Incentivizing the Missing Middle: The role of economic development policy

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The rise in inequality in the U.S. is, in part, attributable to the shrinking middle class; yet, this phenomenon is remarkably heterogeneous across places. State and local policy-makers use economic development incentives to promote local economic growth, and, presumably, provide employment opportunities. However, incentives may have unintended consequences. We combine detailed industry-level detail on incentives with proprietary county-level industry employment data and two methods for defining to middle class industries in instrumental variable regressions to explore how differential economic development policies affect middle class jobs. We find evidence that incentivizing creative-class and high-wage industries may be contributing to the hollowing out of the middle class; that targeting working and middle-class industries alleviates this trend without hurting employment in other industries; and that raising net taxes or reducing incentives on creative-class and high-wage industries could help increase working and middle-class employment without affecting employment in other industries.

Introduction

The middle class in the United States has been falling behind, while the number of people at high-income levels and low-income levels has been growing (Pew Research Center 2015; 2016).[1] This has contributed to increasing inequality, as noted in well-known studies by Chetty et al. (2014) and Piketty (2013). While some inequality can help drive growth, recent research suggests that current levels of inequality in the U.S. may be suppressing economic growth (Partridge and Weinstein 2013; Atems 2013). For reasons that are not yet fully understood, this phenomenon is more pronounced in some locations than others. Some scholars suggest that the geographic variation in industry composition plays an important role (Florida 2017).

Recent research indicates that as opportunities for middle-income workers decline, people are more likely to drop out of the workforce. In the past, occupations in industries such as manufacturing and mining provided relatively high-incomes for those with lower levels of education. However, employment in some of these industries has been on the decline. Consistent with studies of the overall U.S. labor force (such as Weingarden 2017), Stephens and Deskins (2018) find that places with higher unemployment also have lower rates of labor force participation. At the same time, places with higher percentages of the population with less than a high-school degree and places with a higher percentage of working-age (between 25 and 54) males have lower levels of labor force participation – the very demographics that have historically worked in working-class occupations.

Economic development incentives are the primary policy tool for promoting local economic growth and, presumably, providing opportunities for work. However, incentives may have unintended consequences and heterogeneous effects across industries (Patrick, Ross, and Stephens 2017). For example, Harger, Ross, and Stephens (2018) show that targeted incentives may help some industries while hurting others. Patrick (2016) demonstrates that capital subsidies induce changes in firm behaviors and local industry composition that limits job creation associated with such incentives. When viewed through the lens of recent trends in incentives and labor force participation, these results raise a question as to whether these incentive packages are helping minimize the hollowing out or contributing to its increase.

We explore the impact of incentives on the middle class by exploiting the industry-level detail on incentives across locations from the Panel Database on Incentives and Taxes (PDIT) combined with county-level industry employment and establishment data from the WholeData Establishment

and Employment Database. We define middle class industries in two ways. First, using classifications developed by the Martin Prosperity Institute as well as the U.S. Bureau of Labor Statistics Industry-Occupation Matrix[2], we differentiate between creative-class, service-class and working-class industries based on occupations. We also use data on average wages by industry from EMSI Inc. and combine this with definitions of middle class based on average industry-level wages to define low-wage, middle-wage, and high-wage industries. We exploit the panel nature of the data and the relative intensity of incentives across industries to understand how incentives may be either attenuating or contributing to the disappearing middle and how this may vary across space.

Using an instrumental variables approach to account for the endogeneity of economic development incentives, we estimate how incentives on various industry-classes affect employment in four-digit NAICS industries at the county level in 47 cities for which city-level incentive data are available through the PDIT and do so using our both of our typologies for classifying industries. Our results suggest that incentives can affect the distribution of employment across classes. Importantly, it appears that incentivizing high-wage or creative-class industries can hurt middle class jobs (defined as those in middle-wage or working-class industries) which may be contributing to the hollowing out of the middle class. At the same time, there appears to be no downside to reducing those incentives on employment in any type of industry. As we will discuss later, this has important economic development policy implications.

In what follows, we review the relevant previous literature, and provide an overview of our data and discuss trends in employment and incentives. We then present our estimation approach and discuss our results. Finally, we conclude with a discussion about the policy implications.

Literature Review

State and local policy-makers use a wide variety of tools to promote economic development, particularly job growth. Economic development policy may take the form of general reductions in business tax rates, regulatory policy, infrastructure and educational investments as well as targeted tax breaks and financial incentives. While there is an extensive literature studying all these forms of economic development policy, the analysis in this paper is most closely related to the research on targeted tax breaks and financial incentives, such as property tax abatements, job creation tax credits, grants, etc. We refer to these collectively as economic development incentives.

Despite decades of research on the relationship between economic development incentives and jobs, there remains a lack of consensus on its effectiveness (Bartik and Erickcek 2014) and there exist studies reporting positive, negative, and null effects. As Bartik (2018) describes in detail, a number of the differences in results can be linked to biases in the estimating strategies. However, even focusing on those studies with more credible research designs and no obvious direction of bias, there are still a range of estimated effects. For example, Donegan, Lester, and Lowe (2018) compare job creation in establishments that receive incentives with matched establishments that do not receive incentives and find that the average incentivized establishment does not create more jobs (perhaps even creates fewer jobs) than its matched counterfactuals. Similarly, Patrick (2014a) finds that increasing the availability of non-tax capital subsidies is not associated with county-level job creation. On the other hand, Bartik and Hollenbeck (2012) analyze the effect of research and development tax credits using microdata and find that the tax credits do increase jobs (albeit at a high cost). Chirinko and Wilson (2016) and Neumark and Grijalva (2017) also find positive job creation caused by job creation tax credits. Interestingly, the latter paper also finds that these credits generate much more hiring than net employment change.

Within these more reliable studies, differences in results may also be attributable to the different types of incentives being analyzed or the units of analysis. For example, firm-level estimates may vary from county- or state-level analysis because the former analyzes the effects on recipients without considering any general equilibrium effects. Different geographic and industrial scopes of the analysis units also illustrate different positive and negative externalities associated with economic development policies. There is a nascent, but growing, body of literature documenting the heterogeneous effects of economic development policies across industries and locations and providing evidence of unintended consequences associated with these policies.

Hanson and Rohlin (2011) first put forth the idea of heterogeneous effects and unintended consequences of economic development with their analysis of the federal Empowerment Zone labor tax credit. Their results indicate that the program differentially attracts more labor-intensive businesses at the expense of capital-intensive businesses. Patrick (2016) builds upon their work to demonstrate how capital subsidies induce capital-labor substitution within establishments, shift local industry-mix toward capital-intensive industries through their effect on land values, and therefore decrease employment density.

Freedman (2015) and Harger and Ross (2016) also demonstrate how industry-targeted economic development incentives can have unintended consequences. These papers find that the New Markets Tax Credit (NMTC) program, which specifically targets industries such as manufacturing and retail, was successful at attracting more businesses in these industries, but also increased sorting across industries in eligible versus ineligible industries (Patrick, Ross, and Stephens 2017). Harger, Ross, and Stephens (2015) also document sorting across industries associated with the NMTC program and provide evidence that this sorting is not attributable to accelerating firm deaths.

