Household Size	3.593	6.332	6.843	6.761
	(5.053)	(3.564)	(3.659)	(3.658)
Veteran Proportion	0.627*	−0.130	−0.112	−0.108
	(0.314)	(0.247)	(0.285)	(0.280)
Disabled Proportion	−0.176	−0.297	−0.316	−0.313
	(0.317)	(0.172)	(0.206)	(0.207)
Spatial Lag–Labor Share (ρ)		0.086***		0.025
		(0.021)		(0.077)
Spatial Lag–Error (λ)			0.112***	0.097
			(0.018)	(0.055)
Observations	490	490	490	490
R^2	0.161	0.797	0.786	0.791
Note:		*p<0.05; **p<0.01; ***p<0.001		

proposed in Baltagi et al. (2007) support the notion that there is some combination of significant spatially lagged labor shares or spatial dependence in the error terms–though these tests are unable to isolate which spatial lag best captures he spatial effect. Still, the clear need to account for spatial relationships is reflected in the highly significant spatial lag and error coefficients in the SAR and SEM models, respectively.

The results of both the SAR and SEM models lend support to some theories discussed in Section 1.3. As with the OLS specification, unemployment rates, self employment, and union representation are all insignificant in determining labor share values across states. Bachelor's degree attainment is significant in the SAR model, but not the SEM model. While significant in the SAR model, the effect of Bachelor's degrees appears more muted than in OLS and is still negative. Interestingly, Graduate degree attainment becomes significant when spatial relationships are taken into account and the effect is positive. In the SEM model, for example, a one percentage-point increase in the percentage of the population with a Graduate degree implies an increase in the labor share by 0.93 percentage points.[22] This fact has the opposite implication of the coefficient on Bachelor's degree attainment. Namely, increasing the percentage of the population with Graduate degrees increases compensation more than output which would distribute more income to labor. Labor shares would correspondingly rise.

There is also evidence that firm bargaining power plays a role determining labor share values in Accommodation and Food Services. The direct effect is negative and significant at

[22]It should also be noted that for the SAR and SARAR models, the coefficients do not have the same interpretation as in OLS and SEM models. Because we assume that the dependent variable values of each state impact those of surrounding states, there is a feedback effect. As a result, when the value of an independent variable changes in one state, this impacts the labor share in that state, which has a spatially lagged effect on the labor share of other states. There is then a direct effect and an indirect effect. The direct effect is captured by the coefficient, β, while the indirect effect re-enters the labor share of a given state in the form of ρ. The coefficients in the regression results tables should be interpreted as direct effects only.

the 5% level in the SAR model. It would seem that, within a state, increasing firm size exerts downward pressure on compensation relative to output. Indeed, the negative coefficient would indicate that larger firm size drives labor shares down, which exerts downward pressure on neighboring states' Accommodation and Food Services labor shares. Lower neighboring labor shares would re-enter in the spatially lagged labor share term of the initial state so the true effect may be higher.

In the SAR and SEM models, the spatial lag terms are both significant. This suggests that we should strictly reject the OLS specification as it does not account for spatial autocorrelation. When both a spatially lagged dependent variable and spatially lagged error term are included, as in the SARAR model, both ρ and λ become insignificant. It would seem the SARAR model over-controls for spatial elements and so the SAR or SEM model is likely the best fit. Because of the limitations of current tests, either seems appropriate though one may prefer the SEM model to the SAR model due to the ease of interpretation of the coefficients as well as the greater relative significance of the spatial lag term.

1.6.3.2. *Administrative and Support Services.* In Administrative and Support Services, tests indicate that time fixed effects matter and the fixed effects model would be best when compared to pooled OLS and a random effects model. There is also evidence of heteroskedasticity and autocorrelation. The OLS model in Table 1.7 is then a fixed effects model using Arellano clustered robust standard errors.

In the Administrative and Support Services sector, only firm bargaining power appears significant in the OLS model. The coefficient implies that if the number of average employees at each establishment increases by one, we can expect a 0.17 percentage point increase in the Administrative and Social Services labor share. It would seem, then, that larger firms

Table 1.7. Full Regression Results for Administrative and Support Services

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
High School Attainment	−0.084	−0.251	−0.255	−0.315
	(0.371)	(0.214)	(0.221)	(0.226)
Some College Attainment	−0.289	−0.410*	−0.400*	−0.429*
	(0.373)	(0.192)	(0.200)	(0.203)
Bachelor's Attainment	0.320	0.068	0.060	−0.016
	(0.440)	(0.288)	(0.293)	(0.296)
Graduate Attainment	0.791	0.609	0.546	0.414
	(0.700)	(0.314)	(0.325)	(0.340)
Sectoral Unemployment		−0.187	−0.307*	−0.572***
		(0.120)	(0.126)	(0.169)
State Unemployment	−0.086	−0.068	−0.061	−0.074
	(0.159)	(0.122)	(0.123)	(0.122)
Employees per Est.	0.177*	0.213***	0.199***	0.192***
	(0.089)	(0.057)	(0.057)	(0.056)
Self Employment	−0.317	−0.179	−0.218	−0.245
	(0.452)	(0.316)	(0.315)	(0.308)
Union Rep.	0.032	0.036	0.029	0.031
	(0.110)	(0.086)	(0.087)	(0.084)
Cash Percentage	−0.509	−0.456	−0.460	−0.400
	(0.307)	(0.296)	(0.300)	(0.299)
Median Age	0.536	0.463	0.428	0.413
	(0.303)	(0.237)	(0.241)	(0.240)
Dif. House	−0.004	0.122	0.090	0.084
	(0.172)	(0.127)	(0.130)	(0.1219)
Commute Time	−0.413	−0.575*	−0.579*	−0.621*
	(0.383)	(0.261)	(0.269)	(0.271)
Male Proportion	−0.600	−0.601	−0.710	−0.684
	(0.809)	(0.570)	(0.571)	(0.563)
Household Size	−9.868	−9.857**	−10.052**	−10.402***
	(5.334)	(3.024)	(3.659)	(3.038)
Veteran Proportion	0.231	0.417*	0.383	0322
	(0.392)	(0.210)	(0.230)	(0.243)
Disabled Proportion	0.284	−0.016	0.030	0.084
	(0.304)	(0.137)	(0.155)	(0.171)
Spatial Lag–Labor Share (ρ)		0.039		−0.135*
		(0.025)		(0.055)
Spatial Lag–Error (λ)			0.076**	0.134***
			(0.024)	(0.021)
Observations	490	490	490	490
R^2	0.123	0.805	0.803	0.786
Note:				*p<0.05; **p<0.01; ***p<0.001

distribute more income to their workers than smaller firms in this sector–elucidating a clear policy implication should a policymaker be interested in increasing the labor share.

Productivity, unemployment, bargaining power, and the percentage of self employment all appear to be insignificant in this OLS specification.

For the three spatial models, a spatial Hausman test again affirms the use of a fixed effects framework. The spatial Pesaran test strongly suggests spatial autocorrelation which suggests that one of the spatial models will be better than OLS. Unlike the Accommodation and Food Services sector, however, if we assume a significant spatial lag in labor shares, there is statistical evidence of a spatial lag in errors, and vice versa (Baltagi et al., 2007). As a result, it is likely that the SARAR model best captures the relationship and will then be the primary model discussed.

When accounting for space, there is evidence that productivity, unemployment, and firm bargaining power all drive labor share differences across states. This would lend some support for Smith (1817), Marx (1867), and Kalecki (1938), though the coefficient on employees per establishment has a sign opposite of my prediction. The direct effect is positive and significant at the 0.1% level and is far stronger than the observed effect in OLS. This results indicates that larger firms are able to distribute a higher percentage of income to workers in this sector.

An increase in the percentage of of those with some collegiate experience or a junior college degree implies a decrease in the labor share by about 0.43 percentage points. Similarly, an increase in the national unemployment rate for Administrative implies a direct effect decrease in the labor share of 0.57 percentage points.

In the SARAR model, both spatial lag terms are significant so it appears we should account for both in the model. The negative spatial lag on labor shares implies a significant and negative effect on neighboring states if one state's labor share rises. This is a curious result and one that spatial econometricians have observed, but not widely studied (Kao and Bera, 2013).

1.6.3.3. *Arts and Entertainment.* In the Arts and Entertainment sector, tests indicate that time fixed effects matter and the fixed effects model would be best when compared to pooled OLS. There is, however, weak evidence that fixed effects outperforms the random effects model. There is also evidence of heteroskedasticity and autocorrelation. The OLS model in Table 1.8 is then a random effects model using Arellano clustered robust standard errors.[23] This is why there is an intercept term in the OLS specification, while there is none for the spatial models (tests indicate these should have a fixed effects specification).

In the Arts and Entertainment sector, only unemployment appears significant in the OLS model. Both sectoral unemployment at the national level and unemployment rates for the state overall are statistically significant at the 5% level. As the literature on the counter-cyclical nature of the labor share would predict, labor shares rise on average with state unemployment rates. Similarly, the theory of Marx (1867) correctly predicts the negative and significant coefficient on sectoral unemployment. The results imply that for every percentage point increase in the national unemployment rate for Arts and Entertainment workers, the labor share for those workers decreases about 0.66 percentage points. Productivity, bargaining power, and the percentage of self employment all appear to be insignificant in this OLS specification.

While a random effects specification is used in OLS, a spatial Hausman test argues that a random effects model is not suitable for this sector, so fixed effects specifications are again

[23]While it is common to use the standard error estimates presented in White (1980) for random effects models, these standard error estimators are only robust to heteroskedasticity. To be safe, Arellano (1987) standard errors are still used due to serial correlation in the error terms.

Table 1.8. Full Regression Results for Arts and Entertainment

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
Intercept	193.12*			
	(75.609)			
High School Attainment	0.001	−0.072	−0.307	−0.109
	(0.038)	(0.387)	(0.352)	(0.314)
Some College Attainment	−0.223	−0.325	−0.587	−0.437
	(0.369)	(0.350)	(0.321)	(0.295)
Bachelor's Attainment	0.214	−0.223	−0.278	0.230
	(0.419)	(0.527)	(0.496)	(0.462)
Graduate Attainment	−1.031	−1.612**	−1.815***	−1.034*
	(0.618)	(0.574)	(0.524)	(0.501)
Sectoral Unemployment	−0.656*	−0.712**	−0.742***	−0.447**
	(0.273)	(0.235)	(0.197)	(0.173)
State Unemployment	0.575*	0.582**	0.589**	0.431*
	(0.272)	(0.212)	(0.200)	(0.179)
Employees per Est.	0.324	0.416*	0.442*	0.500**
	(0.375)	(0.195)	(0.191)	(0.179)
Self Employment	0.645	0.695	0.983	1.085*
	(0.578)	(0.563)	(0.547)	(0.502)
Union Rep.	−0.098	−0.104	−0.056	−0.096
	(0.206)	(0.154)	(0.147)	(0.133)
Cash Percentage	−0.847	−0.724	−1.150*	−0.841
	(0.686)	(0.522)	(0.488)	(0.445)
Median Age	−1.199*	−1.062*	−1.177**	−1.081**
	(0.516)	(0.416)	(0.388)	(0.344)
Dif. House	−0.060	−0.037	0.033	0.073
	(0.333)	(0.223)	(0.208)	(0.184)
Commute Time	0.319	0.287	0.354	0.464
	(0.358)	(0.464)	(0.429)	(0.373)
Male Proportion	−1.030	−0.676	−0.738	−0.722
	(1.019)	(1.018)	(0.983)	(0.896)
Household Size	−10.750	−10.970*	−10.621*	−7.370
	(6.119)	(5.319)	(5.005)	(4.436)
Veteran Proportion	0.085	−0.291	−0.578	−0.443
	(0.364)	(0.377)	(0.318)	(0.261)
Disabled Proportion	−0.829	−0.927***	−1.146***	−0.774***
	(0.207)	(0.262)	(0.211)	(0.199)
Spatial Lag–Labor Share (ρ)		−0.008		0.102***
		(0.030)		(0.019)
Spatial Lag–Error (λ)			−0.133**	−0.322***
			(0.043)	(0.045)
Observations	490	490	490	490
R^2	0.149	0.870	0.869	0.866
Note:				*p<0.05; **p<0.01; ***p<0.001

used or the spatial models. Further testing indicates that there may be a spatial lag to the dependent variable as well as the error term (Baltagi et al., 2007). As a result, it is likely that the SAR and SEM models do not independently account for enough of the spatial relationships in labor shares for this sector. The SARAR model will then be the primary model discussed.

In the spatial models, there is evidence that productivity, unemployment, firm bargaining power, and self employment rates drive labor share differences across states. This supports for Smith (1817), Marx (1867), Kalecki (1938), and Gomme and Rupert (2004). An increase in the percentage of those with Graduate degrees implies a decrease in Arts and Entertainment labor shares by approximately 1.03 percentage points across states. Sectoral unemployment rates again have an inverse relationship wit the Arts and Entertainment labor shares while the labor share acts counter-cyclically with business cycles. The positive and significant coefficient on employees per establishment suggests that larger firms in this sector compensate their workers better.

This is also the first sector wherein self employment rates appear to matter. Gomme and Rupert (2004) argue that labor shares should be artificially high in sectors with high self employment rates. In this case, a one percentage point increase in self employment rates is associated with an average labor share increase of 1.09 percentage points.

Both spatial lag terms are significant and so it appear we should account for both in the model. The positive and significant spatial lag in labor share values suggests labor shares in Arts and Entertainment increase as those in neighboring states do as well. The negative and significant coefficient on spatially lagged errors indicates that there may be spatially driven omitted variables.

1.6.3.4. *Construction.* In the Construction sector, time fixed effects matter and the fixed effects model would be best when compared to pooled OLS. The fixed effects specification also outperforms the random effects model and there is evidence of heteroskedasticity and autocorrelation. The OLS model in Table 1.9 is then a fixed effects model using Arellano clustered robust standard errors.

In the Construction sector, tests suggest significant spatial autocorrelation so I focus on those results specifically. A spatial Hausman test argues that a random effects model is not suitable for this sector, so fixed effects specifications are used for the spatial models. Further testing indicates that there may be a spatial lag to the dependent variable or error term, but not both. As a result, the spatial characteristics of the relationships can be captured by either the SAR or SEM model, but not the SARAR model. There is no clear-cut answer to which is better, though the results seem stronger in the SEM model.

Regardless of the spatial model selected, there is evidence that productivity, unemployment, and firm bargaining power drive labor share differences across states. This supports for Smith (1817), Marx (1867), and Kalecki (1938). An increase in the percentage of those with Bachelor's degrees implies a decrease in Construction labor shares by approximately 1.16 percentage points across states. Advanced degrees of any kind appear to hurt Construction workers and draw the distribution of income to other factor inputs. Sectoral unemployment rates have an inverse relationship with Construction labor shares while the labor share acts counter-cyclically with business cycles. The positive and significant coefficient on employees per establishment suggests that larger firms in this sector compensate their workers better.

Both spatial lag terms are independently significant in the SAR and SEM models, but it appears that it does not matter which is selected to capture the spatial relationships. The scalar parameters on each of these spatial lags is negative which implies a clustering of dissimilar states. Visually this can be seen in Figure A.2 on page 165. Missouri has the highest labor share value in the country, with Louisiana being a close second. Each of these states is near states with some of the lowest Construction labor share values in Alabama,

Table 1.9. Full Regression Results for Construction

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
High School Attainment	−0.492	−0.776*	−0.768	−0.796
	(0.417)	(0.390)	(0.422)	(0.418)
Some College Attainment	−0.338	−0.373	−0.169	−0.228
	(0.354)	(0.359)	(0.382)	(0.380)
Bachelor's Attainment	−1.140**	−1.353**	−1.159*	−1.225*
	(0.361)	(0.519)	(0.544)	(0.540)
Graduate Attainment	−2.525***	−2.860***	−2.230***	−2.450***
	(0.490)	(0.580)	(0.638)	(0.629)
Sectoral Unemployment		−0.393***	−0.568***	−0.524***
		(0.083)	(0.114)	(0.117)
State Unemployment	0.940*	0.764***	0.935***	0.901***
	(0.377)	(0.222)	(0.234)	(0.234)
Employees per Est.	0.665*	0.562*	0.631**	0.623**
	(0.268)	(0.231)	(0.238)	(0.238)
Self Employment	−0.251	−0.000	0.080	0.081
	(0.458)	(0.581)	(0.578)	(0.580)
Union Rep.	0.044	0.078	0.060	0.064
	(0.130)	(0.160)	(0.161)	(0.162)
Cash Percentage	0.966	0.699	0.981	0.946
	(0.609)	(0.537)	(0.547)	(0.549)
Median Age	1.415**	1.576***	1.644***	1.616***
	(0.490)	(0.460)	(0.483)	(0.483)
Dif. House	−1.028*	−1.053***	−0.985***	−0.992***
	(0.455)	(0.245)	(0.251)	(0.251)
Commute Time	−0.450	−0.301	−0.349	−0.361
	(0.370)	(0.464)	(0.494)	(0.493)
Male Proportion	−1.241	−1.278	−1.294	−1.272
	(1.269)	(1.125)	(1.113)	(1.121)
Household Size	−11.843*	−11.286*	−11.599*	−11.520*
	(4.782)	(5.547)	(5.678)	(5.677)
Veteran Proportion	−0.628	−0.694*	−0.900	−0.822
	(0.350)	(0.420)	(0.492)	(0.485)
Disabled Proportion	−0.010	−0.411	−0.503	−0.484
	(0.286)	(0.281)	(0.286)	(0.342)
Spatial Lag–Labor Share (ρ)		−0.107***		0.039
		(0.018)		(0.074)
Spatial Lag–Error (λ)			−0.143***	0.124**
			(0.013)	(0.043)
Observations	441	441	441	490
R^2	0.158	0.726	0.677	0.702
Note:				*p<0.05; **p<0.01; ***p<0.001

Arkansas, Texas, and Oklahoma. As a result, it is not surprising to see the negative and significant coefficient on the spatially lagged labor share parameter (rho) in the SAR model.

1.6.3.5. *Educational Services.* In the Educational Services sector, time fixed effects are significant and the fixed effects model would be best when compared to pooled OLS. The fixed effects specification also outperforms the random effects model and there is evidence of heteroskedasticity and autocorrelation. The OLS model in Table 1.10 is then a fixed effects model using Arellano clustered robust standard errors.

In Educational Services, tests suggest significant spatial autocorrelation so I focus on those results for the remainder of the section. A spatial Hausman test argues that a random effects model is not suitable for this sector, so fixed effects specifications are used for the spatial models. Further testing indicates that there may be a spatial lag to the dependent variable or error term, but not both. As a result, the spatial characteristics of the relationships can be captured by either the SAR or SEM model, but not the SARAR model. As with the Construction sector, the results seem stronger in the SEM model.

Regardless of which spatial model one selects, there is evidence that productivity and unemployment drive labor share differences across states, but not firm bargaining power or self employment. This only weakly supports Smith (1817) and Marx (1867), however. In this sector, however, the signs of the coefficients are opposite of their predicted values. An increase in the percentage of those with Bachelor's degrees implies an increase in Educational Services labor shares by approximately 0.50 percentage points across states. The labor share also behaves pro-cyclically. As state-level unemployment rises, we can expect a statistically significant decline in Education labor shares and national unemployment rates for Education do not appear to impact labor share values. In this regard, theory fails to accurately predict the impacts of my primary variables on labor share values.

Table 1.10. Full Regression Results for Educational Services

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
High School Attainment	-0.301^{*}	-0.037^{*}	-0.017	-0.043
	(0.139)	(0.102)	(0.107)	(0.108)
Some College Attainment	-0.215	0.118	0.086	0.061
	(0.113)	(0.095)	(0.098)	(0.100)
Bachelor's Attainment	-0.083	0.419^{**}	0.412^{**}	0.373^{**}
	(0.134)	(0.140)	(0.141)	(0.144)
Graduate Attainment	-272	0.378^{*}	0.504^{**}	0.419^{*}
	(0.162)	(0.162)	(0.160)	(0.171)
Sectoral Unemployment		0.027	-0.227	-0.123
		(0.106)	(0.141)	(0.139)
State Unemployment	-0.146^{**}	-0.284^{***}	-0.238^{***}	-0.245^{***}
	(0.049)	(0.053)	(0.056)	(0.056)
Employees per Est.	0.020	0.030	0.027	0.027
	(0.033)	(0.020)	(0.019)	(0.019)
Self Employment	-0.031	-0.171	-0.200	-0.176
	(0.129)	(0.151)	(0.149)	(0.150)
Union Rep.	0.046	-0.001	-0.019	-0.014
	(0.039)	(0.042)	(0.041)	(0.042)
Cash Percentage	-0.118	0.062	-0.103	-0.073
	(0.149)	(0.142)	(0.144)	(0.144)
Median Age	-0.318	-0.245^{*}	-0.197	-0.218
	(0.167)	(0.111)	(0.115)	(0.114)
Dif. House	-0.052	-0.162^{**}	-0.144^{*}	-0.148^{*}
	(0.082)	(0.060)	(0.061)	(0.061)
Commute Time	-0.042	0.124	0.222	-0.206
	(0.120)	(0.124)	(0.130)	(0.129)
Male Proportion	0.193	-0.030	-0.059	-0.042
	(0.284)	(0.270)	(0.271)	(0.270)
Household Size	-2.654	4.817^{***}	4.464^{**}	-11.520^{*}
	(2.445)	(1.416)	(1.451)	(1.444)
Veteran Proportion	0.045	-0.266^{*}	-0.602^{***}	-0.492^{***}
	(0.104)	(0.104)	(0.117)	(0.124)
Disabled Proportion	-0.047	-0.247^{***}	0.210^{**}	0.213^{**}
	(0.079)	(0.065)	(0.080)	(0.342)
Spatial Lag–Labor Share (ρ)		-0.079^{***}		0.046
		(0.015)		(0.026)
Spatial Lag–Error (λ)			0.133^{***}	0.105^{***}
			(0.014)	(0.026)
Observations	490	490	490	490
R^2	0.114	0.906	0.895	0.902

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

1.6.3.6. *Finance, Insurance, and Real Estate.* In the Finance, Insurance and Real Estate sector, tests indicate that time fixed effects matter and the fixed effects model would be best when compared to pooled OLS. There is weak evidence of fixed effects so the random effects model may be appropriate. There is also evidence of both heteroskedasticity and autocorrelation. Because of this, the OLS model in Table 1.11 is then a random effects model using Arellano clustered robust standard errors due to the presence of autocorrelation and heteroskedasticity. Because fixed effects specifications appear best in the spatial models, this is why there is an intercept term for OLS, but not for the other models.

In the Finance, Insurance, and Real Estate, tests suggest significant spatial autocorrelation so I focus on those results for the remainder of the section. A spatial Hausman test argues that a random effects model is not suitable for this sector, so fixed effects specifications are used for the spatial models. Further testing indicates that both a spatial lag to the dependent variable and error term are necessary. As a result, the spatial characteristics of the relationships need to be captured by the SARAR model with two versions of spatial lags.

There is evidence that productivity and firm bargaining power primarily drive labor share differences across states. This supports Smith (1817) and Kalecki (1938). An increase in the percentage of those with a Graduate degree by one percentage point implies an increase in labor shares by approximately 0.43 percentage points across states for this sector. An increase in firm size also indicates that workers are better paid in this sector.

1.6.3.7. *Health Care and Social Services.* In the Health Care and Social Services sector, tests indicate that time fixed effects matter and the fixed effects model would be best when compared to pooled OLS. The fixed effects model also outperforms the random effects model, according to a Hausman test. There is evidence of both heteroskedasticity

TABLE 1.11. Full Regression Results for Finance, Insurance, and Real Estate

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
Intercept	91.556***			
	19.179			
High School Attainment	−0.276*	−0.175	−0.181	−0.190
	(0.124)	(0.123)	(0.131)	(0.130)
Some College Attainment	−0.359**	−0.149	−0.146	−0.182
	(0.112)	(0.111)	(0.118)	(0.117)
Bachelor's Attainment	−0.221	−0.277	−0.291	−0.301
	(0.171)	(0.167)	(0.172)	(0.170)
Graduate Attainment	−0.447**	−0.397*	−0.430*	−0.430*
	(0.171)	(0.183)	(0.193)	(0.196)
Sectoral Unemployment	−0.291*	−0.128	−0.224	−0.241
	(0.127)	(0.091)	(0.115)	(0.136)
State Unemployment	−0.110	−0.084	−0.061	−0.070
	(0.099)	(0.068)	(0.071)	(0.069)
Employees per Est.	0.461*	0.277*	0.333**	0.336**
	(0.197)	(0.110)	(0.107)	(0.102)
Self Employment	−0.015	−0.085	−0.046	−0.006
	(0.177)	(0.181)	(0.181)	(0.173)
Union Rep.	0.013	−0.001	0.010	0.010
	(0.050)	(0.050)	(0.050)	(0.048)
Cash Percentage	−0.264	−0.173	−0.092	−0.054
	(0.191)	(0.168)	(0.173)	(0.167)
Median Age	0.260	−0.462***	0.433**	0.373**
	(0.170)	(0.134)	(0.141)	(0.137)
Dif. House	0.212***	0.221**	0.199**	0.197**
	(0.061)	(0.072)	(0.075)	(0.072)
Commute Time	−0.010	0.005	−0.097	−0.138
	(0.120)	(0.150)	(0.157)	(0.153)
Male Proportion	−1.149***	−0.691*	−0.547	−0.492
	(0.279)	(0.328)	(0.330)	(0.330)
Household Size	1.607	3.254	3.072	2.919
	(2.666)	(1.716)	(1.767)	(1.713)
Veteran Proportion	−0.128**	−0.034*	−0.021	−0.012
	(0.087)	(0.121)	(0.141)	(0.144)
Disabled Proportion	−0.268**	−0.087***	0.015	0.100
	(0.100)	(0.082)	(0.100)	(0.104)
Spatial Lag–Labor Share (ρ)		−0.094***		−0.206***
		(0.019)		(0.051)
Spatial Lag–Error (λ)			0.120***	0.174***
			(0.017)	(0.008)
Observations	490	490	490	490
R^2	0.313	0.953	0.948	0.910
Note:		*p<0.05; **p<0.01; ***p<0.001		

and autocorrelation. Because of this, the OLS model in Table 1.12 is a fixed effects model using Arellano clustered robust standard errors due to the presence of autocorrelation and heteroskedasticity.

In the Health Care and Social Services sector, tests suggest significant spatial autocorrelation. A spatial Hausman test argues that a random effects model is not suitable for this sector, so fixed effects specifications are used for the spatial models. Further testing indicates that either a spatial lag to the dependent variable or error term are necessary, with a spatial lag to the error term being more significant. As a result, the spatial characteristics of the relationships may best be captured with some form of spatially lagged error term.

In the spatial models, the percentage of the population represented by unions appears to be the primary, significant determinant of labor share values. Based on the SEM estimate, a one percentage percent increase in the percentage of the workforce represented by unions increases labor shares by approximately 0.1 percentage points. This may serve as supporting evidence for the theory of Kalecki (1938). However, given that the average union representation rate across states is only 11%, the results do not appear to be very economically significant. There is little evidence that productivity, unemployment, or self employment explain labor shares across states for Health Care and Social Services. and firm bargaining power primarily drive labor share differences across states.

1.6.3.8. *Information Services.* In the Information Services sector, tests indicate that time fixed effects matter and the fixed effects model would be best when compared to pooled OLS. The fixed effects model also outperforms the random effects model, according to a Hausman test. There is evidence of both heteroskedasticity and autocorrelation. Because of this, the OLS model in Table 1.13 is a fixed effects model using Arellano clustered robust standard errors due to the presence of autocorrelation and heteroskedasticity.

Table 1.12. Full Regression Results for Health Care and Social Services

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
High School Attainment	−0.265	−0.102	−0.051	−0.055
	(0.288)	(0.083)	(0.088)	(0.089)
Some College Attainment	−0.038	0.033	0.101	0.095
	(0.186)	(0.075)	(0.080)	(0.081)
Bachelor's Attainment	−0.296	−0.115	−0.022	−0.032
	(0.328)	(0.112)	(0.116)	(0.119)
Graduate Attainment	−0.337**	−0.213	−0.011	−0.030
	(0.294)	(0.126)	(0.132)	(0.140)
Sectoral Unemployment		0.195*	0.137	0.140
		(0.082)	(0.115)	(0.112)
State Unemployment	−0.045	−0.093*	−0.072	−0.073
	(0.050)	(0.044)	(0.046)	(0.046)
Employees per Est.	0.054	0.010	0.026	0.025
	(0.066)	(0.049)	(0.048)	(0.048)
Self Employment	−0.142	−0.245*	−0.230	−0.230
	(0.207)	(0.124)	(0.123)	(0.123)
Union Rep.	0.103*	0.090**	0.096**	0.096**
	(0.051)	(0.034)	(0.034)	(0.034)
Cash Percentage	0.038	−0.001	−0.034*	−0.031
	(0.174)	(0.116)	(0.119)	(0.119)
Median Age	0.132	0.218*	0.205	0.203*
	(0.181)	(0.091)	(0.095)	(0.095)
Dif. House	−0.036	−0.079	−0.074	−0.075
	(0.087)	(0.049)	(0.051)	(0.0.051)
Commute Time	0.020	0.100	0.087	0.085
	(0.134)	(0.102)	(0.107)	(0.0.107)
Male Proportion	0.398	0.538*	0.509*	0.515*
	(0.292)	(0.221)	(0.223)	(0.223)
Household Size	−1.848	−1.150	−1.460	−1.431
	(1.711)	(1.165)	(1.196)	(1.197)
Veteran Proportion	−0.292	−0.249**	−0.376***	−0.362***
	(0.167)	(0.085)	(0.096)	(0.102)
Disabled Proportion	0.154	0.284***	0.299***	0.300***
	(0.101)	(0.053)	(0.066)	(0.065)
Spatial Lag–Labor Share (ρ)		0.108***		0.018
		(0.016)		(0.050)
Spatial Lag–Error (λ)			0.130***	0.121***
			(0.015)	(0.030)
Observations	490	490	490	490
R^2	0.095	0.934	0.925	0.927
Note:		*p<0.05; **p<0.01; ***p<0.001		

Table 1.13. Full Regression Results for Information Services

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
High School Attainment	−0.069	0.510	0.510	0.508
	(0.587)	(0.285)	(0.305)	(0.287)
Some College Attainment	0.305	0.492	0.519	0.489
	(0.453)	(0.257)	(0.274)	(0.265)
Bachelor's Attainment	0.077	0.730	0.768	0.723
	(0.595)	(0.383)	(0.399)	(0.391)
Graduate Attainment	0.729**	1.667***	1.727***	1.661***
	(0.801)	(0.419)	(0.447)	(0.435)
Sectoral Unemployment		−0.031	−0.167	−0.022
		(0.128)	(0.175)	(0.126)
State Unemployment	−0.085	−0.068	−0.030	−0.072
	(0.198)	(0.147)	(0.158)	(0.146)
Employees per Est.	0.008	−0.056	−0.081	−0.054
	(0.128)	(0.089)	(0.092)	(0.088)
Self Employment	−0.072	−0.206	−0.158	−0.217
	(0.422)	(0.418)	(0.420)	(0.417)
Union Rep.	0.482**	0.411***	0.405***	0.411***
	(0.152)	(0.115)	(0.116)	(0.115)
Cash Percentage	−0.874	−0.849*	−0.922*	−0.839*
	(0.482)	(0.394)	(0.410)	(0.392)
Median Age	−0.000	−0.074	0.005	−0.075
	(0.583)	(0.313)	(0.326)	(0.311)
Dif. House	0.118	0.086	0.062	0.091
	(0.250)	(0.167)	(0.174)	(0.168)
Commute Time	−0.384	−0.387	−0.183	−0.410
	(0.517)	(0.346)	(0.365)	(0.344)
Male Proportion	−3.260**	−3.070***	−3.276***	−3.049***
	(1.085)	(0.756)	(0.768)	(0.754)
Household Size	3.804	4.900	4.888	4.881
	(5.422)	(3.993)	(4.119)	(3.973)
Veteran Proportion	0.399	0.206	0.086	0.213
	(0.501)	(0.280)	(0.325)	(0.275)
Disabled Proportion	−0.234	0.251	0.147	0.251
	(0.325)	(0.185)	(0.227)	(0.190)
Spatial Lag–Labor Share (ρ)		0.100***		−0.106***
		(0.019)		(0.037)
Spatial Lag–Error (λ)			0.114***	−0.013
			(0.018)	(0.072)
Observations	490	490	490	490
R^2	0.100	0.843	0.829	0.843
Note:		*p<0.05; **p<0.01; ***p<0.001		

Moran and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A spatial Hausman test argues that a random effects model is not suitable for this sector, so fixed effects specifications are used for the spatial models. The results are similar for each spatial model but the SEM model may best reflect the relationships in the data. The spatial lag in the error term is more significant a predictor of labor shares compared to a spatial lag to labor shares themselves. The SARAR model may be also be an effective model in this sector as the coefficient on the spatial lag to labor shares implies that dissimilar states are grouped (which the SAR model alone does not show). Certain areas of the country have very similar labor shares while others–such as states bordering Pennsylvania, Nebraska, and Oregon–have unique "outlier" states that indicate a degree of dissimilarity in labor shares.[24] While it does change the sign of the coefficient on the spatial lags, the remaining coefficient results are nearly identical so it does not seem to matter in the present analysis.

There is evidence that productivity and worker bargaining power primarily drive labor share differences across states. This supports Smith (1817) and Kalecki (1938). An increase in the percentage of those with a Graduate degree by one percentage point implies an increase in labor shares by approximately 1.7 percentage points across states for this sector. Union representation rates also appear to have a statistically positive relationship with labor shares in the Information Services sector across states.

