Regional Labor Input Price Gaps Across the U.S.[1]

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Widening income inequality in much of the world has prompted intense policy discussions and led to a resurgence of research into the measurement of income inequality at the individual, or household, levels. Regional inequality is an important dimension of this research, however, there is limited discussion of how regional differences in productivity are related to inequality among households. We take a first step in measuring regional productivity accounts using the KLEMS framework by focusing on labor input – measuring labor PPP's at the state level. We estimate hourly labor compensation by industry and demographic groups for each state (or region). We compute purchasing power parities for labor input to show how regional competitiveness changed over time. These accounts are consistent with the official set of industries published by the BEA. The methods used are parallel to those in international productivity comparisons in Jorgenson, Nomura and Samuels (2014).

[1] The views expressed in this paper are those of the authors and do not necessarily represent the U.S. Bureau of Economic Analysis or the U.S. Department of Commerce

Introduction

The supply chain within and across countries is influenced by complicated interactions between local economic conditions, macroeconomic conditions, and economic policy at the local, national, and international levels. Measuring local economic conditions in a framework that can be tied to measuring economic production is an important component is assessing the determinants of productivity, competitiveness, and overall economic outcomes.

Our focus on competitiveness is on the prices of output and inputs. Even in a world of heterogenous goods and factors, substitution is possible and relative prices matter in the ability to sell output, attract investment and workers, and participate in global value chains. This competition operates within very local economies at the firm level, but also plays an important role in understanding economic outcomes across larger geographies within and across countries.

The U.S. Bureau of Economic Analysis (BEA) produces a suite of economic accounts that contain information on regional economic performance, including GDP and Income by State, and regional price parities that can be used to assess living costs across the country. Living costs are, of course, an important component of competitiveness; the ability to attract and maintain workers in a local area. One objective of this paper is to contribute to a measure of another important component of economic competitiveness within the U.S.: labor market competitiveness. The link between local labor markets and local price competitiveness is intuitive in theory (though often more complicated in the real world); producers operating in a local labor market with lower prevailing labor costs (assuming workers of equivalent skills) can pass on lower input prices to consumers. In this paper, we provide the first estimates that we are aware of U.S. local labor market competitiveness that account for skill mix across regions and are consistent with the U.S. national accounts.[2]

A second area where these data are relevant is the analysis of economic inequality. The BEA recently released a report on "Developing Statistics on the Distribution of State Personal Income" that provides statistics on income inequality by state and region. A fundamental question that, to this point, remains unanswered is how this inequality relates to regional differences in productivity. Productivity is defined as regional real output per unit of real input; output is measured either as State Gross Product (value-added) or gross output at the industry level. Inputs cover all primary inputs (labor, tangible and intangible capital, land, etc.) and intermediate inputs. Productivity level differences across regions are an important next step for economic statistics.[3]

Productivity level statistics require measures of output and input price levels that account for heterogeneity of outputs of production and inputs used in production. Inputs used include capital, labor, and intermediate inputs. In this paper we construct measures of labor input prices that could be integrated into regional productivity accounts. An important characteristic of the

[2] The BLS produces employment costs by region: https://www.bls.gov/regions/southwest/news-release/employercostsforemployeecompensation_regions.htm but this does not include skill mix.
[3] The BLS produces productivity growth estimates by state, but not level differences.

measures that we construct is that they are assembled from the perspective of the producer – they reflect costs of production across regions. That is, our measures reflect the marginal cost of hiring workers. It is these production costs that are relevant for assessing economic competitiveness.

These costs from the perspective of the producer translate to income for workers. Therefore, the link between labor costs across regions and income inequality across regions is an important area of study. (Khan & Siddique, 2021) demonstrate that some measures of inequality between states in the U.S. fell after WW2 until the 1990s when it started rising. These state trends are related to, but distinct from, national income inequality trends (Peach and Adkisson 2019). Rising regional inequality in the last three decades is also noted for many other advanced countries (IMF 2019). This income inequality is driven by differences in employment opportunities, nominal wages, and real wages. These gaps have proven to be a huge challenge to local policymakers trying to maintain competitiveness and attract investment.

Model

The starting point for our measure of regional labor market cost competitiveness is model of producer behavior in region (r) in sector (s) using capital (k), intermediate input (x), and heterogenous labor (l) of various types *i* – $Y_{rs}(K,L(l_i),X)$. In our implementation, *i* captures the heterogeneity of the workforce across regions and indexes workers by cross classifying workers by sex, age group, and education group.[4]

The starting point for our measure is the price (or cost) dual to the output function Y(.) for each region and sector and we assume that this dual takes the translog form. Under neoclassical assumptions, this yields an output price equation for each region and sector at time t:

$$\ln p_{Y,r,s,t} = w_{k,r,s,t} \ln p_{k,r,s,t} + w_{x,r,s,t} \ln p_{x,r,s,t} + \sum_i w_{l,i,r,s,t} \ln p_{l,i,r,s,t} - \ln T_{r,s,t} \quad (1)$$

where p_Y, p_k, p_x and $p_{l,i}$ are the price levels of output, capital, intermediate input, and labor of type *i*, respectively. T is the level of (total factor) productivity in each region and sector. The output price equals average cost under competitive neoclassical assumptions. The w terms are the value shares of each input in output. In the cost function specification, the productivity term enters with a negative because a higher productivity level means lower total cost for given levels of input prices. One can see this by formulating the production function based on the quantity of outputs and inputs and using that specification to measure the level of productivity. Under neoclassical assumptions, this level of productivity equals the difference between input prices and output prices.

(Jorgenson, Kuroda, & Nishimizu, 1987) derives translog indexes of productivity gaps between two countries. We follow the same approach and define the sector specific productivity gap

[4] The categories are chosen to be consistent with the worker characteristics used in the BEA-BLS Integrated Industry-level Production Account. (Garner, Harper, Russell, & Samuels, 2021)

between region r and some base region B, $\tilde{T}_{r,s,t}$, by subtracting equation (1) for each region relative to B:

$$\ln \tilde{T}_{r,s,t} = \frac{1}{2}(w_{k,r,s,t} + w_{k,B,s,t}) \ln \tilde{p}_{k,r,s,t} + \frac{1}{2}(w_{x,r,s,t} + w_{x,B,s,t}) \ln \tilde{p}_{x,r,s,t} + \sum_i \frac{1}{2}(w_{l,i,r,s,t} + w_{l,i,B,s,t}) \ln \tilde{p}_{l,i,r,s,t} - \ln \tilde{p}_{Y,r,s,t} \tag{2}$$

$$w_{k,r,s,t} = \frac{p_{k,r,s,t} K_{r,s,t}}{p_{Y,r,s,t} Y_{r,s,t}}$$

The tilde denotes variables relative to base region values, for example, $\tilde{p}_{x,r,s,t} = p_{x,r,s,t} / p_{x,B,s,t}$ is the price of intermediate inputs in region r, sector s at time t, relative to the same price in the Base location. The w's are the shares of input values in gross output value. Equation (2) says that the productivity level gap between two locations can be measured as the log difference between input and output prices in the two locations, weighted by the w's.

