Can Productivity Spillovers Explain the Productivity-Compensation Gap?

Abstract

Historically, compensation and productivity steadily trended in sync with one another. Since the mid-1970s, these two measures have diverged, as productivity increases have outpaced compensation. This divergence is indicative as evidence for wage stagnation, rising income inequality, and the fading American Dream. We provide arguments on the productivity-compensation gap and illuminate possible explanations of whether and why the gap exists in different industries. Following the "peer effect" literature, we hypothesize that workers are not always compensated for productivity spillovers. We confirm that the gap narrows once we account for productivity spillovers between bordering states as well as between trading states using spatially lagged X (SLX) models. The results vary across industries and provide insights for policy makers and firms about productivity and compensation patterns.

Keywords: SLX, spillovers, productivity, compensation
JEL Classification: C21, E24, J24, J3

1 Introduction

Since the 1970s, the growth rates of labor compensation and labor productivity have been steadily diverging in the United States. Several newspapers and magazines,[1] interviews,[2] reports from the Bureau of Labor Statistics,[3] Economic Policy Institute,[4] a book,[5] and research articles[6] have noted the curious divergence between productivity and compensation, commonly referred to as the productivity-compensation gap or productivity-pay gap. Figure 1, developed by Stansbury and Summers (2017), shows that productivity and compensation grew in tandem until the mid-1970s, when productivity began to outpace compensation.

The US productivity-compensation gap has intrigued academics and policy makers, who ask, "What does this stark divergence imply about the relationship between productivity and typical compensation?" (Stansbury and Summers, 2017). Mishel et al. (2012) attribute rising inequality, wage stagnation, and a fading American Dream to the gap. Others are exploring the similar productivity-compensation gap in the United Kingdom (for example, Pessoa and Reenen, 2013; Pessoa and Van Reenen, 2014; Cantillon and Ucal, 2019). Stansbury and Summers (2017) show that the productivity-compensation gap exists and suggest that "other factors orthogonal to productivity have been acting to suppress typical compensation even as productivity growth has been acting to raise it." Our paper posits that workers are not always compensated for productivity spillovers, which could partially explain the productivity-compensation gap.

[1] Meyerson (2014) in American Prospect writes that "for the vast majority of American workers, the link between their productivity and their compensation no longer exists." The Economist (2013) writes that "unless you are rich, GDP growth is not doing much to raise your income anymore." Smith (2017), in Bloomberg Opinion, puts forward some counterarguments.

[2] White (2015) published the interview with Jan W. Rivkin, an economist and senior associate dean for research at Harvard Business School. He explained three causes: an underlying shift in technology and globalization; under-investment in the commons shared resources that every business needs to be productive like education, pools of skilled labor, vibrant network of supplier, strong infrastructure, basic R&D; and shifts in institutions and politics that weakened labor union's collective bargaining power.

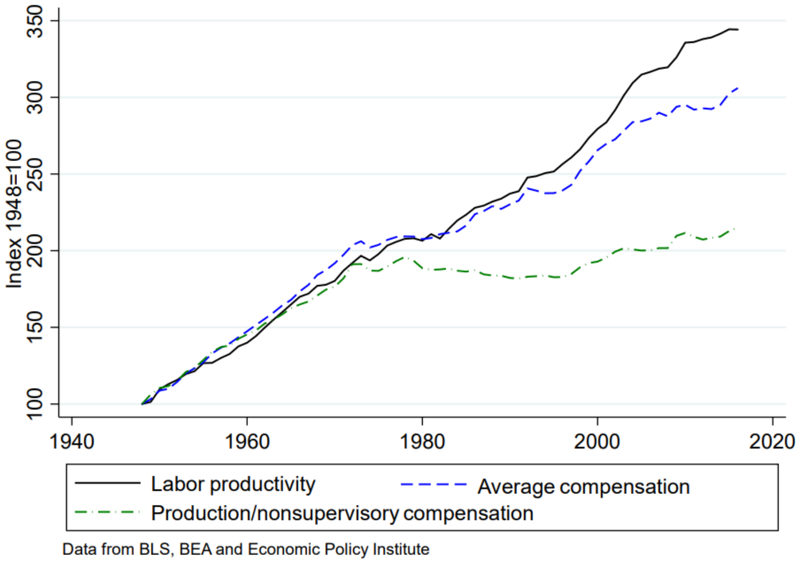
[3] See Fleck et al. (2011); Brill et al. (2017); Sprague (2017).

[4] See Biven et al. (2014); Biven and Mishel (2015); Gould (2018); EPI (2019)

[5] See Mishel et al. (2012)

[6] See Baker (2007), Fleck et al. (2011), Pessoa and Reenen (2013), Pessoa and Van Reenen (2014), Sherk (2013), Biven and Mishel (2015), and Lawrence (2016).