1.6.3.9. *Management of Companies.* In the Management of Companies sector, tests indicate that time fixed effects matter and the fixed effects model would be best when compared to pooled OLS. The fixed effects model also outperforms the random effects model, according to a Hausman test. There is evidence of both heteroskedasticity and autocorrelation.

[24]See Figure A.4 on page 167 to see this.

Because of this, the OLS model in Table 1.14 is a fixed effects model using Arellano clustered robust standard errors due to the presence of autocorrelation and heteroskedasticity.

Moran and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A spatial Hausman test argues that a random effects model is not suitable for this sector, so fixed effects specifications are used for the spatial models. The results are similar for each spatial model but the SARAR model may best reflect the relationships in the data. The spatial lag on both neighboring labor shares and the error are significant in this model, though the coefficients are each negative. The negative coefficient on the spatial lag for labor shares indicate that dissimilar states may be grouped. Indeed, Montana, North Carolina, Tennessee, and Connecticut all appear to be outliers in their regions.[25] The significant spatial lag on the error term indicates there are likely omitted variables in this relationship.

The choice of spatial model appears to have a relatively large effect on coefficient signs and absolute values. This suggests caution when interpreting the results. Specifically, sectoral unemployment has a much larger effect in the SARAR model when compared with the other specifications and the number of employees per establishment has entirely different directional effects, depending on the model selected.

Generally speaking, there is evidence that unemployment, firm bargaining power, and self employment may be important drivers of labor share values in the Management sector. This may serve as support for Marx (1867), Kalecki (1938), and Gomme and Rupert (2004), though the negative sign is the opposite of the prediction in Gomme and Rupert (2004). An increase in the percentage of those with a Graduate degree by one percentage point implies an increase in labor shares by approximately 1.7 percentage points across states for this sector. Interestingly, the rate of self employment has a relatively large effect with a

[25]See Figure A.4 on page 167 to see this.

Table 1.14. Full Regression Results for Management of Companies

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
High School Attainment	0.039	0.056	0.050	0.017
	(0.081)	(0.098)	(0.106)	(0.102)
Some College Attainment	−0.278	−0.190*	−0.160	0.489
	(0.199)	(0.088)	(0.095)	(0.092)
Bachelor's Attainment	−0.073	−0.083	−0.055	−0.081
	(0.176)	(0.133)	(0.139)	(0.133)
Graduate Attainment	0.118	0.094	0.130	0.108
	(0.111)	(0.145)	(0.159)	(0.155)
Sectoral Unemployment		−0.059	−0.286***	−0.376***
		(0.054)	(0.075)	(0.081)
State Unemployment	−0.075	−0.112*	−0.100	−0.112*
	(0.068)	(0.055)	(0.056)	(0.053)
Employees per Est.	0.066	0.072***	−0.077***	0.071***
	(0.045)	(0.012)	(0.012)	(0.011)
Self Employment	−0.484	−0.449**	−0.587***	−0.573***
	(0.388)	(0.145)	(0.142)	(0.135)
Union Rep.	0.047	0.054	0.028	0.023
	(0.057)	(0.040)	(0.039)	(0.038)
Cash Percentage	0.313	0.326*	0.357*	−0.360**
	(0.264)	(0.137)	(0.139)	(0.132)
Median Age	0.374	0.188	0.244*	0.260*
	(0.270)	(0.109)	(0.112)	(0.107)
Dif. House	0.005	−0.077	−0.060	−0.055
	(0.058)	(0.058)	(0.059)	(0.057)
Commute Time	0.070*	−0.083*	−0.119	−0.112
	(0.099)	(0.120)	(0.125)	(0.120)
Male Proportion	−0.179	−0.251	−0.304***	−0.329***
	(0.194)	(0.262)	(0.260)	(0.247)
Household Size	−4.176	−2.886*	−2.785	−2.666*
	(2.443)	(1.378)	(1.406)	(1.341)
Veteran Proportion	−0.103	−0.045	−0.234	0.213*
	(0.116)	(0.097)	(0.117)	(0.115)
Disabled Proportion	−0.175	−0.137*	−0.204*	−0.194*
	(0.147)	(0.063)	(0.083)	(0.081)
Spatial Lag–Labor Share (ρ)		0.144***		−0.208***
		(0.011)		(0.048)
Spatial Lag–Error (λ)			0.159***	−0.186***
			(0.009)	(0.004)
Observations	490	490	490	490
R^2	0.200	0.819	0.742	0.638

Note: BEA employment values used for the estimate of employees per establishment rather than BLS values due to availability of data issues.

*p<0.05; **p<0.01; ***p<0.001

one percentage point increase being associated with a 0.6 percentage point decrease in state labor shares.

1.6.3.10. *Manufacturing.* In the Manufacturing sector, tests indicate that time fixed effects matter and the fixed effects model would be best when compared to pooled OLS. The fixed effects model also outperforms the random effects model, according to a Hausman test. There is evidence of both heteroskedasticity and autocorrelation. Because of this, the OLS model in Table 1.15 is a fixed effects model using Arellano clustered robust standard errors due to the presence of autocorrelation and heteroskedasticity.

Moran and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A spatial Hausman test argues that a random effects model is not suitable for this sector, so fixed effects specifications are used for the spatial models. The results are similar for each spatial model so while it appears that we should account for space, it does not necessarily matter which spatial model is selected.

There is evidence that capital acquisition, productivity, and firm bargaining power are the key determinants of labor share values in the Manufacturing sector. This may serve as support for Ricardo (1821), Smith (1817), and Kalecki (1938), although it should be noted that the coefficient signs are the opposite of prediction for capital expenditures. Capital expenditures are inversely related with labor share values while firm size–the proxy for firm bargaining power–is positively related. This suggests that larger Manufacturing firms compensate their workers better than smaller firms. All higher forms of education significantly impact the labor share, with a one percentage point increase in Bachelor's degree attainment associated with a 1.7 percentage point decline in Manufacturing labor shares.

For capital expenditures, a $10 billion dollar increase in statewide Manufacturing capital expenditures is predicted to decrease labor share values by approximately 5.5 percentage

Table 1.15. Full Regression Results for Manufacturing

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
Capital Expenditures	−5.486*	−5.477**	−5.514**	−5.470**
	(2.194)	(2.080)	(2.084)	(2.085)
High School Attainment	−0.667	−0.360	−0.528	−0.367
	(0.810)	(0.448)	(0.452)	(0.473)
Some College Attainment	−1.236	−0.877*	−0.993*	−0.881*
	(0.767)	(0.393)	(0.402)	(0.406)
Bachelor's Attainment	−1.974	−1.534*	−1.755**	−1.544*
	(1.160)	(0.600)	(0.601)	(0.627)
Graduate Attainment	−2.633*	−2.097**	−2.514***	−2.119**
	(1.199)	(0.668)	(0.660)	(0.741)
Sectoral Unemployment		−0.283	−0.381*	−0.289
		(0.155)	(0.167)	(0.166)
State Unemployment	0.165	−0.061	0.050	0.061
	(0.325)	(0.236)	(0.240)	(0.238)
Employees per Est.	0.435	0.464***	0.487***	0.464***
	(0.275)	(0.131)	(0.135)	(0.135)
Self Employment	−0.179	0.118	0.043	0.108
	(0.870)	(0.630)	(0.634)	(0.631)
Union Rep.	−0.328	−0.313	−0.293	−0.312
	(0.243)	(0.174)	(0.175)	(0.175)
Cash Percentage	−0.466	−0.397*	−0.316	−0.391
	(0.677)	(0.593)	(0.603)	(0.594)
Median Age	0.431	0.160	0.140	0.159
	(0.585)	(0.481)	(0.489)	(0.482)
Dif. House	−0.592	−0.743**	−0.726**	−0.741**
	(0.587)	(0.252)	(0.258)	(0.252)
Commute Time	0.446	−0.403	0.201	0.385
	(0.822)	(0.524)	(0.536)	(0.529)
Male Proportion	−1.134	0.703	−0.808	0.714
	(1.744)	(1.141)	(1.151)	(1.142)
Household Size	−16.366	−16.438**	−15.365	−16.327**
	(11.408)	(6.072)	(6.170)	(6.083)
Veteran Proportion	−0.761	−0.462	−0.373	−0.459
	(0.751)	(0.427)	(0.455)	(0.439)
Disabled Proportion	−1.188	−0.824**	−0.934*	−0.831**
	(0.755)	(0.285)	(0.306)	(0.299)
Spatial Lag–Labor Share (ρ)		0.052*		0.050
		(0.024)		(0.046)
Spatial Lag–Error (λ)			0.051***	0.004
			(0.027)	(0.064)
Observations	490	490	490	490
R^2	0.123	0.877	0.876	0.877
Note: One unit of capital expenditures equal to \$10 Billion.		*p<0.05; **p<0.01; ***p<0.001		

points. The mean dollar expenditure on capital annually across states is $3.1 billion so this would represent a significant change. While the inverse relationship may appear to contradict Ricardo (1821), I would argue it does not. Ricardo (1821) predicted a positive relationship between capital acquisition and labor shares with the idea that capital acquisition increases labor productivity for the worker. In turn, this would induce higher compensation rates for workers. Given the long-run focus of Ricardo's work, this may still be true. This analysis, however, is best characterized as a short-run analysis. Capital expenditures and labor share movements are analyzed contemporaneously and so it is likely that in a given year, if capital acquisition rises, this forces labor shares down. Effectively, firms divert some of their spending from workers to capital. This could explain the pattern observed in this relationship. Indeed, if temporally lagged capital expenditures are used, capital acquisition is far less significant and the coefficient becomes more positive.[26]

1.6.3.11. *Other Services.* In the Other Services sector, tests indicate that time fixed effects matter and the fixed effects model would be best when compared to pooled OLS. The fixed effects model also outperforms the random effects model, according to a Hausman test. There is evidence of both heteroskedasticity and autocorrelation. Because of this, the OLS model in Table 1.16 is a fixed effects model using Arellano clustered robust standard errors due to the presence of autocorrelation and heteroskedasticity.

Moran and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A spatial Hausman test argues that a random effects model is not suitable for this sector, so fixed effects specifications are used for the spatial models. The results are similar for each spatial model but a spatial lag on the error term appears to be the most significant. This significance likely indicates the presence of some omitted labor share determinants, though these omitted

[26]For consistency across sectors, these results are not presented, but are available on request.

Table 1.16. Full Regression Results for Other Services

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
High School Attainment	−0.140	−0.354**	−0.098	−0.105
	(0.157)	(0.119)	(0.125)	(0.124)
Some College Attainment	−0.119	−0.048	0.166	0.149
	(0.147)	(0.106)	(0.112)	(0.112)
Bachelor's Attainment	−0.264	−0.476**	−0.155	−0.186
	(0.204)	(0.159)	(0.162)	(0.163)
Graduate Attainment	−0.082*	−0.434*	0.127	0.060
	(0.201)	(0.172)	(0.188)	(0.190)
Sectoral Unemployment		−0.266***	−0.033	−0.065
		(0.072)	(0.119)	(0.115)
State Unemployment	0.099	0.167**	0.173**	0.171**
	(0.093)	(0.059)	(0.063)	(0.063)
Employees per Est.	0.042	0.317	0.253	0.237
	(0.285)	(0.280)	(0.262)	(0.263)
Self Employment	−0.539**	−0.526**	−0.478**	−0.474**
	(0.186)	(0.176)	(0.166)	(0.166)
Union Rep.	0.235**	0.261***	0.249***	0.254***
	(0.070)	(0.048)	(0.046)	(0.046)
Cash Percentage	−0.327	−0.436**	−0.462**	−0.454**
	(0.233)	(0.168)	(0.162)	(0.162)
Median Age	−0.180	−0.057	0.026	0.022
	(0.221)	(0.131)	(0.132)	(0.131)
Dif. House	0.078	−0.009	0.040	0.047
	(0.105)	(0.070)	(0.069)	(0.069)
Commute Time	0.229	0.306*	0.278	0.260
	(0.174)	(0.146)	(0.147)	(0.147)
Male Proportion	0.055	0.461	0.366	0.417
	(0.436)	(0.461)	(0.305)	(0.306)
Household Size	−2.103	0.940	1.606	1.557
	(1.559)	(1.660)	(1.652)	(1.649)
Veteran Proportion	−0.550*	−0.595***	−0.803***	−0.754***
	(0.238)	(0.121)	(0.138)	(0.138)
Disabled Proportion	−0.010	−0.301***	−0.279**	−0.256**
	(0.149)	(0.087)	(0.306)	(0.097)
Spatial Lag–Labor Share (ρ)		0.118***		0.059*
		(0.009)		(0.028)
Spatial Lag–Error (λ)			0.176***	0.165***
			(0.006)	(0.011)
Observations	490	490	490	490
R^2	0.148	0.955	0.923	0.939
Note:				*p<0.05; **p<0.01; ***p<0.001

variables do not seem to profoundly impact the size and direction of the results regardless of the model selected. In the SARAR model, both spatial lag terms are (weakly) significant, so I focus on these results as representative.

There is evidence that unemployment rates, self employment rates, and union representation are the key determinants of labor share values in the Other Services sector. The coefficient signs only support Kalecki (1938), as self employment has the opposite effect predicted by Gomme and Rupert (2004). Unemployment rates are again counter cyclical with labor shares as a one percentage point increase in unemployment is associated with an approximate increase of 0.17 percentage points of the labor share.

Union representation appears to have a positive effect on labor shares in the Other Services sector. A one percentage point increase implies an increase of the labor share by approximately 0.25 percentage points.

1.6.3.12. *Professional, Scientific, and Technical Services.* In the Professional, Scientific, and Technical Services sector, tests indicate that time fixed effects matter and the fixed effects model would be best when compared to pooled OLS. The fixed effects model also outperforms the random effects model, according to a Hausman test. There is evidence of both heteroskedasticity and autocorrelation. Because of this, the OLS model in Table 1.17 is a fixed effects model using Arellano clustered robust standard errors due to the presence of autocorrelation and heteroskedasticity.

Moran and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A spatial Hausman test argues that a random effects model is not suitable for this sector, so fixed effects specifications are used for the spatial models. The results are similar for each spatial model but a spatial lag on the error term appears to be the most significant so the inclusion of a spatially lagged error may be best.

Table 1.17. Full Regression Results for Professional, Scientific, and Technical Services

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
High School Attainment	0.042	0.548***	0.481**	0.484**
	(0.264)	(0.143)	(0.152)	(0.153)
Some College Attainment	−0.396	−0.178	−0.145	−0.163
	(0.228)	(0.126)	(0.137)	(0.139)
Bachelor's Attainment	−0.186	0.400*	0.385*	0.375
	(0.328)	(0.187)	(0.195)	(0.198)
Graduate Attainment	−0.392	0.177	0.199	0.177
	(0.236)	(0.208)	(0.220)	(0.230)
Sectoral Unemployment		−0.102	−0.310**	−0.273**
		(0.071)	(0.100)	(0.099)
State Unemployment	0.063	−0.164	0.018	0.013
	(0.121)	(0.076)	(0.077)	(0.077)
Employees per Est.	−0.135	−0.093	−0.086	−0.090
	(0.105)	(0.074)	(0.073)	(0.074)
Self Employment	0.044	−0.081	−0.112	−0.105
	(0.298)	(0.203)	(0.201)	(0.202)
Union Rep.	0.134**	0.104	0.098	0.099
	(0.081)	(0.056)	(0.056)	(0.056)
Cash Percentage	0.177	0.173**	0.127**	0.128
	(0.322)	(0.190)	(0.194)	(0.194)
Median Age	0.246	0.053	0.122	0.105
	(0.278)	(0.151)	(0.156)	(0.157)
Dif. House	−0.103	−0.200*	−0.194	−0.193*
	(0.114)	(0.081)	(0.084)	(0.084)
Commute Time	0.027	−0.193	−0.072	−0.088
	(0.208)	(0.166)	(0.175)	(0.175)
Male Proportion	−0.089	0.288	0.022	0.060
	(0.455)	(0.364)	(0.365)	(0.366)
Household Size	−0.002	1.606	1.929	1.873
	(2.931)	(1.930)	(1.977)	(1.977)
Veteran Proportion	−0.693***	−0.949***	−1.106***	−1.082***
	(0.209)	(0.149)	(0.161)	(0.169)
Disabled Proportion	−0.680**	−0.028	−0.271*	−0.236**
	(0.228)	(0.088)	(0.113)	(0.110)
Spatial Lag–Labor Share (ρ)		0.090***		0.028
		(0.015)		(0.038)
Spatial Lag–Error (λ)			0.144***	0.128***
			(0.012)	(0.024)
Observations	490	490	490	490
R^2	0.145	0.941	0.929	0.934

Note: *p<0.05; **p<0.01; ***p<0.001

There is evidence that productivity and unemployment rates may be key determinants of labor share values in this sector. The coefficient signs support Marx (1867), but not Smith (1817), as productivity and unemployment rates impact labor shares positively and negatively, respectively.

1.6.3.13. *Retail Trade.* In the Retail sector, tests indicate that time fixed effects matter and the fixed effects model would be best when compared to pooled OLS. The fixed effects model also outperforms the random effects model, according to a Hausman test. There is evidence of both heteroskedasticity and autocorrelation. Because of this, the OLS model in Table 1.18 is a fixed effects model using Arellano clustered robust standard errors due to the presence of autocorrelation and heteroskedasticity.

Moran and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A spatial Hausman test argues that a random effects model is not suitable for this sector, so fixed effects specifications are used for the spatial models. The results are similar for each spatial model but a spatial lag on the error term appears to be the most significant. However, when a spatial lag is included for both labor share values and the error term, the spatial lag on the error term is no longer significant. This suggests that any of the spatial models could be representative except for the SARAR model, which likely over controls the spatial elements of the labor share.

The model results imply that productivity and unemployment rates are most important in determining Retail labor shares across states. The coefficient signs support Marx (1867) as unemployment rates impact labor shares negatively. Bachelor's degree attainment seems particularly important, though increases in the proportion of the population with degrees are associated with lower labor shares which supports the work of Smith (1817).

Table 1.18. Full Regression Results for Retail

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
High School Attainment	0.261	0.065	−0.023	0.112
	(0.167)	(0.145)	(0.157)	(0.139)
Some College Attainment	0.202	0.050	0.001	0.076
	(0.183)	(0.129)	(0.141)	(0.125)
Bachelor's Attainment	−0.234	−0.608**	−0.681***	−0.572**
	(0.246)	(0.195)	(0.205)	(0.192)
Graduate Attainment	0.080	−0.269	−0.392	−0.210
	(0.225)	(0.219)	(0.234)	(0.221)
Sectoral Unemployment		−0.556***	−0.685***	−0.529***
		(0.094)	(0.129)	(0.089)
State Unemployment	0.285	0.341***	0.308***	0.355***
	(0.146)	(0.083)	(0.088)	(0.080)
Employees per Est.	0.058	0.099	0.112	0.069
	(0.345)	(0.224)	(0.236)	(0.215)
Self Employment	−0.263	0.041	0.048	0.033
	(0.376)	(0.211)	(0.213)	(0.208)
Union Rep.	0.087**	0.141*	0.136*	0.143*
	(0.075)	(0.058)	(0.060)	(0.057)
Cash Percentage	−0.177	−0.284	−0.129	−0.345
	(0.321)	(0.197)	(0.207)	(0.190)
Median Age	0.214	0.205	0.116	0.244
	(0.410)	(0.162)	(0.173)	(0.155)
Dif. House	0.080	0.110*	0.115	0.099
	(0.128)	(0.084)	(0.089)	(0.081)
Commute Time	−0.237	−0.081	−0.278	−0.022
	(0.243)	(0.176)	(0.190)	(0.167)
Male Proportion	0.428	0.473	0.505	0.492
	(0.475)	(0.380)	(0.390)	(0.373)
Household Size	−0.772	−2.249	−1.534	−2.697
	(3.012)	(1.994)	(2.101)	(1.920)
Veteran Proportion	−0.576*	−0.032	−0.039	−0.011
	(0.228)	(0.143)	(0.171)	(0.130)
Disabled Proportion	−0.015	−0.327***	−0.304*	−0.298**
	(0.159)	(0.099)	(0.122)	(0.096)
Spatial Lag–Labor Share (ρ)		0.120***		0.135***
		(0.013)		(0.014)
Spatial Lag–Error (λ)			0.146***	−0.083
			(0.012)	(0.052)
Observations	490	490	490	490
R^2	0.082	0.939	0.921	0.939
Note:		*p<0.05; **p<0.01; ***p<0.001		

Labor shares are counter cyclical in Retail as a one percentage point increase in state-level unemployment implies an increase of the labor share of 0.31 percentage points. Unemployment within the sector fits a Marxian framework as it significantly drives compensation down through the reserve pool of the unemployed.

1.6.3.14. *Transportation and Warehousing.* In the Transportation and Warehousing sector, tests indicate that time fixed effects matter and the fixed effects model would be best when compared to pooled OLS. The fixed effects model also outperforms the random effects model, according to a Hausman test. There is evidence of both heteroskedasticity and autocorrelation. Because of this, the OLS model in Table 1.19 is a fixed effects model using Arellano clustered robust standard errors due to the presence of autocorrelation and heteroskedasticity.

Moran and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A spatial Hausman test argues that a random effects model is not suitable for this sector, so fixed effects specifications are used for the spatial models. The results are similar for each spatial model but a spatial lag on the error term appears to be the most significant.

The SEM model demonstrates that productivity and self employment are most important in determining Transportation and Warehousing labor shares across states. The coefficient signs only support Gomme and Rupert (2004) as both self employment and productivity are positively related to labor shares in the sector. It appears advanced degrees do not have an impact on labor shares, but high school and junior degree attainment do. An increase in high school attainment in a state increases labor shares by an average of 0.74 percentage points.

1.6.3.15. *Wholesale Trade.* In the Wholesale Trade sector, tests indicate that time fixed effects matter and the fixed effects model would be best when compared to pooled OLS. The

Table 1.19. Full Regression Results for Transportation and Warehousing

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
High School Attainment	1.012*	0.710**	0.736**	0.745**
	(0.434)	(0.262)	(0.285)	(0.139)
Some College Attainment	1.181**	0.754**	0.885***	0.892***
	(0.402)	(0.239)	(0.260)	(0.258)
Bachelor's Attainment	0.675	−0.033	0.035	0.048
	(0.492)	(0.352)	(0.371)	(0.369)
Graduate Attainment	1.621*	0.614	0.569	0.618
	(0.705)	(0.385)	(0.425)	(0.425)
Sectoral Unemployment		0.195	0.095	0.135
		(0.154)	(0.219)	(0.208)
State Unemployment	−0.125	−0.149	−0.207	−0.196
	(0.186)	(0.143)	(0.149)	(0.149)
Employees per Est.	0.130	0.231	0.143	0.157
	(0.156)	(0.123)	(0.122)	(0.123)
Self Employment	0.475	1.014**	0.933*	0.937*
	(0.715)	(0.385)	(0.384)	(0.385)
Union Rep.	−0.094	−0.013	−0.035	−0.036
	(0.191)	(0.107)	(0.108)	(0.108)
Cash Percentage	0.261	−0.040	0.221	0.177
	(0.551)	(0.360)	(0.372)	(0.372)
Median Age	0.408	0.068	−0.039	−0.018
	(0.783)	(0.289)	(0.301)	(0.301)
Dif. House	0.111	0.099	0.046	0.048
	(0.222)	(0.154)	(0.160)	(0.160)
Commute Time	0.794	0.623	0.293	0.346
	(0.484)	(0.317)	(0.337)	(0.339)
Male Proportion	0.395	0.465	0.721	0.676
	(0.948)	(0.696)	(0.703)	(0.705)
Household Size	0.589	−2.056	1.381	1.057
	(3.636)	(3.662)	(3.786)	(3.788)
Veteran Proportion	−0.656	0.487	0.788*	0.736*
	(0.603)	(0.260)	(0.308)	(0.309)
Disabled Proportion	0.421	0.194	0.384*	0.356
	(0.329)	(0.171)	(0.219)	(0.212)
Spatial Lag–Labor Share (ρ)		0.127***		0.050
		(0.015)		(0.070)
Spatial Lag–Error (λ)			0.140***	0.120**
			(0.013)	(0.045)
Observations	490	490	490	490
R^2	0.086	0.915	0.901	0.908
Note:		*p<0.05; **p<0.01; ***p<0.001		

fixed effects model also outperforms the random effects model, according to a Hausman test. There is evidence of both heteroskedasticity and autocorrelation. Because of this, the OLS model in Table 1.20 is a fixed effects model using Arellano clustered robust standard errors due to the presence of autocorrelation and heteroskedasticity.

Moran and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A spatial Hausman test argues that a random effects model is not suitable for this sector, so fixed effects specifications are used for the spatial models. The results are similar for each spatial model but a spatial lag on the error term appears to be the most significant. I focus on the SEM model for these results.

The SEM model demonstrates that productivity, unemployment, self employment, and union representation are most important in determining Wholesale Trade labor shares across states. The coefficient signs support Marx (1867) and Gomme and Rupert (2004) as unemployment and self employment negatively and positively impact labor shares, respectively. Bachelor's degree attainment significantly impacts labor shares with an increase in degree attainment exerting downward pressure on labor shares.

With respect to unemployment rates, sectoral unemployment increases are associated with declines in the labor share. This effect is not significant in the SEM specification, but is significant in models featuring a spatial lag of Wholesale Trade labor shares. State-level unemployment rates demonstrate a countercyclical behavior of the labor share; a one percentage point increase in unemployment implies an increase in the labor share of approximately 0.17 percentage points.

The most interesting result from Table 1.20 is the significant negative coefficient on union representation rates. This represents the only sector of fifteen analyzed wherein increased union representation appears to actually distribute income away from workers. The results

Table 1.20. Full Regression Results for Wholesale Trade

	Dependent variable: Labor Share			
	OLS	SAR	SEM	SARAR
High School Attainment	−0.228	−0.215	−0.242	−0.179
	(0.260)	(0.126)	(0.140)	(0.119)
Some College Attainment	0.175	−0.053	−0.057	−0.055
	(0.257)	(0.112)	(0.126)	(0.105)
Bachelor's Attainment	−0.108	−0.372*	−0.398*	−0.341*
	(0.255)	(0.169)	(0.182)	(0.162)
Graduate Attainment	−0.060	−0.129	−0.185	−0.063
	(0.306)	(0.188)	(0.120)	(0.182)
Sectoral Unemployment		−0.222**	−0.185	−0.223**
		(0.078)	(0.120)	(0.069)
State Unemployment	0.107	0.165*	0.165*	0.171*
	(0.107)	(0.070)	(0.074)	(0.067)
Employees per Est.	−0.005	−0.037	−0.030	−0.055
	(0.099)	(0.092)	(0.093)	(0.090)
Self Employment	0.326	0.549**	0.509**	0.603***
	(0.243)	(0.186)	(0.188)	(0.181)
Union Rep.	−0.163	−0.126*	−0.131*	−0.123*
	(0.097)	(0.051)	(0.052)	(0.049)
Cash Percentage	0.102	−0.211	−0.177	−0.213
	(0.306)	(0.174)	(0.183)	(0.164)
Median Age	0.078	0.017	0.043	0.029
	(0.211)	(0.137)	(0.147)	(0.130)
Dif. House	−0.250**	−0.127	−0.121	−0.111
	(0.096)	(0.074)	(0.078)	(0.070)
Commute Time	0.131	0.169	0.252	0.147
	(0.161)	(0.153)	(0.166)	(0.142)
Male Proportion	0.025	0.194	0.141	0.221
	(0.477)	(0.335)	(0.345)	(0.325)
Household Size	5.787*	2.240	1.738	2.507
	(2.408)	(1.760)	(1.856)	(1.674)
Veteran Proportion	0.060	0.308*	0.430**	0.228*
	(0.262)	(0.128)	(0.153)	(0.114)
Disabled Proportion	−0.069	−0.152	−0.176	−0.155*
	(0.154)	(0.081)	(0.110)	(0.070)
Spatial Lag–Labor Share (ρ)		0.132***		0.151***
		(0.013)		(0.013)
Spatial Lag–Error (λ)			0.161***	−0.110
			(0.009)	(0.057)
Observations	490	490	490	490
R^2	0.091	0.939	0.904	0.939
Note:		*p<0.05; **p<0.01; ***p<0.001		

are weakly significant, but this would counter intuitively imply that greater unionization distributes income away from workers. It could be, in this sector, that an increased prevalence of unions results in a backlash against workers with respect to compensation rates.

1.6.4. Summary of Results Across Sectors. With so many sectors, the intent of this section is to concisely summarize which labor share determinants are most important to each sector. Table 1.21 shows each determinant and sector. The positive and negative signs indicate the direction the labor share is predicted to move in each sector as the determinant increases. For example, increases to Graduate degree attainment increase labor shares in Accommodation and Food Service, but decrease labor shares in Arts and Entertainment. Similarly, increases in union representation rates increase the labor share in Other Services, but push labor shares lower in Wholesale Trade. Entries in the table only exist for statistically relevant factors.

Viewing the results in Table 1.21 demonstrates two clear conclusions. First, macroeconomic theory can be applied at the regional level for a variety of sectors (with exceptions such as employees per establishment).[27] Second, while productivity and sectoral unemployment tend to have a negative effect on labor shares, the results are not unanimous across sectors. Similarly, state unemployment rates, self employment rates, and union representation tend to have positive effects on labor shares across states. Nevertheless, these results are not consistent in all cases; there is a tradeoff that must be considered.

Graduate degree attainment, for example, statistically lowers labor shares in four sectors while increasing them in three. The theories of Smith (1817) argue that labor shares should fall as productivity rises due to the fact that gains to output are not fully manifested into

[27]Due to the consistently opposite sign of significant coefficients on this variable, it is clear that a better indicator for firm bargaining power is required. One such proxy for future research will be the proportion of state-level employment that each sector represents.

Table 1.21. Summary of Significant Labor Share Determinants in Each Sector–Direction to Make Labor Share More Positive

	Acco	Admin	Arts	Cons	Educ	FIRE	Heal	Info
High School								
Some College		(-)						
Bachelor's				(-)	(+)			
Graduate	(+)		(-)	(-)	(+)	(-)		(+)
Sector Unemp.		(-)	(-)	(+)				
State Unemp.			(+)	(+)	(-)			
Emp. per Est.		(+)	(+)			(+)		
Self Emp.								
Union Rep.							(+)	(+)
	Mana	Manu	Other	Prof	Ret	Trans	Whole	
High School				(+)		(+)		
Some College		(-)				(+)		
Bachelor's		(-)			(-)		(-)	
Graduate		(-)						
Sector Unemp.	(-)			(-)	(-)		(-)	
State Unemp.	(-)		(+)		(+)		(+)	
Emp. per Est.	(+)	(+)						
Self Emp.	(+)		(-)			(+)	(+)	
Union Rep.			(+)				(-)	

compensation. As a result, the positive coefficients in Accommodation and Food Services, Educational Services, and Information Services run counter to the initial theoretical story. Smith's theories may not be able to account for some of the indirect effects of a greater percentage of more productive workers in a state. In Accommodation and Food Services, Educational Services, and Information Services, the presence of more educated individuals could actually drive up compensations relative to output. Perhaps more educated individuals push through policies that increase compensation for low-wage sectors such as Accommodation and Other Services. On the other hand, more educated individuals likely demand highly-skilled services provided in the Information Services sector and so compensation rates are driven up due to high demand.

Table 1.21 demonstrates that macroeconomic theories can be applied to a more regional analysis, but not with universal directionality. In this regard, the advantage of Table 1.21

is that it lends itself to clear policy changes for any policymaker hoping to impact the distribution of income to workers. It highlights some of the tradeoffs one may experience as these labor share determinants change. An advanced understanding of these tradeoffs will allow a policymaker to better impact the distribution of income accruing to workers in their state. Given the extent to which labor shares are cited, discussed, and researched, a deep understanding of these opportunity costs is paramount.

1.7. Concluding Remarks

Labor shares are an important measure of the distribution of income accruing to workers. This chapter first shows the importance of disaggregating the economy to better describe labor share values. I use a dataset of forty-nine states, fifteen sectors, and ten years (2005-2014) to disaggregate the economy. Along the so-called "three dimensions of the analysis," it is clear that temporal, sectoral, and regional elements cannot be ignored in labor share discussions. At a unit-of-analysis not yet researched, I show that even within a sector and year, there are substantial differences in labor shares across states. These regional characteristics of the labor share generate spatial autocorrelation in every sector's labor shares that should be incorporated in any discussion or analysis of labor shares.

In particular, this spatial element to within-sector labor shares warrants further discussion. I summarize relevant literature on labor shares that indicate determinants of labor share values and dynamics through time. These theories, which stem from work as old as Smith (1817), argue that certain economic factors such as productivity, unemployment, and labor market bargaining power drive labor shares. I hypothesize that these characteristics, which differ by state, cause the observed results of significant cross-state variation in within-sector labor shares. Using spatial panel data models to account for spatial autocorrelation, I provide fifteen sets of models–one for each sector–to assess whether these macroeconomic theories can be applied at a regional unit of analysis. These models account for the interdependent nature of labor share values evidenced within the generated maps of sector-level labor shares for each state. Furthermore, these models test which determinants of the labor share most impact the distribution of income in a given sector and state.

My results show that the employed macroeconomic theories generally perform well, even at the regional level. Educational attainment, used as a proxy for labor productivity, tends to have negative effects on labor share values, as Smith (1817) would argue. Similarly, union representation and self employment rates are generally positively related with labor shares as Kalecki (1938) and Gomme and Rupert (2004) would argue. While most labor share determinants match the predicted impacts of theory, there is a heterogeneity of the effects across sectors that needs to be considered. The implied tradeoffs associated with my results support both the notion that none of the three dimensions of disaggregation should be omitted and that policies impacting labor share determinants should be carefully crafted.