The focus of this paper in on the labor portion of equation (2). The individual i terms in this equation represent each component of labor's contribution to the total labor input price differential between the two locations. That is,

$$\frac{1}{2}(w_{l,r,s,t} + w_{l,B,s,t}) \ln \tilde{p}_{l,r,s,t} \equiv \sum_i \frac{1}{2}(w_{l,i,r,s,t} + w_{l,i,B,s,t}) \ln \tilde{p}_{l,i,r,s,t} \tag{3}$$

The contribution of differences in labor input prices to the productivity gap between the two regions is the weighted sum over each of the cross classified components of labor input. Since our focus is on the labor comparisons, we do not calculate eq. (3) where the *w* weights are shares of gross output, but instead use a formula where the weights measure the labor input price gap between regions. That is, we simply first measure $\ln \tilde{p}_{l,i,r,s,t}$, not $\frac{1}{2}(w_{l,r,s,t} + w_{l,B,s,t}) \ln \tilde{p}_{l,i,r,s,t}$.

Thus, we reformulate the following expression for the relative price of effective labor input, $\ln \tilde{p}_{l,r,s,t}$:

$$\ln \tilde{p}_{l,r,s,t} \equiv \sum_i \frac{1}{2}(\breve{w}_{l,i,r,s,t} + \breve{w}_{l,i,B,s,t}) \ln \tilde{p}_{l,i,r,s,t} \tag{4}$$

$$\breve{w}_{l,i,r,s,t} = \frac{p_{l,i,r,s,t} L_{l,i,r,s,t}}{\sum_{ii} p_{l,ii,r,s,t} L_{l,ii,r,s,t}}$$

The weights $\breve{w}$ are now factor payments for each component of labor input relative to total labor compensation, instead of relative to nominal gross output in (3). The term "effective labor" refers to a measure of total labor input into sector *s* that considers the heterogeneity of the work force instead of using a simple sum of hours worked by all workers in *s*; this recognizes that different types of workers have different marginal products and wages. $L_{l,i,r,s,t}$ denotes the total hours worked by type *i* workers in period t.

Equation (4) is the labor input price gap between two regions and captures the competitiveness between two regions in the market for effective labor. Since it accounts for heterogeneity in the workforce, this measure answers the question "how much would it cost to employ the same effective workforce in the reference state compared to the Base state?" This notion of labor quality can be made explicit by defining an alternative price gap between states that is based solely on the average compensation per hour paid to workers in each location. The underlying assumption of this average wage formulation is that all types of workers within, and across, states are homogenous in their contributions to production; that is, an experienced worker with an advanced degree in the legal sector has the same marginal product as a newly-graduated administrative assistant. This is formulated as:

$$\ln \hat{p}_{l,r,s,t} \equiv \ln \hat{c}_{l,r,s,t} \tag{5}$$

where $\hat{c}_{l,r,s,t}$ is the average hourly compensation per hour in the reference location in comparison to the base location. Notice that this formulation has no separate tabulation for different types of workers (no *i* index), where the caret over p is used to distinguish this average price from $\tilde{p}$.

Jorgenson, Gollop and Fraumeni (1987) defined labor quality as the ratio of effective labor input (L) to the simple sum of hours (H) for an aggregate of workers, e.g., the aggregate of workers in a particular industry or in a country. They assume that all workers of a given demographic type are equally productive (have the same quality). Using L to denote effective labor input aggregated over all types of workers (the primal dual to (4)) and Q_l to denote labor quality:

$$L_t = Tornqvist(L_{it}; p_{lit}); \qquad L_{it} = H_{it}$$

$$Q_{lt} = \frac{L_t}{H_t} = \frac{L_t}{\sum_i H_{it}}; \qquad p_{lt} L_t = \sum_i c_{it} H_{it}$$

Other authors use the term "composition index" to refer to this concept that distinguishes effective aggregate labor input from a simple sum. In a similar way, we now define the labor quality gap between region r and the base region in terms of the labor price duals:

$$\ln \hat{p}_{l,r,s,t} - \ln \tilde{p}_{l,r,s,t} \equiv \ln \tilde{Q}_{l,r,s,t} = \ln Q_{l,r,s,t} - \ln Q_{l,B,s,t} \tag{6}$$

$\ln \tilde{Q}_{l,r,s,t}$ is the portion of the gap in average compensation per hour between the two locations that is due to aggregate worker quality differences. For example, if the average compensation gap between two locations was 30% and the labor price gap in effective labor input was 20%, the quality gap between the locations would be 10%. That is, 10 percentage points of the gap in average labor prices is explained by its higher worker quality.

Measuring the Labor Input Price Gap

In this section, we describe how we measure the labor price gap and make it consistent with the U.S. national accounts.

To capture heterogeneity in the workforce across locations, we classify workers according to their level of education (5 education groups), age (7 age groups), sex, and in some cases, sector. These classifications are chosen to correspond the classification used in the BEA-BLS Integrated Industry-level Production account to adjust its labor input measure for labor composition. However, doing this for the 50 states and 63 industries would amount to over 220K worker price estimates and this is intractable using the available survey or sample data.[5] Thus, in this paper, we construct two measures based on alternative classifications. The first measure includes workers for 50 states and cross-classifies these workers by the education, age, and sex groupings but ignores the industry dimension. The second includes 15 sectors, 8 regions within the U.S. (based on BEA's regional accounts) and the same the education, age, and sex groupings (these 15 sectors are used in BEA national tabulations).