Figure 1: Labor productivity, average compensation, and production/nonsupervisory compensation, 1948–2016



Source: Stansbury and Summers (2017)

The peer-effect literature provides case studies to explain the positive productivity spillover in which firms undercompensate workers (Price, 2017). There are also other examples of productivity spillover. For example, a superstar academic's comments might improve the scholarship of her colleagues, and the untimely or unexpected demise of such an academic lead to a drop of 5-8 percent in the number of her coauthors' publications (Azoulay et al., 2010). Placing the most productive cashiers in full view of the other cashiers results in other cashiers working faster (Mas and Moretti, 2009). Working in teams improves productivity compared to working in isolation (team-production effects) (Falk and Ichino, 2006) A teacher might learn new skills from colleagues by acting as mentees and giving assistance (Papay et al., 2020). Basketball players' selfless passing and picks (where a player blocks a defender, allowing his teammate to get away) raise teammates' performance. Yet players are undervalued by more than five factors relative to their productivity (Arcidiacono et al., 2017). Price (2017) states that productivity spillovers can contribute to team success, although workers are not compensated for them, primarily because these spillovers are difficult to estimate.

We argue that productivity spillovers are relevant to explain the productivity-compensation gap. We hypothesize that productivity spillovers are not necessarily compensated. We account for productivity spillover in two dimensions. First is the spatial dimension, where (we hypothesize) productivity in one state spills over to contiguous states. Second is the trade-network dimension, where (we hypothesize) productivity in one state spills over to trading states. We show that after accounting for states' productivity spillovers, within the industry, to contiguous states or states within their trade network, the productivity-compensation gap narrows significantly in some industries.

The techniques we employ are simple regression, spatial econometrics, and instrumental variables, which we apply to a unique cross-sectional database that comprises state-level industry data on employment, compensation, and gross industrial output for twenty-three industries within all US states for 2012. (See section 2 for more details on IO-Snap software, which we use to retrieve the data, and the data themselves.) We merge this database with the 2012 Community Flow Survey Public Use Microdata file to capture data on gross industrial output and shipment value and flows. Our methodology incorporates spatial econometrics in a spatially lagged X (SLX) model. Additionally, to address endogeneity concerns, we use a standard instrumental-variable approach to investigate whether contiguous states' productivity predicts compensation within a state.

Our primary contribution is to provide some counterarguments on the productivity-compensation gap and provide possible explanations for whether and why these gaps exist in different industries. Previous investigations have not accounted for potential confounding effects. Our paper contributes to the literature by addressing these relationships and developing the idea of peer effects, where one state's productivity affects surrounding states' productivity. We find that the productivity of workers in surrounding states is an essential determinant of labor productivity and, in turn, labor compensation.

Section 2 provides details on data. Section 3 explains our methodology. Section 4 exhibits our results. Finally, in section 5, we discuss our results and conclude.

2 Data

We use IO-Snap[7] software to obtain state-level industry data on employment (in thousands), compensation (in \$1,000s), and gross industrial output (in \$1,000s) for various industries within all fifty states for 2012. We define log labor compensation as the logarithmic transformation of the ratio of total compensation to total employees. The compensation rate is adjusted for state-level regional price parities,[8] which we found in a Bureau of Economic Analysis database. We define log labor productivity as the logarithmic transformation of the ratio of the gross industrial product to total employment.

We collected interstate-trade data from the 2012 Commodity Flow Survey Public Use Microdata File. This database contains data on the origin, destination, shipper NAICS code, and shipment value for approximately 4.5 million shipments (ESMPD, 2012). This study aggregates the microdata to generate industry-specific state-level shipment values for different industries as specified by the NAICS code. We then merge the IO-Snap and Community Flow Survey databases and retain twenty-three industries in our analysis.

3 Methodology

3.1 Productivity-compensation linkage-dislinkage spectrum

To form a base for comparison, we begin the analysis with a log-log regression. We regress the logarithmic transformation of state-level regional-price-parity-adjusted compensation

[7]IO-Snap is a user-friendly graphical user interface software that generates regionalized input-output accounts and coefficients for state and user-customized regional economies (Regional Research Institute, 2020). For this, IO-Snap employs the Randall W. (1998) input-output regionalization method and the Jackson and Court (2015) cross-hauling regionalization method. IO-Snap utilizes the input-output data from US national supply and use tables, available from the Bureau of Economic Analysis and the Bureau of Labor Statistics (Regional Research Institute, 2020). The Regional Research Institute at West Virginia University developed the IO-Snap software.

[8]Regional price parities are regional price levels expressed as a percentage of the overall national price level for a given year. The price levels are determined by the average prices paid by consumers for the mix of goods and services consumed in each region (BEA, 2020).

on the logarithmic transformation of labor productivity, using the following regression:

$$ln(Comp_s) = \alpha + \beta ln(Prod_s) + e_s \tag{1}$$

Here s is the index for states, and $\widehat{\beta} = \frac{dln(Comp_s)}{dln(Prod_s)}$ is the percentage change in compensation associated with a 1 percent change in labor productivity. We conduct separate regressions for each of the industries.