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CHAPTER 2

Temporal, Sectoral, and Regional Characteristics of the Relationship Between Compensation and Productivity

2.1. Introduction

This paper develops a technique that can estimate the relationship between average compensation and productivity across sectors and U.S. states. The goal is to assess whether workers are, on average, compensated according to their productivities at a unit of analysis not yet employed in previous studies. This is a topical issue, given that a wide array of studies indicate a gap between compensation and productivity (Frank, 1984, for a seminal example) that may be growing (Fleck et al., 2011). The limitation of these studies appears to be either the use of aggregated sectors that may miss the nuances of the relationship, or the use of firm-level data that may not be generalizable to labor market outcomes for all workers.

Furthermore, the results of this paper are relevant for popular discourse. A recent economic survey finds that 39% of Americans believe that their remuneration does not match their contributions at work (Glassdoor, 2014). Other news articles provide evidence of worsening labor market outcomes for workers in the form of weakening wages and a general feeling of being underpaid.[1] These new articles depict a narrative often purported across media platforms–US workers are under-compensated and it is getting worse.

Using a panel dataset of fifteen sectors and fifty states over the years 2008-2013, I seek to better understand the temporal, sectoral, and regional characteristics of compensation and

[1]Some examples include: Berman (2013), Cooper (2012), ESPN (2015), Olen (2013), Schachte (2015).

productivity for the average worker. I define a measure, the Compensation-Productivity Difference, that represents the real difference between compensation and productivity for the average worker in a given state, sector, and year. The results demonstrate that while workers may appear underpaid when aggregating the economy to a single-sector, nation-wide analysis, there is significant sectoral and regional variation in the compensation-productivity relationship. This suggests, along with the Chapter 2, the need for a disaggregated look at the economy to truly capture the labor market outcomes for American workers.

A visual analysis of the Compensation-Productivity Difference indicates that workers on the West and East coasts tend to be underpaid while workers in the center of the country are overpaid–even accounting for price differences. With most high population areas concentrated in coastal areas, this drives the observation that workers, on average, are underpaid. However, because prices are already taken into consideration in the relationship between what workers are paid and what they contribute, the regional pattern warrants further explanation. This is left to future work in Chapter 3, with this paper's primary contribution being a more detailed answer to the question of whether or not workers are underpaid.

The remaining sections of this paper are broken down as follows. In Section 2.2, I discuss the literature relevant to pay and productivity comparisons. Section 2.3 discusses pitfalls associated with this comparison and establish how the present analysis will estimate average compensation and average productivity, respectively. Section 2.4 discusses the data sources used and Section 2.5 presents the results of the Compensation-Productivity Difference. In particular, Section 2.5 notes the differing nature of the relationship between compensation and productivity across regions, regardless of sector. Section 2.6 finishes with some concluding remarks and discusses the potential for future research.

2.2. Previous Comparisons of Compensation and Productivity

Direct comparisons between pay and productivity estimates are best broken into microeconomic and macroeconomic studies. This paper largely takes an approach founded in the macroeconomic literature due to the limitations inherent in microeconomic investigations. Despite this, it is worthwhile to see what some key studies have found with respect to relative compensation and productivity for individual workers.

Most microeconomic studies use sample data to directly compare a specific worker's contribution to his or her firm to the level of pay that worker receives. One seminal work in this arena, Frank (1984), uses firm samples from the automobile, real estate, and academic sectors and finds that wages within these firms are far more compressed than would be indicated by marginal revenue product estimates. His results suggest that less productive workers tend to be overpaid and vice versa. Bishop (1987) similarly finds a divergence between current productivity and pay. His results suggest that there is a link between productivity and pay, but there is a lag in the relationship–productivity gains align better with future pay increases.

Fedderke and Mariotti (2002) use a dataset from South African manufacturing firms to estimate compensation and productivity. They find that real compensation rates often differ from productivity, but the link between the two is stronger in industries wherein labor supply and demand are more flexible. Specifically, when workers have the ability to quickly change labor markets and regulations do not hinder firm and worker decision-making, the divergence between productivity and pay is lessened. Other studies use the professional baseball market as a proxy for all labor markets and analyze the relationship between productivity and pay with mixed results.[2] In this market specifically, studies have generally found that baseball player salaries have come closer to productivity estimates as collective bargaining between players and teams has resulted in the advent of the free agent market. This rise in labor market flexibility has been analogous with compensation and productivity drawing closer to one another.

Some sample-level studies suggest that pay exceeds productivity, while others suggest the opposite. The primary difficulty with microeconomic studies is that it is often impossible to collect good data on an individual's productivity outside of very specialized sectors such as agriculture where piecerate data is available. Because many industries suffer from this lack of good observational data, this has typically restricted microeconomic studies to industries with high rates of commission-based pay. This limits the ability of these studies' results to be generalized to a wider array of workers and sectors.

The macroeconomic literature has largely avoided this difficulty by instead focusing on a more aggregated labor market that spans an entire industry or the economy overall. In addition, there does not appear to be any direct comparisons of compensation and productivity. Instead, much of the published literature and releases from government agencies focuses on growth rates of compensation and productivity relative to a base year. While these do not really answer the question of whether or not workers are compensated according to their productivity, they do form the basis for the argument that the gap between worker remuneration and productive contributions is growing.[3]

[2]While these studies are too specific to describe in detail, they support the general conclusions of Frank, Bishop, Fedderke, and others. Namely, an individual worker is often not paid his or her marginal revenue product (Krautmann, 1999, MacDonald and Reynolds, 1994, Scully, 1974, Vrooman, 1996).

[3]Growth rates are used, in particular, due to the lack of consensus about how to assess productivity. A direct comparison of compensation and productivity for workers at the macroeconomic level implicitly comes with a researcher choosing a method with which to estimate productivity.

Feldstein (2008) compares the growth of compensation to lagged productivity growth for all private, non-farm workers in the United States. His paper focuses on the concept of compensation rather than wages as he argues that a significant portion of worker compensation comes in the form of benefits rather than as direct wages and salaries. Indeed, data from the Bureau of Economic Analysis (BEA) supports this idea; wages and salaries only account for about 80% of worker compensation over the last decade and this percentage appears to be falling (BEA, 2017a). Using nominal compensation and productivity data, Feldstein finds that if productivity growth lags are included, both variables appear to be rising at the same rate.

This directly counters the results of two similar studies. In one study performed for the Bureau of Labor Statistics (BLS), Fleck et al. (2011) investigate productivity and real wage growth for the entire US economy from 1949 to 2010. They find that over this time frame, the gap between compensation and productivity did indeed grow–the driving force being inflation differentials prior to 2000 and declining labor shares afterwards. In another study, Mishel and Shierholz (2011) find that US productivity has grown 62.5% while real wages have only grown 12% since 1980. Mishel (2012b) posits that the divergence between median wages and labor productivity is attributed to some combination of decreased terms of trade for labor, rising benefits relative to combination, declining labor shares, and increased wage inequality. Mishel (2012b) argues that since 2000, rising wage inequality and falling labor shares are the primary contributing factors to this phenomenon. Comparing median compensation growth to mean compensation growth further supports the potential importance of rising inequality with respect to the divergence between pay and productivity (Mishel, 2012a).[4]

[4]This result is important for the present analysis as my estimate of productivity uses labor shares to scale average productivity. As labor shares fall this would, all else equal, reduce the estimate of labor productivity and make the Compensation-Productivity Difference more positive.

While the previously discussed studies provide valuable information regarding labor market outcomes for workers in the United States, they each have limitations. The microeconomic literature is too focused on industries for which productivity is easy to measure which makes the results of such studies applicable to only certain workers. Macroeconomic studies often analyze only one or two sectors in aggregate. In this, every worker is included, but such aggregation does not allow for a thorough discussion of the regional and sectoral characteristics of this comparison. Some nuances of labor market outcomes will undoubtedly be lost with over-aggregation. I seek to better elucidate these potentially important dimensions.

2.3. Methodology for Estimating the Compensation-Productivity Difference

This paper adopts a regional approach that looks at the relationship between compensation and productivity for a semi-aggregated economy. More specifically, I analyze fifteen private sectors across each of the fifty states from 2008-2013. This particular sample is used due to data availability of state-level price data. Table 2.1 shows each sector, its corresponding North American Industry Classification System (NAICS) code(s), and its employment rank relative to all two-digit coded NAICS sectors.[5]

Within each sector, I generate a *Compensation-Productivity Difference* variable, denoted D_{ijt}, as the difference between the compensation and average productivity for the average worker. If i represents an index for a particular sector, j indexes a region, and t represents a time index, then the Difference Variable can be expressed generally as:

$$D_{ijt} = (Average\ Real\ Compensation)_{ijt} - (Average\ Labor\ Productivity)_{ijt} \tag{6}$$

[5]Employment ranks are displayed to more easily garner an understanding of the degree to which workers across the United States realize a given labor market outcome.

TABLE 2.1. Fifteen Sectors, Corresponding NAICS Codes, and Ranked Employment–2014

Sector	**NAICS Code(s)**	**Rank**
Accommodation	72	3
Administrative Services	56	5
Arts and Entertainment	71	15
Construction	23	9
Educational Services	61	12
Finance and Real Estate	52-53	7
Health Care	62	1
Information	51	13
Management	55	14
Manufacturing	31-33	4
Other Services	81	10
Professional Services	54	6
Retail	44-45	2
Transportation	48-49	11
Wholesale Trade	42	8

The sign of this Compensation-Productivity Difference would indicate, for an average worker, whether compensation exceeds their contribution to the firm–positive values suggest average pay is larger than average productivity and vice versa. Because the variable itself compares an average worker's compensation in an industry and location to the average level of production, I take the variable's value to be an indication of worker well-being as a result of labor market outcomes. Namely, the more positive D_{ijt} becomes, the better off workers are as a result of labor market participation.

Average real compensation is estimated using the following equation:

$$(Average\ Real\ Compensaton)_{ijt} = \frac{C_{ijt}}{P_{jt}L_{ijt}} \tag{7}$$

C_{ijt} is the total compensation paid to all workers in sector i, region j, and year t. P_{jt} is an estimate of regional prices and focuses on the prices consumers face rather than those of producers. Note that this variable does not include an index for the sector i because I assume that workers in differing sectors do not face a different set of prices as a result of the sector for which they work. L_{ijt} is the level of employment across the noted indices.

The notion of average compensation should be intuitive. However, as mentioned in Section 2.2, productivity estimates often generate more of an issue. I estimate average labor productivity by calculating output per worker and scaling it with an estimate of labor's importance in production. This process yields an intuitive, comparable number for productivity, though one could argue that it implicitly assumes a Cobb-Douglas functional form. While this is a potential drawback, I estimate average labor productivity using the following formula:

$$(Average\ Labor\ Productivity)_{ijt} = \alpha_{ijt}\frac{Y_{ijt}}{L_{ijt}} \tag{8}$$

Where indices are the same as in Equation 6. Y_{ijt} is real output and, like before, L_{ijt} is employment. We can then interpret $\frac{Y_{ijt}}{L_{ijt}}$ as average output per worker. Output is, of course, a function of a variety of inputs, not just labor. In order to estimate the contribution that workers directly make, average output per worker is scaled by α_{ijt}. α_{ijt} is customarily referred to as the labor share and is one way to assess the importance of workers in production. In practice, I estimate the labor share using the common method of pay as a percentage of income. In equation form:

$$\alpha_{ijt} = \frac{C_{ijt}}{N_{ijt}}. \tag{9}$$

C_{ijt} is nominal compensation and N_{ijt} is nominal gross domestic product.[6]

It is worth discussing in greater detail why compensation is used to assess worker contributions to output rather than another measure of worker pay. For example, the BEA

[6]This measure of the labor share is identical to that of Chapter 1.

provides data on three potentially viable measures for pecuniary benefits workers receive: (1) Personal Income, (2) Compensation of Employees, and (3) Wages and Salaries. Personal Income is the broadest category and includes compensation of employees, proprietor's income, rental income, asset income, and net government transfer receipts. Being the broadest category, Personal Income is the largest of the three measures and so using it may overstate the labor share. For this paper, Personal Income is likely not appropriate due to its inclusion of non-employee-related remuneration–government transfer receipts being an obvious example. If the goal is to link labor efforts for workers to their pay, this measure seems ill-suited.

Compensation of Employees is a subset of Personal Income and is broken into (1) Wages and Salaries and (2) Supplements to Wages and Salaries. Supplements include employer contributions to pension funds and social insurance programs. The components of this category certainly incorporate more payments for labor efforts but even this measure is also not perfect. Specifically, benefits in the form of retirement contributions can be viewed as a form of a transfer payment. Worker pay today is delayed to be income in the future. This break between current work performed and pay received could make this measure an unsuitable estimate of income as well. Despite this, the critiques of Krueger (1999) and Feldstein (2008) suggest this may be the best measure with the severe limitations of the last potential measure–Wages and Salaries.

If the goal is to find the most direct link between hours worked and pay, Wages and Salaries is certainly the best. The issue, as Feldstein (2008) points out, is that non-wage compensation has become an increasingly important component of the pecuniary benefits workers receive.[7] As such, choosing Wages and Salaries as the measure of income for use in

[7] About 80% of compensation comes in the form of wages, but this number has steadily declined since the 1980s.

labor share calculations could systematically understate the labor share and subsequently bias the estimate of Compensation-Productivity Difference. Even though there is no perfect measure, this paper will use compensation as the estimate of worker remuneration, given that it captures the monetary benefits of working and is not restricted to the declining portion of pay that comes in the form of wages and salaries.

In full, the Compensation-Productivity Difference is expressed as:

$$D_{ijt} = \frac{C_{ijt}}{P_{jt}L_{ijt}} - \alpha_{ijt}\frac{Y_{ijt}}{L_{ijt}}. \tag{10}$$

2.4. Data Used for Compensation and Productivity

Almost every element needed to calculate the Compensation-Productivity Difference comes from the BEA. *Compensation of Employees by NAICS Industry* (CA6N), denoted C_{ijt}, is used for compensation. *Total Full-Time and Part-Time Employment by NAICS Industry* (CA25N) is used for employment, L_{ijt}. Nominal GDP and real GDP, labeled N_{ijt} and Y_{ijt}, respectively values are also collected for each state, sector and year (BEA, 2017a).

The last remaining element is the measure of prices used to adjust nominal compensation in Equation 7, P_{jt}. I assume prices for each worker do not change based on the sector, so P_{jt} represents a measure of overall state prices–a classic difficulty with state level analyses. Recently, the BEA began posting a *Regional Price Deflator* (RPD) for each state. Unfortunately, RPD's for each state are only available from 2008-2013 (at time of writing) so the analysis is restricted to these six years. The RPD itself is derived from a combination of data from the Consumer Price Index (CPI) program of the Bureau of Labor Statistics (BLS) and the American Community Survey (ACS) of the Census Bureau.

The number expresses an estimate of price level in a region as a percentage of the overall national price level. The number provided by these RPD values combines CPI and ACS numbers to assess the average prices paid by consumers on the goods and services they most consume in their region. On their own, the RPD values don't tell us much because they speak to a state's prices relative to the nation overall. Since workers receive their income and spend it on consumption, and since I aim to see how well-off workers are, I use the CPI from the BLS as my measure of national prices (BLS, 2013). The CPI in tandem with these RPD measures yield the estimate of P_{jt} used in the Compensation-Productivity Difference.

At the national-level, there is significant variation in real compensation, average productivity, and labor shares across sectors. Before explicitly discussing and visualizing the difference between compensation and productivity for the average worker across sectors in Section 2.5, Table 2.2 displays some summary statistics for each sector.

The productivity measure in Table 2.2 represents average products (simply dividing total output in the sector by the level of employment), and so has not been scaled to reflect labor's contribution to that output. There is also a significant degree of variation in average products at the national level. Other Services appears to have the lowest average productivity with \$32,405 while Information Services has the highest with \$225,290. There is also far more variation across years in productivity than compensation, likely reflecting the chaotic nature of the years included in the sample (2008-2013), particularly with respect to output.

Mean real compensation rates range from \$19,793 dollars annually in Accommodation and Food Services to \$102,788 in Management. Ignoring sector, the mean real compensation rate in the United States is approximately \$43,444 over this time period–indicating a right-skewed distribution for this measure. The standard errors for real compensation also vary significantly across sector. This indicates the distribution of compensation rates in industries

Table 2.2. Descriptive Statistics of Average Real Compensation, Average Real Productivity, and Labor Shares by Sector–National Level

	Compensation		Productivity		Labor Share	
Sector	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.
All Sectors	**$43,444**	**$567**	**$83,544**	**$478**	**53.89**	**0.29**
Accommodation	$19,793	$258	$33,112	$255	63.61	0.23
Admin. Services	$28,164	$368	$42,138	$387	70.58	0.46
Arts/Entertainment	$20,505	$268	$38,070	$253	55.69	0.46
Construction	$38,638	$504	$62,263	$488	63.85	0.56
Education	$32,493	$424	$39,997	$432	86.88	0.49
Finance/Insurance	$41,567	$542	$170,033	$1,509	23.48	0.46
Health Care	$43,201	$564	$55,256	$263	83.14	0.27
Information	$70,965	$926	$225,290	$5,220	35.62	0.38
Management	$102,788	$1,341	$132,152	$2,392	84.40	0.43
Manufacturing	$64,521	$842	$143,152	$2,507	47.40	0.89
Other Services	$22,847	$298	$32,405	$488	71.19	0.30
Professional	$55,129	$719	$86,675	$576	67.61	0.60
Retail	$26,012	$339	$48,195	$462	55.81	0.60
Transportation	$42,269	$552	$74,693	$823	58.99	0.49
Wholesale Trade	$64,513	$842	$141,234	$1,658	48.13	0.46

Source and Notes: Data comes from the BEA and BLS. Sample size is six as reported mean values represent values for each sector at the national level averaged over the six available years, 2008-2013.

such as Accommodation and Food Services is far tighter than that of Information Services or Management of Companies.

As noted in Chapter 1, labor shares differ significantly across sectors, as expected. Labor shares vary from 23.48% in Finance, Insurance, and Real Estate to 86.88% in Educational Services. This is not surprising, as workers contribute very different amounts to the productive process, depending on sector. The data used for labor share estimates in this Chapter represents a subset of the data used in Chapter 1 due to the restricted number of years.

2.5. Compensation and Productivity Compared Along Three Dimensions

Together, the three measures in Table 2.2 combine to form the basis of the Compensation-Productivity Difference from Equation 10 on page 88. This section is divided into a discussion of national differences in compensation and productivity, and the same differences at the level of the state. The hope of breaking up the analysis as such is to highlight the potential dangers associated with over-aggregation. Namely, even if we break up the economy into multiple sectors–beyond the two or three sectors often used in such discussions–ignoring the spatial characteristics of compensation and productivity comparisons misses a key part of the story.

2.5.1. Compensation and Productivity at the National Level. Table 2.3 displays the Compensation-Productivity Difference as estimated using Equation 10. This table also provides key statistics for each of the fifteen sectors, ignoring region, as well as summary statistics for a single-sector, aggregated economy. In the fully aggregated case, it would appear that productivity exceeds compensation. This suggests that workers are underpaid by approximately \$1,571 annually and represents a 3.62% divergence of productivity relative to compensation, as a percentage of compensation. Furthermore, the construction of 95% confidence intervals for the Compensation-Productivity Difference suggests that the average worker is statistically underpaid in the United States with that degree of confidence. The Compensation-Productivity Difference estimated here then appears to support the topical narrative that workers do not receive compensation in line with their productive efforts (Glassdoor, 2014).

Table 2.3 also displays the Compensation-Productivity for each sector and categorizes sectors as either low, medium, or high compensation industries. These distinctions are only granted through a direct comparison between average compensation rates of each included sector, and are not mathematically determined.[8] They are placed in the table to better allow the reader to compare sectoral outcomes. In particular, there does not appear to be a pattern with respect to the degree to which compensation rates drive the Compensation-Productivity Difference.

[8]The sectors with the five lowest compensation rates are categorized as "Low," the next five lowest are labeled as "Med," and so on.

TABLE 2.3. Descriptive Statistics of Compensation-Productivity Difference by Sector–National Level

Sector Name	Comp. Level	D_{ijt} Mean	D_{ijt} St. Err.	95% CI Lower	95% CI Upper	D_{ijt} as a % of Comp.
All Sectors		**−$1,571**	**$577**	**−$3,055**	**−$87**	**3.62%**
Accommodation	Low	−$1,269	$394	−$2,281	−$257	6.41%
Admin. Services	Low	−$1,578	$682	−$3,332	$176	5.60%
Arts/Entertainment	Low	−$692	$271	−$1,271	$4	3.37%
Construction	Med	−$1,109	$570	−$2,573	−$356	2.87%
Education	Med	−$2,249	$358	−$3,168	−$1,330	6.92%
Finance/Insurance	Med	$1,668	$708	−$153	$3,488	4.01%
Health Care	Med	−$2,734	$489	−$3,991	−$1,478	6.33%
Information	High	−$9,307	$3,186	−$17,498	−$1,116	13.12%
Management	High	−$8,777	$3,614	−$18,066	$513	8.54%
Manufacturing	High	−$3,309	$705	−$5,121	−$1,498	5.13%
Other Services	Low	−$227	$218	−$788	$333	0.99%
Professional	High	−$3,473	$1,325	−$6,878	−$68	6.30%
Retail	Low	−$873	$339	−$1,745	−$1	3.36%
Transportation	Med	−$1,780	$517	−$3,108	−$452	4.21%
Wholesale	High	−$3,446	$1,101	−$6,276	−$616	5.34%

Source and Notes: Data comes from the BEA and BLS. Sample size is six as reported mean values represent the Compensation-Productivity Difference for each sector at the national level averaged over the six available years, 2008-2013.

Table 2.3 includes a constructed 95% confidence interval for the Compensation-Productivity Difference in order to statistically compare sectors. The final column takes the Compensation-Productivity Difference and divides it by average compensation rates within that sector. This is used in tandem with the compensation rankings of each industry to better compare sectors. It is clear that there is significant variation in the Compensation-Productivity Difference across sectors, however there is no evidence that this result stems from the relative pay in each industry.

As the economy is broken into sectors, fourteen of the fifteen sectors appear to have average productivity levels that exceed average compensation at the national-level. Indeed, only the Finance, Insurance, and Real Estate sector pays the average worker in excess of productive contributions. Even at the sectoral level, the results of Table 2.3 align with the widespread narrative that worker's remuneration does not match what they are estimated to produce in value. Based on the constructed confidence intervals for each sector, we can say with 95% confidence that ten of the fifteen sectors display a statistically negative Compensation-Productivity Difference. The remaining five sectors have compensation and productivity levels that are roughly indistinguishable from zero.

In absolute value terms, it makes sense that the Compensation-Productivity Difference diverges from zero by larger magnitudes in sectors with higher levels of productivity and compensation. In those sectors, there is a greater opportunity for there to be a mismatch between the two values. There is weak evidence that this bears out in percentage terms, as higher compensation industries sometimes exhibit higher D_{ijt} percentages and sometimes do not. This suggests that we cannot predict the within sector magnitude of the difference between compensation and productivity armed with knowledge of the compensation structure in the industry alone.

Figure 2.1 displays the Compensation-Productivity Difference through time for each of the five largest sectors: Accommodation and Food Services, Administrative Services, Health Care and Social Assistance, Manufacturing, and Retail.[9] While each of the sectors exhibit different patterns through time, each of the fifteen sectors witnesses a spike in the Compensation-Productivity Difference from 2008 to 2009 with declines thereafter. In particular, the Manufacturing sector seems volatile as the Compensation-Productivity Difference rises most dramatically between 2008 and 2009 and then falls faster than the other sectors in subsequent years. This likely due to Manufacturing being the only "high" compensation sector in Figure 2.1, the remaining four classified as either medium or low compensation levels in Table 2.3.

[9]Similar graphics for the remaining sectors can be found in Figures B.1 and B.2 on page 172.

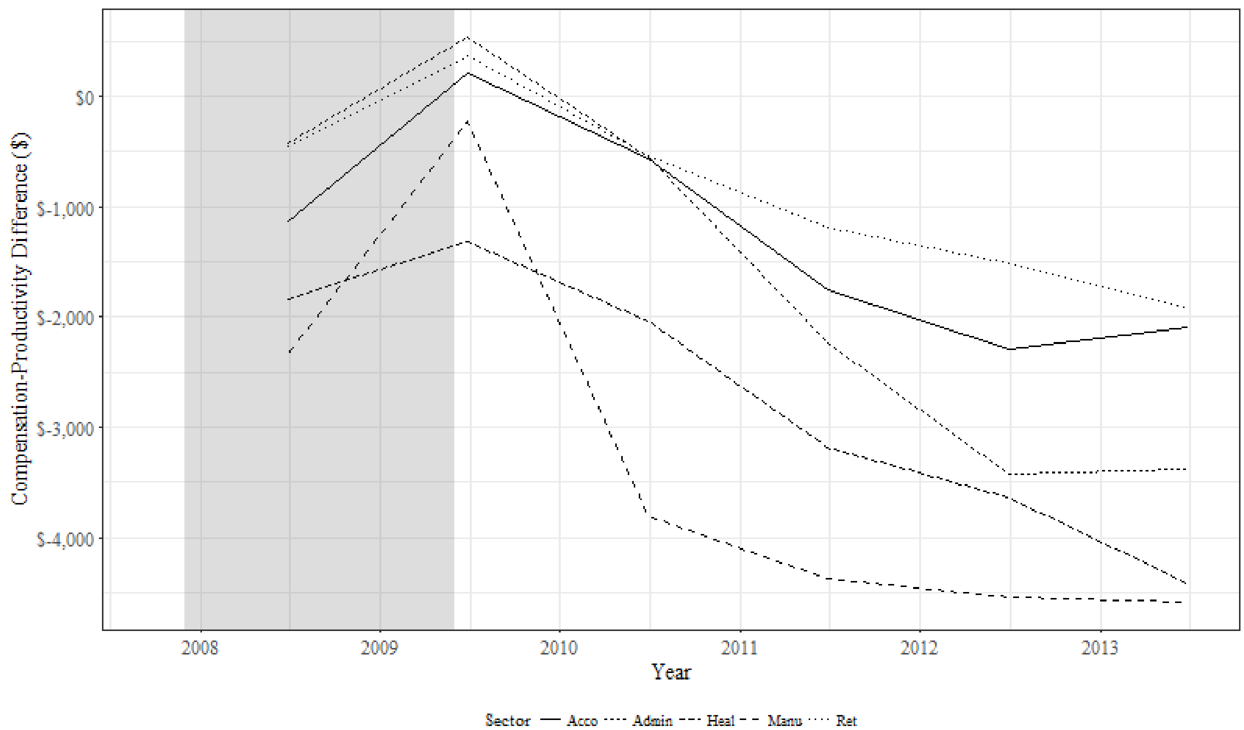


FIGURE 2.1. Compensation-Productivity Difference Estimates for Five Largest Sectors by Employment–United States

Through time, the structure of the Compensation-Productivity Difference estimate allows for a discussion of what drives these results. D_{ijt} can only rise if one of three ceteris paribus changes occur: 1) an increase in average real compensation; 2) a decrease in the labor share; or 3) a decrease in the average productivity of workers. With such a distinct pattern in Manufacturing, I display individual graphs for the labor share, average real compensation, average productivity per worker, and the Compensation-Productivity Difference in Manufacturing in Figure 2.2. These demonstrate that two of the three conditions listed above drive the Manufacturing result. Specifically, average real compensation rises by approximately $1,000 per worker across the United States between 2008 and 2009 before steadily declining thereafter. This, in tandem, with the behavior of the labor share drive the observed Compensation-Productivity Difference changes in the fourth panel of Figure 2.2.[10]

[10]A similar graph for Retail can be found in the Appendix on page 173.

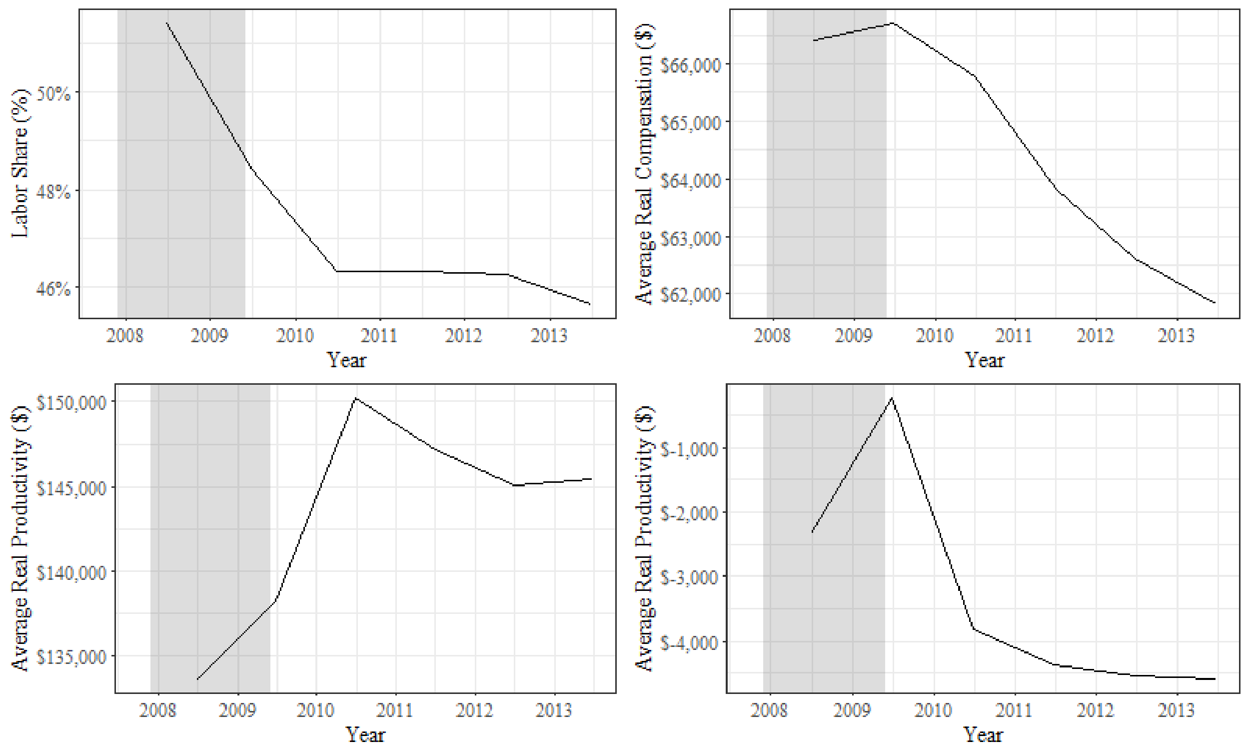


FIGURE 2.2. Labor Share, Compensation, and Productivity Changes for Manufacturing Sector–United States

Figures 2.1, B.1, and B.2 all suggest some clear patterns. Comparing 2008 to 2013, there has been a downward trend in the Compensation-Productivity Difference in most sectors. In Figure 2.1, for example, all five sectors have a more negative Compensation-Productivity Difference in 2013 than in 2008. This supports the results of Fleck et al. (2011), Mishel and Shierholz (2011), Mishel (2012b), and Glassdoor (2014), all of which argue that workers are experiencing worsening labor market outcomes. These results are particularly meaningful as approximately 57% of the labor force is employed in Accommodation and Food Services, Administrative Services, Health Care and Social Services, Manufacturing, or Retail. In these sectors that employ such a significant percentage of workers, more negative Compensation-Productivity Differences would surely be noticed and likely drive the prevalence of the sentiment described in numerous news articles. The question becomes how we can describe this phenomenon for better clarity on a topical issue.

After 2009, increasingly negative values for the Compensation-Productivity Difference imply lower average compensation relative to productivity. There are three ways this could happen: 1) Both compensation and productivity are falling, but compensation is falling at a faster rate than productivity; 2) Both compensation and productivity could be rising, but productivity is rising faster; or 3) Compensation decreases have occurred simultaneously with productivity increases. Independent time-based analyses of average real compensation and average labor productivity suggest that declines to compensation largely drive the observed declines in the Compensation-Productivity Difference across sectors (Option 1). For the aggregated economy, as an example, both compensation and productivity fell over the years 2008 to 2013, but compensation fell 6.9% while productivity fell only 0.9%. Analogous declines happened within in each sector as well. Declining labor shares (which cause the average labor productivity estimate to fall as well) across many sectors, seemingly compensate for the increases to output per worker–labeled Average Real Productivity in Figure 2.2–enough to cause productivity estimates to fall.

Finally, there is a distinct countercyclical nature to the Compensation-Productivity Difference in almost every sector. During economic contractions, which are displayed as shaded regions in Figures 2.1 and 2.2, the Compensation-Productivity Difference rises before falling in expansions. This pattern holds for all sectors with the exception of Educational Services and Other Services. Namely, the Compensation-Productivity Difference rises between 2008 and 2009. The measure then falls beginning in 2009 and continues its decline to a value below its 2008 level as 2013 approaches. This outcome is driven by largely stagnant ("sticky") wages between 2008 and 2009 before compensation rates begin to fall thereafter. Indeed, the data supports the widespread notion that compensation responds slower to output fluctuations in the short-run.

2.5.2. Compensation and Productivity at the State Level. A national view of the economy suggests higher productive contributions to firms than workers receive in compensation with a trend of this gap growing over this time frame, regardless of sector. When the economy is broken into regions, however, there appears to be much greater variation in the Compensation-Productivity Difference. The median of the mean Compensation-Productivity Difference for these state-level, aggregated economies is \$2,050. This indicates, contrary to the results of the national economy, that the majority of states exhibit a Compensation-Productivity Difference that is actually positive. Through the construction of 95% confidence intervals, twenty-nine of the fifty states have compensation rates that are statistically higher than productivity. Conversely, thirteen have statistically negative Compensation-Productivity Differences and the remaining eight are indistinguishable from zero. Because Table 2.3 shows a negative value for the Compensation-Productivity Difference for the economy overall, this means that the majority of workers must live in areas that feature higher productivity relative to pay. Indeed, two of the most "underpaid" states regardless of sector, California and New York, employ a combined 18% of all US employees on their own.