The primary dataset that we use to account for differences across workers is the 1% microdata from the American Community Survey (ACS). This is a 1% sample of the U.S. population and includes information on about 1.6M workers. For our first labor measure that is only by state (not sector) this results in about 450 observations per worker type, and for the measure including region and sector, about 190 observations per worker type. Obviously, there are small cells (e.g. a young worker with an advanced degree in Alaska) so for many cells there may be very few observations.[6]

The ACS includes information on work status, worker age, level of education, industry, location of work (this is important because we want to construct measures based on the perspective of the producer), usual hours worked, and wage and salary income. The ideal measure would be actual hours worked, but that is not available. It would be possible to adjust from usual to actual hours worked at a higher level of detail in the "control total" process described later, but we leave that for future work. An additional complication with using the ACS is that is conducted on a rolling month basis. That is, a respondent's answers about wages and hours that were collected in January of a given year would reflect their wages for the prior year. We do not make any attempt to adjust the micro data for this, but we do adjust for this using the control totals discussed

[5] BEA-BLS have conducted research on using estimation methods to improve measurement of small cells, so a potential future approach is to use similar methods to construct a dataset that covers those groupings. See work presented here: tac20211119.pdf (bls.gov)

[6] We drop workers without a reported state, these are mainly U.S. citizens working overseas who we want to exclude from our analysis.

below. Therefore, our measures are consistent with calendar year at the level of the control total, but the demographic data could be thought of as a 12-month rolling average measure. We use the ACS to tabulate total workers, average weekly hours worked, and average annual salary for each of the demographic groups.

We control the matrices of ACS-based labor data to totals of the number of workers and employee labor compensation from the BEA regional economic accounts. These accounts are constructed to be consistent with the national accounts estimates of labor compensation for the economy at the industry level.

We take the following steps for the state-based estimates:

1) Within each state *r*, scale the number of total workers to the estimate in BEA's regional accounts[7]. The regional accounts measure total jobs rather than total workers, so this produces a measure that reflects workers paid at each job (some workers may work at more than one job).
2) Multiply the worker estimate from step 1) by the ACS measure of usual hours and weeks worked to arrive at total annual hours worked for each demographic group.
3) Within each state *r*, scale the total wages paid to each demographic group to match total labor compensation by state from BEA's accounts. The difference between wages and labor compensation is that the latter includes fringe benefits like health insurance and contributions to retirement that are paid by the employer but not received as wages by the worker. The underlying assumption of this approach is that these benefits are distributed proportionally across all worker types within the state. That is, the highly experienced, highly educated worker in Montana gets the same proportional increase over wages as the young worker with little education.
4) Divide labor compensation by each demographic group from step 3) by the total hours worked from step 2). This yields a measure of average hourly labor compensation cross classified by each demographic group and state that is consistent with BEA's regional economic accounts.

We follow the same basic steps to construct the second dataset by region and sector, but scale to the corresponding regional-sector controls based on BEA's regional accounts. We construct these datasets from 2006 to 2019; while the ACS was introduced a few years earlier, there were some changes to the tracking of educational attainment that we wanted to avoid in this first effort at calculating regional labor input.

With the data described above, the relative labor input price is based on aggregating labor input prices for comparable demographic groups as given in (4).To recall, the price of labor input of type *i* from the perspective of the producer in state r is $p_{l,i,r,s,t}$. At this most detailed level, this price corresponds to the compensation per hour measured in steps 1-4. This is the amount paid out by the employer to hire the corresponding worker to perform an hour's worth of work,

[7] The BEA regional data is given at https://apps.bea.gov/regional/downloadzip.cfm . Series CAEMP25 and CAEMP27 gives the employment by state/region and industry, while CAINC6 gives compensation by state and industry.

$p_{l,i,r,s,t} = c_{l,i,r,s,t}$ where c is the measured labor compensation per hour for the corresponding group.

To compare this price across locations, we construct $\tilde{p}_{l,i,r,s,t} = \frac{p_{l,i,r,s,t}}{p_{l,i,B,s,t}}$. If $\tilde{p}_{l,i,r,s,t}$ is greater than 1.0 then hiring this worker of the type i quality in location r is higher than in the Base location, and is cheaper if this measure is less than 1.0. $\ln \tilde{p}_{l,i,r,s,t}$ is the (log) percentage gap in the prices. It is important to remember that the underlying assumption is that workers at this detailed level of sex-age-education classification are of the same quality in all locations and industries.

To aggregate these individual prices to a state-wide or region-sector labor input price gap we use equation (4). That is, we take a weighted average of these individual log price gaps. Under the assumption that both locations have a translog functional from for the corresponding cost function, these weights correspond to the simple average of each type of worker's compensation share in the total labor compensation in each state or region-sector. This weight is constructed with the labor compensation measure described in step 4) above. This yields a measure of the aggregate price gaps for each state and each region-sector versus the Base location. In our empirical work, we choose Ohio as the Base state and the Great Lakes region as the Base in the regional comparisons since these are close to the national means.[8]

Labor Input Price Gaps by State

Figure 1 shows the wide range in effective labor input price gaps across the fifty states plus the District of Columbia (map in Figure 1b). The most expensive location to hire workers, holding worker quality fixed, is the District of Columbia. According to our measures, an "effective" worker employed in DC is almost 30 percent more expensive in comparison to Ohio. The role of the labor quality gap between Ohio and DC, based on equation (6), can be understood by the results in Figures 2 and 3. Figure 2 shows that the average hourly wage was over 50 percent higher in DC compared to Ohio. That is, treating all workers within each state as homogeneous, the average wage of the DC-based worker is 50% higher than the average in Ohio. But, when we account for the composition of the workforce in DC relative to Ohio, we see that the effective labor input price is only 30% higher. Thus, the difference between the two reflects the compositional difference of the workforce in DC in comparison to Ohio. Said alternatively, if DC had the same distribution of workers as Ohio, its average wage would be 30% higher. But because it has higher educated workers on average, and perhaps older workers, its average wage is 50% higher. From the perspective of analyzing the competitiveness of labor markets across locations, it is the effective labor input price that is relevant as this is constructed to keep quality constant across locations. Figure 3 shows that these compositional differences are most important in DC, New York, Massachusetts, but play an important role across many states. Texas

[8] The Great Lakes region includes Indiana, Illinois, Michigan, Ohio, and Wisconsin.

and Arizona have a different pattern where the quality gap adds to the nominal wage gap (Texas: 2.5+4=6.5%). The implication of this is that using simple average hourly compensation is problematic when assessing labor market competitiveness.

The states typically associated with expensive living costs are also relatively expensive to hire workers. In addition to DC, which is a somewhat special case due its federal government workers and related professional workers, other states with relatively high labor input prices are California, New York, Massachusetts, Connecticut and New Jersey on the coasts. Washington state, which has the perception as a great place to live and work, also has a relatively high price of labor. Recall that our normalization means that states that have a price gap above zero are more expensive to hire labor than Ohio.