The estimation of β or $\widehat{\beta}$ can shed light on the spectrum from linkage ($\widehat{\beta} = 1$) to dislinkage ($\widehat{\beta} = 0$) of productivity and compensation (Stansbury and Summers, 2017). Exploring this spectrum allows us to better understand middle-income stagnation and the fading American Dream, and it might help us design effective policy solutions.

Dislinkage refers to blockage of the "transmission mechanism from productivity to compensation such that increases in productivity growth do not systematically translate into increases in typical workers compensation" (Stansbury and Summers, 2017). It might not mean a causal link is absent, as orthogonal factors might confound the relationship between productivity and compensation and hence suppress the causal link. These factors include an underlying shift in technology and globalization, underinvestment in the common shared resources that every business needs to be productive (such as education, pools of skilled labor, a vibrant network of suppliers, robust infrastructure, research and development), shifts in institutions and politics that weaken the collective bargaining power of labor unions, globalization, and market power (White, 2015; Stansbury and Summers, 2017).

3.2 Productivity spillover

We estimate the potential linkage or dislinkage by exploring two dimensions. First is the spatial dimension, where we hypothesize that states' industrial productivity spills over to contiguous states. Second is the trade network, where we hypothesize states' industrial productivity spills over to the states they trade with. We analyze both dimensions within each industry.

We argue that spillovers of productivity can be a possible confounding factor, and not accounting for them could lead scholars to underestimate the productivity-compensation gap. LeSage and Pace (2009) state that neglecting any spillover, if any exists, leads to biased and inconsistent estimation because of omitted variable bias.

Spillovers can be local or global. Spillovers to neighboring states are called local spillovers. Spillovers to all states within a trade network are called global spillovers. A local-spillover specification is more plausible within applied regional models (such as ours) than a global-spillover specification (LeSage, 2014). Given the assumption of local spatial-productivity spillover, we develop an SLX model. We assess the model to analyze the industry-specific productivity spillovers.

$$lnComp_s = \alpha + \gamma lnProd_s + \theta \mathbf{W} lnProd_s + e_s \tag{2}$$

Here $\mathbf{W}$ is the row-standardized spatial-contiguity-weight matrix. This matrix identifies whether two states share a border. γ and θ are the direct and indirect effects of productivity on compensation. The sum of the two is the total impact of a 1 percent change in productivity on compensation.

We then test whether productivity has direct and indirect effects on compensation within trading states for each industry. To do so, we run similar estimates as equation 2 but use the row-standardized shipment-value-weighted trade-network matrix $\mathbf{N}$.

$$lnComp_s = \alpha + \gamma lnProd_s + \theta \mathbf{N} lnProd_s + e_s \tag{3}$$

Here the elements of $\mathbf{N}$ are individually row-standardized bilateral-trade-flow or shipment-flow values from exporter state i to importer state j and given as $\widehat{n}_{ij,i\neq j} = \frac{n_{ij,i\neq j}}{\sum_j n_{ij,i\neq j}}$. The variable $n_{ij,i\neq j}$ represents bilateral-trade-flow or shipment-flow values from exporter state i to importer state j—that is, trade volume. We assume that this (between state) trade volume indicates the strength of trade networks. We define diagonal elements of $\mathbf{N}$ as zero or $n_{ij,i=j} = 0$. Chen and Dall'erba (2019) implement a similar strategy to model the US interstate trade.

3.3 Endogeneity

We apply instrumental-variable techniques to address for endogeneity. Following Halleck Vega and Elhorst (2015), we use spatial lag $\mathbf{W}lnProd_s$ as an instrument for $lnProd_s$, and we undertake a two-stage least square (2SLS) estimation.

$$\begin{aligned} lnProd_s &= \alpha_0 + \delta \mathbf{W} lnProd_s + e_s \\ lnComp_s &= \alpha_1 + \phi \widehat{lnProd}_s + \epsilon_s \end{aligned} \tag{4}$$

$\mathbf{W}lnProd_s$ can be used as an instrument for $lnProd_s$ and does not need to be instrumented if it is exogenous (Halleck Vega and Elhorst, 2015). $\mathbf{W}lnProd_s$ represents how the spatial lag of productivity affect itself, while ϕ identifies the impact of productivity on compensation after accounting for potential endogeneity in productivity.