Figure 2.3 shows this to be the case. The top map displays the average of the Compensation-Productivity Difference in each state from 2008-2013 for an aggregated sector. Darker shading indicates a more negative Compensation-Productivity Difference. Immediately evident, states with higher populations see larger negative Compensation-Productivity Differences while lower population states such as North Dakota and South Dakota see workers paid above their productive contributions, on average. In general, states on the coasts tend to pay workers less than average productivity while the Midwest pays workers more. The average worker in New York contributes \$7,966 in output more than he or she receives in compensation, while the average worker in North Dakota receives \$6,058 dollars of compensation in excess of productivity.

The results of Figure 2.3 could also be explained by sectoral composition of each state. It may be, as an example, that states such as California and New York have a higher concentration of employment in sectors wherein workers are more likely to contribute more to their firms than they receive in compensation. This would imply that, were similar plots to be made for each sector, we should see a convergence of Compensation-Productivity Differences across states. With fifteen sectors, I focus on each of the five largest sector by employment within the body of the paper and present cursory results for remaining sectors, for those interested, in the Appendix on page 172.

The Health Care sector employs more people than any other in the United States. At the national-level, this sector has middling compensation rates and workers' productive contributions statistically exceed their compensation, on average. The average Compensation-Productivity Difference, ignoring the state, over 2008 to 2013 is approximately $-\$2{,}734$, or 6.33% of compensation rates. The bottom map in Figure 2.3 shows the average Compensation-Productivity Difference for each state over 2008-2013.

Immediately evident from this figure is the similar pattern of positive or negative values of the Compensation-Productivity Difference displayed in the graphic with an aggregated sector on page 99. As before, states closer to the coasts tend to have a negative Compensation-Productivity Difference while those in the Midwest appear to have positive values. There does not seem to be any convergence of Compensation-Productivity Differences that one would expect if sectoral composition were driving the results alone. Indeed, similar regional patterns hold for all of the sectors discussed in this paper. Figures 2.4 and 2.5 show maps for

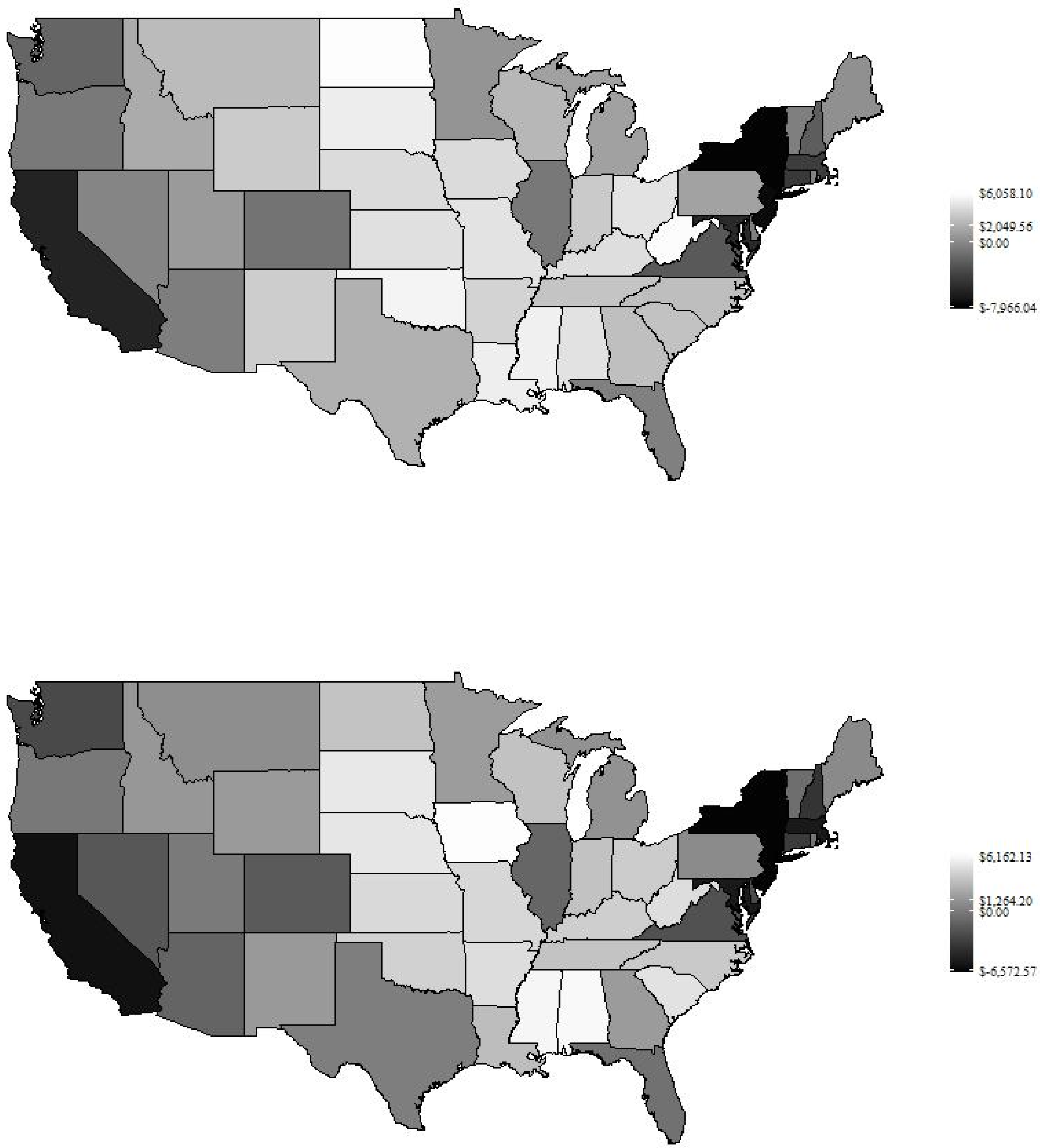


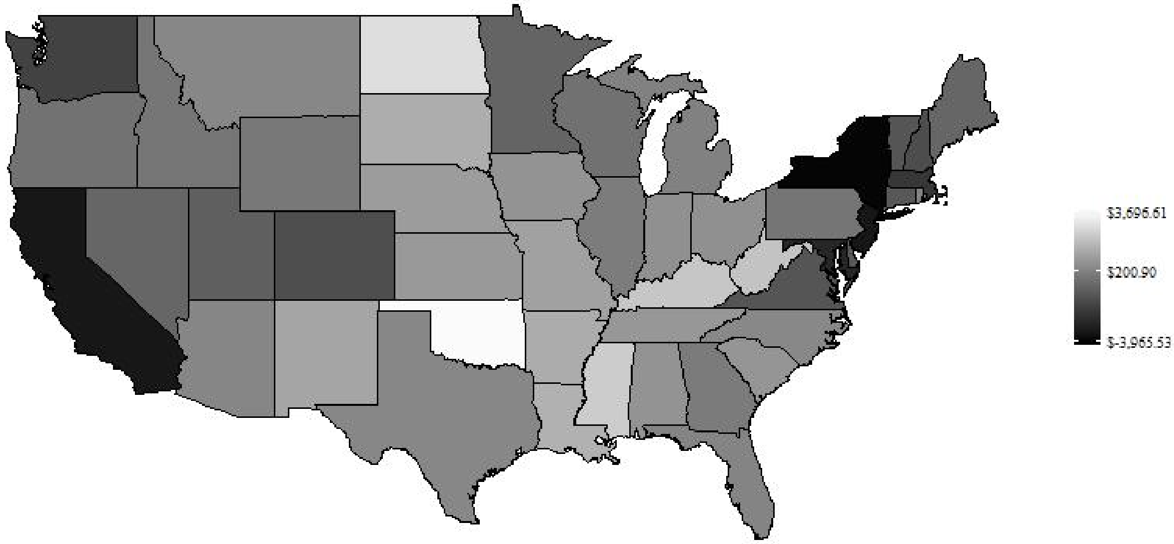
FIGURE 2.3. Compensation-Productivity Difference Map–Aggregated Sectors (Above) and Health Care (Below), Averaged Over 2008-2013

the remaining four largest sectoral employers in the United States and maps for remaining sectors can be found in the Appendix beginning on page 174.

To better summarize the inter-sectoral variation in the Compensation-Productivity Difference, Table 2.4 displays the percentage of states with statistically negative, zero, and positive values for D_{ijt} with 95% confidence. For reference, each sector is labeled with it's relative level of compensation compared to other sectors.[11] There appears to be no distinguishing pattern with respect to the level of compensation and the percentage of states with statistically negative, zero, or positive values for the Compensation-Productivity Difference. Table 2.4 further shows two main conclusions from the state-level estimates of D_{ijt} for each sector. First, the majority of states compensate the average worker in excess of productivity levels for most sectors. This stands in contrast to the results of an economy aggregated to the national-level, which would suggest that regardless of sector, workers tend to contribute more to their firms than they receive in remuneration. Secondly, while many states exhibit statistically positive Compensation-Productivity Differences, there is a variation across states that cannot be ignored.

The last column of Table 2.4 displays whether the majority of US states statistically underpay, overpay, or compensate the average worker in a given sector in accordance with their productive contributions. In twelve of the fifteen sectors, the majority of states witness average compensation rates that exceed the estimate of productive contributions. At face value, this may seem like a counter intuitive result. After all, what incentive would firms have to pay workers in excess of the value they generate? Based on the estimation technique used for the Compensation-Productivity Difference, this result could be rational for firms in the same way that a negative Compensation-Productivity Difference could be

[11]Either low, medium, or high, as in Table 2.3.



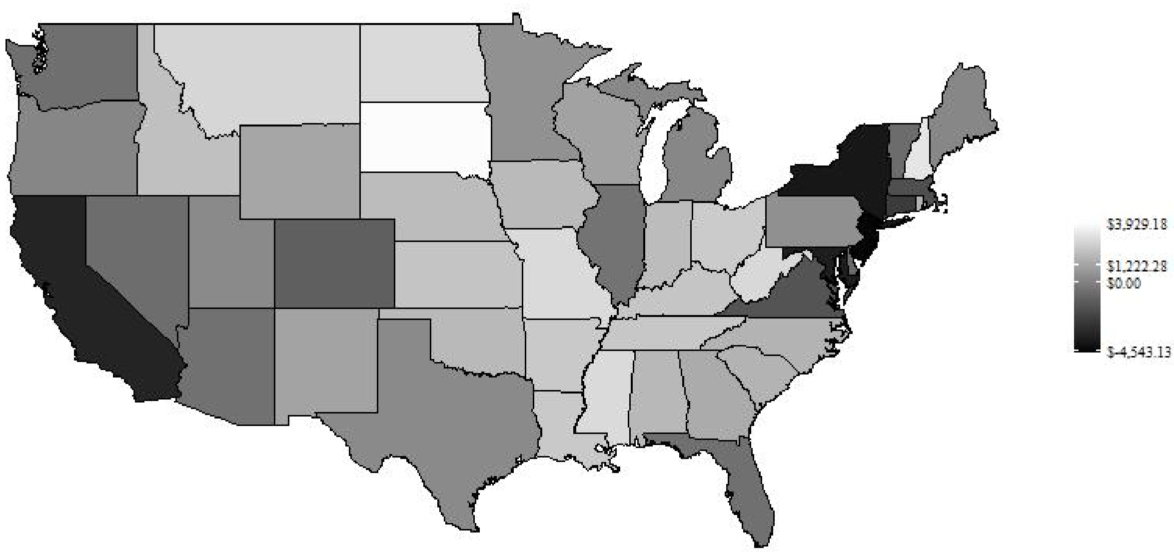
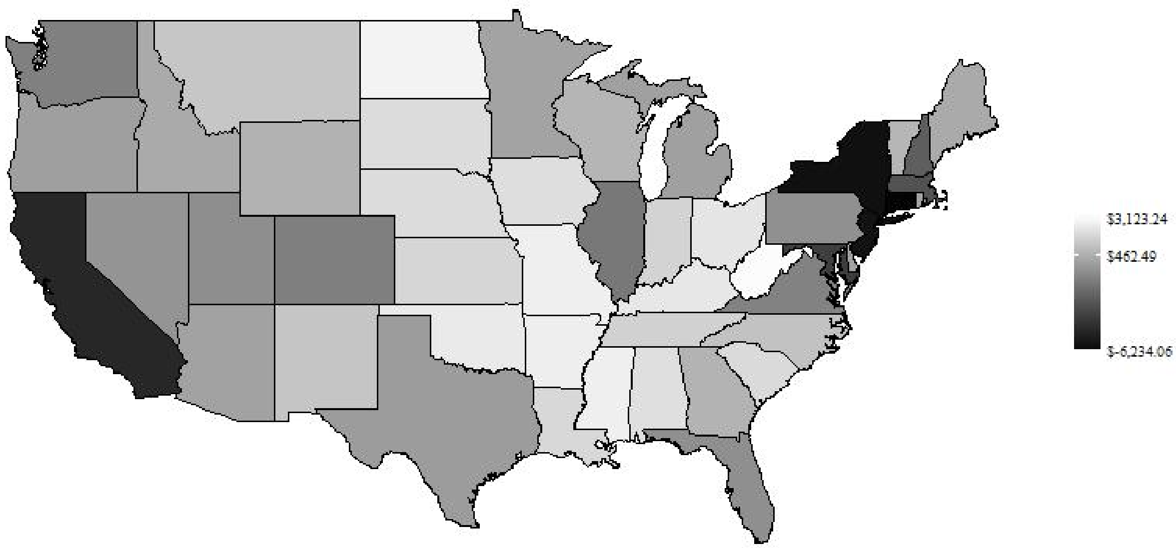


FIGURE 2.4. Compensation-Productivity Difference Map–Accommodation (Above) and Retail (Below), Averaged Over 2008-2013



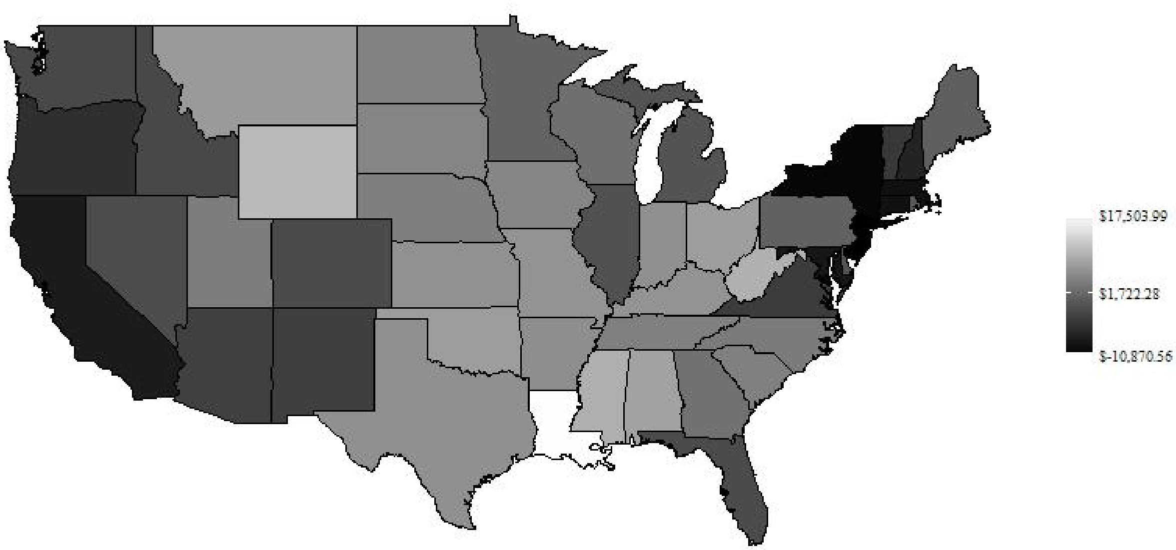


Figure 2.5. Compensation-Productivity Difference Map–Administrative Services (Above) and Manufacturing (Below), Averaged Over 2008-2013

Table 2.4. Percentage of States with Statistically Negative, Zero, or Positive Compensation-Productivity Differences–2008-2013

Sector	Comp. Type	Negative	Zero	Positive	Majority
Accommodation/Food Services	Low	30%	38%	32%	(0)
Administrative Services	Low	30%	26%	44%	(+)
Arts/Entertainment	Low	44%	30%	26%	(-)
Construction	Med	28%	34%	38%	(+)
Educational Services	Med	20%	32%	48%	(+)
Finance/Real Estate	Med	30%	16%	54%	(+)
Health Care/Social Services	Med	34%	10%	56%	(+)
Information Services	High	30%	44%	26%	(0)
Management	High	28%	28%	44%	(+)
Manufacturing	High	28%	22%	50%	(+)
Other Services	Low	20%	22%	58%	(+)
Professional/Technical Services	High	32%	12%	56%	(+)
Retail	Low	30%	14%	56%	(+)
Transportation/Warehousing	Med	26%	24%	50%	(+)
Wholesale Trade	High	20%	36%	44%	(+)

rationally acceptable to workers. From the firm perspective, the last worker hired should have a marginal product equal to his or her value of marginal product, which determines the prevailing compensation rate. However, this compensation rate–which is effectively set by this last worker–may be at a level that exceeds the *average* productive contributions of other workers. Firms would still be profitable in this situation and it would still be rational for them to hire. A representation of the labor market via supply and demand in Figure 2.6 demonstrates this idea.

From Figure 2.6, one conclusion becomes clear. The distinct spatial patterns witnessed across all sectors may be best characterized in terms of an intuitive supply and demand model. The interaction of labor supply and firm's demand for labor ultimately determine the statistically positive or negative Compensation-Productivity Differences of Table 2.4. For a given area, the labor supply and firm demand will depend on a variety of factors inherent to the region in question. It could then be that space is a key determinant of the Compensation-Productivity Difference results.

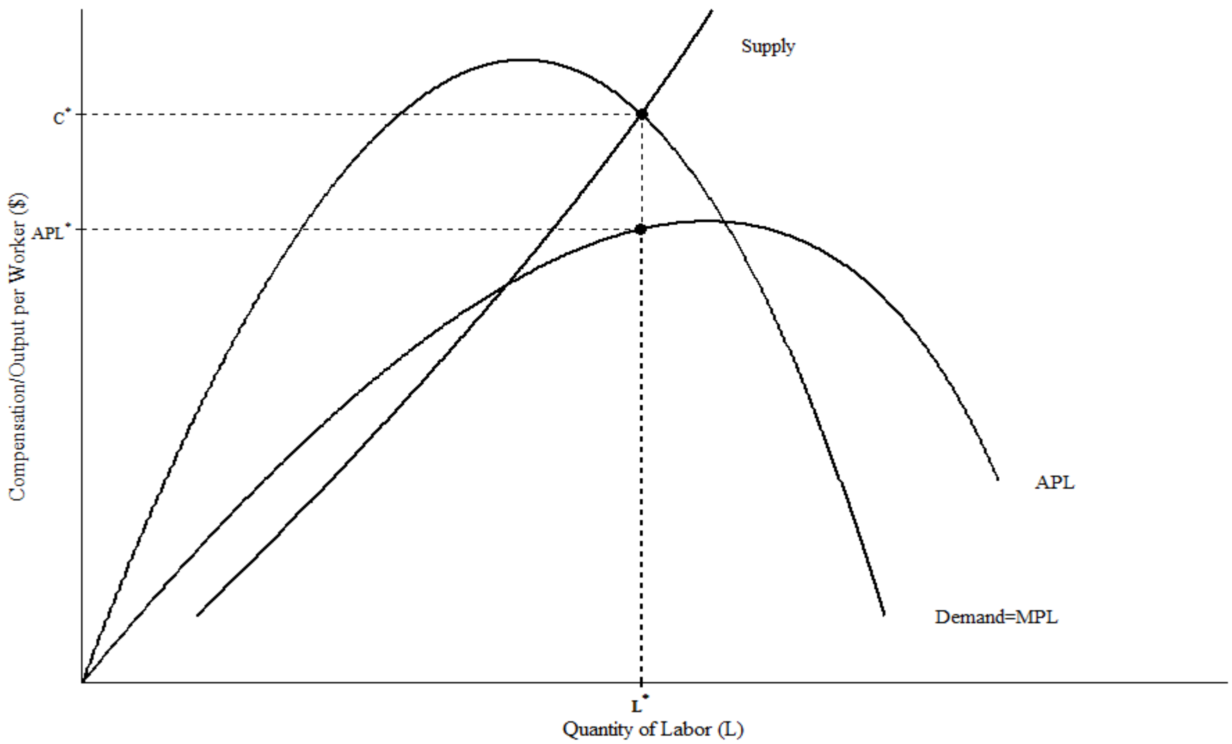


FIGURE 2.6. Labor Market Supply and Demand–Positive Compensation-Productivity Difference

To see how important a determinant space is in these results, I perform Moran (1950) tests for each year and sector, across states. This test, attempts to identify the degree to which the Compensation-Productivity Difference is related across spatial units using a weighting matrix that indicates how closely neighboring units are located. If, as an example, a Compensation-Productivity Difference observation for one state has predictive power for surrounding states, then the Moran test will reject the null hypothesis that spatial units are independent of one another. These tests unanimously indicate the presence of significant spatial autocorrelation in the values of the Compensation-Productivity Difference.

It is clear, then, that space matters when attempting to answer the question: does worker compensation match productive contributions? In short, the answer to this question is no. At the national level, the average worker receives less in compensation than his or her productive contributions while the opposite is true if one looks across US states, regardless of sector.

Aggregating the economy may allow for an overarching discussion of labor market outcomes for workers in the United States, but my results demonstrate that too much aggregation across sectors or regions may be misleading.

2.6. Concluding Remarks

In this paper, I develop a unique methodology to add to the growing discussion about whether worker compensation matches that of productivity in the United States. A survey of previous studies notes pitfalls associated with too narrow or too broad a focus–as each may prevent the results from being generalizable or could fundamentally oversimplify the economy. I attempt to add to these studies by adding both sectoral and regional elements to the economy to see how the results differ.

Using a dataset spanning 2008-2013 and data from the BEA and BLS, I estimate a so-called "Compensation-Productivity Difference" that represents the difference between compensation rates and labor's contribution to production for the average worker. This variable is calculated across six years, fifteen sectors, and fifty states to assess how these temporal, sectoral, and regional elements may influence the relationship between pay and productivity.

Through time, the Compensation-Productivity Difference behaves counter-cyclically–indicating that the average worker becomes compensated higher than average productive contributions as the economy contracts. This is largely due to relatively sticky compensation rates during recessions.

My results align with previous BLS studies indicating that average worker productivity tends to exceed compensation rates at the national-level, regardless of sector. Visualizations of the Compensation-Productivity Difference show a distinct pattern wherein average productivity tends to exceed average compensation in coastal states while the opposite is true in the Midwest. This result accounts even when accounting for price differentials and so these could not explain the observed pattern. This phenomena holds across all sectors analyzed and certainly stresses the importance that regional characteristics have on labor market outcomes. Moran tests further support the importance of space on these results.

This Chapter sought to answer the question of whether or not worker compensation matches that of productive contributions. No matter the unit of analysis, the answer to this question appears to be no. That said, my results highlight that time, sector, and space cannot be ignored in the present discussion of pay and productivity comparisons. In particular, national productivity-pay comparisons would indicate the average worker receives too little compensation while a state-level unit of analysis suggests that the majority of states exhibit compensation rates in excess of productivity for the average worker.

This motivates a clear research agenda. The visible patterns between coastal and Midwestern states in all sectors warrant further explanation. I briefly present a labor supply and demand model to demonstrate how these results may come to fruition. However, subsequent papers could better employ this in tandem with the labor market location decision literature to elucidate the pattern in the Compensation-Productivity Difference.

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CHAPTER 3

Can State-Level Policies Be Considered Amenities?

3.1. Introduction

The present investigation contributes to the labor productivity, compensation, and amenity literature using a unique dataset of compensation, productivity, and state-level characteristics. The primary research question is how state-level policies can impact the relationship between compensation and productivity for the average worker across sectors and states. Specifically, can policies be viewed through the lens of amenities–either drawing workers and firms to a given state or repelling them? Said otherwise, to what extent do policies attract or repel firms and workers?

Consider taxes. With near perfect certainty, taxes represent a disamenity of a region that workers would attempt to avoid in their location decision, ceteris paribus.[1] If there is a ceteris paribus personal income tax increase in a state, then workers would avoid locating there, thereby reducing labor supply. This effect, I argue, should have predictable effects on the relationship between compensation and productivity for the average worker in each sector. In this specific example, reduced labor supply should drive compensation rates higher relative to productivity. While predictable, it is likely that some sectors will be impacted more than others as a result of any policy change. Understanding how policies can generate certain labor market outcomes lends itself to more informed choices on the part of policymakers and the inherent, associated tradeoffs.

[1]Of course, taxes are often used to fund the provision of public goods, which would attract workers and firms to a location. As a result, the impact of tax increases may be conflicted if public good provision is not adequately accounted for.

Much of the motivation for this analysis comes from a recent economic survey which finds that 39% of Americans believe that their remuneration does not match their contributions at work (Glassdoor, 2014). Other news articles provide evidence of worsening labor market outcomes for workers in the form of weakening wages and a general feeling of being underpaid.[2] Previous work shows the distinctly heterogeneous nature of pay and productivity across sectors and states within the US economy.[3] In particular, this previous work notes that even within a sector, there are regional disparities in the relationship between productivity and pay that follow a pattern. Regardless of sector, workers in states along the coasts tend to receive less in compensation than their estimated output contributions. In contrast, workers in the Midwest tend to receive greater remuneration than their productive contributions, on average. These results both account for price differentials.

If price differences cannot explain the observed relationship, then something about the regions themselves must be driving the results. In this chapter, I discuss the relevant amenity literature and develop a supply and demand framework for labor markets. This supply and demand model of the labor market shows the circumstances under which workers would be compensated above or below their productive contributions, on average. Viewing amenities as determinants of either labor supply or demand in this framework elucidates the link between amenities and the estimated comparisons of compensation and productivity. Namely, in areas with high consumer-specific amenities, labor supply will be higher and workers will generally be willing to take a pay cut and vice versa in areas with lower amenities. This would explain why workers in high amenity states like California and New York, tend to be underpaid on average while workers in the Midwest tend to be overpaid to induce more workers to supply their labor in these areas.

[2]Some examples include: Berman (2013), Cooper (2012), ESPN (2015), Olen (2013), Schachte (2015).

[3]See Chapter 2 on page 2.1 for further discussion.

A variety of spatial regression models are used to discover how state policies such as unemployment insurance, tax rates, and the proportion of the population on food assistance programs significantly impact the relationship between pay and productivity. This lends meaningful, policy-based support to the amenity literature at a unit of analysis not often used.[4] Furthermore, these results differ greatly by sector–highlighting policy-related opportunity costs.

The rest of the Chapter can be broken down as follows. Section 3.2 briefly summarizes the estimation of the relationship between compensation and productivity, as well as previous results from Chapter 2. Section 3.3 discusses existing literature on the determinants of worker location decisions that may drive the results of Section 3.2. In Section 3.4, I develop a labor market supply and demand framework as a lens through which the results of Section 3.2 become more tractable. The literature on amenities and imperfectly competitive labor markets is outlined as these branches of thought shed light on the compensation-productivity divergence. Section 3.5 discusses the data sources for variables used in the regression analysis, highlighting their relationship to the literature. The results of these regressions, using the difference between compensation and productivity as the dependent variable, are then displayed and addressed in Section 3.6. Section 3.7 concludes with a brief discussion of whether policies can be viewed as amenities and remarks on potential research extensions.

3.2. Compensation-Productivity Difference

This paper adopts a regional approach that looks at the relationship between compensation and productivity for a semi-aggregated economy. More specifically, I analyze fifteen private sectors across each of the fifty states from 2008-2013. This particular sample is

[4]Most amenity literature focuses on the amenities of more finite labor markets, such as Metropolitan Statistical Areas (MSAs).

Table 3.1. Fifteen Sectors, Corresponding NAICS Codes, and Ranked Employment–2014

Sector	**NAICS Code(s)**	**Rank**
Accommodation/Food Services	72	3
Administrative/Support Services	56	5
Arts/Entertainment	71	15
Construction	23	9
Educational Services	61	12
Finance/Insurance/Real Estate	52-53	7
Health Care/Social Services	62	1
Information	51	13
Management	55	14
Manufacturing	31-33	4
Other Services	81	10
Professional/Scientific Services	54	6
Retail	44-45	2
Transportation/Warehousing	48-49	11
Wholesale Trade	42	8

used due to data availability of state-level price measures. Table 3.1 shows each sector, its corresponding North American Industry Classification System (NAICS) code(s), and its employment rank relative to all two-digit coded NAICS sectors.[5]

Within each sector, I generate a *Compensation-Productivity Difference* variable, denoted D_{ijt}, as the difference between the compensation and average productivity for the average worker. If i represents an index for a particular sector, j indexes a region, and t represents a time index, then the Difference Variable can be expressed generally as:

$$D_{ijt} = (Average\ Real\ Compensation)_{ijt} - (Average\ Labor\ Productivity)_{ijt} \tag{11}$$

The sign of this Compensation-Productivity Difference would indicate, for an average worker, whether compensation exceeds their contribution to the firm–positive values suggest average pay is larger than average productivity and vice versa. Because the variable itself compares an

[5]Employment ranks are displayed to more easily garner an understanding of the degree to which workers across the United States realize a given labor market outcome.

average worker's compensation in an industry and location to the average level of production, I take the variable's value to be an indication of worker well-being as a result of labor market outcomes. Namely, the more positive D_{ijt} becomes, the better off workers are as a result of labor market participation.

Average real compensation is estimated using the following equation:

$$(Average\ Real\ Compensaton)_{ijt} = \frac{C_{ijt}}{P_{jt}L_{ijt}} \tag{12}$$

C_{ijt} is the total compensation paid to all workers in sector i, region j, and year t. P_{jt} is an estimate of regional prices and focuses on the prices consumers face rather than those of producers. Note that this variable does not include an index for the sector i because I assume that workers in differing sectors do not face a different set of prices as a result of the sector for which they work. L_{ijt} is the level of employment across the noted indices.

The notion of average compensation should be intuitive. However, as mentioned in Section 2.2, productivity estimates often generate more of an issue. I estimate average labor productivity by calculating output per worker and scaling it with an estimate of labor's importance in production. This process yields an intuitive, comparable number for productivity, though one could argue that it implicitly assumes a Cobb-Douglas functional form. While this is a potential drawback, I estimate average labor productivity using the following formula:

$$(Average\ Labor\ Productivity)_{ijt} = \alpha_{ijt}\frac{Y_{ijt}}{L_{ijt}} \tag{13}$$

where indices are the same as in Equation 11. Y_{ijt} is real output and, like before, L_{ijt} is employment. We can then interpret $\frac{Y_{ijt}}{L_{ijt}}$ as average output per worker. Output is, of course, a function of a variety of inputs, not just labor. In order to estimate the contribution that workers make, average output per worker is scaled by α_{ijt}. α_{ijt} is customarily referred to as the labor share and this represents the importance of workers in production. In practice, I estimate the labor share using the common method of pay as a percentage of income. In equation form:

$$\alpha_{ijt} = \frac{C_{ijt}}{N_{ijt}}. \tag{14}$$

C_{ijt} is nominal compensation and N_{ijt} is nominal gross domestic product.

It is worth discussing in greater detail why compensation is used to assess worker contributions to output rather than another measure of worker pay.[6] For example, the BEA provides data on three potentially viable measures for pecuniary benefits workers receive: (1) Personal Income, (2) Compensation of Employees, and (3) Wages and Salaries. Personal Income is the broadest category and includes compensation of employees, proprietor's income, rental income, asset income, and net government transfer receipts. Being the broadest category, Personal Income is the largest of the three measures and so using it incorrectly would tend to overstate the labor share. For this paper, Personal Income is likely not appropriate due to its inclusion of non-employee-related remuneration–government transfer receipts being an obvious example. If the goal is to link labor efforts for workers to their pay, this measure is ill-suited.

Compensation of Employees is a subset of Personal Income and is broken into (1) Wages and Salaries and (2) Supplements to Wages and Salaries. Supplements include employer contributions to pension funds and social insurance programs. The components of this category certainly incorporate more payments for labor efforts but even this measure is not

[6]Even though, this is briefly discussed in Chapter 2.

perfect. Specifically, benefits in the form of retirement contributions can be viewed as a form of a transfer payment. Specifically, worker pay today is delayed to be income for the future worker. This break between current work performed and pay received could make this measure an unsuitable estimate of income as well.

The last potential candidate for a measure of income lies in the narrowest category–Wages and Salaries. If the goal is to find the most direct link between hours worked and pay, this measure is certainly the best. The issue, as Feldstein (2008) points out, is that non-wage compensation has become an increasingly important component of the pecuniary benefits workers receive.[7] As such, choosing Wages and Salaries as the measure of income for use in labor share calculations could systematically understate the labor share and subsequently bias the estimate of Compensation-Productivity Difference. Even though there is no perfect measure, this paper will use compensation as the estimate of worker remuneration, given that it captures the monetary benefits of working and is not restricted to the declining portion of pay that comes in the form of wages and salaries.

In full, then, the Compensation-Productivity Difference is expressed as:

$$D_{ijt} = \frac{C_{ijt}}{P_{jt}L_{ijt}} - \alpha_{ijt}\frac{Y_{ijt}}{L_{ijt}}. \tag{15}$$

Using this equation to estimate the Compensation-Productivity Difference and data described in Section 3.5, Table 3.2 displays some descriptive statistics, broken down by sector, at the national-level. As described in Chapter 3, there is also a significant amount of regional variation in these values within a given sector. This table is provided as a reminder of the

[7] About 80% of compensation comes in the form of wages, but this number has steadily declined since the 1980s.