Our results indicate that in 2019, more than half of the states were more competitive than Ohio from the perspective of producers looking to hire workers. The case of Louisiana is also a useful case to consider the role of labor quality. It is about 2% less expensive to hire workers in Louisiana compared to Ohio. Figure 2 shows that average wages are about 8% less. The difference between the two (Figure 3) means that the composition of workers in LA brings the effective labor price up because to hire the same composition as workers employed in Ohio would require raising the effective price of labor input by hiring more educated, more experienced workers than are currently employed in LA. Even after accounting for these composition differences, the states on the lower portion of Figure 1 are significantly cheaper to hire workers in comparison to the states at the top end of the distribution.

Next, we consider how these state-level price gaps changed over time. Figure 4 shows the labor input price gap in 2019 less the price gap in 2006; if prices in the reference state relative to Ohio grew over this period, then this difference is positive, and negative if labor prices became cheaper over time relative to Ohio. Figure 4 shows that effective labor input prices grew by a substantial percentage in the states at the top portion of the figure. In North Dakota, our measures indicate that labor input prices grew by over 20% relative to Ohio over this period. One way to view this is that North Dakota became a less competitive state for locating labor-oriented production over this period. An alternative, but not exclusive view, is that factors emerged in North Dakota that became attractive to employers (e.g. the oil and gas mining boom) that increased the demand for workers in ND, thus raising wages. Washington, Montana, and South Dakota each had labor input prices that grew by more than 10% relative to Ohio over this period. Only in a few states, did labor become less expensive relative to Ohio over the period; Connecticut and Delaware were the only states where labor input became less expensive by 3% or more; it is worth noting that these states started from a very large positive gap in 2006.

We next compare labor price differences to cost-of-living differences. The regional price parities (RPP), produced by BEA, measure the gaps in price levels by state for all items consumed by households in a state including goods, housing, utilities, and other services[9]. We renormalize the 2019 regional price parities as a log price gap relative to Ohio to compare these to the labor price

[9] The BEA Regional Price Parities are given at: https://www.bea.gov/data/prices-inflation/regional-price-parities-state-and-metro-area

gaps in Figure 5 (consumer prices in the y-axis, labor price in x-axis). An effect of doing this is that the interpretation of the difference between the price parity gap and the labor input price gap is relative to Ohio, and the wage-RPP gap for Ohio itself is zero. Future work could renormalize each of these to be relative to the U.S. a whole.

All states above the 45-degree line in Figure 5 have consumption prices that are higher than labor input prices, relative to Ohio, and this is the case for the majority of states. For example, Hawaii has a general price level (cost of living) that is significantly higher than the price of hiring workers. Stated differently, the price of employing workers is low in Hawaii relative to Ohio but the cost of living is significantly higher; that is, real wages are lower in Hawaii. This may be due to a captive labor force in Hawaii that find it difficult to relocate out of Hawaii, or uncounted benefit to Hawaii residents – a benefit that is not captured by incomes (e.g. public goods or climate). Alternatively, one may interpret this to mean that it is difficult to find workers at wages that employers can afford to pay. In most states, the cost of living is similar to the price of labor input (most states close to the 45-degree line) but there are some exceptions. In addition to Hawaii, there are low real wages in South Dakota, Maine, and Vermont. On the other end of the spectrum, DC and Connecticut have the highest real wage, highest price of labor relative to the cost-of-living. Interestingly, Virginia, as a whole, has a cost of living that aligns very closely to the relative price of hiring workers even if northern Virginia often is considered as a close alternative to DC in setting up a business.[10]

Labor Price Gaps by Region and Sector

In this section, we present estimates of labor price gaps by sector and region for 2019. There are 8 regions, and our indices are relative to the Great Lakes region. The top portion of Table 1, which presents the results where the ACS micro data are controlled to the total labor compensation and number of workers in BEA's official accounts, shows that when making regional comparisons that it is important to consider the role of industry composition. For example, the quality adjusted price of hiring workers in New England is about 11% higher than in the Great Lakes region, but this is not proportional across sectors. The price of labor input in the Finance and Professional and business services is over 20% higher in New England in comparison to the Great Lakes, but the price of workers in the Agriculture, Mining, and Transportation and warehousing sector is actually lower in New England. Similar overall labor prices to New England prevail in the Mideast (which includes DC) but the price of government workers is significantly higher in Mideast region in comparison to all other regions in the country. The results also suggest that labor prices are higher in sectors where there is relatively more production by region. For example, prices of mining workers are higher in the Southwest, Rocky Mountain and Far West regions. Workers in the Information sector are 72% more expensive in the Far West (California, Washington, etc) in comparison to the Great Lakes. This suggests that there may be specialized workers in each sector that our cross-classified data is not

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[10] Housing prices are notoriously difficult to compare and if comparable housing -amenity prices are not well estimated then the RPP is not accurately reflecting attainable utilities.

accounting for (not everyone with a BA degree in the IT sector have the same skills and marginal product). Nevertheless, the basic result indicates that it is much more expensive to hire Information workers in the Far West, which is consistent with recent movement of high-tech industries to other areas of the country.

The bottom portion of Table 1, which presents the labor input price estimates using wage data in the ACS that are not adjusted to labor compensation controls from the national accounts, shows that it is important to consider fringe benefits when analyzing labor market competitiveness. At the regional level, the labor price input gaps are similar before and after adjustment, but there are some large differences at the sector level. In the Information sector, the labor input price gap is 72% higher in the Far West when fringe benefits are accounted for and only 40 percent higher when using unadjusted wages to measure the labor input price gap. In the government sector, fringe benefits account for about a third of the labor cost difference between the Mideast and Great Lakes. Additions to wages in the Southwest play an important role in its relatively high price paid for Mining workers. Retail workers in the Rocky Mountain region would have basically been paid on par with the workers in the Great Lakes if it wasn't for fringe benefits.

Conclusions

The method and data that we have provided in the paper are useful tools for gauging labor market competitiveness across the U.S. The results show large differences in prices paid to workers across states and across region-sector groups. Most of the labor input price gaps align with cost-of-living measures across states, but there are some notable locations where there is a large gap between the cost of living and the labor input price measures. This may reflect other non-labor costs of production, unaccounted geographical benefits of living in particular areas, or barriers to mobility, and may indicate difficulty in attracting and maintaining a workforce. An important feature of our estimates is that they are constructed to adjust for worker quality across locations and the results show that this adjustment is empirically important when assessing labor market conditions. Furthermore, using simple average hourly wages instead of wages adjusted to total labor compensation obscure the assessment of labor market competitiveness. Next steps for this research include using statistical methods to improve the measurement of small cells, produce a longer time series, and to fill in the remaining pieces in equation (2) to measure productivity differences across locations.