Using a similar logical framework, we implement a spatial lag of row-standardized shipment-value trade-network matrix $\mathbf{W}lnProd_s$ as an instrument for $lnProd_s$ in the 2SLS framework.

$$\begin{aligned} lnProd_s &= \alpha_0 + \delta \mathbf{N} lnProd_s + e_s \\ lnComp_s &= \alpha_1 + \phi \widehat{lnProd}_s + \epsilon_s \end{aligned} \tag{5}$$

4 Results

4.1 Summary statistics

Figure 2 illustrates the twenty-three industries studied. The boxplots for industries are ordered by state-level median values. Figure 2, panel (a) depicts a boxplot of the logarithmic transformation of compensation (adjusted for state-level regional price parities in \$1,000s per employee). Figure 2, panel (b) contains a series of boxplots of logarithmic transformation of labor productivity. We label states as outliers if the logarithmic transformation of compensation rate and labor productivity is above or below a 1.5 interquartile range of the mean. We can see that compensation rates and productivity vary drastically across industries.

4.2 Row-standardized geographic-weighted matrix W

In table 1, we present results of a simple regression (OLS) in column (1). This estimation is the relationship that people typically cite when discussing the productivity-compensation gap. We use this naive model as a baseline for comparison. The OLS is followed by SLX-model estimates, in columns (2–5), and instrumental variable (IV) estimates, in columns (6–8). This table implements the row-standardized geographic-weight-matrix methodology outlined in equation 2 for the twenty-three industries. We arrange the results in descending order based on column (5), which shows the difference between the total impact estimated by the SLX model in column (4) and the OLS elasticity estimates in column (1).

The OLS estimates, given as $\widehat{\beta}$, in table 1, column (1) exhibits the productivity-compensation elasticity. These estimates are positive, confirming the theoretically predicted positive relationship between productivity and compensation. However, estimates in column (1) range from 0.154 (for motor vehicle and parts dealers) to 0.767 (for management of companies and enterprises), suggesting potential productivity-compensation dislinkages suggesting that $0 < \widehat{\beta} < 1$.

As noted, Stansbury and Summers (2017) argue that “other factors orthogonal to productivity have been acting to suppress typical compensation even as productivity growth has been acting to raise it.” Following LeSage and Pace (2009), we attempt to account for spillover dependence using a row-standardized geographic-weight matrix. Following LeSage (2014) and Halleck Vega and Elhorst (2015), we assume that a local-spillover specification is more plausible than a global-spillover specification and we implement the SLX model to test whether these estimates shift toward $\widehat{\beta} \longrightarrow 1$ or less-dislinkages. Table

1, columns (2), (3), and (4) provide estimates of $\widehat{\gamma}$, $\widehat{\theta}$, and $\widehat{\gamma}+\widehat{\theta}$, which are the direct, indirect, and total impact of a state's productivity spillover on its neighbor's compensation rate, respectively.

In Table 1, column (3), we observe several significant positive indirect effects of contiguous-state productivity affecting the compensation rates. We observe patterns of positive indirect effects in many industries that require high-use of physical labor—for example, mining, except oil and gas; fabricated metal products; and machinery. It is intuitive that the largest effect is in mining, as mining is dependent on the location of natural resources, which are generally found within a region consisting of multiple states. The estimates of total impact, in column (4), are larger than the OLS estimates, in column (1), implying $(\widehat{\gamma}+\widehat{\theta}) > \widehat{\beta}$, which corroborate our hypothesis that states' industrial productivity spills over to contiguous states. We find such results for all industries except for petroleum and coal products, management of companies and enterprises, and wholesale trade. It is intuitive that management and wholesale trade have low indirect spillovers, as these industries are such that when a firm is incredibly successful, there are less likely to be competitors within those industries nearby. The set of industry effects found using the SLX model are essential for policy makers because they show the interconnection of industry compensation is correlated with the nature of the industry and productivity across contiguous borders.

We also implement an IV strategy to test for potential endogeneity. Following the logic of Halleck Vega and Elhorst (2015), $\mathbf{W}lnProd_s$ can be used as an instrument for $lnProd_s$. However, in almost all cases, we find $\mathbf{W}lnProd_s$ and $lnProd_s$ are uncorrelated (see table 1, column (6) for this, and see column (8) for the Wald test of exogeneity), leading to the conclusion that the estimates presented in column (7) are more likely to be biased. These results do not incorporate corrections for potential endogeneity, but $\mathbf{W}lnProd_s$ and $lnProd_s$ are likely to be uncorrelated. Therefore, the use of SLX is an empirically adequate model choice, as the SLX model can include both $\mathbf{W}lnProd_s$ and $lnProd_s$.

4.3 Row-standardized shipment-value trade network N

The structure of table 2 is the same as that of table 1. However, instead of a row-standardized geographic-weighted matrix $\mathbf{W}$, we employ SLX and IV methods using row-standardized bilateral-trade-flow or shipment-flow values from exporter state i to importer state j. Our results are based on trading relationships of states, within various industries, rather than across state borders. We define the row-standardized shipment-value-weighted trade-network matrix as $\mathbf{N}$.