The analysis of how state taxes affect high-wage employment in Fatehin and Sjoquist (2018) finds differential sorting across states by wage classes in response to overall per capita taxes – suggesting the potential for tax policies to influence the distribution of jobs classes without directly tying it to economic development policies or business establishments. Taken together, these studies suggest that economic development incentives, particularly targeted economic development incentives, may have very different general equilibrium, industry-specific, and firm-specific effects. To date, this burgeoning literature on the heterogeneous effects of economic development policies has yet to explore how heterogeneous economic development policies across industries affect the distribution of industries belonging to different occupational and wage classes. Yet, rising income inequality, driven in large part by growth in the tails of the income distribution and a decline in the middle-class, is one of the most important issues facing policy-makers today. The research herein takes the first step towards filling that gap by examining the relationship between spatial variation in economic development policy across industries and spatial variation in employment changes by class.

Recent work on income inequality in the U.S. documents substantial variation in inequality across space that has increased over time (Baum-Snow and Pavan 2013; Moretti 2013). Focusing specifically on the variation in the share of middle-class residents (defined by income) in U.S. metropolitan areas, Berube (2018) documents both the considerable variation across cities and significant variation in the changes in that share. The decline of middle-income, and rise of low- and high-income, jobs has been linked to skill-biased technology change, metropolitan size, agglomeration-biased technological change, and changes in industry composition, among other causes (Florida and Mellander 2016; Baum-Snow, Freedman, and Pavan 2018). Foote and Ryan (2015) argue that the trends in labor market polarization are driven by losses in middle-skill occupations, particularly during the Great Recession, and increases in low- and high-skill occupations. Similarly, Autor (2019) asserts that the polarization in wage inequality and job growth

is really about changes in occupations. Using the Martin Prosperity Institute occupational class typology, Florida, Mellander, and King (2017) document significant variation across metropolitan areas in relative shares of jobs in different occupational classes, which Florida (2017) links to variation in industry composition across locations. The research herein therefore looks at both industries classified by wage and industries classified by occupational class to understand the extent to which economic development policy is exacerbating or attenuating the geographic variation in inequality.

Data

We draw from several primary data sources for this research.

Class Typologies

Our first task is to define "middle class" industries. We take two approaches to operationalizing middle class industries based upon the existing literature on spatial variation in inequality. The first approach classifies industries based upon their occupational composition, while the second approach classifies industries based upon mean wages in the industry.

Occupation-based industry typology

The Martin Prosperity Institute at the University of Toronto has developed an occupation-based class typology that differentiates occupational classes by the type of work performed. The Martin Prosperity Institute (MPI) provided us with an occupational typology that classifies each occupational group of the American Community Survey's (ACS) occupation codes (OCC) into one of four classes: "creative", "working", "service", and "agriculture". Creative class occupations are those occupations that require higher levels of cognitive and problem-solving skills, including: computer, life, and social scientists; mathematicians and engineers; professional and knowledge occupations; art and design occupations; entertainment. Working class occupations are characterized by routine manual skills, such as construction, production, and material moving occupations. Service class occupations are occupations characterized by routine service skills, such as food preparation and serving, personal care services, administrative support, healthcare support, social services.

In order to use the occupational typology to classify industries, we first concatenate all available U.S. Bureau of Labor Statistics Industry-Occupation Matrices. We use the MPI typology to assign

5

each occupation in the Industry-Occupation matrix to one of the four aforementioned classes based on its OCC code. We then calculate the percent composition of each industry by MPI typology class using the percent composition of an industry by each occupation in the industry-occupation matrix. We place industries in a MPI class if the highest percentage of jobs is in that class. For purposes of our analysis, we exclude industries in the agricultural class.

Wage-based industry typology

We also consider a definition of middle-class industries based on wages. Following guidance from work by the Pew Research Center (2015; 2016) and using American Community Survey (ACS) data for 2016, we calculate a range in 2016 dollars for middle-class incomes. To do so, for each of 41 household income range categories, we assign a value. For those at the top and bottom (less than $5,000 and $200,000 and above) we assign $5,000 and $200,000, respectively. For the others, we choose the middle of the range. We then scale the income by the size of the average household in that range, following the guidance from the Pew Research Center.[3] We do so by making the following adjustment:

Adjusted household income = Household income / (Household size)^0.5

In other words, the household income for each category is divided by average household size in that income category, exponentiated to 0.5. Together, adjusting for household size but scaling it, accounts both for the fact that $40,000 goes farther for a one-person household than a four-person household and that there are economies of scale in terms of costs. In other words, a household does not necessarily need twice the amount of money if there are two people rather than one.

Once we adjust the household income in each income category to account for size, we then divide by the mean number of earners in that category to get the average individual income in each category.

Finally, to get the median income across all categories, we multiply the individual income for each category by the share of total earners in that category and sum up over all the categories. This produces a middle income of $30,727. Since the middle-class has been defined as between two-thirds the median income and twice the median income, we then get calculate this range. Thus, the range for middle-class **individual** incomes (in 2016 dollars) is defined as between $20,485 and $61,455.

We then draw upon data from EMSI, Inc. which contains unsuppressed detailed county-level data on industry employment and wages at the four-digit NAICS industry code level from 2001 to 2016. We adjust previous years' incomes into 2016 dollars by using the consumer price index (CPI) and then calculate an average wage for each four-digit industry. We then assign each industry into one of three classes based on average wages – low wage, middle wage, or high wage; with middle-wage industries' average wages being those within the range calculated above and low-class and high-class industries below and above this range, respectively. The Brookings Institution has defined the middle class as constituting 60 percent of households (Reeves and Guyot 2018). We use this to truth our definition of middle class and find that about 60 percent of jobs are classified as middle class.

Comparing Typologies

Our initial thought was that middle class would be defined by middle-wage and working-class industries and that these two classifications would be approximately equivalent. However, we find that is not the case. Comparing four-digit NAICS industries, only 36.8% of industries that are classified as working class are also classified as middle wage. This may be due to the fact that middle wage may not be tied to specific occupations but to what people earn, and many working-class occupations may pay less or more than middle-wage incomes. For example, many administrative and support service industries are classified as middle wage based upon the wage classifications and service class based upon the occupational classifications, such as the skilled nursing facility industry (NAICS code 6231). Industries where workers may need specialized training, on the other hand, may be classified as working class due to their manual labor, but may pay their employees more than middle wages, and be classified in the high-wage class. This includes the oil and natural gas pipeline industries (NAICS codes 4861, 4862, and 4869) as well as chemical manufacturing (NACIS code 3251). At the same time, many jobs that require higher cognitive thinking or problem solving skills, may not pay high wages. Examples include a number of service industries that are classified as middle wage, but also as creative class; including the architecture industry (NAICS code 5413), the performing arts (NAICS code 7111), and community colleges (NAICS code 6113).

Measuring Economic Development Policy

We take advantage of a new data set developed by researchers at the W.E. Upjohn Institute for Employment Research to measure economic development incentives – the Panel Database on Incentives and Taxes (PDIT). The PDIT provides rich detail on the taxes paid net of tax and financial incentives across 45 industries (comprising over 90% of private sector employment and wages) in 47 cities (comprising 92% of U.S. private sector Gross Domestic Product in 2013) in 33 states from 1990 through 2015 (Bartik 2017). The data combine information on state and local taxes and economic development programs as well as industry specific information on sales, capital, etc. For example, there is information on the state and local property tax rates as well information on the typical property tax abatements (if any) granted to establishments in particular industries.