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Table 1. Labor input price gaps, 2019

Adjusted to Labor Compensation Controls	New England	Mideast	Great Lakes	Plains	South East	South west	Rocky Mountain	Far West
Total	0.11	0.14	0.00	-0.07	-0.03	0.05	0.02	0.21
Agriculture, forestry, fishing	-0.06	-0.40	0.00	-0.02	-0.19	-0.24	-0.19	0.22
Mining	-0.03	0.11	0.00	0.22	-0.01	0.31	0.29	0.19
Utilities	0.06	0.01	0.00	-0.10	-0.10	-0.02	-0.12	0.08
Construction	0.07	0.05	0.00	-0.13	-0.11	0.01	-0.05	0.14
Manufacturing	0.05	-0.03	0.00	-0.06	-0.02	0.14	0.00	0.24
Wholesale trade	0.11	0.09	0.00	-0.05	0.02	0.11	0.08	0.08
Retail trade	0.10	0.08	0.00	-0.07	0.00	0.07	0.12	0.26
Transportation, warehousing	-0.02	0.00	0.00	-0.08	-0.01	0.07	0.04	0.27
Information	0.24	0.31	0.00	-0.08	0.06	0.13	0.21	0.72
Finance, insurance, real estate	0.24	0.28	0.00	-0.09	-0.06	0.03	-0.03	0.14
Professional and business svc	0.21	0.16	0.00	-0.01	0.01	0.11	0.09	0.21
Education, health, social assis	0.03	0.03	0.00	-0.03	0.01	0.03	-0.04	0.09
Arts, entert., accom., food svc	0.08	0.16	0.00	-0.09	-0.03	0.02	0.13	0.26
Other services, except govt	0.00	0.08	0.00	-0.08	-0.03	-0.02	0.08	0.03
Government	0.13	0.30	0.00	-0.09	-0.04	-0.03	-0.02	0.29

Unadjusted	New England	Mideast	Great Lakes	Plains	South East	South west	Rocky Mountain	Far West
Total	0.13	0.15	0.00	-0.03	-0.06	0.01	0.02	0.18
Agriculture, forestry, fishing	-0.03	0.08	0.00	0.01	-0.08	-0.08	-0.07	0.08
Mining	0.14	-0.02	0.00	0.01	-0.03	0.12	0.13	0.21
Utilities	0.03	0.01	0.00	-0.10	-0.14	-0.01	-0.07	0.08
Construction	0.07	0.11	0.00	-0.03	-0.15	-0.09	-0.04	0.12
Manufacturing	0.11	0.09	0.00	-0.02	-0.04	0.07	0.04	0.19
Wholesale trade	0.07	0.13	0.00	-0.03	-0.05	0.02	0.08	0.15
Retail trade	0.13	0.10	0.00	0.01	-0.03	0.03	0.01	0.21
Transportation, warehousing	0.05	0.08	0.00	0.02	0.03	0.09	0.16	0.15

Information	0.12	0.26	0.00	-0.11	0.00	0.03	0.11	0.40
Finance, insurance, real estate	0.20	0.24	0.00	-0.05	-0.04	0.03	0.03	0.19
Professional and business svc	0.15	0.17	0.00	-0.04	-0.03	0.02	0.04	0.22
Education, health, social assis	0.10	0.08	0.00	0.02	-0.01	0.01	0.04	0.18
Arts, entert., accom., food svc	0.13	0.12	0.00	-0.03	-0.05	-0.02	0.04	0.21
Other services, except govt	0.09	0.16	0.00	-0.01	-0.06	-0.03	0.01	0.12
Government	0.11	0.21	0.00	-0.08	-0.07	-0.06	-0.03	0.15