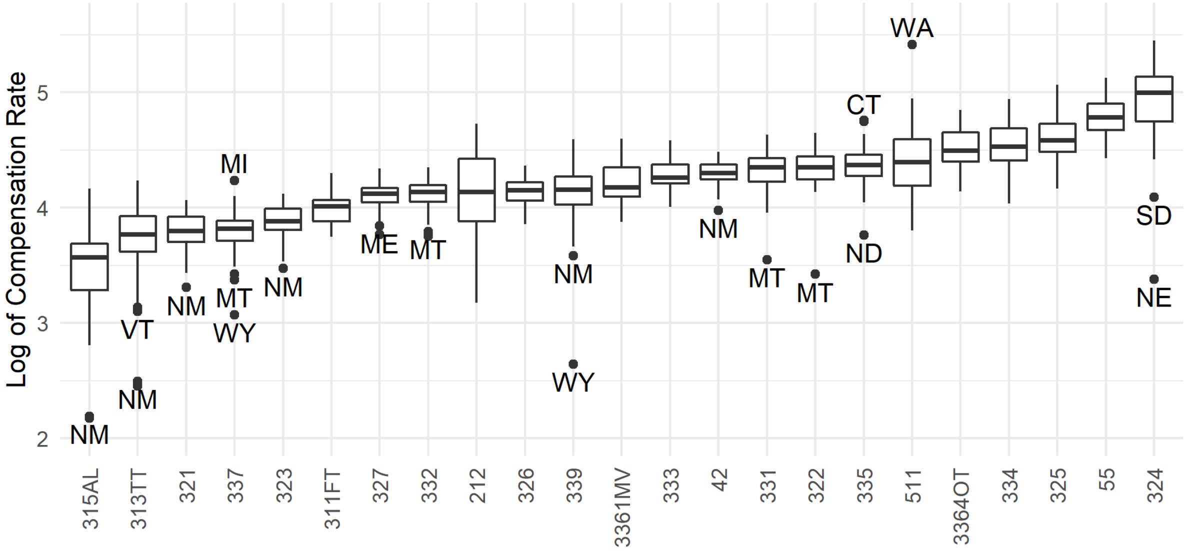
The OLS estimates of table 2 are the same as those of table 1, and they still represent the naive relationship between productivity and compensation. We arrange the results in this table 2 in descending order based on column (5), which shows the difference between total impact estimated by the SLX model in column (4) and OLS elasticity estimates in column (1). We do not provide the SLX models for petroleum and coal products, paper products, and management of companies and enterprises. This is because one or more rows of $\mathbf{N}$ sum to zero or one or more states do not trade in these industries, which violates the network matrix's properties.

Incorporating the idea that productivity spillover may occur across trading states, we notice that some industries have large, indirect effects of trade-network productivity on compensation. The industries with the most considerable network effects are the ones that have heavy trade in durable goods—for example, printing and related support activities, furniture and related products, and plastics and rubber products.

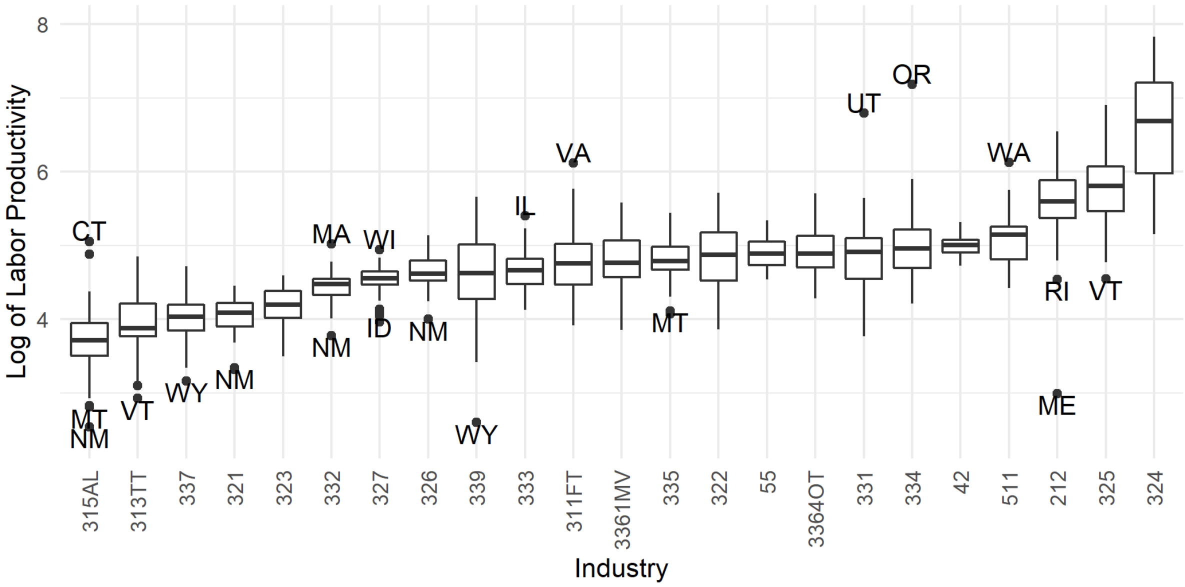
We find the estimates of total impacts are more considerable than OLS estimates—or $(\widehat{\gamma} + \widehat{\theta}) > \widehat{\beta}$—again corroborating our hypothesis that productivity spillover affects the relationship between productivity and compensation. This is true for all the industries except electrical equipment, appliances, and components; computer and electronic products; and wholesale trade. The total effects of the SLX model for printing and related support activities and furniture and associated products are larger than 1. Table 2, columns (6–8) provides IV estimates; however, these estimates fail the Wald test of exogeneity, as the $F-stat < 10$ (Staiger and Stock, 1997) leads to inconclusive estimates.