These data are then used to simulate the net tax rate for a typical new firm in each covered industry over a 20 year period. First, The PDIT simulates the state and local tax liability before economic development incentives for a new firm in each year from creation for 20 years, accounting for (accelerated) depreciation and other features of state and local tax law. The PDIT then calculates eligibility for economic development incentives, such as property tax abatements, job tax credits, research and development tax credits, etc. and simulates the value of those as well. While the PDIT reports each of these separately, we employ the net tax rate data that combine the tax and incentive information expressed as a share of industry value-added. Specifically, we use the net tax rate discounted 12 percent, such that a given year's net tax rate value is the net present value of the 20 year net tax rate discounted 12 percent. The 12 percent discount rate is chosen because this is the discount rate typically attributed to business decision-makers (Bartik 2017).

The PDIT does not contain data on all local governments in a state, but, rather, on economically important cities. We therefore focus on the city-level PDIT data because, as discussed in more detail below, our employment data are at the county-level and we do not want to extrapolate urban area economic development policy to rural counties in the same state. Instead, we focus on the core-based statistical area (CBSA) for the 47 cities for which specific tax and incentive policy information was collected. CBSAs are established by the U.S. Office of Management and Budget (OMB) and defined as the counties including major cities and those surrounding major cities, based on commuting. We are able to calculate annual (discounted) net taxes by city and industry. We then classify each industry in the PDIT dataset using our two typologies (working-class, service-class, creative class and middle-class, low-class, and high-class) and calculate the average of city-class net taxes.[4]

There are two primary assumptions underlying our use of the PDIT data. First, the PDIT does not contain net tax data for all industries in each class and we must therefore assume that average net taxes for each class are representative for the missing industries in each class. Given that the PDIT contains data on the industries that comprise most employment in each class, we feel this is a reasonable assumption. Second, we assume that state and local net tax rates in each of the 47 cities are representative of their respective CBSA net tax rates. Given the nature of tax and incentive competition within labor markets and the fact that much of the variation comes from state level taxes and incentives, we believe this is also a reasonable assumption.

Employment Data

Finally, to measure county-level industry employment changes (and whether they are impacted by incentives), we utilize the data from the WholeData Establishment and Employment Database produced by the W.E. Upjohn Institute for Employment Research. The WholeData database contains unsuppressed county-level employment data using consistent 6-digit NAICS industry definitions from 1998 to 2015. We use the 4-digit NAICS industry detail to look at industry-level employment at the county-level for each county in the 47 CBSAs for which we have PDIT data. We then classify each 4-digit NAICS industry based on our typologies and use county employment in 4-digit NAICS industry as our dependent variable.

Trends in Employment and Incentives by Class

Since we are interested in how incentives may affect the employment in industries that may hire a lot of middle-class workers, we first examine the trends in employment and incentives by class.

In Figure 1, we consider the trends in employment in the classes defined using the typology derived from the Martin Prosperity Institute (MPI classes), where we assume middle-class industries are those defined as working class. Overall, service-class jobs comprise the highest shares of employment. Over time, working-class jobs have been declining while service-class and creative-class jobs have been growing. On average, creative-class jobs now exceed working-class jobs as a share of regional employment. However, the confidence intervals (C.I.) indicate that there is tremendous heterogeneity across space, and that in some places, there are still more jobs in working-class industries than creative-class industries.

Interestingly, in Figure 2, we find a different story. Here, middle-class jobs are assumed to be those that are middle wage. As noted earlier, this means that about 60 percent of jobs are considered middle wage and that is visible here. However, we still see a visible decline in the shares of employment in middle-wage industries and increases in the job shares of low-wage and high-wage industries. But, in this case, the confidence intervals are smaller, suggested less heterogeneity across regions.

Given the declines in the shares of employment using both of our middle-class definitions, we now examine the incentives or net taxes for the various classes. Figure 3, using the MPI definitions of class, illustrates that net taxes for all classes declined in the 2000s but rose slightly, on average, for the creative-class and service-class industries between 2010 and 2015. Overall, working-class industries appear to face the lowest net taxes and service-class industries the highest net taxes and the gap between classes has been increasing over time. However, as with the employment shares, there is tremendous heterogeneity across space, especially in recent years – with working-class industries facing higher net taxes than creative-class industries in at least some regions.

Figure 4 illustrates the differences in net taxes using the wage-based definitions of class. The lower-wage industries face the highest net taxes, consistent with what we saw in Figure 3 (where the service-class industries had the highest net taxes). However, using the wage-based definitions, in this case the high-wage industries appear to be the most incentivized, facing the lowest net taxes and a generally downward trend. However, again, there is tremendous variation across space and, in some places, middle-wage industries face the lowest net taxes.

To further explore the variation across space, Figures 5 and 6 contain maps showing the regional variation in which class was "targeted," or had the lowest net taxes in a CBSA in the year 2000 and the year 2015, using each of our two typologies. Figure 5 illustrates the targeted classes using the MPI definitions of class. While, overall, working-class industries appear to be the most incentivized, between 2000 and 2015, some cities that had been targeting working-class industries switched to targeting service-class or creative-class industries, thus raising relative net taxes on working-class industries. Figure 6 illustrates that high-wage industries are more likely to get favorable tax treatment overall. However, between 2000 and 2015, some cities that had been targeting high-wage industries switched to targeting low-wage and middle-wage industries. At the same time, at least one city moved from targeting middle-wage industries to targeting high-wage industries. This variation will be important when we discuss the results.

Empirical Methodology

Our estimation approach considers the impact of incentives in different classes of industries using our two typologies as defined above. We are interested both in the effect of those incentives on jobs in that same class as well as the impact on jobs in other classes. We also want to look at the relative impacts between incentives in the different classes. We estimate the following using both of our typologies for classifying industries separately.

First, to consider the impacts of incentives on jobs by class, for each class $c \in C$, we separately estimate (log) employment in industry i (four-digit NAICS industry) belonging to class $c(i) = c$ in county j in CBSA k at time t as a function of own-class and other class incentives by:

$$\ln\left(emp_{i,c(i),j,k,t}\right) = \alpha + \sum_{c \in C} \delta_c \overline{net\ taxes}_{c,k,t-1} + \mu_{it} + \vartheta_{kt} + \varepsilon_{i,c(i),j,k,t} \tag{1}$$

where $\overline{net\ taxes}_{c,k,t-1}$ is the average simulated PDIT net tax rate (discounted 12%) for class c industries in CBSA k at time t-1. We use one-year lags of the net tax rate to address concerns over endogeneity and to allow for lagged employment responses to changes in economic development policy. However, we recognize that the lag likely does not address all concerns over the endogenous relationship between industry employment outcomes and economic development incentives policy. Thus, we utilize an instrumental variable approach to estimate (1) using two sources of exogenous variation in economic development policies by class that we detail below.

Our estimation also includes μ_{it} which is an industry-time fixed effect that controls for year-specific common shocks in each four-digit NAICS industry and ϑ_{kt}, a CBSA-time fixed effect that allows for CBSA-specific shocks in each year.

To get at the relative impact of incentives, we also separately estimate for each class $c \in C$, the (log) employment in industry i (four-digit NAICS industry) belonging to class $c(i)=c$ in county j in CBSA k at time t as a function of own-class incentives relative to other class incentives using:

$$\ln\left(emp_{i,c(i),j,k,t}\right) = \alpha + \sum_{c \neq c(i)} \delta_c \left(\overline{net\ taxes}_{c,j,t-1} - \overline{net\ taxes}_{c(i),j,t-1}\right) + \mu_{it} + \vartheta_{kt} + \varepsilon_{i,c(i),j,k,t}$$

(2)

In other words, Equation (2) estimates the change in industry *i* employment as a function of the change in economic development policy for its class relative to the other classes and industry-year and CBSA-year specific shocks.