Table 3.2. Descriptive Statistics of Compensation-Productivity Difference by Sector–National Level

Sector Name	Comp. Level	D_{ijt} Mean	D_{ijt} St. Err.	95% CI Lower	95% CI Upper	D_{ijt} as a % of Comp.
All Sectors		**−$1,571**	**$577**	**−$3,055**	**−$87**	**3.62%**
Accommodation	Low	−$1,269	$394	−$2,281	−$257	6.41%
Admin. Services	Low	−$1,578	$682	−$3,332	$176	5.60%
Arts/Entertainment	Low	−$692	$271	−$1,271	$4	3.37%
Construction	Med	−$1,109	$570	−$2,573	−$356	2.87%
Education	Med	−$2,249	$358	−$3,168	−$1,330	6.92%
Finance/Insurance	Med	$1,668	$708	−$153	$3,488	4.01%
Health Care	Med	−$2,734	$489	−$3,991	−$1,478	6.33%
Information	High	−$9,307	$3,186	−$17,498	−$1,116	13.12%
Management	High	−$8,777	$3,614	−$18,066	$513	8.54%
Manufacturing	High	−$3,309	$705	−$5,121	−$1,498	5.13%
Other Services	Low	−$227	$218	−$788	$333	0.99%
Professional	High	−$3,473	$1,325	−$6,878	−$68	6.30%
Retail	Low	−$873	$339	−$1,745	−$1	3.36%
Transportation	Med	−$1,780	$517	−$3,108	−$452	4.21%
Wholesale	High	−$3,446	$1,101	−$6,276	−$616	5.34%

Source and Notes: Data comes from the BEA and BLS. Sample size is six as reported mean values represent the Compensation-Productivity Difference for each sector at the national level averaged over the six available years, 2008-2013.

cursory Compensation-Productivity Difference results, with more detail provided in Chapter 3 on page 90.

3.3. Relevant Discussions of Labor Market Location Decisions and Amenities

From Section 2.5.2, there is evident regional, sectoral, and temporal variation in the relationship between compensation and productivity, the question becomes how to describe this phenomena. In this section, I introduce literature that may help describe these observed outcomes. Subsequently, in Section 3.4, I introduce a methodological framework that incorporates this literature, in an effort to intuit the impact policy changes may have on the Compensation-Productivity Difference. Generally, the relevant literature demonstrates the need to incorporate measures of both imperfect labor market competition and amenities.

Since Robinson (1933) first theorized that under imperfect competition firms may be able to exploit workers, many economists have sought to explain how characteristics of any labor market may generate a divergence between productivity and pay. Because my previous results demonstrate that regardless of market, there tends to be a non-zero Compensation-Productivity Difference, this strand of literature seems like a good place to start. A truly competitive labor market would have all the same characteristics of any other competitive market. Namely, there would be many "buyers and sellers" of labor, perfect information, the absence of price controls, and perfect mobility. In such a world, theory would argue a direct link between productivity and pay. However, as any of these conditions breaks down, we may expect significant divergences in productivity and pay. Models in this field focus on the various ways that a market for labor may not be as well-functioning as a perfectly competitive market. I restrict this section to studies that are directly translatable to this empirical analysis, using the literature survey of Manning (2011) as a guide.

In his survey, Manning argues that imperfect competition within labor markets can be viewed through the lens of rent attainment–or, more specifically, the employer and/or the employee acquire rents from continuing an employment relationship. Jacobson et al. (1993) compare worker earnings before and after a layoff and find that displaced workers across most industries suffer from substantial long-term earning losses, even prior to their exit from the firm. This finding is mirrored in a study Schmieder et al. (2010) perform on the German labor market. These two studies make a clear case for the costs workers experience as a result of labor market turnover, but workers are not the only labor market participants that suffer as a result of transitions in the labor market. Firms often have significant expenditures related to hiring workers, including candidate search and training, which would result in firms attempting to minimize turnover where possible (Oi, 1962). If the two major players in the supply and demand for labor prefer to minimize turnover, this speaks to the existence of rents that accrue to both employer and employee. These rents stem from *status quo maintenance* and imply that the labor market itself is imperfectly competitive; mobility, in particular, is not perfect. For this paper, suppose that imperfect competition in the labor market stems from some combination of frictions or idiosyncrasies and institutions–each of which will impact the flexibility of labor supply.

In a general setting, Stigler (1961) argues that there are costs associated with collecting and employing information for buyer or seller in a market. This idea forms the basis of search theoretic models of the labor market, which focus on the relationship between offers workers receive, their reservation wage, and the potential difficulty of job matching.[8] Specifically, workers face innumerable potential employers and will never be able to inform themselves on the "prospective earnings which would be obtained from every one of these potential employers at any given time, let alone keep this information up to date" (Stigler, 1962). Overall, it may not be difficult to find a job; rather, it is difficult to find a job that is a good match. The friction is that information about matches is positively related to the expenditure of time and money invested in the job search, yet workers will only collect information about potential job matches so long as the expected marginal return of the search exceeds the marginal cost. Information asymmetries in the labor market incentivize lower worker turnover for both workers and firms which again supports the idea that labor supply may not be fully responsive to changing labor market conditions.

Becker (2009) describes another potential labor market friction in the form of specific human capital. Workers–through on-the-job training and experience–gain human capital specific to their present job. While this makes them more attractive job market candidates,

[8]For a good survey of this literature, see Rogerson et al. (2005), or for a specific example, Rogerson and Shimer (2011).

this acquired human capital does not perfectly apply to all forms of employment. As a result, each day on the job workers garner rent that incentivizes continued employment with the same firm. Firms similarly gain rent as each day workers with more experience become more valuable to that firm, even if the skills are applicable to a wide array of jobs (Lazear, 2003). This specific human capital makes it less likely workers will switch jobs and again impact labor supply between markets.

Frictions of a labor market may indirectly restrict labor supply of certain areas and industries, but the institutions of a region (e.g. regulations, amenities) can also play a role in determining labor supply. As an example, unions exist with the explicit goal of increasing the bargaining power of workers in order to drive up wages. While rates of union membership have declined significantly in recent decades and currently hover around 20%, they may still have an effect on labor market outcomes. Employers similarly collude in certain industries, professional sports and nursing being classic examples in the United States. Viewed from the perspective of labor supply, union membership and the opportunity to collude as employees for better bargaining position would increase the attractiveness of a given industry to prospective labor suppliers. This could potentially increase labor supply overall if new workers enter the market, or at the very least, the quantity of labor supplied.

Specific legislation generates institutional labor market impacts as well. One such example comes from Naidu (2010) who looks at the impact of a policies in the US South that punished employers for "poaching" employees from other firms in the early 20th century. Ultimately he found that the anti-enticement policy disproportionately impacted non-white workers through lower wages due to decreased labor market flexibility (Naidu, 2010). A more recent example comes from a study of wages in the dental hygienist labor market by Kleiner and Park. Some states allow dental hygienists to practice without supervision from dentists, which would arguably increase the bargaining power of hygienists. Their results suggest that in states where hygienists are allowed to practice without supervision, they do in fact receive higher wages (Kleiner and Park, 2010). While specific examples that are difficult to quantify, in some cases, institutions seem to impact labor market outcomes through regulations and policy.

Finally, there may be an observed divergence between productivity and pay for the average worker if the location of the job plays a significant role in a worker's employment decision. There are certain pros and cons associated with living in a given area–including, but not limited to, better weather, access to activities, and relative access to desirable geographic areas such as mountains and beaches. The notion that location may induce workers to live in certain areas is widely termed as an amenity effect of location decisions.

One of the earliest amenity-based studies comes from Sjaastad (1962). He discusses the monetary and non-monetary costs of migration and the individual location decision. Of note, he finds that age plays a significant role in migration patterns in addition to market structure and policies of state and local governments. In this way, the policies of an area–through taxes and subsidies–represent amenities or disamenities to potential migrants.

Cebula and Vedder (1973) use city-level data to couch migration patterns in terms of weather, crime, and income levels. Later, Graves (1976) improves this model, arguing that some of the variables and their specification represent a misspecification of the model. This revised model finds strong effects of unemployment, race, and weather on migration patterns into and out of larger cities. Graves (1983) subsequently adds to the literature by arguing that significant collinearity exists between many different measures of amenities (access to beaches and warmer weather, as an example). He seeks a single composite measurement of amenities and finds that rent would be a good surrogate for all amenities and reduce the impact of multicollinearity and omitted variable bias. At the state-level, it is difficult to use rent as part of the discussion, but it is worth noting that amenity variables need to be selected carefully when used as part of regressions in Section 3.6.

Roback (1982) finds that wage gradients are impacted by amenities in addition to rent gradients. This notion, combined with the results of Roback (1984), is a contribution with invaluable implications for the present analysis. Prior to Roback (1982) in particular, the amenity literature focuses primarily on consumer amenities that impact migration decisions of workers. Roback (1982) demonstrates that if an amenity is also productive, then the sign of the wage gradient may be indeterminant. In the labor supply and demand model introduced in the next section, this highlights that care needs to be taken when considering how amenity changes may impact the Compensation-Productivity Difference. Of primary concern, does each amenity used in the analysis impact labor supply, labor demand, or both?

Combined, the amenity literature suggests that labor market outcomes may depend heavily on the perceived amenities and labor market frictions in a region. However, most argue that prices capture these amenities–whether that be the models of Graves (1983) or Roback (1982). As more workers and firms demand living in areas with nice weather, clean streets, clean air, more productive workers, etc., this will tend to increase prices in the area. This is what makes the results of Chapter 3 so strong. Because prices are accounted for through the RPDs provided by the BEA, amenities alone cannot be tell the whole story. For this reason, I attempt to collect a combination of policy variables and institutional measures that could be viewed as (dis)amenities or generate frictions in the labor market. Combined, these could help explain the observed variation in the Compensation-Productivity Difference across states within a given sector.

3.4. Methodological Framework for Assessing Policy Impacts on Compensation-Productivity Difference

To better describe the relationship between compensation and productivity and incorporate the literature of the previous section, I construct a simple and oft-used model of a labor market. This model relies on the assumption that output per worker and compensation per worker are very closely related. There is no doubt that on some level, workers are paid according to their productive contributions, but even if this link is not perfect, I assume this relationship is close enough that we can consider them the same. A firm will determine worker compensation rates based on the productivity of the marginal worker hired and the corresponding compensation level is observed for all workers in that specific labor market.

If this assumption holds, then we can use a general supply and demand framework to show compensation rates relative to average labor productivity–effectively providing a visualization for the Compensation-Productivity Difference. Generally, higher rates of compensation incentivize workers to supply their labor in higher quantities as the greater pay increases the opportunity cost of not accepting that job. With higher compensation, some prospective workers of a labor market may decide that greater pay supersedes their desire for leisure or the compensation they currently receive from a different labor market. This will cause prospective workers to enter the labor market in question, thereby increasing the quantity supplied of labor. In addition, increased compensation induces workers already in a given labor market to forgo their leisure in favor of working more.

The demand side of the labor market focuses on firms. Firms desire workers because they facilitate in the generation of output, but are restricted by the compensation they must pay the worker relative to the price they can receive for their products. In real terms, the specific quantity demanded of labor at a given compensation rate will be determined by the marginal

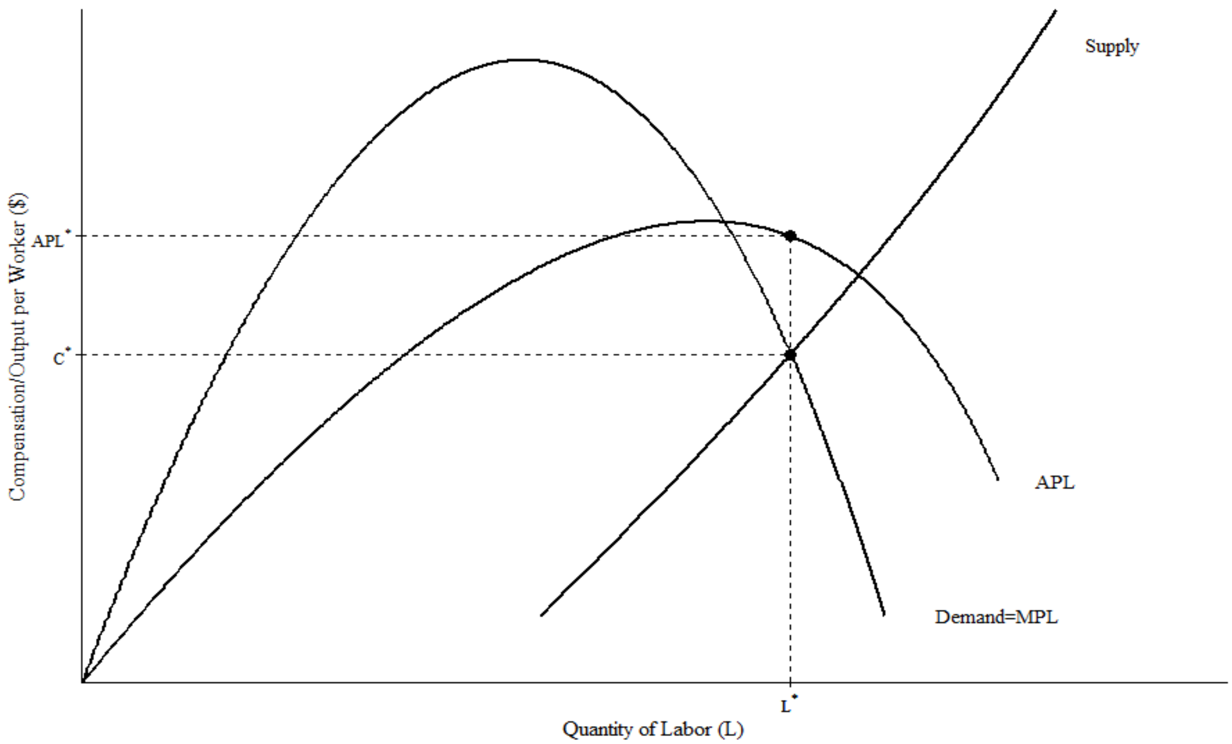

FIGURE 3.1. Labor Market Supply and Demand–Negative Compensation-Productivity Difference

productivity of the laborer hired because firms will not hire a worker unless the benefits at least match the costs. In a labor market, then, labor supply will generally be upward sloping and labor demand will generally be downward sloping, after diminishing returns set in. Firms will hire workers, in a competitive market, up until the point where the last worker hired earns a level of compensation equal to their productive contributions–further hiring would force the firm to pay a worker beyond their productive contributions.

The present analysis does not look at decisions exclusively on the margin because the marginal hiring decision only impacts the rate of compensation–this paper focuses on the average employee's labor market outcome. If the marginal product of labor takes a standard shape, increasing initially as labor is added due to efficiency gains and falling as diminishing returns set in, then the average product curve takes a similar shape. Together, Figure 3.1 shows one potential outcome of a labor market. C^* represents equilibrium compensation rate and L^* the equilibrium employment. At this level of employment, the corresponding average product of workers is labeled as APL^*. The prevailing compensation rate for this labor market is C^*, which is assumed to match the average level of compensation.

In this particular case, there is a negative difference between compensation and productivity; average productivity exceeds compensation. As Section 3.3 notes, the level of competition in a market and amenities to a region impact the decision of workers and firms to locate in a given area. This is how the results of Table 3.2 can best be understood for most sectors. Based on the results of this table, most sectors at the national level have productivity rates that exceed compensation for the average worker. Similarly, Figure 3.1 would represent the many of the coastal states in the United States, regardless of sector. Each of these has a tendency for average productivity rates to be above compensation. The question is why. In these regions, there is greater access to amenities and larger markets which would reduce the frictions workers may experience in labor market participation–both increasing labor supply. As labor supply increases, compensation rates are driven further down relative to productivity.

A negative Compensation-Productivity Difference is not the only outcome one might observe in a labor market. For a tractable example, suppose a circumstance causes labor supply to fall. Perhaps working conditions are poor, the job itself is less attractive relative to other jobs, or the region in which the job is located is not desirable. Each of these examples would cause labor supply to fall, forcing workers to supply their labor only at higher wages for all levels of employment. If labor supply fell low enough, the outcome in the market may be better represented using Figure 3.2. Here, the firms still hire up to the point at which they benefit, but there are fewer workers available. This drives compensation rates up and employment levels down. If this effect goes far enough, the average worker would

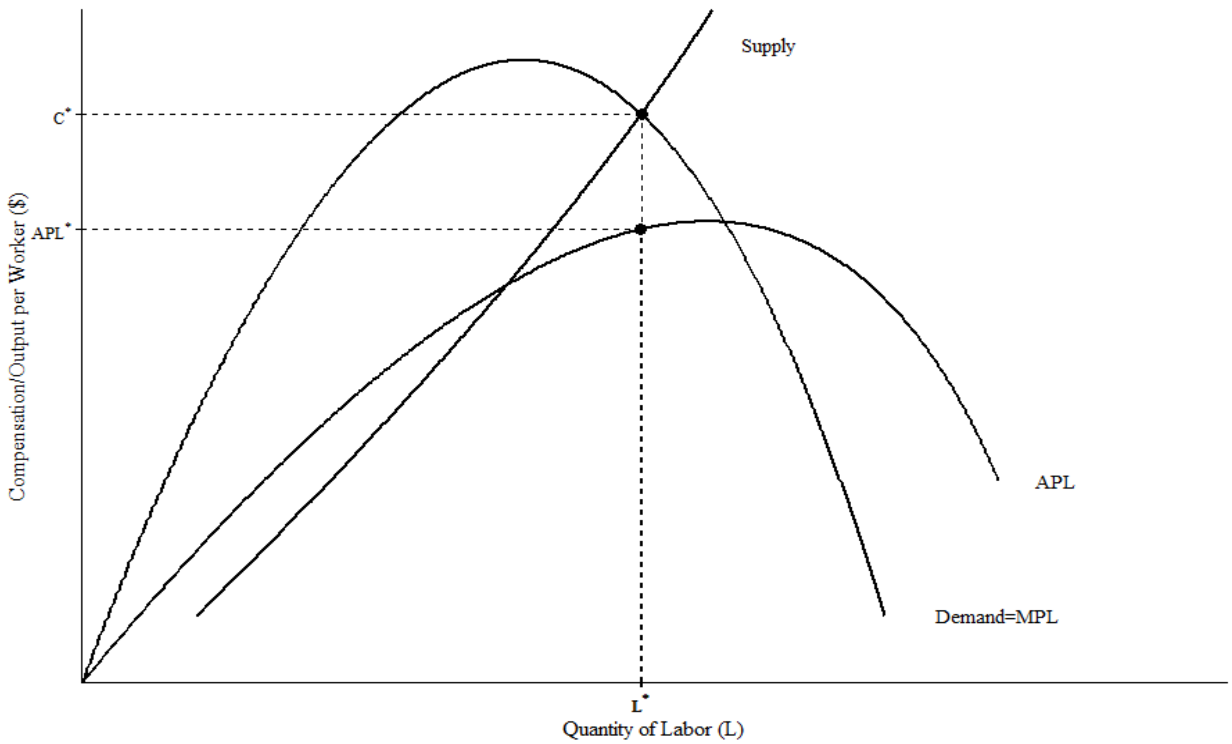

Figure 3.2. Labor Market Supply and Demand–Positive Compensation-Productivity Difference

now be paid at a rate above average productivity for that level of employment. As a result, Figure 3.2 shows a circumstance in which the Compensation-Productivity Difference would be positive. This may better represent the observed outcome in many Midwestern states, regardless of sector.

These graphs provide intuitive ways of interpreting the Compensation-Productivity Difference across sectors, states, or both. As one example, consider the Accommodation and Food Services sector compared to the Manufacturing sector. Mapping the average Compensation-Productivity Difference for Accommodation, as in Chapter 3, over 2008-2013, there is significant regional variation in how workers are paid relative to productive contribution. As with many sectors, the coastal states tend to be underpaid while the Midwest tends to be overpaid. This result, shown in Figure 3.3, is intuitive given that Accommodation and Food Service jobs are generally low-skilled labor positions which are simultaneously

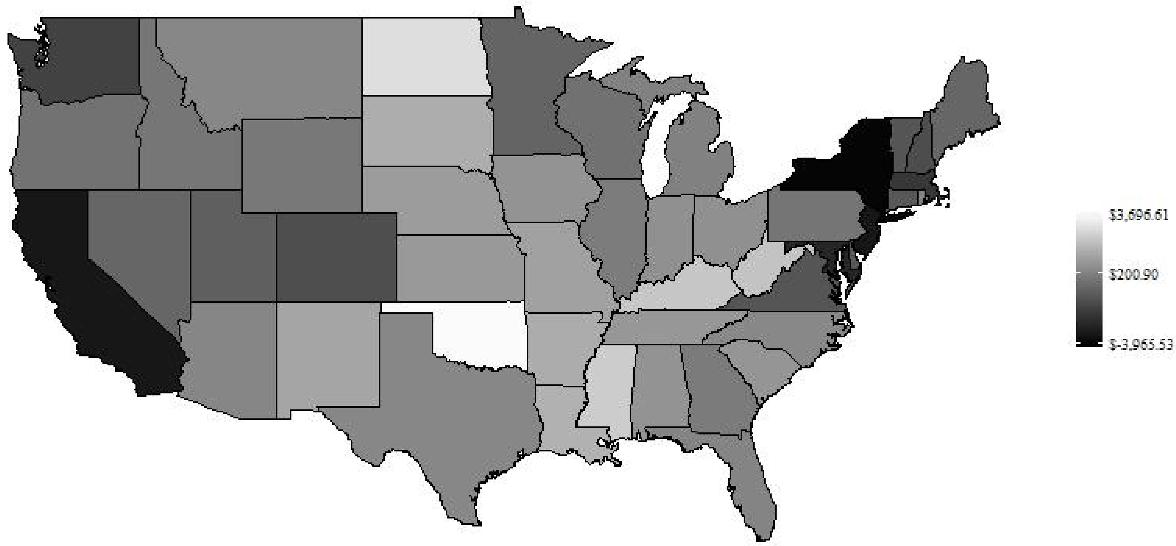

FIGURE 3.3. Compensation-Productivity Difference Map–Accommodation and Food Services, Averaged Over 2008-2013

characterized by lower productivity and pay–making it less likely for the Compensation-Productivity Difference to be significant. Relating Figure 3.3 to the notion of labor supply, firms in the Accommodation and Food Services sector in the Midwest, as an example, will likely not need to scour the country to find workers with sufficient human capital to complete their job duties. In other words, there is less of a need to overpay workers to induce them to move to that region, though they do still have to pay a slight wage, salary, or benefit premium.

Manufacturing, on the other hand, behaves very differently. As a high-compensation sector, it is not surprising that Figure 3.4 shows a higher absolute value of the Compensation-Productivity Difference than Accommodation and Food Services. In the context of labor supply, we would expect states to have a greater disparity in the Compensation-Productivity Difference because of amenities. Workers with higher skills will be even less inclined to live

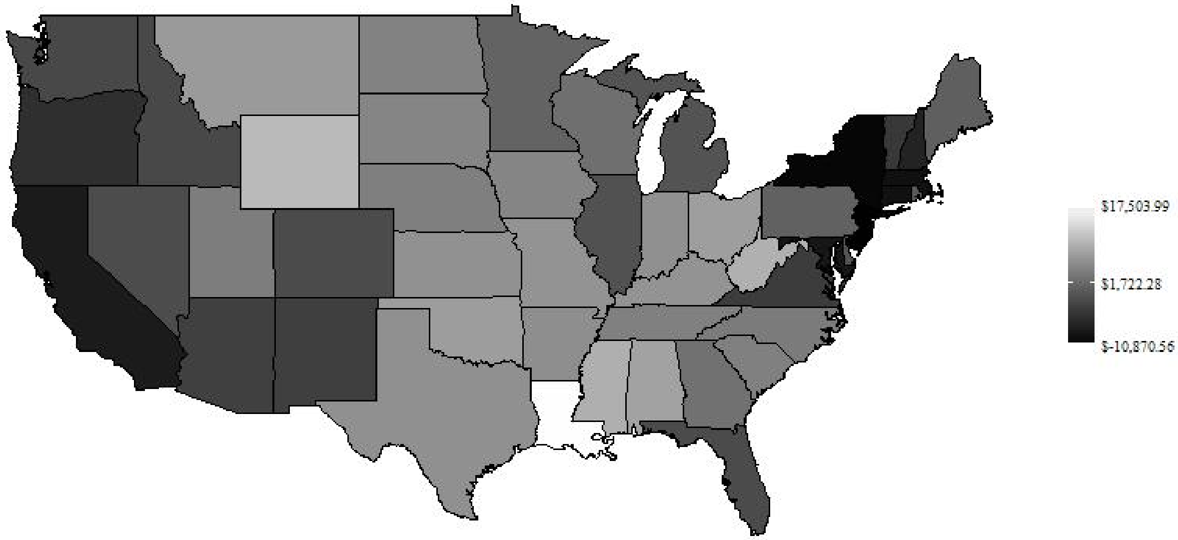

FIGURE 3.4. Compensation-Productivity Difference Map–Manufacturing, Averaged Over 2008-2013

and work in areas with relatively low amenities because their skills allow them the luxury of greater freedom in the labor market. As a result, high-skill workers in sectors such as Manufacturing will need a greater pay incentive to live in areas such as the Midwest than low-skilled workers with lesser options. Further supporting this argument, the range of average Compensation-Productivity Differences over 2008-2013 in Accommodation is only about $7,000 while the range in Manufacturing is closer to $27,000.

These two examples are but a subset of a near infinite number of possibilities to explain the Compensation-Productivity Difference. Moreover, these examples only demonstrate the effects of a labor supply shift. The work of Graves (1983) and Roback (1982) argue that labor demand may be impacted by certain amenities as well. As the demand curve from Figures 3.1 and 3.2 shifts, there is a simultaneous shift in the average product of labor curve. Regardless of the direction of the demand shift, average compensation and productivity will both change and the impact on the Compensation-Productivity Difference will be less clear.[9] The ultimate impact will be determined by the relative shapes of each of the three curves displayed in the labor supply and demand models.

With a methodological framework to intuit labor market outcomes established, I turn to how this can be used to test whether polices can be viewed through the lens of amenities. Policies that add to the benefits of the workforce should induce higher labor supply and drive the Compensation-Productivity Difference lower. Conversely, policy changes that add to the costs to workers (e.g. personal income taxes) will reduce labor supply, all else equal, and drive the Compensation-Productivity Difference higher. Productivity-impacting amenities will shift labor demand and the average product curves and should statistically impact the Compensation-Productivity Difference as well, though the sign on the coefficients will be unpredictable.

To test the impacts of policies on the divergence between compensation and productivity, I implement a statistical strategy similar to that of Chapter 2. There are three dimensions to the analysis so I perform a series of regressions–one for each sector analyzed.[10] Suppose we continue to denote the Compensation-Productivity Difference as D_{ijt}, as in Equation 15. Per the initial notation, i indexes the fifteen sectors of Table 3.1, j indexes the fifty states analyzed, and t indexes the six years from 2008-2013. If we drop the indices for the sake of simplicity, the Compensation-Productivity Difference for each sector across states and years, D, can be written in vector form as:

$$\mathbf{D} = \mathbf{X}\beta_1 + \epsilon_{\mathbf{1}} \tag{16}$$

[9]In the current application, this indeterminacy of Compensation-Productivity Difference changes is what Roback (1982) would describe as the unclear effect of productivity-specific amenities.
[10]The three dimensions are temporal, sectoral, and regional.

β_1 represents the vector of slope coefficients and is the primary motivation for the model's estimation. $\mathbf{X}$ represents a matrix of regressors–both theory-based and controls. Specifically, $\mathbf{X}$ contains measures of policies and labor market frictions, in addition to control variables meant to capture observable state characteristics. ϵ represents a vector of errors.

Moran (1950) tests indicate significant spatial relationships that should be accounted for in the analysis. While intuitively simple, these spatial characteristics muddles the choice of estimation technique. I discuss four popular models that could best reflect the relationships between the variables to attain a robust estimate of β. The first model would use Ordinary Least Squares (OLS) and compare specifications of pooled OLS (ignoring cross-sections), fixed effects (assuming the regressors and the error term are related via the cross-sections), and random effects (assuming the regressor values are independent from the error term). While these models may be informative, OLS often fails to adequately account for spatial components of relationships, which would bias the coefficients and standard errors of the model.

As a result, it is more likely that one of the remaining three models best captures the true relationship in the data. This section uses the notation of Zhukov (2010) for these specifications of spatial panel data models. A second model assumes that the residuals of a linear model are correlated (spatial autocorrelation). The Spatial Autoregressive Model (SAR Model) uses the Maximum Likelihood Estimator (MLE) to estimate an adaptation of Equation 16:

$$\mathbf{D} = \rho \mathbf{W} \mathbf{D} + \mathbf{X}\beta_2 + \epsilon_{\mathbf{2}} \tag{17}$$

This model assumes contemporaneous spatial autocorrelation with the dependent variable of one cross-sectional unit with other cross-sectional units in the same time period. The matrix $\mathbf{W}$ represents a weighting matrix that defines the relationship between each cross-sectional unit. ρ is a scalar that must be less than unity and indicates the degree of spatial autocorrelation between cross-sectional units.

A third specification of the model in Equation 16, the Spatial Error Model (SEM), attempts to minimize the effects of omitted variable bias and spatial heterogeneity. When unobserved variables are not incorporated in any model, they collapse into the error term, ϵ. In a spatial framework, it is likely that these omitted variables are at least partially determined by location. The key argument for this model, then, is that any present autocorrelation is attributable missing spatial covariates in the data. To account for this, the SEM model can be expressed as:

$$\mathbf{D} = \mathbf{X}\beta_3 + \lambda\mathbf{W}\mathbf{u} + \epsilon_{\mathbf{3}} \tag{18}$$

Here, the spatial weights matrix, $\mathbf{W}$ weights the error term instead of dependent variables of neighboring areas. λ indicates the degree to which there is spatial dependence in the error terms. A positive λ coefficient could indicate a strong and positive spatial dependence in the error terms, depending on its significance. The SEM model can be estimated through Maximum Likelihood estimation techniques.

A fourth specification is the Spatial Autoregressive Model with Spatial Autoregressive Errors (SARAR). This model allows for both a spatial dependent variable lag as well as spatial lag in the error term. As a result, it can be though of as a combination or the SAR and SEM models. The SARAR model can be expressed as:

$$\mathbf{D} = \rho\mathbf{W}\mathbf{D} + \mathbf{X}\beta_4 + \lambda\mathbf{W}\mathbf{u} + \epsilon_{\mathbf{4}} \tag{19}$$

The spatial weights matrix, $\mathbf{W}$ now adjusts both the error term and the dependent variables of neighboring areas. λ still indicates the degree to which there is spatial dependence in the error terms while ρ is the analogous relationship in the dependent variables. Because both effects are included, this model is primarily used to assess which effect–a spatial lag in dependent variables or error terms–is strongest. The SARAR model can be estimated through Maximum Likelihood estimation techniques.

The various β vectors are of primary interest in this paper as this vector will indicate whether policies can be viewed as amenities. I will perform a series of tests to determine the best possible models for each sector and present each of the above specifications to increase the robustness of the results. For each sector, I will select between Pooled Ordinary Least Squares, Fixed Effects, and Random Effects non-spatial models as well as the SAR, SEM, and SARAR spatial models. For these, the weighting matrix uses Euclidean distance between states to weight observations and account for spatial dependence. Euclidean distance is calculated using the central geographic point of each state based on longitude and latitude (Ink Plant, 2017).[11] Different weighting schemes, such as a binary indication of neighboring status are left for future work.

3.4.1. Variables Used For Policy Impacts and Their Predicted Impact on the Compensation-Productivity Difference. The theories of labor market frictions and amenities motivate the collection of state-level policy variables that may impact the Compensation-Productivity Difference. The key measures of interest are listed in Table 3.3 along with some summary statistics and the predicted impact on D_{ijt}, using the supply and demand models of Section 3.4 as a guide.[12] For the present analysis, average governmental

[11]The website uses zip code databases to assess the average latitude and longitude of zip codes within the state. This average generates an estimate for the central point within the state.
[12]For a listing of control variables used, see Table C.1 in Appendix C on page 179.

Table 3.3. List of Policy Variables That May Be Viewed As Amenities and Impact Labor Supply and Demand

Variable	**Mean**	**Std. Dev.**	**Shifts**	D_{ijt} **Impact**
Cash Transfers	\$3,278.37	\$704.78	$S\uparrow$	(−)
Commute Times (minutes)	23.59	3.46	$S\downarrow, D\downarrow$	(?)
Min. Corporate Tax	5.36%	2.93%	$S\downarrow, D\downarrow$	(?)
Max. Corporate Tax	6.52%	2.84%	$D\downarrow$	(−)
Min. Income Tax	2.41%	1.80%	$S\downarrow$	(+)
Max. Income Tax	5.61%	2.87%	$S\downarrow$	(+)
Minimum Wage	3.43%	116.22%	$S\uparrow, D\downarrow$	(?)
Sales Tax	5.03%	1.96%	$S\downarrow, D\downarrow$	(?)
Union Representation	12.25%	5.47%	$S\uparrow, D\downarrow$	(?)

Notes: Minimum wage calculated by dividing state minimum wage by federal minimum wage in that year. Data sources include the Census Bureau, TaxFoundation.org, and the BLS.

cash transfers to households, average worker commute times, corporate taxes, income taxes, minimum wage (relative to federal minimum wage), sales taxes, and union representation rates are used to capture state-level policies.