Chen and Dall'erba (2019) use physical quantities of interstate shipments to avoid a confounding effect. Their approach is similar to ours; hence, failing to identify $\mathbf{N}lnProd_s$ as an instrument for $lnProd_s$ probably does not indicate a lack of identification. Rather, the lack of an instrumental relationship indicates the adequacy of the use of the SLX model as it include both $\mathbf{N}lnProd_s$ and $lnProd_s$.

Figure 2: Box plots



(a) Log of compensation rates adjusted for state-level regional price parities



(b) Log of labor productivity

Notes: Mining, except oil and gas (212), food and beverage and tobacco products (311), textile mills and textile product mills (313), apparel and leather and allied products (315), wood products (321), paper products (322), printing and related support activities (323), petroleum and coal products (324), chemical products (325), plastics and rubber products (326), nonmetallic mineral products (327), primary metals (331), fabricated metal products (332), machinery (333), computer and electronic products (334), electrical equipment, appliances, and components (335), motor vehicles, bodies and trailers, and parts (3361), other transportation equipment (3364), furniture and related products (337), miscellaneous manufacturing (339), wholesale trade (42), publishing industries, except internet (includes software) (511), and management of companies and enterprises (55). Enclosed numbers in parentheses are NAICS codes.

Table 1: OLS, SLX, and IV results with row-standardized geographic-weighted matrix **W**

			SLX				IV		
Industry	NAICS	**OLS** $\widehat{\beta}$ (1)	Direct $\widehat{\gamma}$ (2)	Indirect $\widehat{\theta}$ (3)	Total $\widehat{\gamma}+\widehat{\theta}$ (4)	Difference $\widehat{\gamma}+\widehat{\theta}-\widehat{\beta}$ (5)	First-stage $\widehat{\delta}$ (6)	Second-stage $\widehat{\phi}$ (7)	$F-stat$ (8)
Mining, except oil and gas	212	0.446*** [0.070]	0.402*** [0.061]	0.486*** [0.118]	0.888*** [0.123]	0.442	0.023*** [0.008]	0.836*** [0.228]	8.562***
Fabricated metal products	332	0.431*** [0.055]	0.430*** [0.045]	0.364*** [0.072]	0.793*** [0.085]	0.362	0.003 [0.004]	0.720 [0.783]	0.369
Machinery	333	0.284*** [0.053]	0.289*** [0.051]	0.282** [0.122]	0.571*** [0.134]	0.287	-0.001 [0.005]	2.460 [22.296]	0.010
Printing and related support activities	511	0.450*** [0.055]	0.413*** [0.051]	0.309*** [0.091]	0.722*** [0.094]	0.272	0.008 [0.005]	0.327 [0.293]	1.898
Apparel and leather and allied products	315	0.723*** [0.071]	0.637*** [0.075]	0.333** [0.130]	0.971*** [0.118]	0.248	-0.007 [0.012]	0.764 [0.872]	0.310
Primary metals	323	0.241*** [0.042]	0.236*** [0.039]	0.217** [0.081]	0.453*** [0.088]	0.212	0.002 [0.009]	0.875 [3.138]	0.049
Furniture and related products	337	0.469*** [0.061]	0.428*** [0.062]	0.251** [0.118]	0.679*** [0.115]	0.210	-0.001 [0.007]	-1.140 [8.701]	0.037
Motor vehicles, bodies and trailers, and parts	327	0.290*** [0.052]	0.260*** [0.052]	0.232** [0.105]	0.491*** [0.104]	0.201	0.004 [0.007]	0.853 [1.183]	0.317
Nonmetallic mineral products	3364	0.357*** [0.066]	0.371*** [0.067]	0.168 [0.133]	0.539*** [0.159]	0.182	0.000 [0.004]	12.224 [161.141]	0.005
Plastics and rubber products	331	0.331*** [0.061]	0.284*** [0.063]	0.229* [0.114]	0.513*** [0.109]	0.182	-0.007 [0.004]	0.033 [0.341]	2.356
Electrical equipment, appliances, and components	335	0.425*** [0.058]	0.409*** [0.059]	0.191 [0.136]	0.600*** [0.137]	0.175	0.007 [0.006]	0.004 [0.458]	1.640
Wood products	321	0.493*** [0.065]	0.418*** [0.079]	0.245 [0.149]	0.663*** [0.121]	0.170	-0.012** [0.005]	0.314 [0.217]	5.334**
Textile mills and textile product mills	313	0.555*** [0.103]	0.519*** [0.109]	0.175 [0.176]	0.693*** [0.173]	0.138	-0.001 [0.010]	5.823 [41.074]	0.017
Chemical products	325	0.254*** [0.049]	0.245*** [0.049]	0.145 [0.096]	0.390*** [0.102]	0.136	0.006 [0.008]	-0.055 [0.548]	0.697
Motor vehicle and parts dealers	3361	0.154*** [0.036]	0.160*** [0.036]	0.100 [0.068]	0.260*** [0.081]	0.106	-0.003 [0.004]	0.464 [0.597]	0.440
Miscellaneous manufacturing	339	0.476*** [0.039]	0.472*** [0.039]	0.083 [0.077]	0.556*** [0.083]	0.080	0.001 [0.012]	-0.382 [17.001]	0.003
Paper products	324	0.318*** [0.054]	0.295*** [0.058]	0.100 [0.094]	0.395*** [0.091]	0.077	0.005 [0.007]	0.037 [0.612]	0.578
Other transportation equipment	322	0.317*** [0.067]	0.323*** [0.068]	0.066 [0.143]	0.389** [0.170]	0.072	-0.003 [0.006]	-0.730 [2.346]	0.237
Food and beverage and tobacco products	311	0.205*** [0.038]	0.203*** [0.039]	0.016 [0.070]	0.219*** [0.072]	0.014	0.009 [0.008]	0.817 [0.621]	1.171
Computer and electronic products	334	0.331*** [0.044]	0.330*** [0.048]	0.007 [0.076]	0.337*** [0.073]	0.006	0.006 [0.009]	-0.197 [0.919]	0.442
Petroleum and coal products	326	0.268*** [0.056]	0.269*** [0.057]	-0.004 [0.103]	0.264** [0.111]	-0.004	-0.004 [0.010]	0.935 [1.915]	0.161
Management of companies and enterprises	55	0.767*** [0.042]	0.794*** [0.045]	-0.116 [0.074]	0.678*** [0.071]	-0.089	0.001 [0.004]	3.338 [7.651]	0.115
Wholesale trade	42	0.659*** [0.088]	0.672*** [0.090]	-0.108 [0.155]	0.564*** [0.163]	-0.095	-0.003 [0.002]	0.108 [0.597]	1.928