As stated above, in order to address concerns that state and local industry, or industry-class, economic development policies are endogenously determined by changes in county-level four-digit industry employment or that there is some omitted variable affecting both, we instrument for the lagged value of CBSA-class net tax rates. We use four main instruments.

First, we use an updated version of the Incentive Environment Index (IEI) developed by Patrick (2014a). The IEI is based upon the state and local scores for three clauses in state constitutions that limit and structure the ability of governments to use public monies, credit, and property in the aid of private enterprise —typically referred to as the credit, current appropriations, and stock clauses. These state constitutional provisions provide a structural constraint on the ability of state and local governments to provide incentives, as well as bounding jurisdictional ability to match and innovate in response to economic circumstances. The provisions originated in the nineteenth century from public participation in a variety of economic development projects, some of which failed and instigated fiscal crises for the public entities involved, resulting in long-term debt obligations, default, and bankruptcy. The public policy response in places which faced negative consequences associated with risky public investments was constitutional reform that constrained particular governmental avenues for the promotion of economic development and created barriers to prevent abuses (Patrick 2014b; Tarr 1998). The fact that the events precipitating constitutional change were different across locations means that the constraints are remarkably heterogeneous. As shown in Patrick (2014a; 2014b; 2015; 2016), these state constitutional provisions directly govern the availability of economic development programs like industrial revenue bonds, venture capital funds, loan guarantee programs, etc. available in locations across the United States today as well as how these programs are financed.

In addition to providing an excellent predictor of available economic development incentives, the IEI provides plausibly exogenous variation in economic development incentive availability because of the historical context of the constitutional provisions on which its based and to the extent that changes in any one county's industry employment will not be able to exert sufficient influence to cause state constitutional change.

However, we are also using the industry-class variation in available incentives and it is possible that (within) CBSA variation in industry-class incentives could be attributable to changes in (within) CBSA shocks to industry employment. We therefore also calculate Bartik-style instruments, predicting the employment level in each CBSA in each industry class using both of our industry-class typologies. We first calculate the lagged national employment growth rate by industry. We then use lagged county-level employment data in each industry to calculate the predicted county-level, industry employment and aggregate that to the CBSA-class level.

We estimate each of models (1) and (2), above, using instrumental variable regression and do so for each of our industry-class typologies separately. Our models are estimated on panel data from the 47 metropolitan areas as shown in Figures 5 and 6 for the period 1999 to 2015.

Estimation Results

We now turn to the results of our instrumental variable estimation of our main models. In all cases, as shown in Tables 1 through 4, the instrumental variables were strong, as evidenced by the fact that the P-values for the Multivariate F-test of Excluded Instruments are all less than 0.05, and in most cases they are close to 0.0000; in other words, indicating they are statistically significant at the 95% and 99% levels.

Table 1 illustrates the impact on county employment by four-digit NAICS industry in each of the three MPI classes from differential net-tax rates. Overall, the results show that higher net taxes (or lower economic development incentives) for working-class industries will lower employment in all three classes of industries; however, it will hurt the working-class industries the most. The results in Table 1 Column (2) indicate a 2.9% decrease in working-class industry employment caused by reducing working-class industry incentives by the mean annual change in working-class industry net taxes in our data. Evaluated at the mean county employment in working-class industries, this suggests 16 fewer jobs per county per four-digit NAICS industry or 1,248 fewer jobs in a county with an average number of working class four-digit NAICS industries. [5]

Working-class industries appear particularly sensitive to changes in the net-tax rates for other classes as well. Higher net taxes (or fewer incentives) for service-class industries do not have a statistically-significant effect on service-class industries, but do have a significant negative impact on working-class industries. And, the only statistically-significant result from higher net taxes on

creative-class industries is higher employment in working-class industries, and the magnitude of this effect exceeds the combined negative effects from the other industries' net taxes. Increasing creative-class industry net taxes (or reducing incentives) increases employment in working-class industries by 5.99%, approximately 34 jobs per county per four-digit working-class NAICS industry, or 2,652 jobs in a county with the average number of working class four-digit NAICS industries.[6]

Since net taxes are, on average, the lowest for working-class industries, the results suggest that increasing taxes (or reducing incentives) on creative-class industries be one way to help middle-class workers. And, there is little evidence that this will negatively affect either creative-class or service-class jobs, as both coefficients are positive, albeit statistically insignificant.

We further explore the impact of net taxes on employment using the MPI classes in Table 2, which presents the results for relative net taxes. Focusing on the employment in working-class industries (Column 2) and creative-class industries (Column 3), it appears that the strong negative effects on employment from higher working-class taxes in Table 1 are primarily driven by the relative net taxes between working-class and creative-class industries. As the difference between net taxes for working-class industries and creative-class industries increases – either through increasing incentives for creative-class industries or decreasing incentives for working-class industries, holding the other's net taxes constant – this significantly decreases employment in working-class industries by about 2.21% (Column 2). On the other hand, reducing incentives for creative-class industries or increasing incentives for working class industries will increase employment in creative-class industries (Column 3), albeit by a small 0.49% when evaluated at the average change in this difference over the sample period, and increase employment in working-class industries. Increasing the difference between service-class and working class net tax rates increases employment in both industries (Columns 1 and 2). There is also no evidence that the relative creative-class/service-class net taxes make a difference. Thus, it appears that incentivizing the working-class industries or increasing net-taxes on creative-class jobs may be ways to help overall employment.

In Table 3, we present the results for the estimation of the impact on employment by four-digit NAICS industry in each of the three wage-based classes from the differential net-tax rates. Overall, the results suggest that higher net taxes on low-wage industries will increase employment in all three classes of industries; which is somewhat different than from what was found using the MPI

14

class definitions. The strongest increase is for the middle-wage industries. However, evaluated at the mean change in low-wage industry net taxes in the data, these effects are fairly small at 0.29%, 0.34%, and 0.19% for low-, middle-, and high-wage industries, respectively. This is approximately 4, 3, and 2 jobs, respectively, for the average four-digit NAICS industry in a county or 139, 417, and 39 jobs for the average county in the data.[7]

At the same time, raising the net-tax rate on middle-wage industries decreases middle-wage industries' employment, which is similar to what was found for working-class industries. The effect is economically meaningful, with an approximately 2.1% decrease in middle-class industry employment from increasing middle-class industry net taxes by the mean change in the data. This is approximately 17 jobs in the average four-digit middle-wage NAICS industry and 2,595 jobs in the average county. There is also some evidence that raising net taxes on high-wage industries will help both high-wage and middle-wage employment, as the coefficients are positive (although statistically insignificant).

The results in Table 4 further explore the impact on wage-based class employment using the relative net taxes. In this case, the only statistically-significant result is a lowering of employment in middle-wage industries when the relative net taxes between middle-wage and low-wage industries increases. In other words, consistent with Table 3, lower taxes or more incentives for middle-wage industries can increase middle-wage employment.