The fourth column of Table 3.3 predicts how labor supply and demand might change due to an increase in the variable in question. Because each of these variables is meant to capture a policy (dis)amenity, it is worth discussing the logic behind these predicted shifts prior to presenting the results. Cash transfers to households represent an exogenous increase to income. Increases to these transfer payments should draw additional workers to a state and unambiguously make the Compensation-Productivity Difference more negative as labor supply shifts along a given labor demand curve.

Commute times in minutes are included as a proxy for infrastructure quality of a state. From the worker perspective, increases to the length of daily commute times represent a disamenity that should repel prospective migrants. In isolation, this leftward shift of labor supply should exert upward pressure on the Compensation-Productivity Difference. Firms also must deal with commute times and operate within the current infrastructure of a given state. From the firm perspective, increased commute times likely correspond with congestion levels that make daily operations more difficult. Generally, this would dissuade firms from locating in a given state. The resulting leftward shift of the labor demand curve would ambiguously affect the Compensation-Productivity Difference as the ultimate impact would depend on the curve shapes.

Both the lowest and highest corporate income tax faced by firms is included in the collection of policy variables.[13] In states with progressive corporate tax rates, it is likely that the highest marginal rate faced primarily impacts very large firms only. Increases to the highest tax rate would then diminish firm desire to locate in an area and reduce labor demand. Bartik (1985) notes that state corporate taxes have a negative impact on firm location decisions. If we assume that firms "pass along" these tax payments through lower compensation rates, then this would imply a negative coefficient on maximum corporate tax rates. The effect of minimum corporate tax rates are likely to be more ambiguous. When small business owners make their location decision, this decision impacts both labor demand *and* supply; they effectively are the labor supply and labor demand. Ceteris paribus, reductions in labor supply unambiguously increase the Compensation-Productivity Difference but simultaneous shifts in supply and demand would result in an unclear outcome.

Personal income taxes should primarily impact labor supply and would have a ceteris paribus disamenity effect. As with corporate taxes, both the minimum and maximum marginal income taxes are used to capture progressive tax systems. For both the minimum and maximum rates, increases should reduce labor supply and exert a clear positive effect on the Compensation-Productivity Difference.

Increases to minimum wage and the percentage of workers represented by unions should both increase labor supply and decrease labor demand. Low-skill workers in particular would

[13]Some states have flat corporate taxes and so for those, the observations of these two variables would be the same.

view minimum wage increases as a benefit. This will increase labor supply and cause the Compensation-Productivity Difference more negative. On the other hand, firms would view minimum wage increases as an increase in labor costs and tend to substitute into other factors of production. This would reduce labor demand and result in an unclear impact that depends on the shapes of each curve.

Similar arguments can be made for greater union representation as the increased presence of unions should propel compensation rates up as workers increase their bargaining power. This amenity would increase labor supply but represent a cost to firms that would likely reduce labor demand.

Finally, the final impact of an increase in sales taxes is likely to be ambiguous. Individual workers would view sales tax increases as a disamenity that reduces labor supply to a region and exert upward pressure on the Compensation-Productivity Difference. Firms would experience a reduction in sales for consumers that are particularly price sensitive and so would similarly view these taxes as a disamenity. The resulting reduction in demand muddles the final impact of sales tax changes on the Compensation-Productivity Difference.

3.5. Data Used for Compensation-Productivity Difference and Amenities

The data used in this paper comes from a variety of governmental surveys and a select number of private sources. This section summarizes those sources and provides cursory summary statistics for important variables. Generally speaking, data for the Compensation-Productivity Difference comes from the BEA, demographic characteristics come from the American Community Survey, and tax-related data comes from TaxFoundation.org. Each of the data sources is described in detail in this section.

Almost every element needed to calculate the Compensation-Productivity Difference comes from the BEA. *Compensation of Employees by NAICS Industry* (CA6N), denoted

C_{ijt} is used for compensation. *Total Full-Time and Part-Time Employment by NAICS Industry* (CA25N) is used for employment, L_{ijt}. Nominal GDP and real GDP, labeled N_{ijt} and Y_{ijt}, respectively values are also collected (BEA, 2017a,b) for each state, sector and year.

The last remaining element is the measure of prices used to adjust nominal compensation in Equation 12, P_{jt}. I assume prices for each worker do not change based on the sector, so P_{jt} represents a measure of overall state prices–a classic difficulty with state level analyses. Recently, the BEA began posting a *Regional Price Deflator* (RPD) for each state. Unfortunately, RPD's for each state are only available from 2008-2013 at time of writing so the analysis is restricted to these six years. The RPD itself is derived from a combination of data from the Consumer Price Index (CPI) program of the Bureau of Labor Statistics (BLS) and the American Community Survey (ACS) of the Census Bureau.

The number expresses an estimate of price level in a region as a percentage of the overall national price level. The number provided by these RPD values combines CPI and ACS numbers to assess the average prices paid by consumers on the goods and services they most consume in their region. On their own, the RPD values don't tell us much because they speak to a state's prices relative to the nation overall. Since workers receive their income and spend it on consumption and since I aim to see how well-off workers are, I use the CPI from the BLS as my measure of national prices (BLS, 2013). The CPI in tandem with these RPD measures yield the estimate of P_{jt} used in the Compensation-Productivity Difference

Cash transfer and commute times data come from the US Census Bureau's American Community Survey (Census Bureau, 2017a). All tax-related data comes from TaxFoundation.org (Tax Foundation, 2015). Union representation data comes from BLS (2017d).

Table C.1 on page 179 provides similar summary statistics for the control variables in the Chapter 3 Appendix. These control variables include demographic information, educational attainment rates, migration rates, and household characteristics. Each of these comes from the American Community Survey (Census Bureau, 2017a). In addition, a measure of state-level agglomeration is included as a control variable. This is calculated as the proportion of a sectoral employment to total employment within the state. This should account for the known agglomeration effects that would increase labor demand as firms observe productivity gains from co-locating.[14]

3.6. Regression Results and Discussion of Policies as Amenities for Each Sector

While there may be many countervailing effects on the Compensation-Productivity Difference due to changes in the policy variables employed, this approach should still be able to answer the primary research question of this Chapter. Are state-level policies viewed as amenities? If the answer is yes, we should see relatively unanimous effects of cash transfers, corporate tax rates, and income tax rates with respect to coefficient sign, as well as heterogeneous significance of the remaining policy variables.

With each sector undergoing a series of tests to ensure proper modeling, it seems fitting to devote a section to each of the fifteen sectors listed in Table 3.1. Each section will include a description of the tests results, noting any potential issues with spatial autocorrelation and heteroskedasticity, as well as a summary of the model results.

Spatial model specification is primarily discussed in Anselin (2013). Testing methodology and implementation relies heavily on the work of Breusch and Pagan (1979), Breusch and Pagan (1980), Pesaran (2004), Baltagi et al. (2007) and Millo and Piras (2012). Breusch and Pagan (1979) describe a method through which heteroskedasticity can be identified. Breusch and Pagan (1980) and Pesaran (2004) generate methods through which one can test

[14]See Rosenthal and Strange (2005) for a good summary of this literature.

and subsequently account for autocorrelation. Baltagi et al. (2007) combines and summarizes the work of spatial econometricians from the mid 1990s to 2007. Their main contribution in this paper is to generalize previous studies by deriving test statistics for models employing spatial panel data to discover serial autocorrelation in the remainder error term, ϵ. Millo and Piras (2012) generate a package in the statistical program R to implement spatial panel data models and perform the tests of Baltagi et al. (2007) and others.

I estimate a non-spatial panel model (pooled OLS, fixed effects, or random effects), an SAR spatial panel model, an SEM spatial panel model, and an SARAR spatial panel model for robustness. These reflect the four models discussed in Section 3.4 and Moran Tests are used to assess the presence of spatial autocorrelation. As a robustness check, a spatial equivalent to the autocorrelation test of Pesaran (2004) is implemented (Millo, 2016). Testing across all fifteen sectors indicates that spatial models strictly outperform a non-spatial panel model. Spatial Hausman tests are used to determine whether fixed effects or random effects specifications are best suited for the spatial panel models.

While three separate spatial panel models are employed, the coefficients in each of the spatial panel models are relatively homogeneous and consistent with respect to statistical significance. Because of this, only the results of the SEM model are reported in the body of the paper. Other model results are available, on request.

3.6.1. Results by Sector. This section divides up the results of each sector into subsections. Within these subsections, I will briefly describe the results of the tests performed, then present and discuss the regression results for the representative SEM model.

3.6.1.1. *Accommodation and Food Services.* Both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that fixed effects panel specifications are not needed for the Accommodation and Food Services Sector.

The results in the first column of Table 3.4 represent a Random Effects SEM model for this sector. This table also includes the results of Administrative and Support Services, Arts and Entertainment, and Construction in an effort to present the results in a consolidated fashion.

Of the policy variables listed in Table 3.3, commute times, maximum income tax rates, and union representation are all statistically significant. The negative coefficient on commute times indicates that firm demand impacts outweigh the reduction in labor supply, which would cause the Compensation-Productivity Difference to rise. This further implies that, if commute times serve as a proxy for infrastructure quality in a state, that firms value infrastructure more than workers. In this instance, a one minute increase in average commute times for workers is associated with a \$188.77 decrease in the Compensation-Productivity Difference. Because it is doubtful that increased commute times generate an increase in productivity, the negative coefficient more likely reflects the downward pressure on compensation rates as firms attempt to account for their loss in productivity.

Maximum income taxes have a surprising negative and significant impact on the Compensation-Productivity Difference. If income taxes only impact labor supply, then this coefficient should be positive due to a decrease in labor supply. It is unlikely that income taxes are considered in firm location decisions so the only possible way to explain this coefficient is with an increase in supply. Based on the coefficient sign, this is likely picking up the fact that higher state taxes are often used to fund public goods. This further suggests that using cash transfers may not be the best measurement of public good provision. Other specifications attempted to use unemployment benefits and SNAP benefits but ultimately these were omitted to prevent significant collinearity and endogeneity.

Table 3.4. Regression Results for Accommodation and Food Services, Administrative and Support Services, Arts and Entertainment, and Construction

	Dependent variable: Compensation-Productivity Difference			
Sector	Acco	Admin	Arts	Cons
Specification	RE	FE	RE	FE
Cash Transfers	−0.11	0.36*	−0.19	−0.46
	(0.10)	(0.14)	(0.13)	(0.33)
Commute Times	−184.77***	−177.34	−329.05***	504.04
	(48.43)	(161.33)	(99.13)	(376.34)
Min. Corporate Tax	44.13	391.47***	295.58***	340.86
	(40.99)	(91.68)	(74.23)	(219.04)
Max. Corporate Tax	68.88	−148.53	−344.91***	−678.64*
	(45.74)	(135.35)	(93.48)	(319.82)
Min. Income Tax	−26.44	−6.03	796.93	341.51
	(53.56)	(118.12)	(97.51)	(276.30)
Max. Income Tax	−136.63***	−377.09***	15.81	−22.87
	(36.46)	(92.94)	(72.04)	(219.66)
Minimum Wage	−1.07	−1.34	2.72*	1.99
	(0.66)	(1.22)	(1.07)	(2.84)
Sales Tax	−1.99	−173.91	2.15	−137.55
	(48.29)	(185.47)	(110.08)	(435.02)
Union Representation	−52.02**	−78.74	28.70	−173.57
	(19.21)	(54.75)	(36.28)	(127.50)
High School Attainment	−68.04	−336.77*	−47.18	28.78
	(64.08)	(152.68)	(114.63)	(362.79)
Some College Attainment	−28.04	−72.38	−38.99	−231.32
	(56.71)	(137.38)	(90.47)	(319.03)
Bachelor's Degree Attainment	−39.84	−2.46	−181.88	119.83
	(75.75)	(172.38)	(124.44)	(415.32)
Graduate Degree Attainment	−180.57*	−527.69**	−25.62	174.45
	(72.85)	(192.24)	(129.69)	(451.17)
Single Proportion	68.21	−7.94	−121.92	−115.49
	(54.00)	(99.86)	(84.46)	(231.44)
Household Size	−2,745.93**	3,220.74	−1,082.10	8,583.50*
	(1,003.87)	(1,789.93)	(1,495.40)	(4,169.20)
Male Proportion	−217.04	835.59*	−241.94	205.91
	(174.93)	(327.05)	(260.99)	(792.59)
Median Age	−73.93	127.82	304.61*	−779.79
	(75.49)	(175.93)	(126.09)	(434.28)
Disability Proportion	255.19***	53.84	58.26	−100.89
	(61.04)	(117.04)	(96.80)	(276.54)
Veteran Proportion	−177.74*	310.46	−65.18	213.93
	(73.33)	(158.64)	(101.72)	(357.32)
Caucasian Proportion	−9.17	−56.19	−9.97	−21.11
	(10.73)	(68.46)	(23.20)	(176.99)
Hispanic Proportion	2.47	−160.50	−6.69	−711.72
	(14.42)	(166.08)	(32.11)	(383.78)
Moved to Different House	47.79	161.04*	88.68	971.71***
	(51.79)	(76.52)	(71.48)	(179.33)
Sectoral Unemployment	60.97	259.27**	133.48	23.98
	(80.89)	(90.09)	(77.70)	(78.69)
State Unemployment	−13.38	−31.83	−26.93	249.63
	(48.94)	(85.24)	(69.65)	(199.70)
Agglomeration	−460.88	−5,982.94	−34,326.00	−30,697.00
	(4,447.97)	(12,657.91)	(53,216.00)	(41,154.00)
Spatial Lag–Error (λ)	0.852***	0.155***	0.025	0.125***
	(0.23)	(0.013)	(0.049)	(0.020)
Observations	300	300	300	300
R^2	0.791	0.902	0.341	0.873

Notes: *p<0.05; **p<0.01; ***p<0.001

Union representation is significant and has the predicted sign. Greater union representation induces more workers to move to a state for the benefits these unions provide. The resulting increase in labor supply suggests that if union representation rates rise by one percentage point (a sizable change), the Compensation-Productivity Difference will fall approximately $52.

3.6.1.2. *Administrative and Support Services.* In Administrative and Support Services, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that fixed effects panel specifications are required to capture the relationships in this sector. The results in the second column of Table 3.4 represent a Fixed Effects SEM model for this sector.

Of the policy variables included, cash transfers to households, minimum corporate tax rates, and maximum income tax rates are all statistically significant. While the coefficient suggests a relationship between cash transfers and the Compensation-Productivity Difference in this sector, the effect is not economically significant. It implies that a $1 increase in average cash transfers to households is associated with an increase in the Compensation-Productivity Difference by approximately $0.36. This result is antithetical to the predicted sign of cash transfers if we assume that labor supply would shift to the right as a result of increased cash transfers. Due to the similarly unexpected sign on maximum income tax rates, it is likely that this model specification does not adequately capture the effects of policy on the Compensation-Productivity Difference.

Minimum corporate tax rates are significant and match the predicted theory. Small business owners are the most likely to be affected by an increase in lower end corporate tax rates and the resulting reduction in labor supply would suggest a positive coefficient. A one percentage point increase in the lowest marginal corporate tax rate is associated with a $391 increase in the Compensation-Productivity Difference.

As with Accommodation and Food Services, maximum income taxes have a surprising negative and significant impact on the Compensation-Productivity Difference. If income taxes only impact labor supply, then this coefficient should be positive due to a decrease in labor supply. It is unlikely that income taxes are considered in firm location decisions so the only possible way to explain this coefficient is with an increase in supply. Based on the coefficient sign, this is likely picking up the fact that higher state taxes are often used to fund public goods. This further suggests that using cash transfers may not be the best measurement of public good provision. Other specifications attempted to use unemployment benefits and SNAP benefits, but ultimately these were omitted to prevent significant collinearity and endogeneity.

3.6.1.3. *Arts and Entertainment.* In Arts and Entertainment, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that fixed effects panel specifications are not needed for modeling. The results in the third column of Table 3.4 represent a Random Effects SEM model for this sector.

Of the policy variables included, average commute times, minimum corporate tax rates, maximum corporate tax rates, and minimum wage are all statistically significant. The negative coefficient on commute times indicates that firm demand impacts outweigh the reduction in labor supply, which would cause the Compensation-Productivity Difference to rise. This further implies that, if commute times serve as a proxy for infrastructure quality in a state, that firms value infrastructure more than workers. In this instance, a one minute increase in average commute times for workers is associated with a $329 decrease in the Compensation-Productivity Difference. Because it is doubtful that increased commute times generate an increase in productivity, the negative coefficient more likely reflects the downward pressure on compensation rates as firms attempt to account for their loss in productivity.

Minimum corporate tax rates are significant and match the predicted theory. Small business owners are the most likely to be affected by an increase in lower end corporate tax rates and the resulting reduction in labor supply would suggest a positive coefficient. A one percentage point increase in the lowest marginal corporate tax rate is associated with a $295 increase in the Compensation-Productivity Difference.

Maximum corporate tax rates also have an effect on this sector and indicate that the reduction in labor demand from firms facing a higher tax bracket pushes the Compensation-Productivity Difference lower.

The sign on minimum wage is positive which does not match with a ceteris paribus increase in labor supply. Because firms likely do not demand more workers as wage rates increase, the positive coefficient means that as labor demand falls, the Compensation-Productivity Difference rises due to the shape of the curves. This result could be interpreted as a positive in that workers are not made worse off even if labor demand falls in this sector.

3.6.1.4. *Construction.* In Construction, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that fixed effects panel specifications are needed for accurate modeling. The results in the fourth column of Table 3.4 represent a Fixed Effects SEM model for this sector.

Of the included policy variables included, only maximum corporate tax rates are significant. The coefficient is negative and implies that a one percentage point increase in the maximum marginal corporate tax bracket is associated with a decrease in the Compensation-Productivity Difference by approximately $678. This indicates a reduction in labor demand;

it may be the case in this sector that higher corporate tax rates induce firms to push compensation rates down as a result of potential profit loss.

3.6.1.5. *Educational Services.* In the Educational Services sector, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that fixed effects panel specifications are needed for modeling purposes. The results in the first column of Table 3.5 represent a Fixed Effects SEM model for this sector. This table also includes the results of Finance, Insurance, and Real Estate, Health Care and Social Services, and Information Services in an effort to present the results in a consolidated fashion.

Of the policy variables included, minimum corporate tax rates, maximum corporate tax rates, and union representation rates are all statistically significant. Minimum corporate tax rates are significant and match the predicted theory of a leftward shift of labor supply. Small business owners are the most likely to be affected by an increase in lower-end corporate tax rates and the resulting reduction in labor supply would suggest a positive coefficient. A one percentage point increase in the lowest marginal corporate tax rate is associated with a $194 increase in the Compensation-Productivity Difference.

Maximum corporate tax rates also have an effect on this sector and the coefficient sign indicates that the reduction in labor demand from firms facing a higher tax bracket pushes the Compensation-Productivity Difference lower.

Union representation is significant and has the predicted sign. Greater union representation induces more workers to move to a state for the benefits these unions provide. The resulting increase in labor supply suggests that if union representation rates rise by one percentage point, the Compensation-Productivity Difference will fall approximately $17.

Table 3.5. Regression Results for Educational Services, Finance, Insurance and Real Estate, Health Care and Social Services, and Information Services

	Dependent variable: Compensation-Productivity Difference			
Sector	Educ	Fire	Heal	Info
Specification	FE	RE	FE	RE
Cash Transfers	−0.10	−0.26	−0.21***	−0.05
	(0.06)	(0.16)	(0.06)	(0.82)
Commute Times	44.33	−273.72*	53.82	−640.55
	(63.30)	(112.12)	(62.83)	(687.69)
Min. Corporate Tax	194.45***	1.50	85.23*	63.79
	(35.70)	(84.11)	(35.04)	(516.98)
Max. Corporate Tax	−114.23*	−138.30	−139.58**	−535.44
	(52.87)	(104.72)	(51.83)	(678.24)
Min. Income Tax	68.73	150.88	73.03	−106.80
	(46.29)	(110.92)	(45.11)	(668.25)
Max. Income Tax	−39.35	−128.71	0.35	1,462.50**
	(36.08)	(80.38)	(35.26)	(506.94)
Minimum Wage	−0.84	−2.40	−0.44	6.67
	(0.48)	(1.24)	(0.47)	(7.00)
Sales Tax	−0.77	−55.43	−16.35	28.56
	(74.86)	(121.78)	(71.11)	(801.60)
Union Representation	−16.86**	−43.31	−64.93**	−215.27
	(21.31)	(41.48)	(20.90)	(254.84)
High School Attainment	109.69	−132.45	−120.37*	−2,305.10**
	(59.32)	(130.91)	(59.11)	(761.28)
Some College Attainment	69.78	−160.77	−105.66*	−235.23***
	(54.16)	(108.46)	(53.23)	(595.87)
Bachelor's Degree Attainment	199.60**	−192.26	−169.09*	−1,887.60*
	(68.17)	(143.71)	(66.73)	(817.67)
Graduate Degree Attainment	86.59	−549.17***	−265.00***	−4,336.30***
	(77.29)	(149.16)	(75.67)	(877.97)
Single Proportion	73.72	−102.44	−16.16	860.31
	(38.96)	(96.81)	(38.15)	(539.71)
Household Size	−1,308.70	−3,201.64	−2,013.90**	5,468.10
	(711.30)	(1,709.20)	(689.83)	(9,466.90)
Male Proportion	−451.06***	−184.03	−265.71*	1,636.40
	(127.74)	(308.33)	(125.11)	(1,721.00)
Median Age	267.81***	3.38	78.16	−610.90
	(69.82)	(142.30)	(69.40)	(808.66)
Disability Proportion	83.35	139.81	−117.96**	304.82
	(46.45)	(112.43)	(44.83)	(633.16)
Veteran Proportion	−163.38*	−53.52	−54.38	761.39
	(64.07)	(126.38)	(62.45)	(606.79)
Caucasian Proportion	−82.50**	−0.44	−46.87	124.78
	(27.56)	(25.70)	(26.95)	(180.11)
Hispanic Proportion	268.94***	−52.37	−12.74	−648.76**
	(65.65)	(35.62)	(65.52)	(242.15)
Moved to Different House	9.53	−48.57	−53.42	480.05
	(29.97)	(81.89)	(29.54)	(450.27)
Sectoral Unemployment	395.29***	−150.92	473.38***	539.18*
	(78.24)	(112.03)	(78.97)	(249.76)
State Unemployment	−6.59	−13.96	−57.32	−299.20
	(31.79)	(80.54)	(31.15)	(350.56)
Agglomeration	29,984.00*	24,248.82	10,342.00	661,870.00**
	(13,154.00)	(17,045.87)	(6,932.10)	(228,550.00)
Spatial Lag–Error (λ)	0.171***	0.090**	0.172***	−0.119
	(0.009)	(0.033)	(0.008)	(0.068)
Observations	300	300	300	300
R^2	0.980	0.950	0.992	0.903

Notes: *p<0.05; **p<0.01; ***p<0.001

3.6.1.6. *Finance, Insurance, and Real Estate.* In Finance, Insurance, and Real Estate, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that fixed effects panel specifications are not needed for modeling. The results in the second column of Table 3.5 represent a Random Effects SEM model for this sector.

Of the policy variables included, only average commute times are statistically significant. The negative coefficient on commute times indicates that firm demand impacts outweigh the reduction in labor supply, which would cause the Compensation-Productivity Difference to rise. This further implies that, if commute times serve as a proxy for infrastructure quality in a state, that firms value infrastructure more than workers. In this instance, a one minute increase in average commute times for workers is associated with a \$274 decrease in the Compensation-Productivity Difference. Because it is doubtful that increased commute times generate an increase in productivity, the negative coefficient more likely reflects the downward pressure on compensation rates as firms attempt to account for their loss in productivity.

3.6.1.7. *Health Care and Social Services.* In Health and Social Services, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that fixed effects panel specifications are required to capture the relationships in this sector. The results in the third column of Table 3.5 represent a Fixed Effects SEM model for this sector.

Of the policy variables included, cash transfers to households, maximum corporate tax rates, and unionization rates are all statistically significant. The coefficient on cash transfers is negative, but not economically significant. It implies that a \$1 increase in average cash transfers to households is associated with an decrease in the Compensation-Productivity

Difference by approximately \$0.21. This result matches the predicted sign of cash transfers and likely reflects a shift to the right of labor supply.

Union representation is significant and has the predicted sign. Greater union representation induces more workers to move to a state for the benefits these unions provide. The resulting increase in labor supply suggests that if union representation rates rise by one percentage point, the Compensation-Productivity Difference will fall approximately \$65.

3.6.1.8. *Information Services.* In Information Services, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that a random effects model is adequate for capturing the relationships. The results in the fourth column of Table 3.5 represent a Random Effects SEM model for this sector.

Of the policy variables included, only maximum income tax rates are statistically significant. The coefficient is positive, as expected, and is very economically significant. A one percentage point increase in the maximum marginal tax rate is associated with an increase in the Compensation-Productivity Difference of approximately \$1,462 across states. The positive sign is expected as workers would avoid high income tax rates and labor supply would thereby be reduced. This would cause an unambiguous rise of the Compensation-Productivity Difference.

3.6.1.9. *Management of Companies.* In the Management of Companies sector, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that fixed effects panel specifications are needed for modeling purposes. The results in the first column of Table 3.6 represent a Fixed Effects SEM model for this sector. This table also includes the results of Manufacturing, Other Services, and Professional, Scientific, and Technical Services in an effort to present the results in a consolidated fashion.

Table 3.6. Regression Results for Management of Companies, Manufacturing, Other Services, and Professional, Scientific, and Technical Services

	Dependent variable: Compensation-Productivity Difference			
Sector	Mana	Manu	Other	Prof
Specification	FE	FE	FE	RE
Cash Transfers	−0.24	−0.19	−0.02	−0.09
	(0.17)	(0.46)	(0.05)	(0.13)
Commute Times	−160.63	568.03	60.27	−337.28***
	(194.75)	(542.48)	(55.18)	(96.81)
Min. Corporate Tax	389.12***	11.30	54.37	223.72**
	(108.29)	(300.93)	(31.30)	(71.66)
Max. Corporate Tax	−494.30**	117.05	−94.97*	−319.44***
	(160.28)	(442.25)	(46.13)	(89.85)
Min. Income Tax	90.79	−216.41	43.97	106.41
	(140.50)	(384.44)	(40.17)	(95.01)
Max. Income Tax	−229.54*	756.21*	59.74	−96.75
	(110.09)	(304.94)	(31.45)	(68.66)
Minimum Wage	−0.98	−2.93	−0.65	−0.64
	(01.45)	(3.94)	(0.42)	(1.04)
Sales Tax	85.96	−788.05	32.27	−12.98
	(220.07)	(605.69)	(63.45)	(105.71)
Union Representation	92.50**	328.60	−35.11	−126.08***
	(65.11)	(176.69)	(18.92)	(35.74)
High School Attainment	−400.00*	−592.11	−76.79	−169.55
	(183.33)	(496.40)	(51.79)	(113.55)
Some College Attainment	−146.75	869.54	−2.00	−71.70
	(166.59)	(445.11)	(46.62)	(93.11)
Bachelor's Degree Attainment	−595.98**	−747.97	−9.05	−327.54**
	(208.08)	(560.76)	(59.04)	(122.05)
Graduate Degree Attainment	−1,087.38	−463.00	−74.49	−736.83***
	(234.55)	(632.16)	(66.92)	(131.63)
Single Proportion	136.35	384.94	−74.86*	6.79
	(120.12)	(322.39)	(34.09)	(82.57)
Household Size	−1,876.51	5,116.84	−822.77	−3,460.40
	(2,160.76)	(5,823.09)	(615.15)	(1,450.70)
Male Proportion	670.68***	434.02	−21.51	−257.01
	(392.85)	(1,063.44)	(111.21)	(255.93)
Median Age	603.68**	3.38	111.65	−213.29
	(212.33)	(573.16)	(61.05)	(123.00)
Disability Proportion	−135.80	−1,740.53***	35.86	244.18**
	(139.46)	(379.77)	(40.04)	(93.37)
Veteran Proportion	317.24	−468.36	−215.49***	−314.37**
	(195.58)	(491.83)	(55.10)	(110.76)
Caucasian Proportion	−37.34	−530.43*	−73.43**	21.00
	(81.95)	(220.56)	(23.90)	(22.43)
Hispanic Proportion	−683.11***	184.92	190.13***	−39.37
	(202.00)	(530.33)	(57.05)	(31.03)
Moved to Different House	0.61	−387.56	−51.02*	−11.45
	(91.59)	(247.25)	(26.03)	(70.04)
Sectoral Unemployment	1,047.91***	−314.57	144.60***	244.47***
	(120.84)	(173.64)	(43.36)	(73.26)
State Unemployment	139.61	728.34**	25.78	−153.90*
	(99.48)	(263.08)	(28.02)	(70.48)
Agglomeration	−6,267.14	31,943.21	−36,522.00	7,349.70
	(22,432.80)	(58,326.10)	(18,751.00)	(11,663.00)
Spatial Lag–Error (λ)	0.186***	0.111***	0.169***	−0.113***
	(0.004)	(0.023)	(0.009)	(0.026)
Observations	300	300	300	300
R^2	0.971	0.883	0.971	0.976

Notes: *p<0.05; **p<0.01; ***p<0.001

Of the policy variables included, minimum corporate tax rates, maximum corporate tax rates, maximum income tax rates and union representation rates are all statistically significant. Minimum corporate tax rates are significant and match the predicted theory of a leftward shift of labor supply. Small business owners are the most likely to be affected by an increase in lower-end corporate tax rates and the resulting reduction in labor supply would suggest a positive coefficient. A one percentage point increase in the lowest marginal corporate tax rate is associated with a $389 increase in the Compensation-Productivity Difference.

Maximum corporate tax rates also have an effect on this sector and the coefficient sign indicates that the reduction in labor demand from firms facing a higher tax bracket pushes the Compensation-Productivity Difference lower.

As with Accommodation and Food Services, maximum income taxes have a surprising negative and significant impact on the Compensation-Productivity Difference. Based on the coefficient sign, this is likely still picking up the fact that higher state taxes are often used to fund public goods (and cash transfers may not adequately account for this provision).

Union representation is significant, but has a positive sign. While labor supply may still be drawn to greater unionization rates in this sector, the most likely explanation is that this downward pressure on the Compensation-Productivity Difference is countered by a reduction in labor demand. Based on the curve shapes, this demand shift increases the Compensation-Productivity Difference as union representation increases.

3.6.1.10. *Manufacturing.* In the Manufacturing sector, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that fixed effects panel specifications are needed for modeling purposes. The results in the second column of Table 3.6 represent a Fixed Effects SEM model for this sector.

Only maximum income tax rates are significant in this sector. The positive coefficient aligns with the prediction of labor supply reductions. Manufacturing workers, then, responds strongly in the face of increasing income taxes. Given that Manufacturing is a high compensation sector, this result should come as no surprise. The coefficient suggests that a one percentage point increase in the maximum income tax rate reduces labor supply enough to increase the Compensation-Productivity Difference by approximately $756.

3.6.1.11. *Other Services.* In the Other Services sector, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that fixed effects panel specifications are needed for modeling purposes. The results in the third column of Table 3.6 represent a Fixed Effects SEM model for this sector.

Only maximum corporate tax rates are significant in this sector. The negative coefficient suggests that firms are particularly sensitive to higher corporate tax rates and that this decreases labor demand. A one percentage point increase in the highest corporate tax rate that firms face reduces the Compensation-Productivity Difference by approximately $95.

3.6.1.12. *Professional, Scientific, and Technical Services.* In the Professional, Scientific, and Technical Services sector, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that the fixed effects panel specification is not needed for modeling purposes. The results in the fourth column of Table 3.6 represent a Random Effects SEM model for this sector.

Of the policy variables included, commute times, minimum corporate tax rates, maximum corporate tax rates, and union representation rates are all statistically significant. The negative coefficient on commute times indicates that firm demand impacts outweigh the reduction in labor supply, which would cause the Compensation-Productivity Difference to rise. This further implies that, if commute times serve as a proxy for infrastructure quality in a state, that firms value infrastructure more than workers. In this instance, a one minute increase in average commute times for workers is associated with a $337 decrease in the Compensation-Productivity Difference. Because it is doubtful that increased commute times generate an increase in productivity, the negative coefficient more likely reflects the downward pressure on compensation rates as firms attempt to account for their loss in productivity.

Minimum corporate tax rates are significant and match the predicted theory of a leftward shift of labor supply. Small business owners are the most likely to be affected by an increase in lower-end corporate tax rates and the resulting reduction in labor supply would suggest a positive coefficient. A one percentage point increase in the lowest marginal corporate tax rate is associated with a $224 increase in the Compensation-Productivity Difference.

Maximum corporate tax rates also have an effect on this sector and the coefficient sign indicates that the reduction in labor demand from firms facing a higher tax bracket pushes the Compensation-Productivity Difference lower.

Union representation is significant and has the predicted sign. Greater union representation induces more workers to move to a state for the benefits these unions provide. The resulting increase in labor supply suggests that if union representation rates rise by one percentage point, the Compensation-Productivity Difference will fall approximately $126.

3.6.1.13. *Retail Trade.* In the Retail Trade sector, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that fixed effects panel specifications is needed for modeling purposes. The results in the first column of Table 3.6 represent a Fixed Effects SEM model for this sector. Table 3.6 also includes the results for Transportation and Warehousing and Wholesale Trade to conserve space.