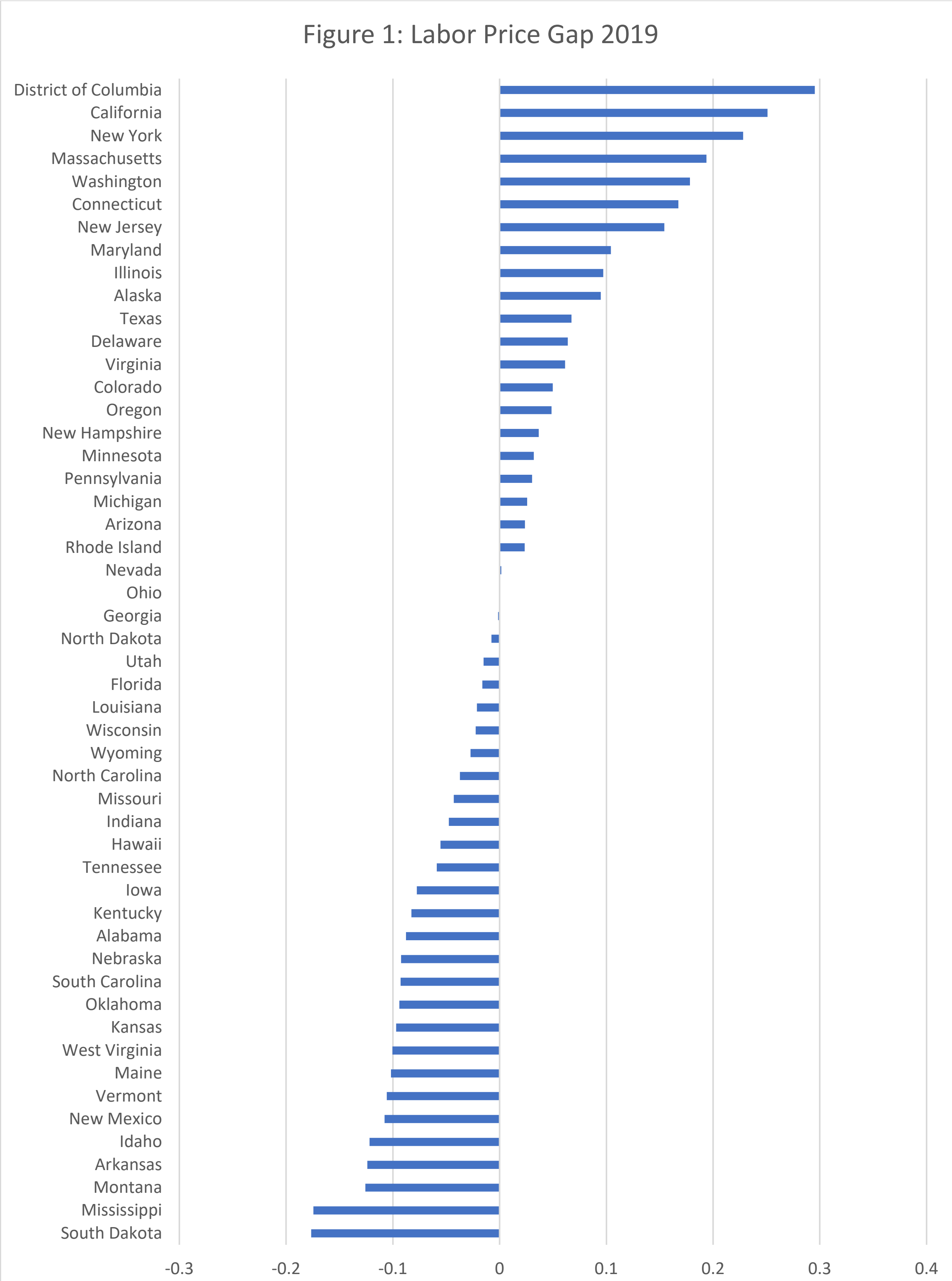
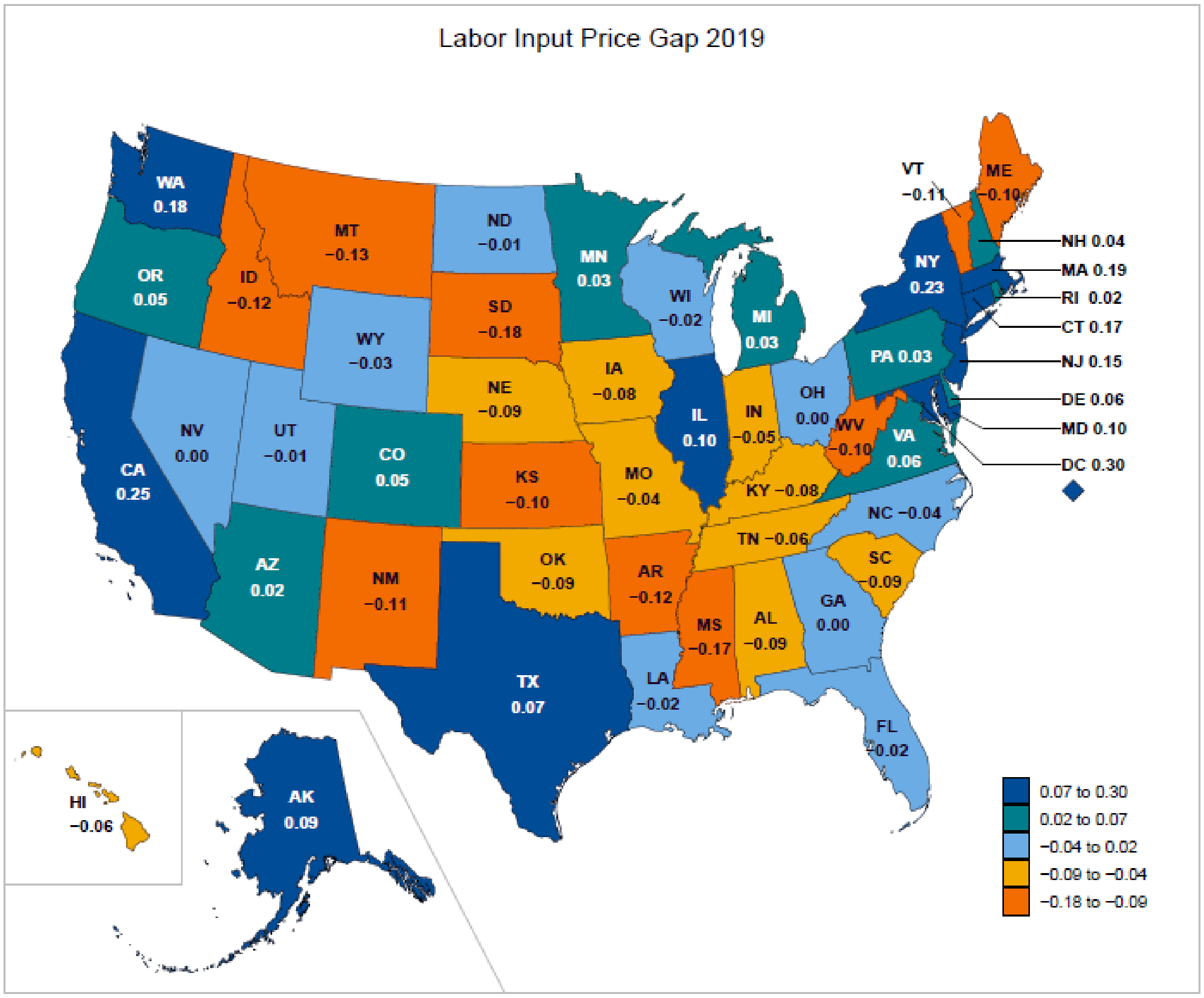


Figure 1: Labor Price Gap 2019
District of Columbia
California
New York
Massachusetts
Washington
Connecticut
New Jersey
Maryland
Illinois
Alaska
Texas
Delaware
Virginia
Colorado
Oregon
New Hampshire
Minnesota
Pennsylvania
Michigan
Arizona
Rhode Island
Nevada
Ohio
Georgia
North Dakota
Utah
Florida
Louisiana
Wisconsin
Wyoming
North Carolina
Missouri
Indiana
Hawaii
Tennessee
Iowa
Kentucky
Alabama
Nebraska
South Carolina
Oklahoma
Kansas
West Virginia
Maine
Vermont
New Mexico
Idaho
Arkansas
Montana
Mississippi
South Dakota
-0.3
-0.2
-0.1
0
0.1
0.2
0.3
0.4