Both sets of results combined suggest that incentives can affect the distribution of employment across classes. Using the wage-based definitions of classes, the high-wage industries are most incentivized or face the lowest net taxes. However, there is no evidence that raising high-wage industries' net taxes would hurt employment (in any of the classes). At the same time, it appears that lowering net taxes or incentivizing middle-wage industries would have positive payouts for middle-wage jobs without any negative effects on jobs in other industries. Using the MPI-based class definitions, working-class industries face the lowest net taxes, and the results suggest this may be a good policy as it appears that lowering net taxes or incentivizing working-class industries has positive employment effects, not just for working-class jobs but also for all the other classes as well. Additionally, that the net taxes on working-class industries affect overall employment (in all industries) may suggest the importance to economic stability and vitality of having a critical mass of working-class industries. Since the net taxes for working-class industries are, on average, already low, the results suggest one option would be to raise taxes on creative-class industries, which would

increase working-class jobs without any corresponding harm for either the creative-class or service-class industries

Conclusion

Understanding how incentives may affect the middle class could affect the allocation of future incentives. It can also provide insights into how policy-makers can prevent further inequality and the hollowing out of the middle, which other research suggests may be contributing to lower levels of economic growth. We find that the way in which locations target their economic development policies across industries does affect the distribution of industry employment across wage and occupation classes. In other words, our results indicate that policy-makers in some locations can effectively reduce (or worsen) the decline of middle class jobs in their area through their economic development policy decisions.

In particular, we find that incentivizing working-class and middle-wage industries has positive employment effects for those industries as well as other industries. This suggests some sort of critical importance of these industries to the economic vitality of communities that future research may want to explore.

Importantly, we also find no evidence that reducing incentives (or raising taxes) on creative-class and high-wage industries has negative employment effects for any industry type; and doing so actually increases employment in working-class and middle-wage industries. This suggests that redirecting public resources from reduced taxes and other financial incentives for creative-class and high-wage industries to other policy areas could be viewed as a middle class economic development strategy.

As other research has shown, economic development incentives may have unintended consequences or may not be effective. Our results suggest that the recent trends towards targeting creative-class and high-wage industries with economic development incentives may have helped hasten the decline of working-class and middle-wage industries; without any corresponding benefit for the industries they are designed to help.

While middle-wage jobs make up 60 percent of employment across the United States, high-wage industries face the lowest tax rates and the gap has been increasing. We find little evidence

that high-wage and creative-class industries' employment is driven by economic development incentives, suggesting that these industries benefit more from public goods funded through higher taxes or that the cost reductions from targeted economic development policies comprise too small a share of overall costs to differentially influence their location and employment decisions. The negative effects on working-class and middle-wage industries' employment caused by increasing incentives for high-wage and creative-class industries could be attributable to several potential mechanisms, including upward pressure on input costs or housing values. Our results suggest future research could help policy-makers understand the unintended consequences of such targeted policies by considering these mechanisms. The positive employment effects across all industries associated with low net tax rates for working-class and middle-wage industries also suggests these industries serve as important intermediate inputs for creative- and high-wage industries as well as important drivers of demand for service- and low-wage industries. Additional research should consider these mechanisms in their evaluation of economic development policies as well.

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Endnotes

[1] The Pew Research studies use a definition of middle class based on being middle-income but they note that it also can be linked to education, type of work, etc.

[2] https://www.bls.gov/emp/tables/industry-occupation-matrix-industry.htm

[3] http://www.pewsocialtrends.org/2016/05/11/methodology-4/

[4] PDIT industries correspond to NAICS industries with different levels of precision, so some manual matching was required. The Appendix includes the matched typology.

[5] The mean annual change in in working class industry net tax rates in our sample is -0.0006095, the mean 4-digit NAICS industry county employment in working class industries is 563.1214, and the mean number of working class 4-digit NAICS codes per county is 78.46.

[6] Calculated using the mean annual change in creative class industry net tax rates in our sample if -0.0004316 and the mean 4-digit NAICS industry employment and industries per county above.

[7] The mean change in net tax rates is -0.0001191, -0.0004486, and -0.0004829 for low- , middle- , and high- wage industries. The employment per county is 1,469, 828, and 1,268 for low-, middle-, and high-wage 4-digit NAICS industries.
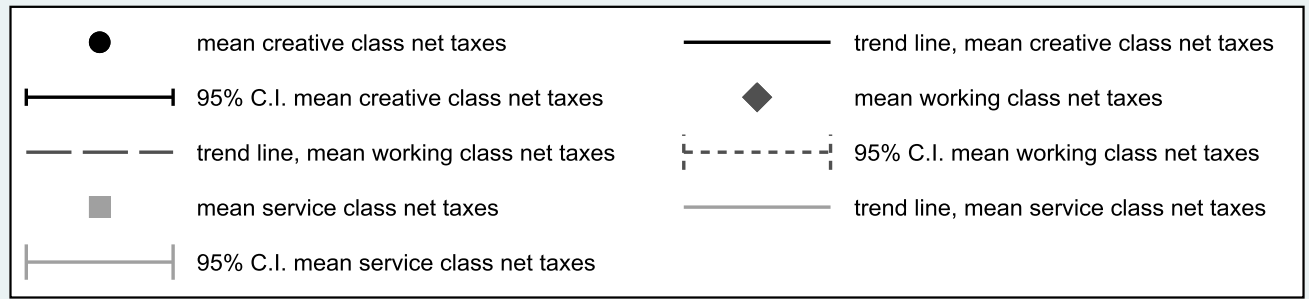
Figure 1: Trends in Employment by MPI Class
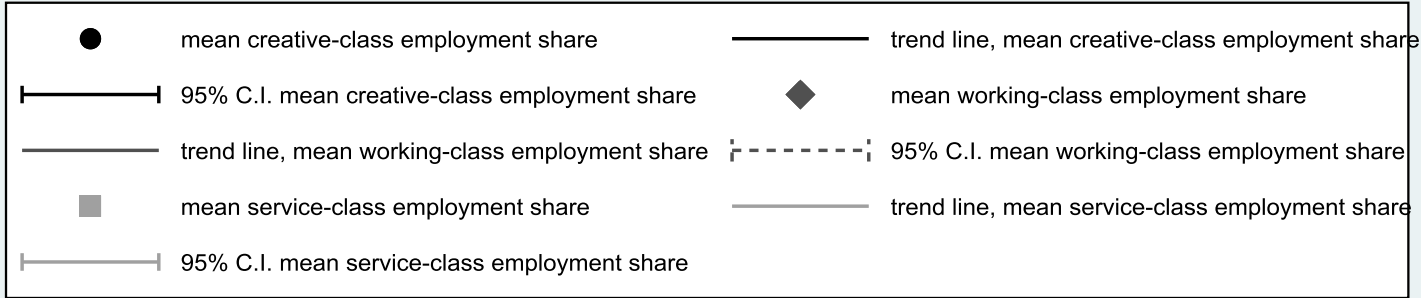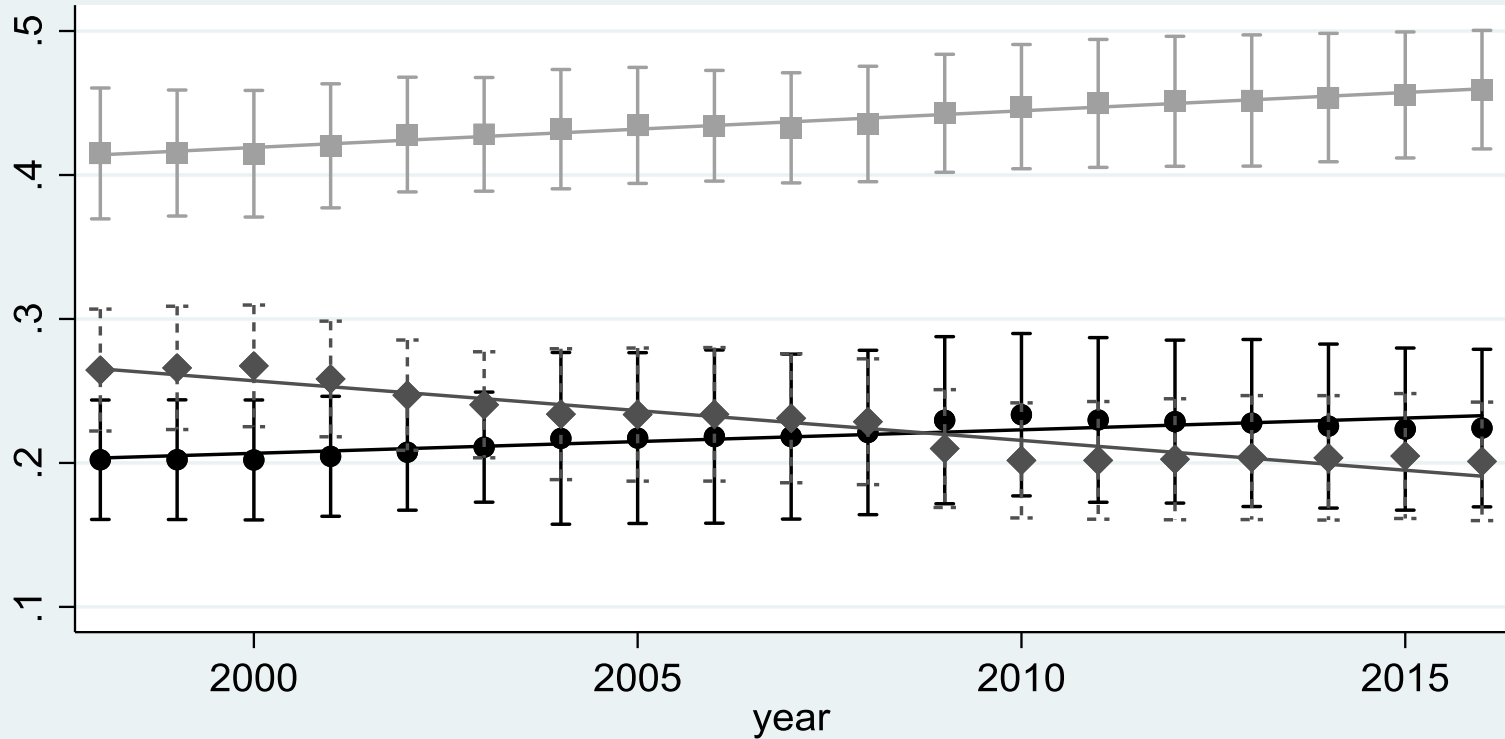
NOTES: The figure illustrates the mean, standard deviation, and trend in employment shares by MPI class in our sample of CBSAs.