Table 3.7. Regression Results for Retail Trade, Transportation and Warehousing, and Wholesale Trade

	Dependent variable: Compensation-Productivity Difference		
Sector	Ret	Trans	Whole
Specification	FE	FE	FE
Cash Transfers	−0.05	−0.20	−0.08
	(0.08)	(0.26)	(0.24)
Commute Times	−83.03	−306.14	120.02
	(90.32)	(295.90)	(273.46)
Min. Corporate Tax	68.63	−24.97	544.08***
	(53.73)	(168.09)	(159.42)
Max. Corporate Tax	−71.51	−55.53	−371.85
	(78.81)	(248.07)	(234.20)
Min. Income Tax	42.46	110.63	166.40
	(67.59)	(216.33)	(199.33)
Max. Income Tax	6.71	46.15	−327.67*
	(54.34)	(171.08)	(157.43)
Minimum Wage	−0.15	−226	−4.30*
	(0.70)	(2.22)	(2.09)
Sales Tax	−5.65	243.18	138.41
	(107.75)	(345.36)	(313.95)
Union Representation	−33.14	175.06	289.19**
	(30.84)	(99.84)	(92.02)
High School Attainment	−225.13**	−745.73**	260.89
	(86.36)	(283.36)	(256.24)
Some College Attainment	−51.14	−298.74	415.87
	(72.65)	(249.81)	(222.50)
Bachelor's Degree Attainment	−128.12	−323.33	643.88*
	(96.71)	(317.12)	(288.24)
Graduate Degree Attainment	−169.56	−979.10**	92.0
	(109.40)	(349.66)	(320.99)
Single Proportion	−94.30	−424.83*	26.11
	(55.32)	(182.69)	(166.79)
Household Size	−776.78	−1,092.73	−237.84
	(995.73)	(3,266.65)	(3,000.10)
Male Proportion	250.70	474.65	262.58
	(187.17)	(604.98)	(561.04)
Median Age	−160.53	63.19	125.64
	(95.68)	(329.90)	(293.50)
Disability Proportion	−117.83	−689.40**	−494.55*
	(67.14)	(215.66)	(198.67)
Veteran Proportion	−95.05	−1,363.34***	−1,130.70***
	(79.00)	(286.89)	(257.93)
Caucasian Proportion	−62.71	−453.79***	−319.33**
	(39.01)	(124.86)	(117.92)
Hispanic Proportion	−93.15	299.94	659.22*
	(89.42)	(300.70)	(273.37)
Moved to Different House	−52.42	−51.00	180.42
	(43.14)	(143.12)	(128.50)
Sectoral Unemployment	19.80	−98.35	930.00***
	(50.15)	(179.81)	(173.46)
State Unemployment	49.13	85.16	46.92
	(45.45)	(150.00)	(138.40)
Agglomeration	−31,398.00*	52,685.34	41,175.00
	(14,164.00)	(66,200.89)	(77,732.00)
Spatial Lag–Error (λ)	0.046	0.141***	0.125***
	(0.036)	(0.017)	(0.020)
Observations	300	300	300
R^2	0.967	0.876	0.957

Notes: *p<0.05; **p<0.01; ***p<0.001

None of the included policy variables are significant in the Retail sector. There are a variety of reasons why this may be the case. As one explanation, labor supply and demand may not be flexible in this relatively low-compensation sector. As a result, neither firms nor workers respond strongly to policy changes, especially since the sector generally requires relatively low skill compared to other sectors. The strongly significant agglomeration effect that suggests increases in productivity over compensation supports this hypothesis. There are clear productivity benefits to co-locating for Retail firms and this reduces flexibility to respond to policies for both parties–malls are a primary example.

The troubling aspect of these results is that they suggest fostering groups of retail firms may actually generate more negative Compensation-Productivity Differences. Furthermore, policy (as measured in this paper) appears impotent in changing the labor market outcomes for workers. It could be the case that these policies do not adequately capture what impacts the relationship between compensation and productivity in this sector, but initial results do not seem promising.

3.6.1.14. *Transportation and Warehousing.* In the Transportation and Warehousing sector, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that fixed effects panel specifications is needed for modeling purposes. The results in the first column of Table 3.6 represent a Fixed Effects SEM model for this sector.

None of the included policy variables are significant in the Transportation and Warehousing sector. Similar to Retail, there are a variety of reasons why this may be the case. Labor supply and demand may not be flexible in this sector. Because compensation rates are not low, as in Retail, this explanation falls short. There may be an agglomeration effect as these firms benefit from relative proximity, but even these effects seem insignificant in the model.[15]

The results in this sector clearly warrant further investigation because there is not an easy explanation for the observed results. The current models and variables selected appear to suggest that the Compensation-Productivity Difference cannot be impacted with policy changes.

3.6.1.15. *Wholesale Trade.* In the Wholesale Trade sector, both Moran (1950) and Baltagi et al. (2007) tests suggest significant spatial autocorrelation. A Spatial Hausman Test indicates that the fixed effects panel specification is not needed for modeling purposes. The results in the third column of Table 3.6 represent a Fixed Effects SEM model for this sector.

Of the policy variables included, minimum corporate tax rates, maximum income tax rates, minimum wage, and union representation rates are all statistically significant. Minimum corporate tax rates are significant and match the predicted theory of a leftward shift of labor supply. Small business owners are the most likely to be affected by an increase in lower-end corporate tax rates and the resulting reduction in labor supply would suggest a positive coefficient. A one percentage point increase in the lowest marginal corporate tax rate is associated with a $544 increase in the Compensation-Productivity Difference.

Maximum income tax rates also have an effect on this sector and the coefficient sign indicates that there may be a public-good-provision-effect that is not captured with the current data. While workers would generally avoid higher income tax rates, they may seek out states that provide more goods and services corresponding to these higher taxes.

[15]For examples, multiple bus companies use the same stops, shuttles routinely co-locate pickup locations, etc.

Minimum wage has a negative and significant effect on the Compensation-Productivity Difference. As state-level minimum wages rise by 1%, these results suggest that the Compensation-Productivity Difference falls by $4.30. This would be consistent with an increase in labor supply.

Union representation is significant, but does not have the predicted sign. Because of the positive coefficient, it may be the case that unionization in this sector is successful in increasing compensation rates relative to productivity. As a result, while not predicted a priori, this significant sign is intuitive.

3.6.2. Summary of Sector Results. Across sectors, there is some evidence that policies can be viewed through the lens of amenities. While not perfect, the supply and demand framework of Section 3.4 does predict some of the observed results across sectors intuitively. Policies that workers and firms may consider beneficial do seem to have the predicted impact in many cases. Similarly, policies that would likely dissuade workers and firms from locating in an area appear to drive those economic agents away.

With the sheer quantity of results inherent in this type of analysis, Table 3.8 displays a summary of key results by sector. Namely, Table 3.8 shows how a policymaker may implement a policy change to make the Compensation-Productivity Difference more positive. The hope of the table is to present succinct way to see all the results of this paper.

Minimum income tax rates and sales taxes are not listed as policies in Table 3.8. Neither of these policies seem to affect the Compensation-Productivity Difference in any sector. This is good news for policymakers that may consider worker (voter) compensation relative to productivity when changing state-level sales taxes or income taxes. In situations where additional revenue must be raised to fund government services, these results imply an insignificant impact on D_{ijt} across sectors.

Table 3.8. Summary of All Results–Direction a Given Policy Should Change to Make D_{ijt} More Positive

	Acco	Admin	Arts	Cons	Educ	Fire	Heal	Info
Cash Transfers		(+)				(+)	(−)	
Commute Times	(−)		(−)			(−)		
Min. Corporate Tax	(+)	(+)	(+)		(+)			
Max. Corporate Tax			(-)	(+)	(−)		(−)	
Max. Income Tax	(−)	(-)						(+)
Minimum Wage			(+)					
Union Representation	(−)				(−)		(−)	
	Mana	Manu	Other	Prof	Ret	Trans	Whole	
Cash Transfers								
Commute Times				(−)				
Min. Corporate Tax	(+)			(+)			(+)	
Max. Corporate Tax	(−)		(−)	(−)				
Max. Income Tax	(−)	(+)	(+)				(−)	
Minimum Wage							(−)	
Union Representation	(+)			(−)			(+)	

Finally, another benefit of Table 3.8 is that it also highlights the inherent tradeoffs policymakers face with any policy change. Excepting commute times and minimum corporate tax rates, every single policy change would have different effects on compensation relative to productivity across sectors. Generally, the signs of the coefficients have intuitive explanations though this may not always be the case. Understanding these differences is paramount to good policy development.

3.7. Concluding Remarks

There is significant regional variation to the relationship between compensation and productivity even within a given sector. To better understand what may be driving these differences, I take advantage of an estimate of compensation minus productivity for the average worker in a given sector, state, and year. This so-called Compensation-Productivity Difference indicates that workers along the coasts tend to underpaid while those in the middle of the United States tend to be overpaid. While the magnitude changes by sector, these patterns consistently emerge, even accounting for price differentials. Much of the previous literature focuses on how prices partially capture how high demand is for a given area yet my results show that prices may not be fully accounting for this demand.

As a result, one possible explanation for these differences could be amenities. Amenities (or benefits) of an area should draw greater in-migration of firms and workers while disamenities (or costs) should drive away prospective worker and firm migrants away. These amenity impacts can be seen using a labor supply and demand model, with changes to policies impacting one, or both of these curves. Analogously, this model is used to explain the observed regional differences in the Compensation-Productivity Difference and predict how policy changes, viewed as (dis)amenities, will change this labor market outcome.

After collecting data on state-level policies such as tax rates, cash transfers, and other programs, I perform a variety of regressions with the Compensation-Productivity Difference as the dependent variable and state-level variables as the regressors. Each of fifteen sectors are discussed independently and multiple models used to account for the inherently spatial nature of the data. I find mixed evidence to support the notion that state-level policies can be viewed as (dis)amenities. While the results are not unanimous, they do generally demonstrate that state-level policies can be viewed as amenities that change the location decision of workers, firms, or both.

Poor infrastructure quality–as measured via commute times–appears to severely impact firm decision-making. The associated reduction in firm demand universally repels firms and generates a decrease in the Compensation-Productivity Difference. Minimum corporate tax rates primarily impact labor supply, as this tax rate is often observed by small business owners. The coefficient across all sectors is consistent with a reduction in labor supply that makes the Compensation-Productivity Difference more positive.

All remaining polices have heterogeneous results. Depending on the sector, changes to cash transfers to households, maximum corporate tax rates, income tax rates, minimum wage, and union representation may increase or decrease the Compensation-Productivity Difference.

Two main conclusions come from this paper. The first is that state-level policies do have an impact on compensation relative to productivity for the average worker, in most sectors. This is good news for a policymaker looking to impact this relationship in a desired direction. Additionally, the bevy of recent news stories citing worsening labor market outcomes for workers makes this a topical issue. To alleviate this stress, policymakers may choose to change taxes and benefits in such a way that increases the Compensation-Productivity Difference, as in Table 3.8. The second main conclusion is that while policies can impact the relationship between compensation and productivity, the effects are heterogeneous across sectors. These tradeoffs would be important to consider before undertaking an policy change.

While this model successfully finds evidence that policies can be viewed as amenities in most sectors, two outliers exist. In Retail Trade and Transportation and Warehousing, the chosen policies do not adequately describe changes in the Compensation-Productivity estimates. For these sectors, then, there is a clear need for future work to expand on the number of included policies and continue to better understand the efficacy of policies in impacting labor market outcomes.

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APPENDIX A

Chapter 1 Additional Content

This appendix contains a variety of maps, tables, and equations that present information relevant to the analysis, but not necessary in the body of the text. Figures A.1, A.2, A.3, A.4, A.5, and A.6 display maps for the remaining ten sectors not explicitly discussed in the paper. Table A.1 on page 170 shows the summary statistics for the control variables used in the statistical analyses. The Moran (1950) test is described in greater detail on page 171.

A.1. Labor Share Graphs

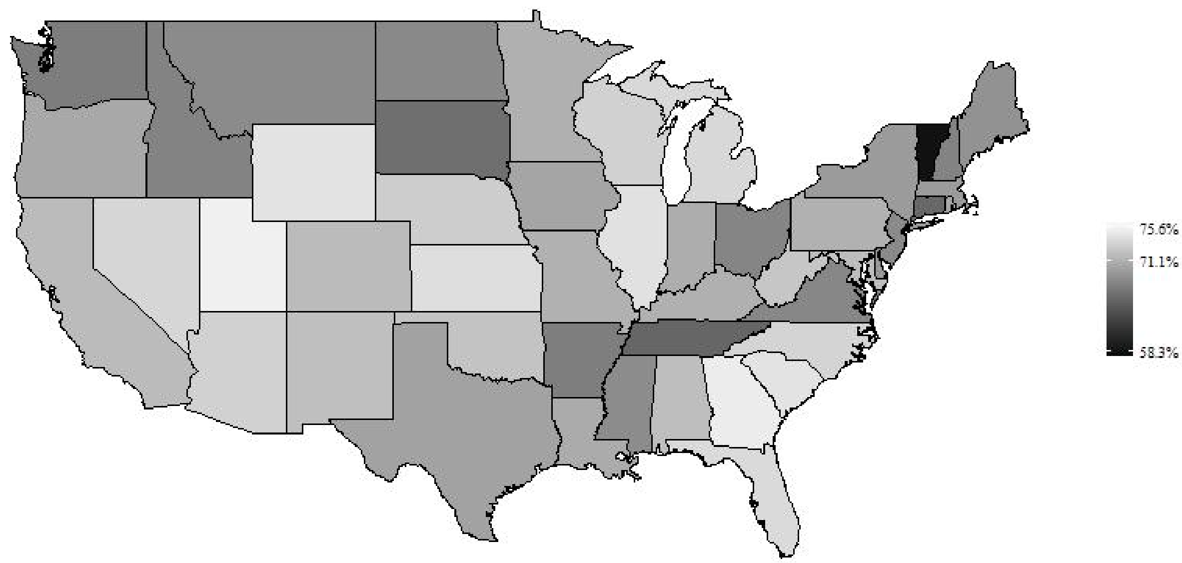
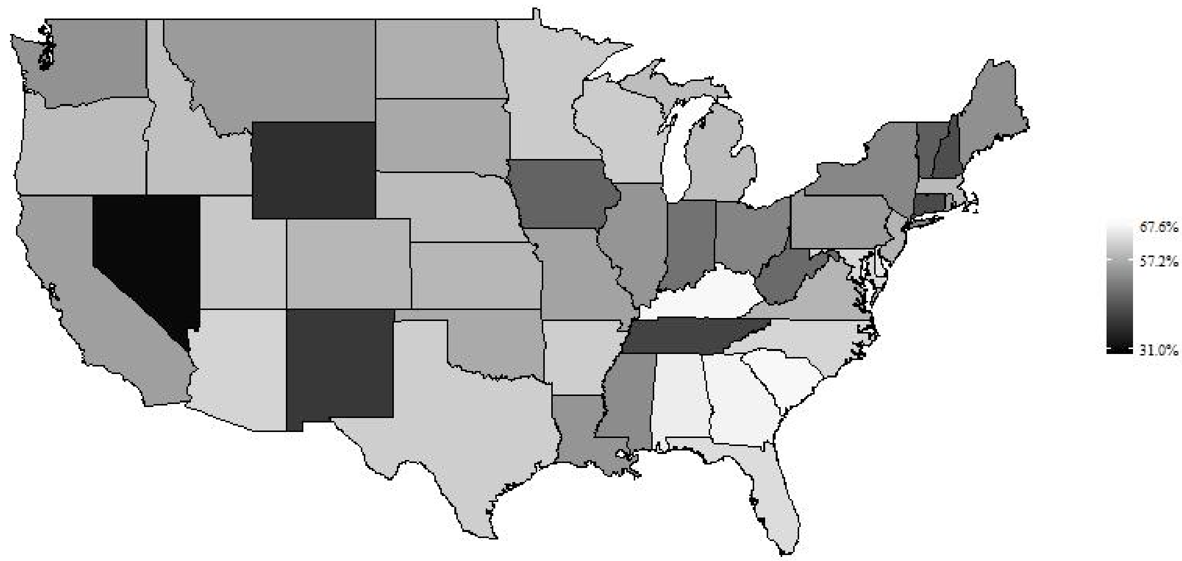


Figure A.1. Labor Share by State–Administrative and Support Services, Averaged 2005-2014



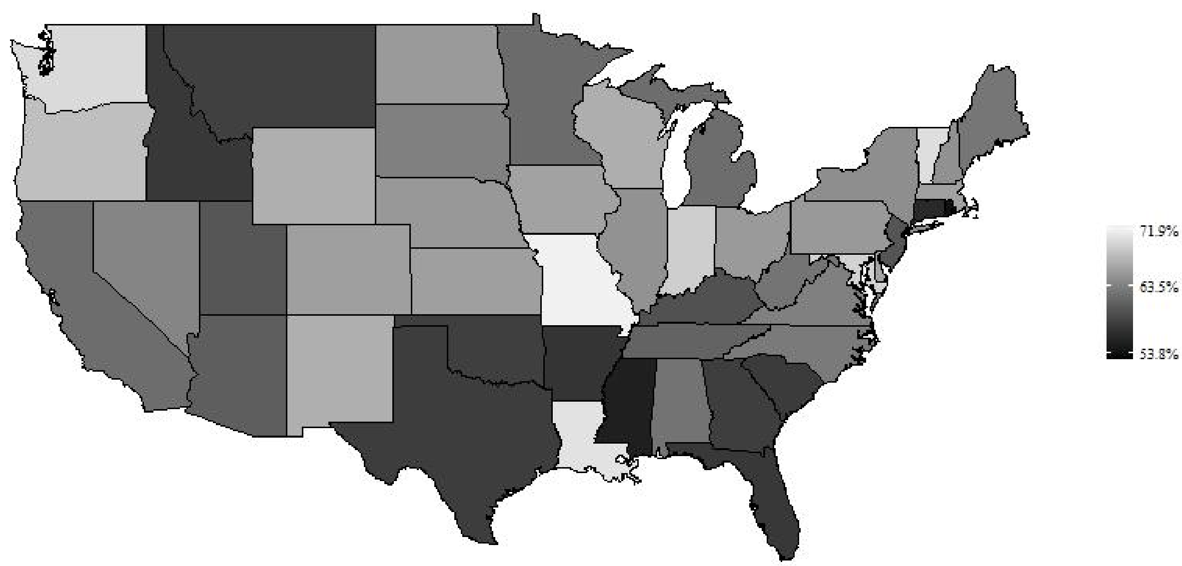


FIGURE A.2. Labor Share by State–Arts and Recreation (Above) and Construction (Below), Averaged 2005-2014

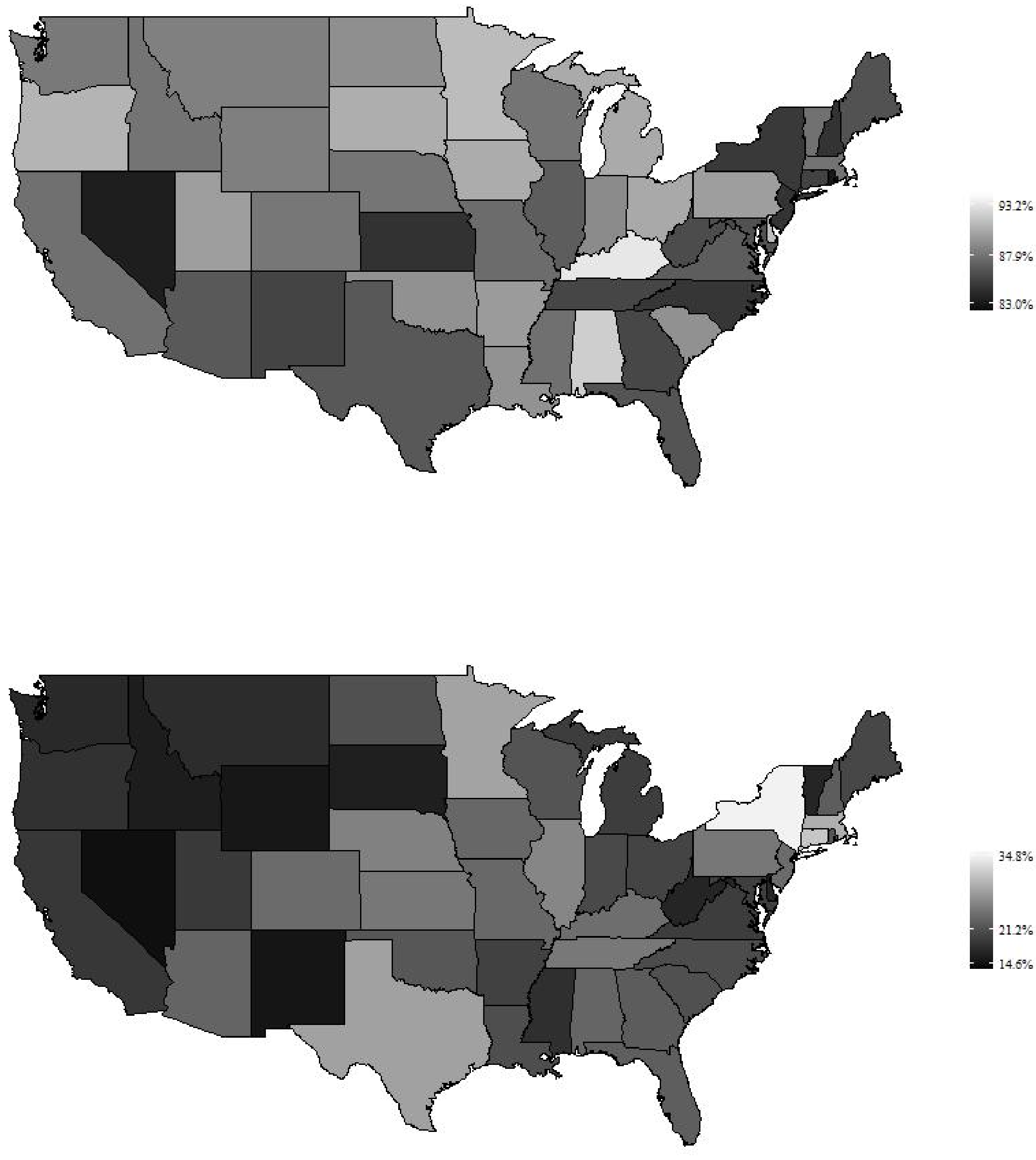
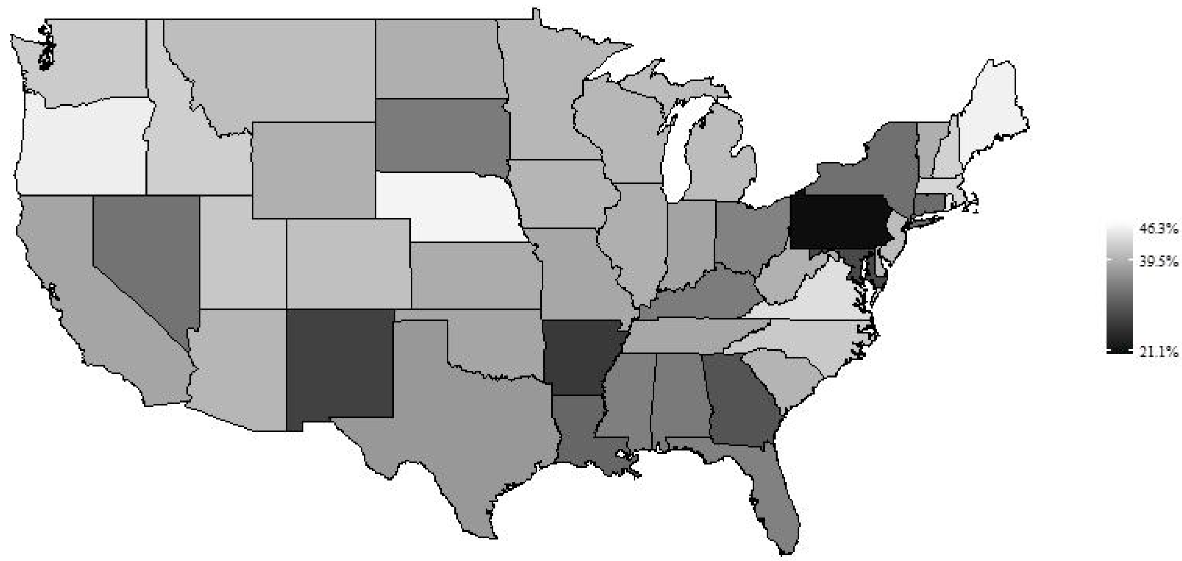


FIGURE A.3. Labor Share by State–Educational Services (Above) and Finance, Insurance, and Real Estate (Below), Averaged 2005-2014



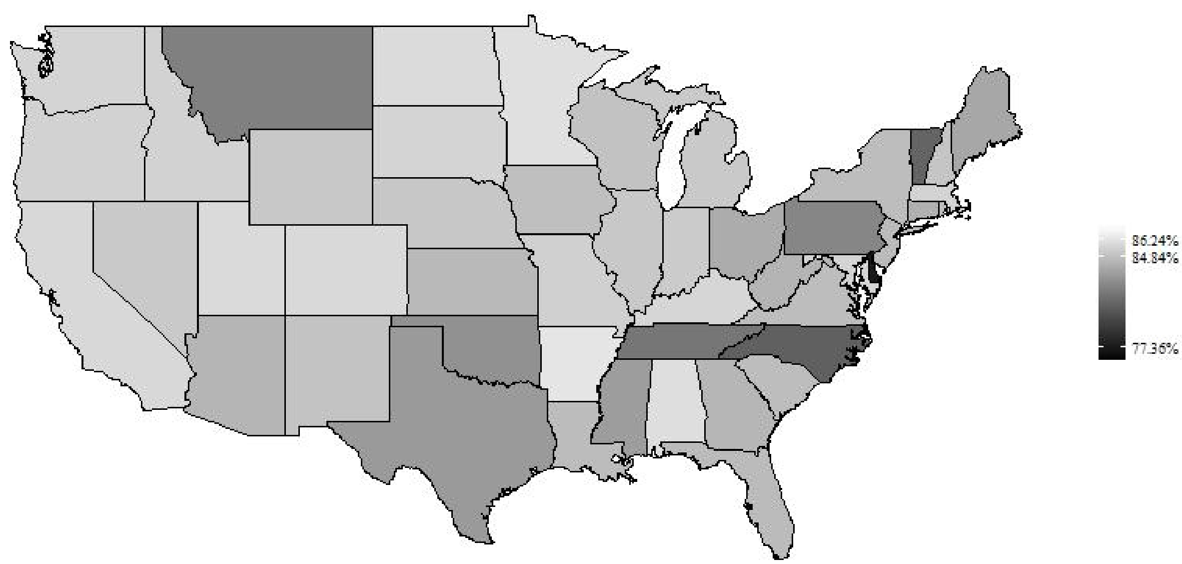


FIGURE A.4. Labor Share by State–Information Services (Above) and Management of Companies (Below), Averaged 2005-2014

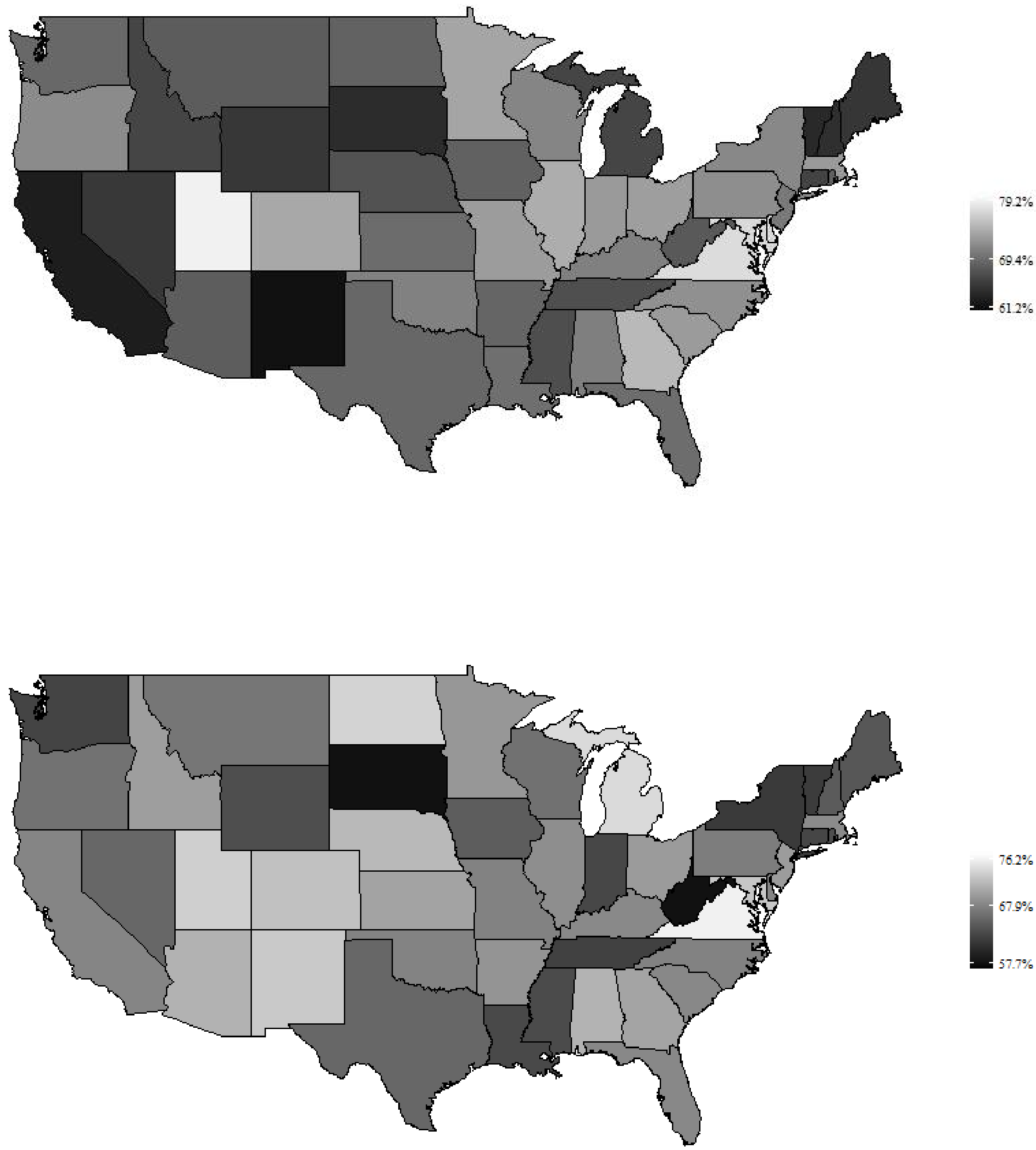


FIGURE A.5. Labor Share by State–Other Services (Above) and Professional, Scientific, and Technical Services (Below), Averaged 2005-2014

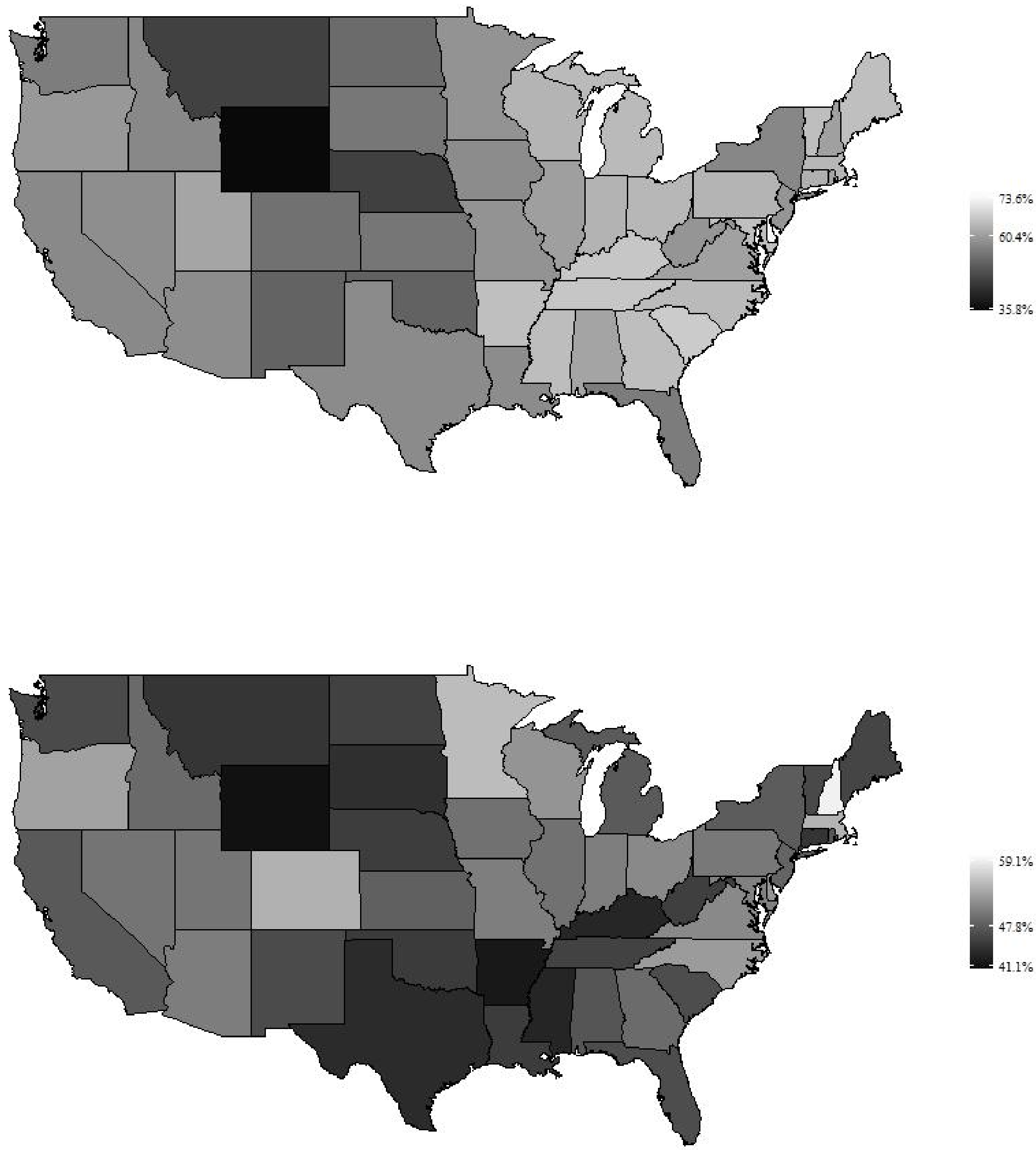


FIGURE A.6. Labor Share by State–Transportation and Warehousing (Above) and Wholesale Trade (Below), Averaged 2005-2014

A.2. Summary Statistics of Control Variables

Table A.1. Summary Statistics of Control Variables Variables Across States, 2015 Only

Variable	**Units**	**Count**	**Mean**	**St. Dev.**
Median Age	Years	49	38.086	2.413
Male	Percentage	49	49.376	0.751
Head of Household	Percentage	49	57.371	3.396
Family Households	Percentage	49	65.447	2.432
Veteran Status	Percentage	49	8.694	1.522
Disability Status	Percentage	49	13.210	2.206
Moved to Different House	Percentage	49	14.706	2.213
Moved to Different State	Percentage	49	2.867	0.933
Commute Times	Minutes	49	24.108	3.633
Cash Assistance Recipients	Percentage	49	2.680	0.812
Cash Assistance Mean	Dollars	49	2,951.20	623.72

Median age is the median age of the population in a given state. Male is the proportion of the population with a sex of male. Head of household is a variable describing what percentage of the population is the head of household or the spouse of the head of the household. Family households is a measure of the percentage of the population that lives in a family (non-single) household. Veteran and disability status are the percentage of the population in a given state that are veterans or disabled, respectively. Moved to a different house captures migration and represents the percentage of the population that moved from one US house to another, regardless of location. Moved to a different state is a measure of migration wherein a person moves from one residence to another in a different state. Commute times are meant to proxy infrastructure quality and represents the average number of minutes workers spend daily commuting to work, regardless of means of transportation. Cash assistance recipients is the percentage of the population receiving some form of government cash transfer assistance while cash assistance mean is the average state-level payout of these transfers to an individual.