Figure 1b. Map of labor price gaps, 2019



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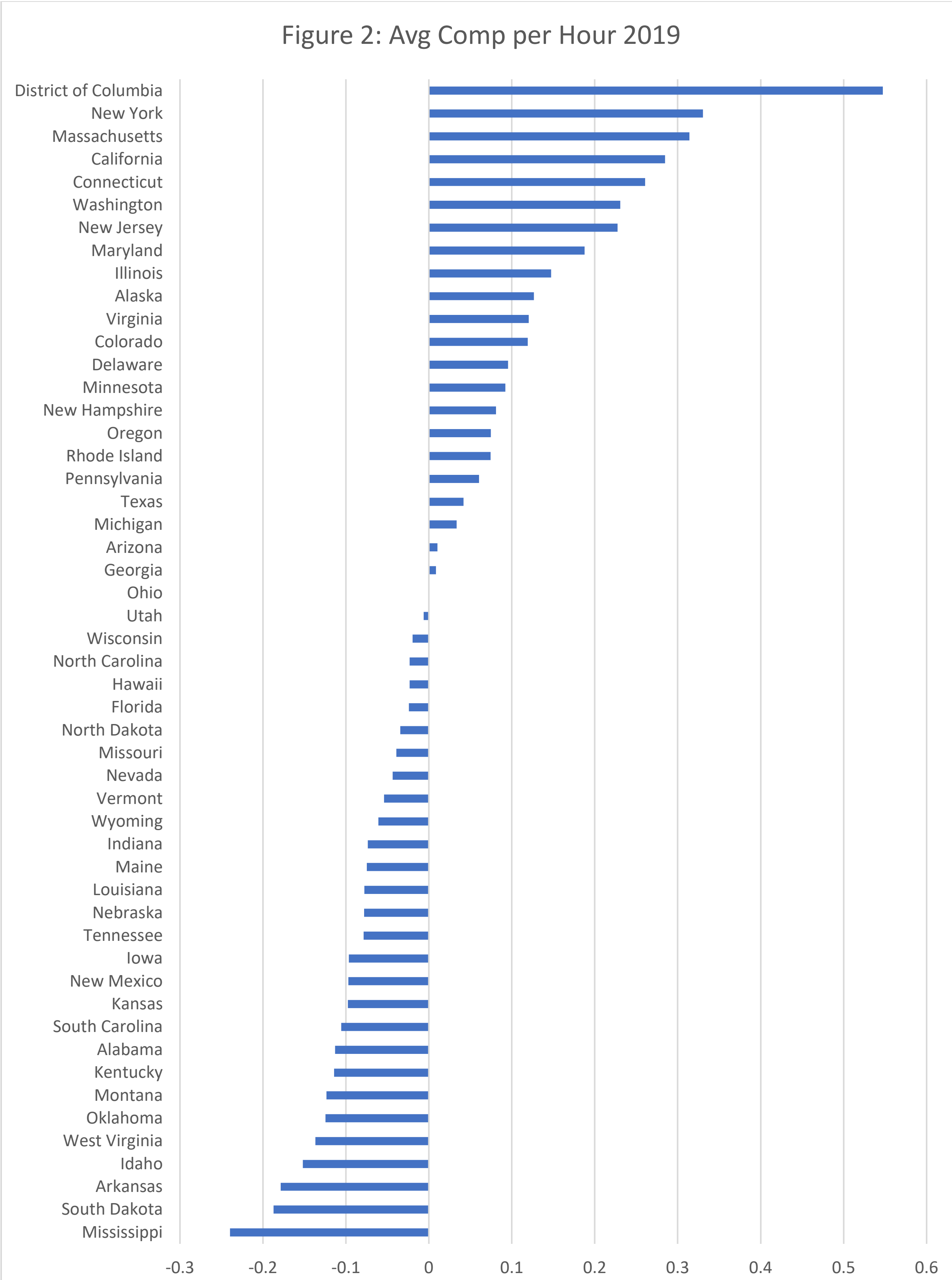
Figure 2: Avg Comp per Hour 2019
District of Columbia
New York
Massachusetts
California
Connecticut
Washington
New Jersey
Maryland
Illinois
Alaska
Virginia
Colorado
Delaware
Minnesota
New Hampshire
Oregon
Rhode Island
Pennsylvania
Texas
Michigan
Arizona
Georgia
Ohio
Utah
Wisconsin
North Carolina
Hawaii
Florida
North Dakota
Missouri
Nevada
Vermont
Wyoming
Indiana
Maine
Louisiana
Nebraska
Tennessee
Iowa
New Mexico
Kansas
South Carolina
Alabama
Kentucky
Montana
Oklahoma
West Virginia
Idaho
Arkansas
South Dakota
Mississippi
-0.3
-0.2
-0.1
0
0.1
0.2
0.3
0.4
0.5
0.6

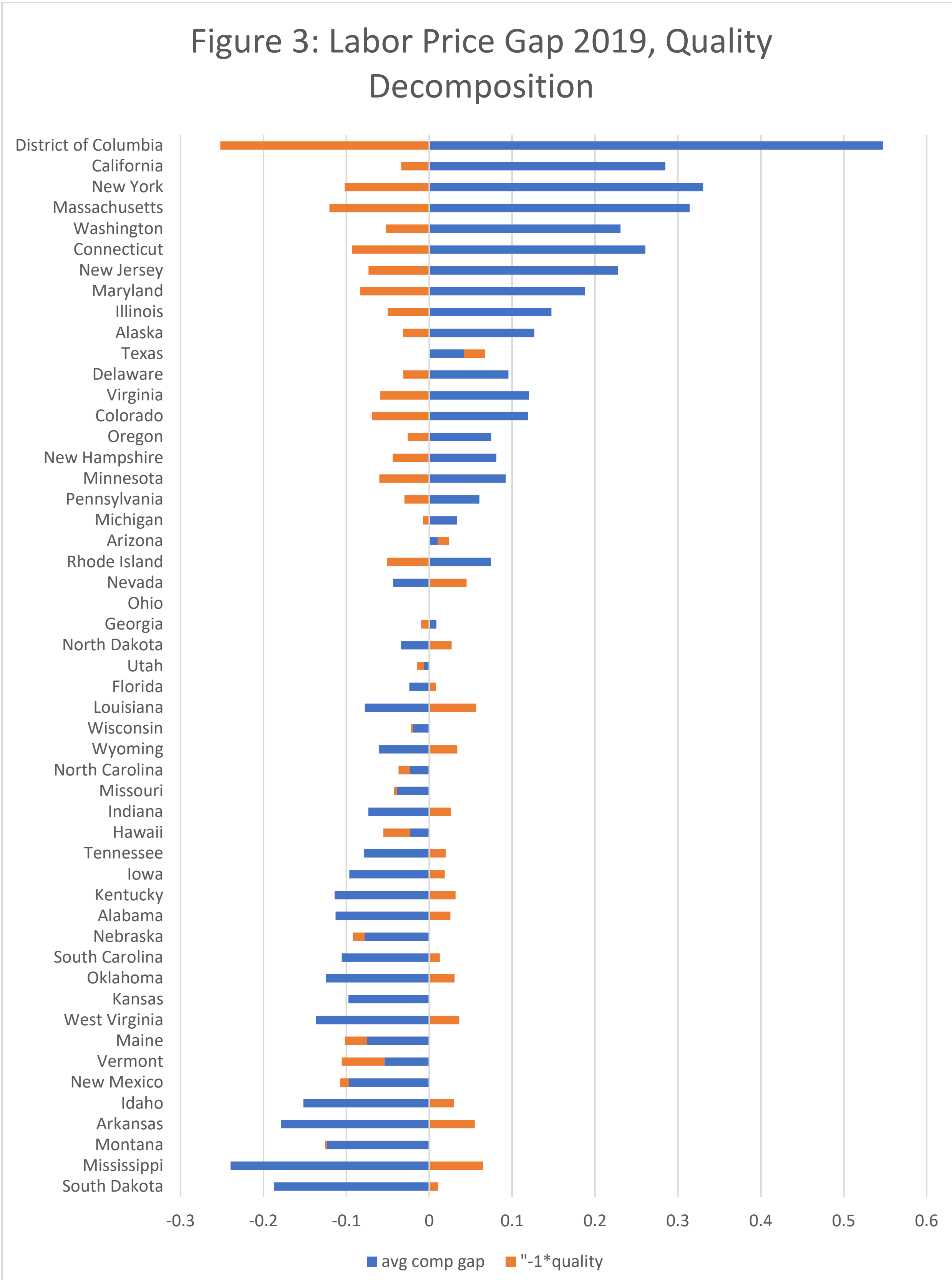
Figure 3: Labor Price Gap 2019, Quality Decomposition
District of Columbia
California
New York
Massachusetts
Washington
Connecticut
New Jersey
Maryland
Illinois
Alaska
Texas
Delaware
Virginia
Colorado
Oregon
New Hampshire
Minnesota
Pennsylvania
Michigan
Arizona
Rhode Island
Nevada
Ohio
Georgia
North Dakota
Utah
Florida
Louisiana
Wisconsin
Wyoming
North Carolina
Missouri
Indiana
Hawaii
Tennessee
Iowa
Kentucky
Alabama
Nebraska
South Carolina
Oklahoma
Kansas
West Virginia
Maine
Vermont
New Mexico
Idaho
Arkansas
Montana
Mississippi
South Dakota
-0.3
-0.2
-0.1
0
0.1
0.2
0.3
0.4
0.5
0.6
avg comp gap
"-1*quality