Figure 2: Trends in Employment Share by Wage Class
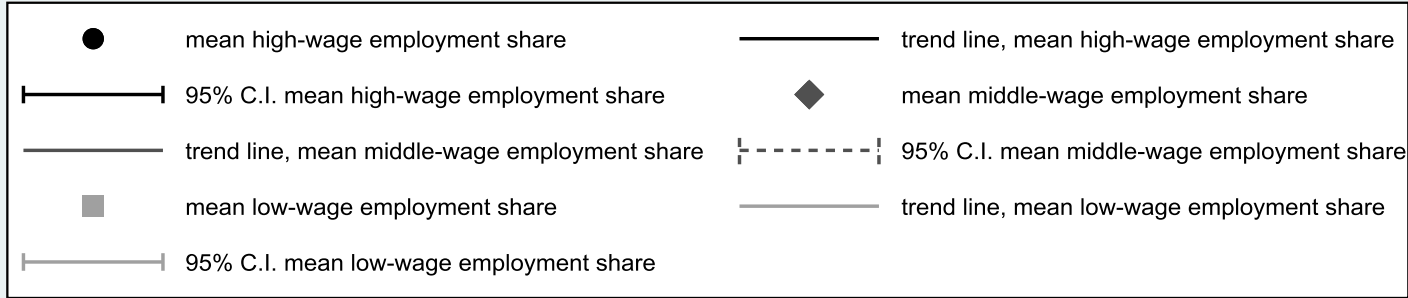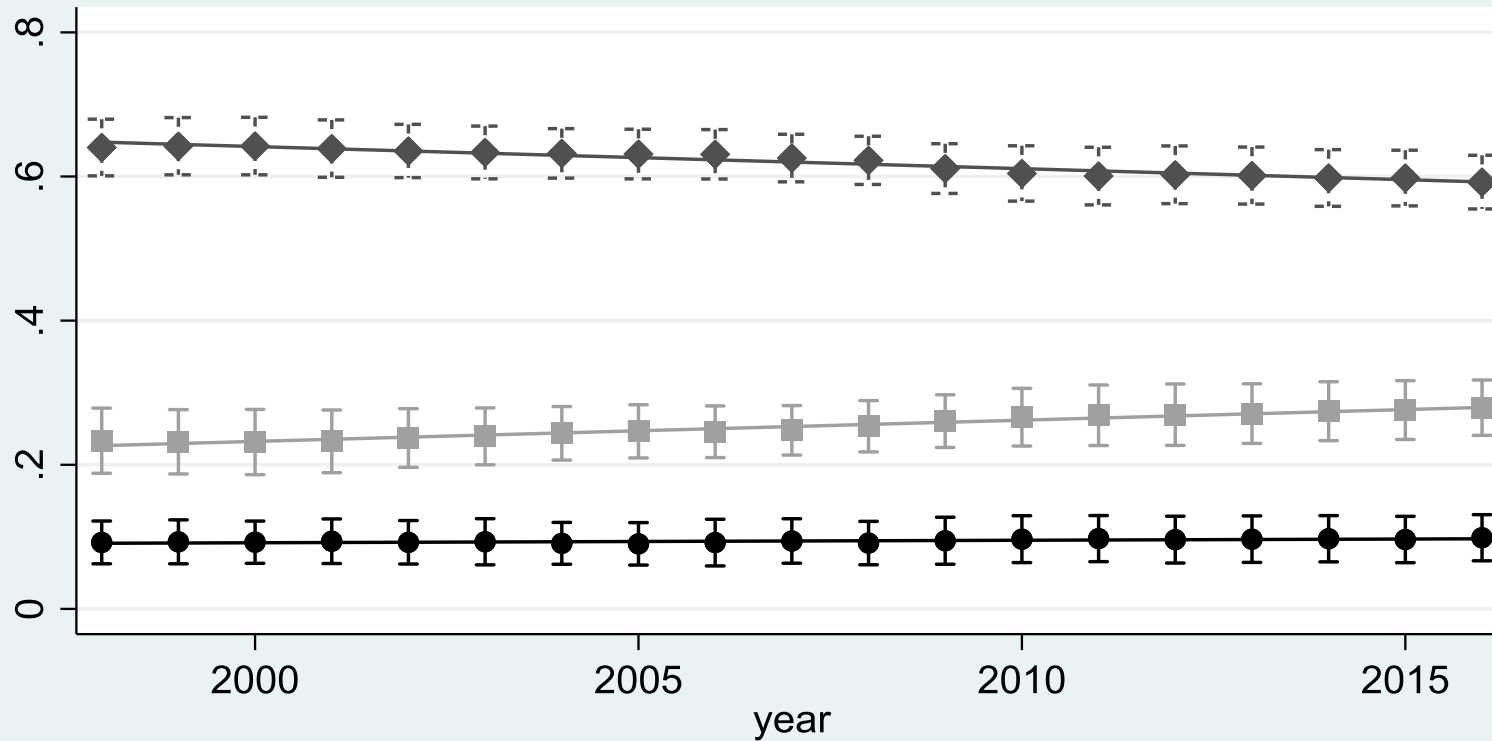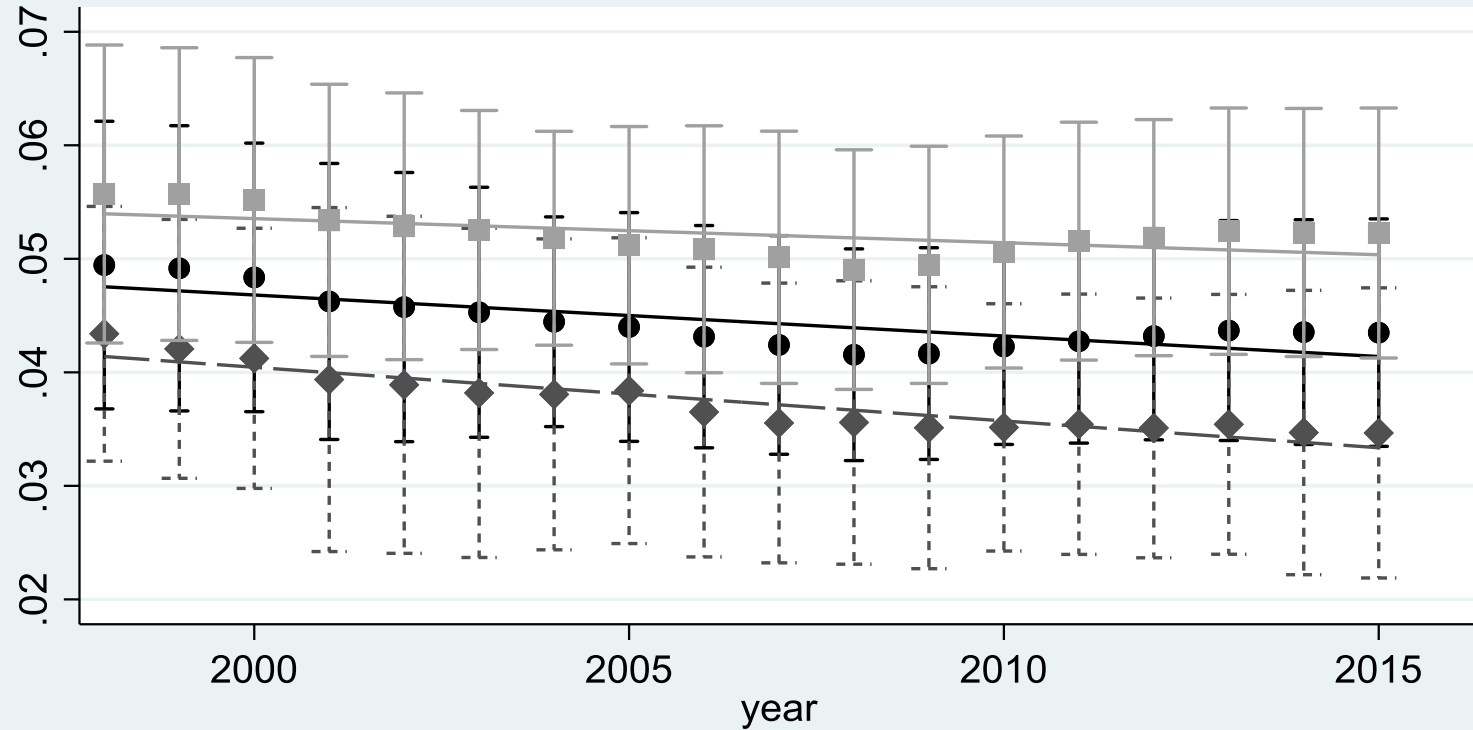