Table 2: OLS, SLX, and IV results with row-standardized trade-flow network matrix **N**

Industry	NAICS	**OLS** $\widehat{\beta}$ (1)	**SLX** Direct $\widehat{\gamma}$ (2)	Indirect $\widehat{\theta}$ (3)	Total $\widehat{\gamma}+\widehat{\theta}$ (4)	Difference $\widehat{\gamma}+\widehat{\theta}-\widehat{\beta}$ (5)	**IV** First-stage $\widehat{\delta}$ (6)	Second-stage $\widehat{\phi}$ (7)	$F-stat$ (8)
Printing and related support activities	323	0.450*** [0.055]	0.412*** [0.048]	0.992*** [0.23]	1.404*** [0.227]	0.954	0.885 [0.697]	1.533 [0.918]	1.612
Furniture and related products	337	0.469*** [0.061]	0.445*** [0.057]	0.718*** [0.243]	1.163*** [0.241]	0.694	0.599 [0.619]	1.644 [1.301]	0.936
Plastics and rubber products	326	0.331*** [0.061]	0.297*** [0.059]	0.718** [0.273]	1.015*** [0.266]	0.684	1.020 [0.667]	1.001* [0.528]	2.335
Mining, except oil and gas	212	0.446*** [0.070]	0.388*** [0.063]	0.632*** [0.166]	1.020*** [0.162]	0.574	0.633* [0.377]	1.387** [0.645]	2.825*
Nonmetallic mineral products	327	0.357*** [0.066]	0.360*** [0.065]	0.508* [0.283]	0.868*** [0.292]	0.511	-0.114 [0.644]	-4.081 [25.132]	0.032
Motor vehicles, bodies and trailers, and parts	3361	0.290*** [0.052]	0.252*** [0.052]	0.406** [0.168]	0.658*** [0.160]	0.368	0.985** [0.456]	0.664** [0.250]	4.661**
Primary metals	331	0.241*** [0.042]	0.215*** [0.041]	0.392** [0.169]	0.607*** [0.163]	0.366	1.114* [0.582]	0.567** [0.234]	3.667*
Fabricated metal products	332	0.431*** [0.055]	0.416*** [0.056]	0.318 [0.232]	0.734*** [0.228]	0.303	0.813 [0.599]	0.807** [0.399]	1.841
Textile mills and textile product mills	313	0.555*** [0.103]	0.537*** [0.106]	0.258 [0.360]	0.795** [0.351]	0.240	0.784 [0.487]	0.867* [0.487]	2.586
Machinery	333	0.284*** [0.053]	0.279*** [0.053]	0.201 [0.154]	0.481*** [0.160]	0.197	0.178 [0.430]	1.411 [2.864]	0.171
Chemical products	325	0.254*** [0.049]	0.264*** [0.050]	0.177 [0.160]	0.441** [0.176]	0.187	-0.572 [0.466]	-0.046 [0.371]	1.506
Wood products	321	0.493*** [0.065]	0.475*** [0.069]	0.170 [0.220]	0.645*** [0.207]	0.152	1.095** [0.439]	0.630*** [0.197]	6.211**
Apparel and leather and allied products	315	0.723*** [0.071]	0.714*** [0.073]	0.159 [0.229]	0.872*** [0.227]	0.149	0.591 [0.457]	0.982** [0.430]	1.676
Other transportation equipment	3364	0.317*** [0.067]	0.319*** [0.067]	0.096 [0.180]	0.416** [0.197]	0.099	-0.205 [0.393]	-0.150 [1.250]	0.272
Food and beverage and tobacco products	311	0.205*** [0.038]	0.195*** [0.041]	0.105 [0.159]	0.300** [0.149]	0.095	1.433*** [0.532]	0.268** [0.106]	7.264***
Petroleum and coal products	324	0.268*** [0.056]	–	–	–	–	0.188 [0.230]	0.610 [0.623]	0.667
Paper products	322	0.318*** [0.054]	–	–	–	–	1.033 [0.692]	0.353 [0.220]	2.231
Management of companies and enterprises	55	0.767*** [0.042]	–	–	–	–	0.513 [0.316]	0.432 [0.286]	2.636
Publishing industries, except internet (includes software)	511	0.847*** [0.044]	0.839*** [0.044]	-0.153 [0.123]	0.686*** [0.137]	-0.161	-0.401 [0.405]	1.221** [0.489]	0.981
Miscellaneous manufacturing	339	0.476*** [0.039]	0.467*** [0.038]	-0.215* [0.112]	0.252** [0.123]	-0.224	-0.364 [0.430]	1.058 [0.759]	0.717
Electrical equipment, appliances, and components	335	0.425*** [0.058]	0.428*** [0.058]	-0.254 [0.232]	0.174 [0.236]	-0.251	0.178 [0.588]	-0.998 [4.879]	0.092