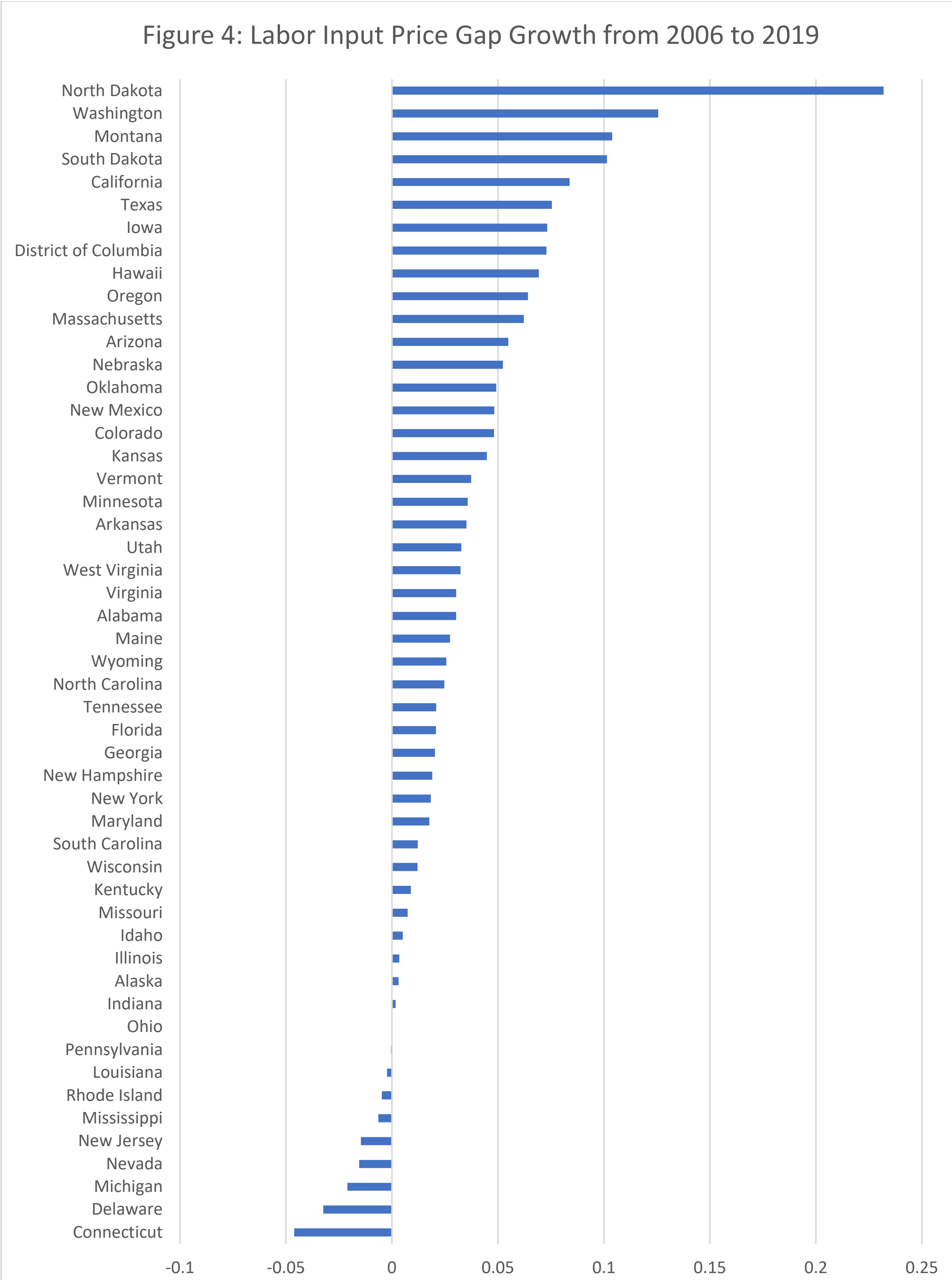
Figure 4: Labor Input Price Gap Growth from 2006 to 2019
North Dakota
Washington
Montana
South Dakota
California
Texas
Iowa
District of Columbia
Hawaii
Oregon
Massachusetts
Arizona
Nebraska
Oklahoma
New Mexico
Colorado
Kansas
Vermont
Minnesota
Arkansas
Utah
West Virginia
Virginia
Alabama
Maine
Wyoming
North Carolina
Tennessee
Florida
Georgia
New Hampshire
New York
Maryland
South Carolina
Wisconsin
Kentucky
Missouri
Idaho
Illinois
Alaska
Indiana
Ohio
Pennsylvania
Louisiana
Rhode Island
Mississippi
New Jersey
Nevada
Michigan
Delaware
Connecticut
-0.1
-0.05
0
0.05
0.1
0.15
0.2
0.25

Figure 5: RPP Price Gaps versus Labor Input Prices, 2019