NOTES: The figure illustrates the mean, standard deviation, and trend in employment shares by wage class in our sample of CBSAs.

Figure 3: Trends in Economic Development Policies by MPI Class

NOTES: The figure illustrates the mean, standard deviation, and trend in net taxes by MPI class in our sample of 47 CBSAs.

Figure 3: Trends in Economic Development Policy by Wage Class
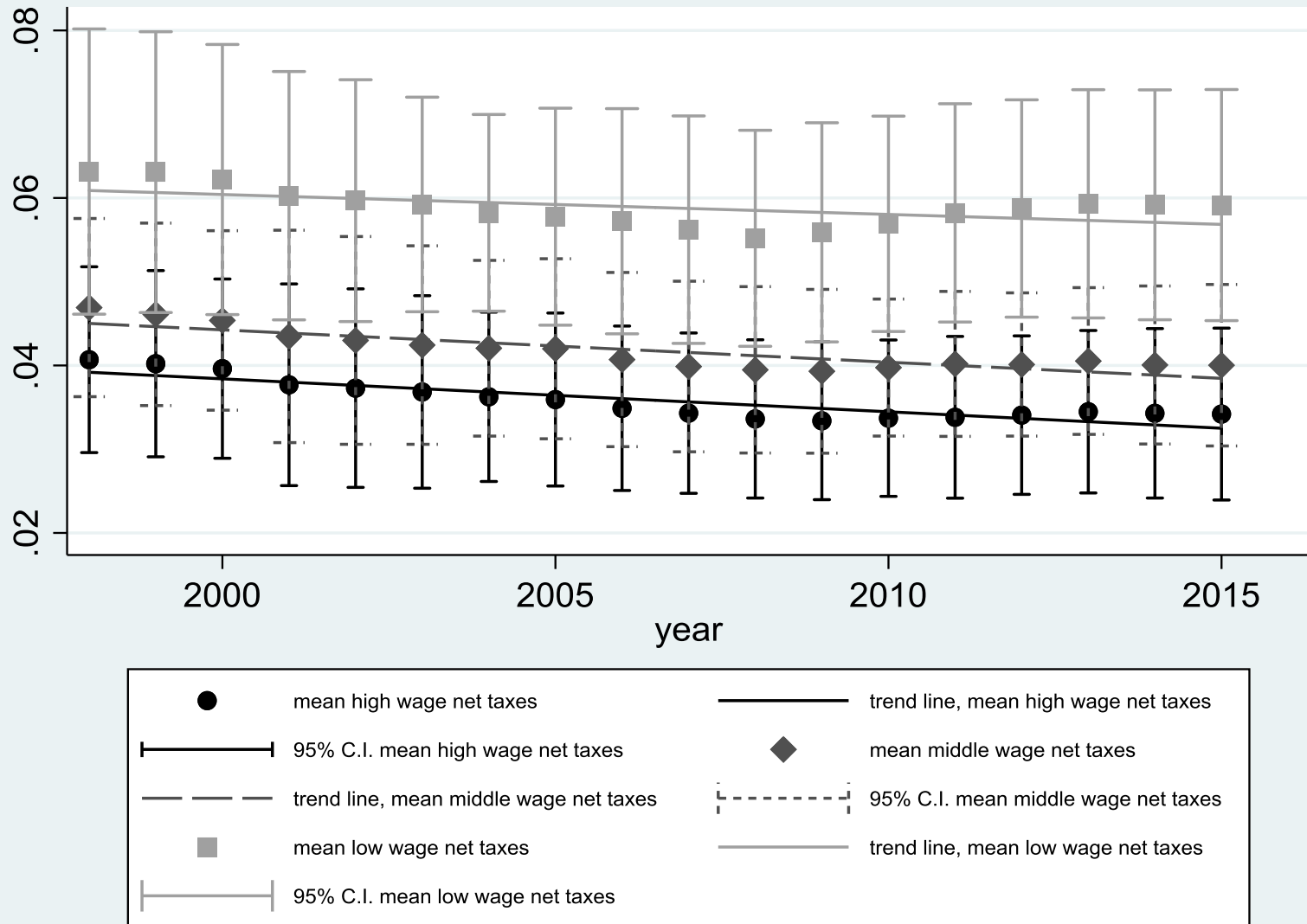

NOTES: The figure illustrates the mean, standard deviation, and trend in net taxes by wage class in our sample of 47 CBSAs.