A.3. Moran Test Description

The Moran (1950) test is often used as an indicator of the degree to which observations of a variable are spatially correlated. The equation for the general form of the test statistic can be written as:

$$I = \frac{N}{W} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{20}$$

The test statistic, denoted I, is assumed to have a normal distribution and so a z-score can be estimated from its value. The total number of observational units (states, in this example) is denoted N and the total value of summed weights from the weighting matrix is denoted W. The second fraction represents the weighted covariance between an independent variable observation in state i versus state j, divided by the variance of the state in question. w_{ij} indicates the spatial weight between states i and j. The test statistic can then be interpreted as the degree to which the observational variation of a variable in a state moves with that of others (second fraction), scaled by the total value of the relationships (W) and multiplied by the number of observational units (N).

APPENDIX B

Chapter 2 Additional Content

This appendix contains a variety of figures and maps that present information relevant to the analysis, but not necessary in the body of the text. Figures B.1 and B.2 display time trends of the Compensation-Productivity Difference for smaller sectors in the United States. A visualization of the labor share, average compensation, average productivity, and the Compensation-Productivity Difference is presented as a robustness check to the similar graphic for Manufacturing found on page 95. This visual can be found on page 173.

Beginning on page 174, maps are presented to visualize how the Compensation-Productivity Difference varies across space. Figures B.4, B.5, B.6, B.7, and B.8 each display maps for two sectors.

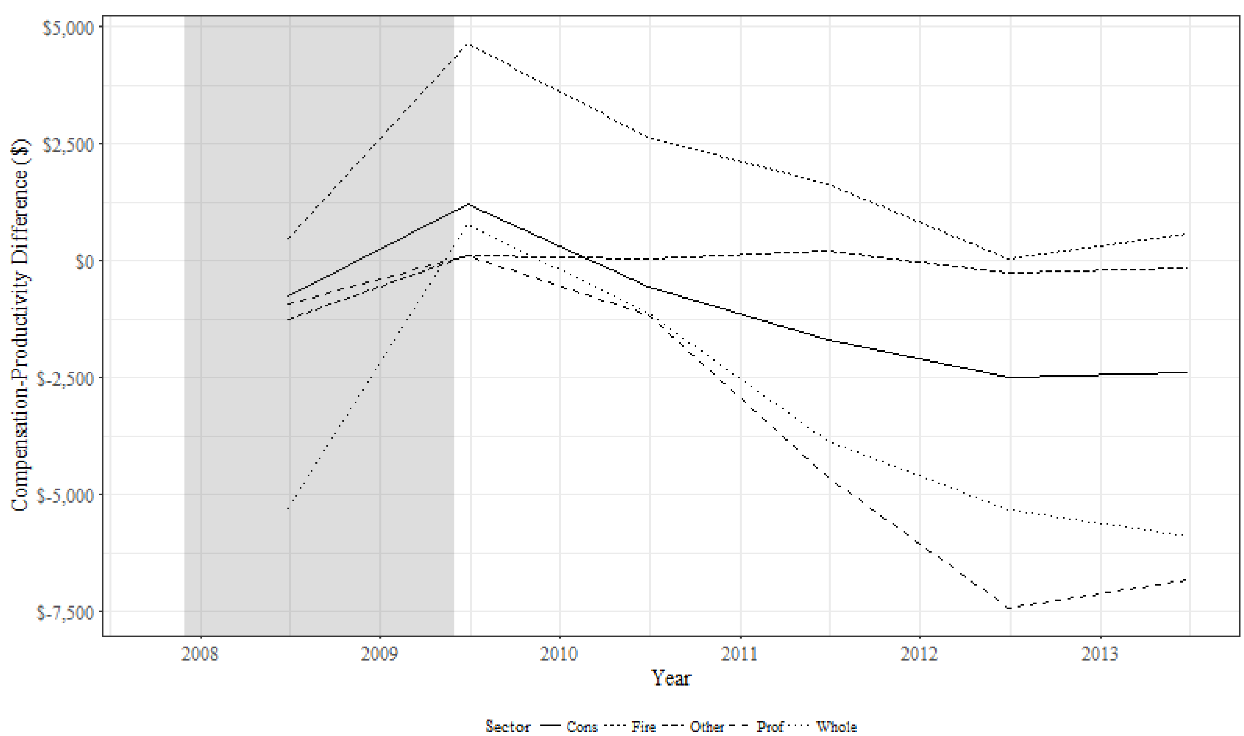


Figure B.1. Compensation-Productivity Difference Estimates for Five Middle Sectors by Employment–United States

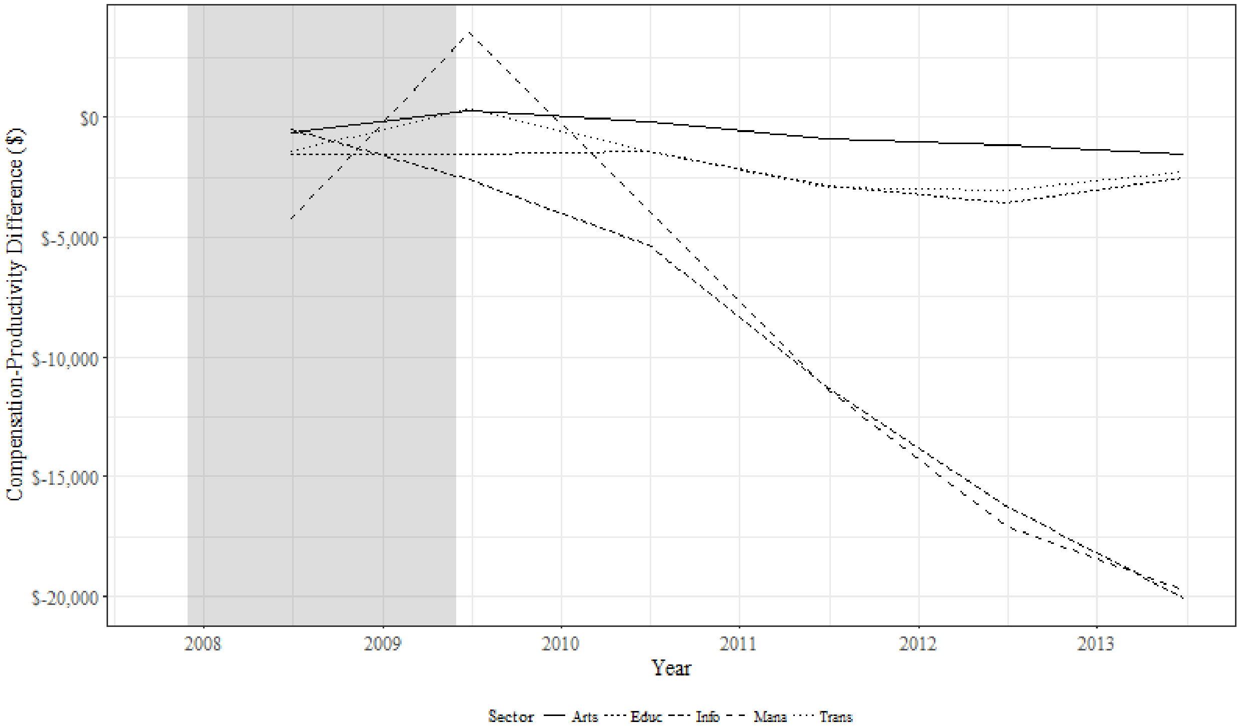


FIGURE B.2. Compensation-Productivity Difference Estimates for Five Smallest Sectors by Employment–United States

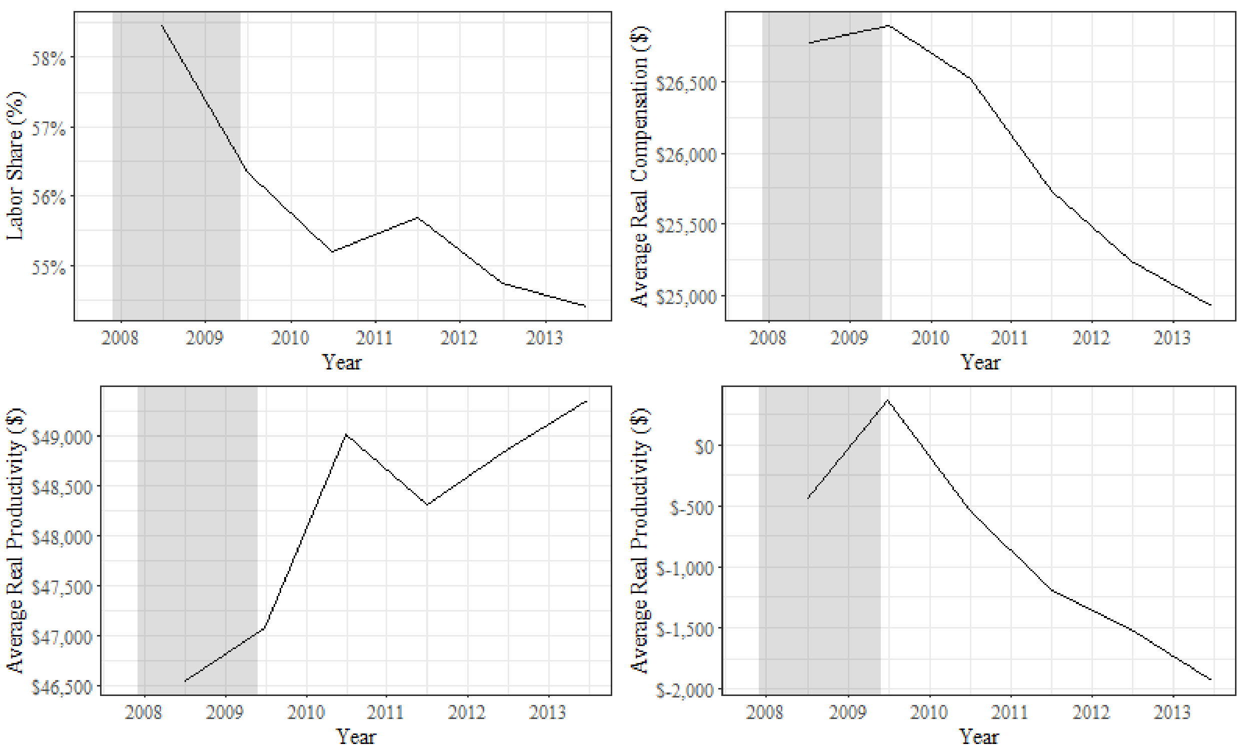


FIGURE B.3. Labor Share, Compensation, and Productivity Changes for Retail Sector–United States

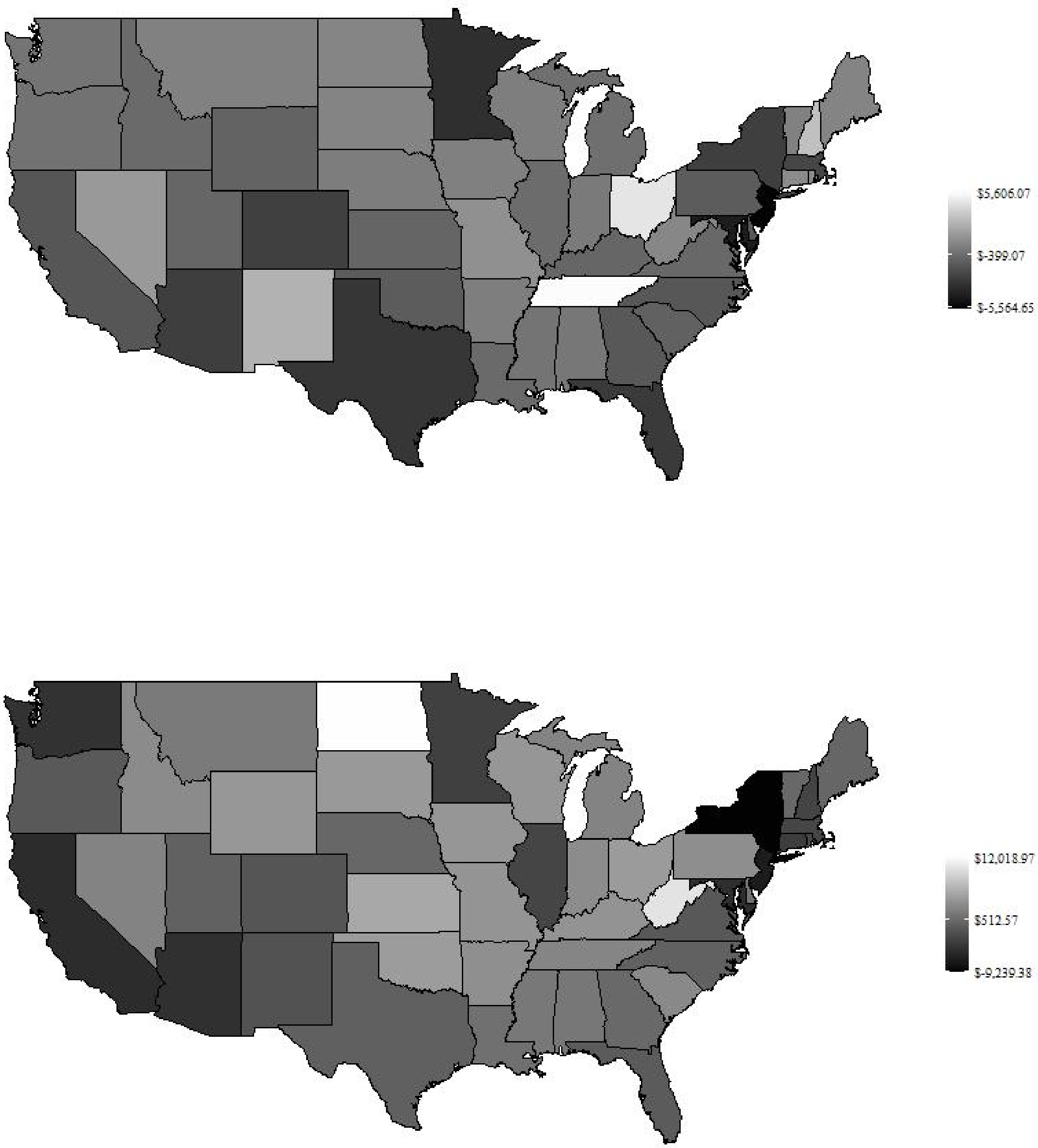


FIGURE B.4. Compensation-Productivity Difference Map–Arts and Entertainment (Above) and Construction (Below), Averaged Over 2008-2013

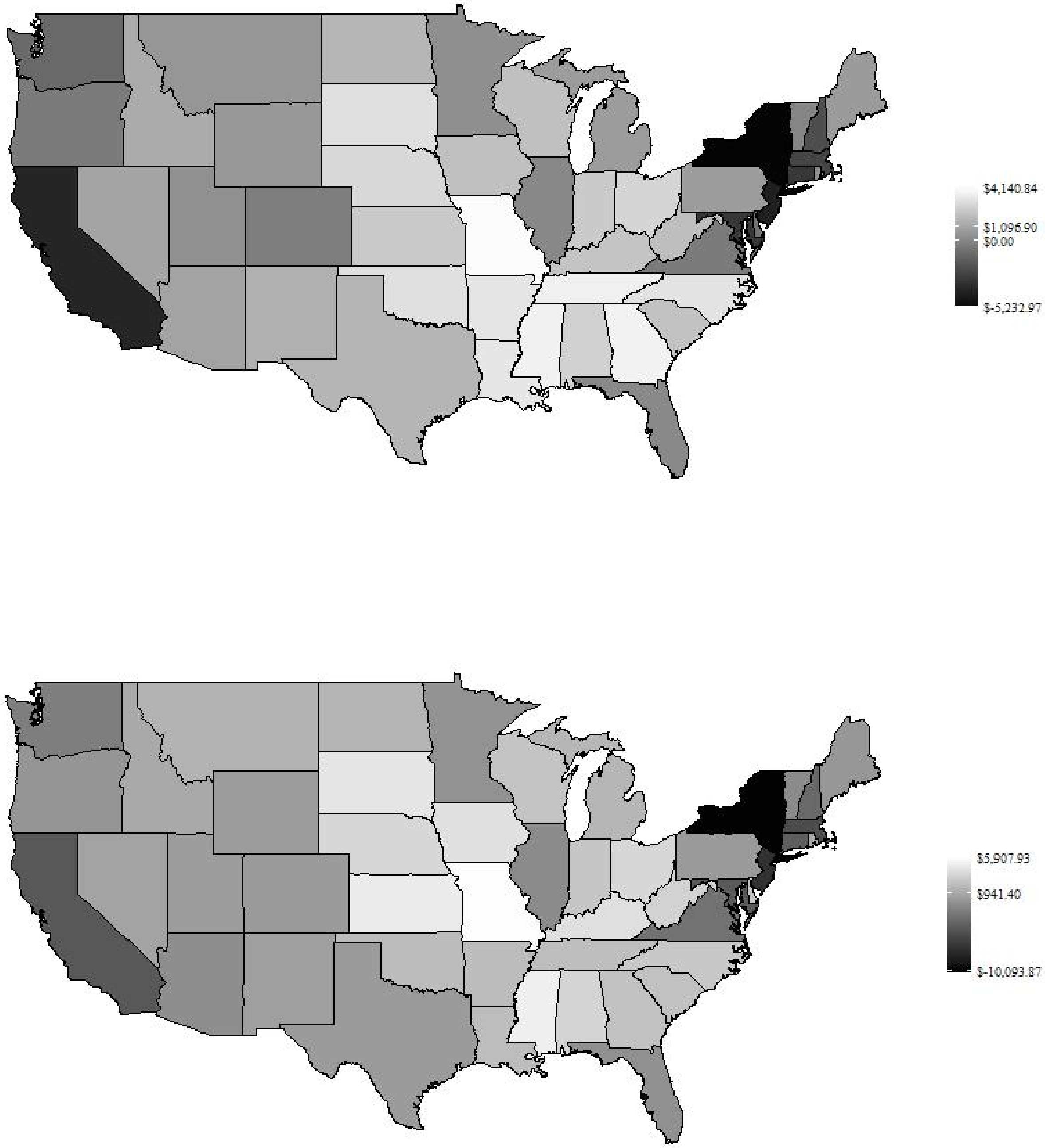
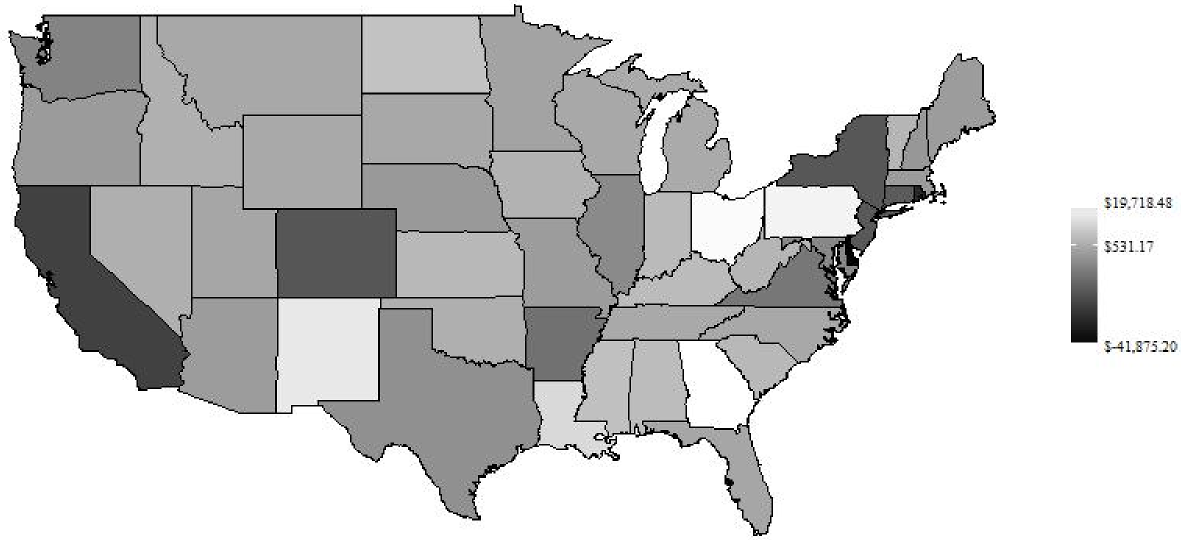


Figure B.5. Compensation-Productivity Difference Map–Educational Services (Above) and Finance, Insurance, and Real Estate (Below), Averaged Over 2008-2013



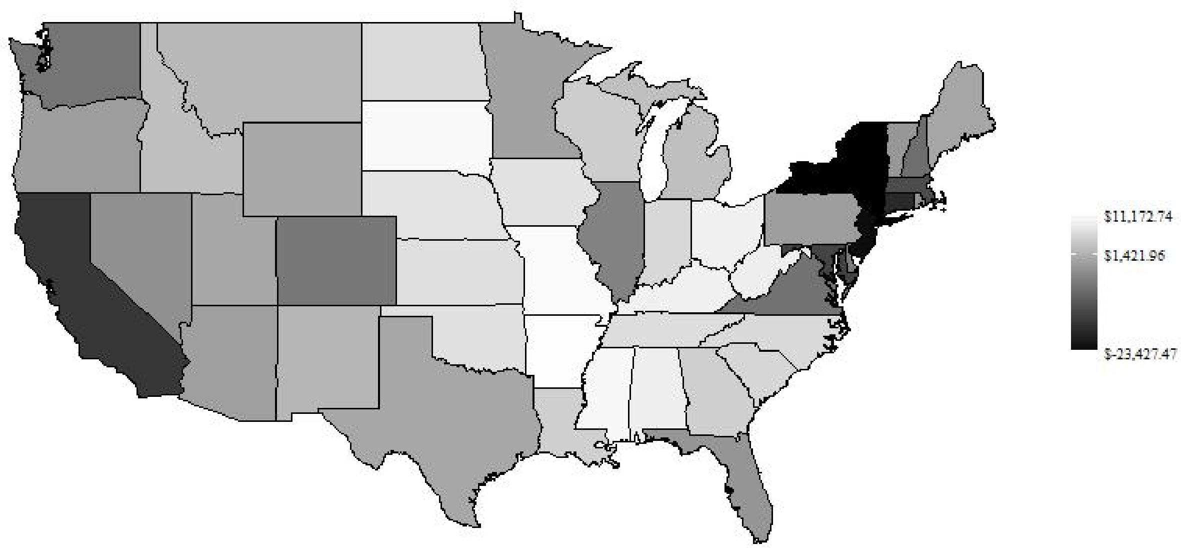
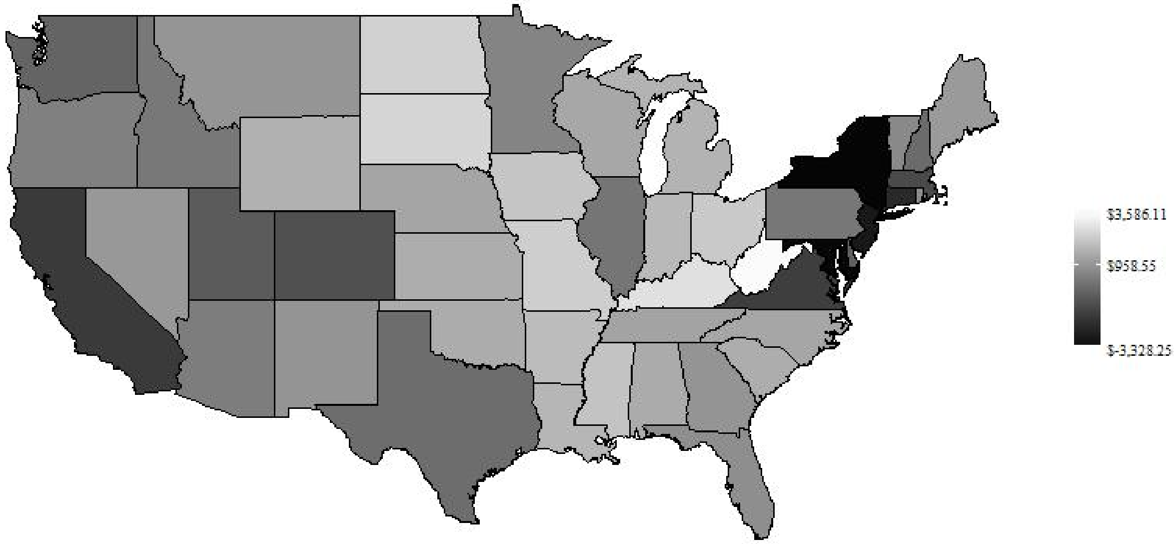


FIGURE B.6. Compensation-Productivity Difference Map–Information (Above) and Management of Companies (Below), Averaged Over 2008-2013



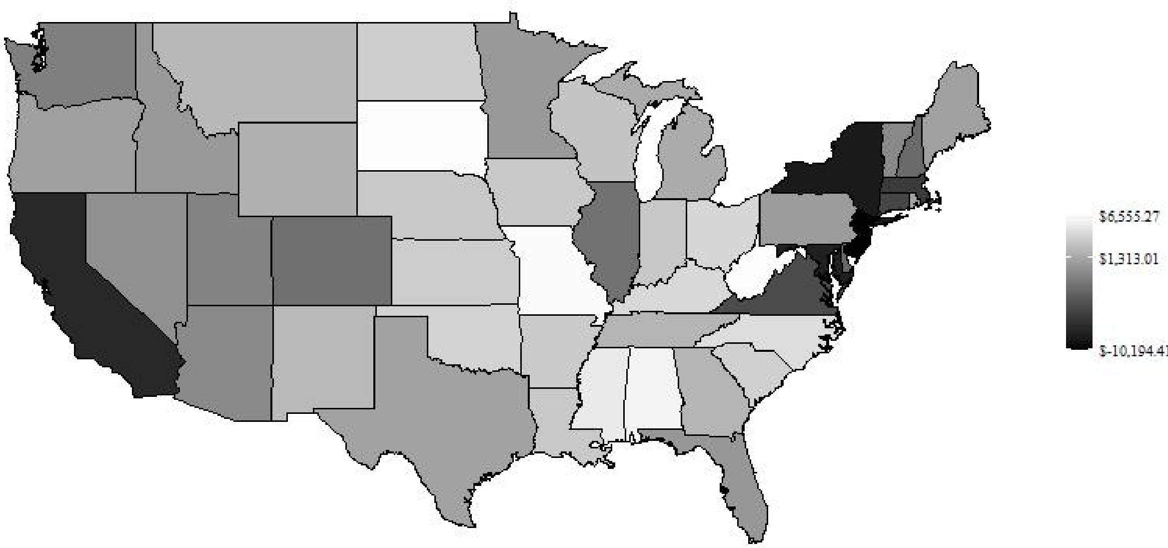


FIGURE B.7. Compensation-Productivity Difference Map–Other Services (Above) and Professional, Scientific, and Technical Services (Below), Averaged Over 2008-2013

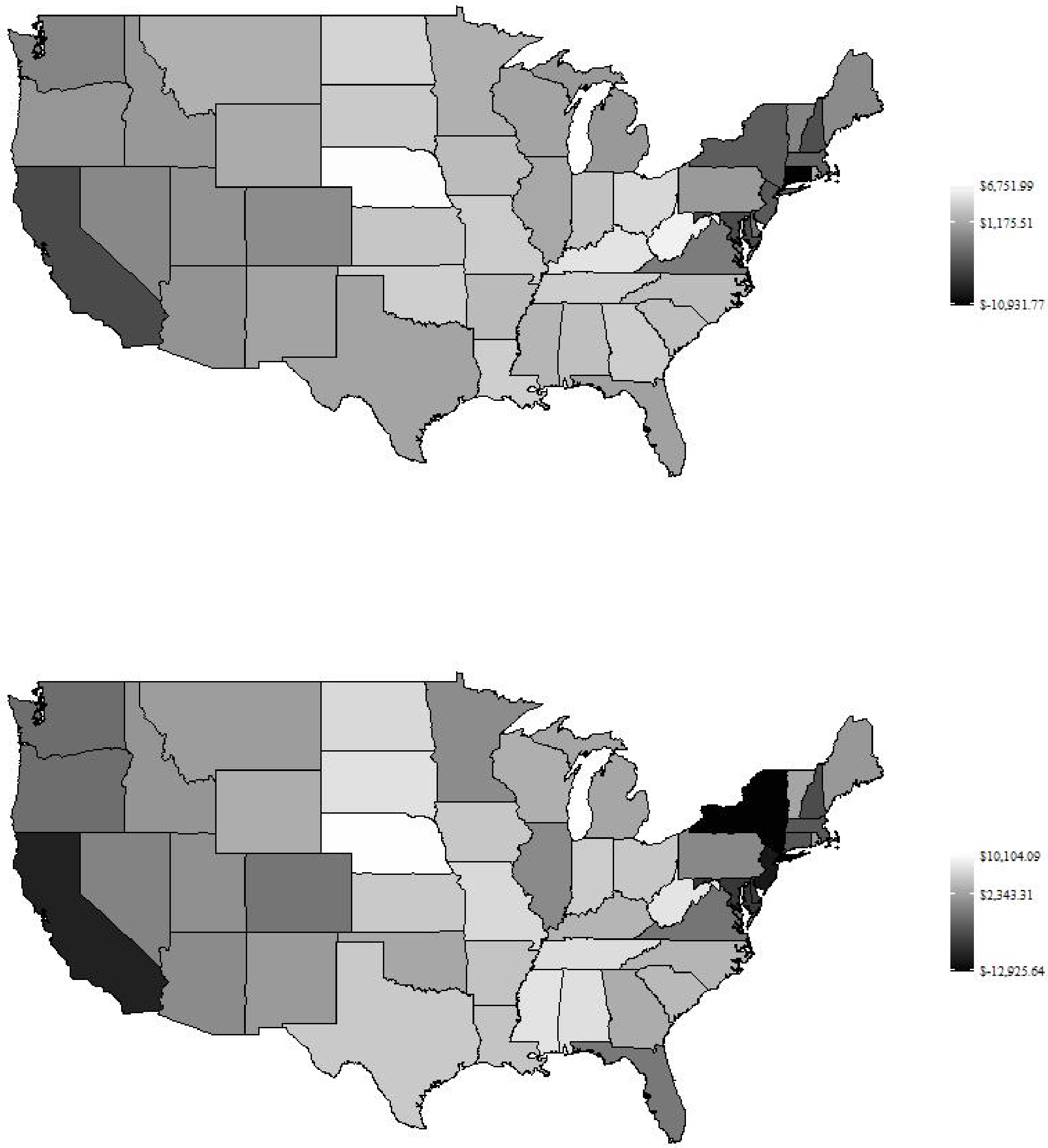


FIGURE B.8. Compensation-Productivity Difference Map–Transportation and Warehousing (Above) and Wholesale Trade (Below), Averaged Over 2008-2013

APPENDIX C

Chapter 3 Additional Content

This appendix contains a table granting summary statistics for the control variables used in the analysis.

Table C.1. Descriptive Statistics of Control Variables Used in Analysis–Averaged Across All States, 2008-2013

Variable	**Mean**	**Std. Dev.**
High School Attainment	29.49%	3.96%
Some College Attainment	30.09%	3.68%
Bachelor's Degree Attainment	17.67%	2.73%
Graduate Degree Attainment	10.13%	2.51%
Proportion of Households with Single Occupant	27.77%	2.04%
Household Size	2.58	0.16
Proportion of Population Male	49.37%	0.76%
Median Age	37.60	2.31
Percentage of Population–Disabled	10.76%	2.34%
Percentage of Population–Veteran	10.01%	1.63%
Percentage of Population–Caucasian	78.15%	12.53%
Percentage of Population–Hispanic	10.59%	9.95%
Percentage of Population–Moved in Last Year	15.08%	2.40%
Annual Unemployment in a Sector–Nationally	8.47%	2.98%

Notes: Data comes exclusively from the American Community Survey of the Census Bureau.