Computer and electronic products	334	0.331*** [0.044]	0.350*** [0.041]	-0.289*** [0.096]	0.061 [0.099]	-0.270	0.347 [0.337]	-0.484 [0.855]	1.058
Wholesale trade	42	0.659*** [0.088]	0.686*** [0.089]	-0.494 [0.334]	0.192 [0.327]	-0.467	0.774 [0.543]	0.048 [0.612]	2.036

Notes: The SLX models for industries such as petroleum and coal products, paper products, and management of companies and enterprises are infeasible to estimate. This occurred because one or more rows of **N** sum to zero, or one or more states do not trade in these industries.

5 Conclusion

The purpose of this study is to investigate whether the productivity-compensation gap can be partially explained through productivity spillovers. We analyze two channels for productivity spillovers. First is the effect of productivity spillover between contiguous states. Second is the effect of productivity spillovers within trade networks. We use novel state-level industry data gleaned through IO-Snap and incorporated interstate-trade data from the 2012 Commodity Flow Survey Public Use Microdata file. These data allow us to take a rare look at interstate trade networks at the state level.

Using an SLX framework, we find that the productivity-compensation gap shrink when we consider productivity spillover. Many results are intuitive. For example, industries that require regionwide resources or rely on physical labor are affected by productivity across a state's borders, while industries that are more independent or deter competition in close geographical proximity have much smaller reductions in the productivity-compensation gap.

When considering trade networks' effect, we find that industries that produce durable goods have larger productivity-spillover effects on compensation. When we incorporate trade relationships, we find that the productivity-compensation gaps for most industries narrow compared to the naive OLS model in all but a few industries (those related to technology or distribution).

These results are essential for designing policy. Depending on the industry, raising wages or moving to a new region may or may not have indirect effects on the surrounding states and states within the trade network. For example, increasing productivity in the mining industry may affect the compensation rates in both the surrounding states and trading states. The economic-impact studies that are related to wage changes and minimum wage should incorporate a robust analysis of potential indirect impacts. On the other hand, some industries, such as wholesale trade, improving productivity and are unlikely to have indirect spillover effects on industries competing in surrounding states.

This interplay of compensation can also help firms predict changes in future compensation patterns.

We believe our study contributes to the productivity-compensation literature by providing a unique perspective on the interplay of compensation and productivity along both geographic and trade-network dimensions. Our research is limited, however, as we only have one year of available data and therefore cannot analyze changes over time.

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