Table 1: Effect on Net taxes by MPI Class on Employment by MPI Class

	(1) ln(employment) in service-class industries	(2) ln(employment) in working-class industries	(3) ln(employment) in creative-class industries
Net-tax rate on service-class industries	-21.38 (28.71) [-0.48%]	-78.61** (33.29) [-1.77%]	0.630 (22.17) [0.01%]
Net-tax rate on working-class industries	-40.13*** (14.28) [-2.45%]	-47.24*** (14.44) [-2.88%]	-27.81*** (10.68) [-1.70%]
Net-tax rate on creative-class industries	67.02 (46.97) [2.89%]	138.9*** (46.50) [5.99%]	28.68 (34.84) [1.24%]
Observations	356,398	393,738	164,662
P-values on Multivariate F-test of Excluded Instruments:			
Net-tax rate on service-class industries	0.0074	0.0146	0.0097
Net-tax rate on working-class industries	0.0000	0.0000	0.0000
Net-tax rate on creative-class industries	0.0000	0.0001	0.0000

Robust standard errors clustered at the CBSA-level in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
All explanatory variables are lagged by one year.
All models are estimated using instrumental variables regression, using the following instruments: the economic development incentive index and predicted employment levels in each of the three MPI classes for each CBSA and year.
All models use four-digit NAICS industries within each MPI class.
All models include industry-year and CBSA-year fixed effects.
The percentage change in county-level 4-digit NAICS employment evaluated at the absolute value of the mean change in class net-tax rates over sample period is presented in brackets below the estimate from which it is calculated. The mean change is -0.0002248, -0.0006095, and -0.0004316 for service-, working-, and creative-class industries, respectively.

Table 2: Effect of Relative Taxes on Employment in MPI Classes

	(1) ln(employment) in service-class industries	(2) ln(employment) in working-class industries	(3) ln(employment) in creative-class industries
Service class net taxes/Working class net taxes	39.10*** (13.43) [1.5%]		
Service class net taxes/Creative class net taxes	-62.86 (43.65) [-1.3%]		
Working class net taxes/Service class net taxes		80.99** (33.30) [3.1%]	
Working class net taxes/Creative class net taxes		-124.3*** (48.10) [-2.21%]	
Creative class net taxes/Service class net taxes			0.00722 (22.99) [0.00%]
Creative class net taxes/Working-class net taxes			27.52*** (10.30) [0.49%]
Observations	356,398	393,738	164,662

P-values on Multivariate F-test of Excluded Instruments:			
Service class net taxes/Working class net taxes	0.0000		
Service class net taxes/Creative class net taxes	0.0000		
Working class net taxes/Service class net taxes		0.0165	
Working class net taxes/Creative class net taxes		0.0001	
Creative class net taxes/Service class net taxes			0.0009
Creative class net taxes/Working class net taxes			0.0000

Robust standard errors clustered at the CBSA-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All explanatory variables are lagged by one year. All models are estimated using instrumental variables regression, using the following instruments: the economic development incentive index and predicted employment levels in each of the three MPI classes for each CBSA and year. All models use four-digit NAICS industries within each MPI class. All models include industry-year and CBSA-year fixed effects. The percentage change in county-level 4-digit NAICS employment evaluated at the absolute value of the mean change in class net-tax rates over sample period is presented in brackets below the estimate from which it is calculated. The absolute value of the mean change is 0.0003847, 0.0002068, and 0.0001779 for the difference in net taxes between service and working class, service and creative class, and working and creative class, respectively.

Table 3: Effect of Net Taxes on Wage Classes on Employment by Wage Class

	(1) ln(employment) in low-wage industries	(2) ln(employment) in middle-wage industries	(3) ln(employment) in high-wage industries
Net-tax rate on low-wage industries	24.06*** (8.064) [0.29%]	28.20*** (10.46) [0.34%]	15.95** (7.930) [0.19%]
Net-tax rate on middle-wage industries	-10.56 (28.81) [-0.47%]	-46.64** (23.48) [-2.09%]	-11.60 (21.34) [-0.52%]
Net-tax rate on high-wage industries	-18.46 (30.94) [-0.89%]	40.56 (25.74) [1.95%]	20.76 (22.96) [1.00%]
Observations	171,361	758,117	81,454

P-values on Multivariate F-test of Excluded Instruments:			
Net-tax rate on low-wage industries	0.0000	0.0000	0.0000
Net-tax rate on middle-wage industries	0.0000	0.0000	0.0000
Net-tax rate on high-wage industries	0.0000	0.0000	0.0000

Robust standard errors clustered at the CBSA-level in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All explanatory variables are lagged by one year.
All models are estimated using instrumental variables regression, using the following instruments: the economic development incentive index and predicted employment levels in each of the three wage classes for each CBSA and year.
All models use four-digit NAICS industries within each wage class.
All models include industry-year and CBSA-year fixed effects.
The percentage change in county-level 4-digit NAICS employment evaluated at the absolute value of the mean change in class net-tax rates over sample period is presented in brackets below the estimate from which it is calculated. The mean change is -0.0001191, -0.0004486, and -0.0004829 for low-, middle-, and high-wage industries, respectively.

Table 4: Effect of Relative Taxes on Employment in Wage Classes

	(1) ln(employment) in low-wage industries	(2) ln(employment) in middle-wage industries	(3) ln(employment) in high-wage industries
Low wage net taxes/Middle wage net taxes	13.78 (32.21) [0.45%]		
Low wage net taxes/High wage net taxes	13.42 (34.96) [0.49%]		
Middle wage net taxes/Low wage net taxes		-14.72*** (1.728) [-0.49%]	
Middle wage net taxes/High wage net taxes		-10.01 (16.99) [-0.03%]	
High wage net taxes/Low wage net taxes			-0.566 (1.078) [-0.02%]
High wage net taxes/Middle wage net taxes			-12.25 (11.87) [-0.04%]
Observations	171,361	758,117	81,454
P-values on Multivariate F-test of Excluded Instruments:			
Low wage net taxes/Middle wage net taxes	0.0000		
Low wage net taxes/High wage net taxes	0.0007		
Middle wage net taxes/Low wage net taxes		0.0000	
Middle wage net taxes/High wage net taxes		0.0014	
High wage net taxes/Low wage net taxes			0.0000
High wage net taxes/Middle wage net taxes			0.0000

Robust standard errors clustered at the CBSA-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1 All explanatory variables are lagged by one year. All models are estimated using instrumental variables regression, using the following instruments: the economic development incentive index and predicted employment levels in each of the three wage classes for each CBSA and year. All models use four-digit NAICS industries within each wage class. All models include industry-year and CBSA-year fixed effects. The percentage change in county-level 4-digit NAICS employment evaluated at the absolute value of the mean change in class net-tax rates over sample period is presented in brackets below the estimate from which it is calculated. The absolute value of the mean change is 0.0003295, 0.0003638, and 0.0000344 for the difference in net taxes between low- and middle- wage industries, low- and high- wage industries, and middle- and high- wage industries, respectively.