Impact of Tech Companies on Wages

In The Local Economy

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Abstract

The tech industry is known for its high salaries. As the number of new tech companies increase and existing tech companies grow, it's increasingly important to know if the benefits of these high salaries are reaching everyone in the local economy. In this study, I examine how the growth of tech employees impacts the wages of the non-tech residents. I utilize the number of tech employees to reflect the growth of tech companies. I analyze data from 2005 to 2020 and I perform multiple regression models on the number of tech employees vs the wage of non-tech residents. My regressions show that the number of tech employees has a statistically significant positive correlation with local wages.

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1. INTRODUCTION

The tech industry stands out amongst other industries as a career option due to its high levels of compensation. In 2020, the average US annual salary was $53,383 while the average US tech worker's salary was $146,000. Since tech companies provide their employees with higher salaries, it is assumed that they play a larger role than other companies in shaping the economy of the cities they occupy due to the multiplier effect. The multiplier effect refers to the concept that the direct employment of people, in the tech industry in this case, creates additional jobs and employment. This occurs because the people that were directly hired will spend their money in their local economy and generate demand for additional services which results in the creation of additional jobs and employment. The multiplier effect and the large impact of tech companies on their local economy is evidenced by the economic booms created in tech-dense areas such as the Silicon Valley, the Seattle area, and recently the Austin area. Therefore, cities provide incentives such as tax breaks for tech companies to choose their city in order to help their economy grow. Tech companies stand out as investments for cities since cities hope that the multiplier effect will apply and everyone in the city will benefit from the direct employees hired by the tech companies.

However, tech hubs such as Silicon Valley have an increased cost of living, increased poverty, and a larger wealth gap. From 2010 to 2020, San Francisco's real housing prices have increased by 23.25%, poverty has increased by 15.58%, and the top quintile's income grew 10.11% more than the bottom quintile's income growth (US Census Bureau). Since there has also been a growth in negative factors in tech hubs, it's important to analyze the benefits of tech companies and whether those benefits apply to everyone who resides in the local economy. For this paper, the benefit for those in the non-tech industry is represented as an increase in their wage. This paper uses an increase in the wages of non-tech employees as a reflection of the benefit they receive because an increase in wage increases the standard of living. In addition, an increase in wage helps offset the negative factors that tech hubs experience. For example, if the growth in non-tech real wages is equal to or greater than the growth in real housing prices, then it doesn't change the ability for people in the non-tech sector to buy houses. An increase in wages also decreases poverty and decreases the income gap.

The number of tech companies has been increasing across the US with 13,400 tech startups launched in 2019 alone. Therefore, it's becoming increasingly important to determine whether the benefits of tech companies go beyond the employees who receive salaries directly from the tech companies and to the other residents in the area. In addition, since COVID started, there has been an increase in the adoption of remote work in the tech industry, causing tech employees to move and live outside of the tech hubs (Castrillon). Therefore, tech wages are dispersed in more local economies. Therefore, it's important to determine the impact of the tech wages on the local economies. In this paper, I examine the impact of tech companies on the local economy during the 15-year period from 2005 through 2020 across 290 metropolitan areas and determine if there is a strong correlation between the number of tech companies and the wages of non-tech employees in the metropolitan area they reside.

2. LITERATURE REVIEW

2.1 Relationship Between Tech Companies and Local Multipliers

In Moretti's research paper, "Local Multipliers", he discusses how every new job generated in a local economy has the possibility to create additional jobs. However, the creation of jobs in different sectors generates different amounts of additional jobs. In his paper, he defines a local multiplier which represents how many new jobs will be created in the local economy for every new job generated (Moretti). Therefore, a larger local multiplier means that there will be more additional jobs created for every new job. In the paper, Moretti found that skilled jobs have a higher local multiplier than unskilled jobs and specifically high tech industries have a large multiplier. This is explained by the high wages of tech industry employees. Tech employees have higher wages so they generate more demand for local goods and services compared to unskilled employees who receive lower wages.

In the *New Geography of Jobs*, Moretti exemplifies tech's high local multiplier through an example of Apple hiring 12,000 workers. By hiring the 12,000 workers, the multiplier effect took place and 60,000 more jobs were created in the metro area (Moretti). Of those 60,000 new jobs, 24,000 jobs created are skilled jobs and 36,000 jobs created are unskilled jobs. Therefore, Apple has a larger impact on the employment of non-tech jobs than on the employment of tech jobs in its metropolitan area. Therefore, the local multiplier that Apple has is 60,000:12,000 which simplifies to 5:1. This means that for every new employee Apple hires, there will be 5 new jobs created in Apple's metropolitan area. As part of FAANG, an acronym for the 5 most popular and best performing American tech companies, and the first company to reach a $3 trillion market value, Apple is the model tech company and continues to innovate by securing the best talent through high salaries. Therefore, Apple's large local multiplier is explained by the high salaries that the company provides .

2.2 Contribution

My paper will expand on research done on the impact of tech companies on their local economy by determining how the tech industry impacts the wages of people who do not work in tech. While we understand that tech companies produce more jobs in the local economy, it's also important to look at the impact that tech companies have on wages in the local economy. My paper varies from other research since it is based on how I define the data points as part of the tech or non-tech industry. Therefore, since I defined which data should be categorized as tech conservatively, my values might not fully encompass the impact that tech companies have since some data points might be miscategorized. However, since I'm performing the regressions on a large dataset of over 12 million rows after data cleaning, the small number of possibly miscategroized rows should not have a large impact on the results.

3. DATA

3.1 Representing the Number of Tech Companies

To reflect the growth of tech companies in each city, I utilized the growth in the number of people who are employed in the tech industry in each city. I believe this accurately reflects the growth of tech companies because if the number of tech companies increases or existing tech companies grow, they hire more employees. In addition, it's important to utilize the number of people who work in tech as a variable since the number of tech employees is proportional to the amount of money spent by tech workers in the economy which is what stimulates the local economy and impacts the wages of everyone else in the local economy.

3.2 Dataset

For my analysis, I utilized the IPUMS (Integrated Public Use Microdata Series) USA dataset which is composed of over 60 integrated samples of the American population from the federal census, American Community Surveys, and Puerto Rican Community Surveys. From the IPUMS dataset, I created my own custom dataset by selecting the variables I need for my analysis. The variables I selected make up the columns of my dataset. The variables I selected were used for analysis either as data frequency weights, control variables, independent variable calculations, dependent variables, or categorization variables. I utilized data from 2005 to 2020 since my analysis requires me to categorize by metropolitan area using the MET13 location variable which is only available from 2005 to 2020.

Table 1: Variables from IPUMS used in Custom Dataset

Variable Name	**Category**	**Description**
AGE	Control Variable	Respondent's age in years
MET13	Categorization Variable	Metro areas of residence as defined by the 2013 definitions for metropolitan statistical areas (MSAs)
CPI99	Data Frequency Weights	Provides multiplier to convert dollar figures into 1999 inflation-adjusted dollars
EDUC	Control Variable	Respondents' highest level of education completed
INCWAGE	Dependent Variable	Respondents' pre-tax wage and salary income for the previous year.
IND	Independent Variable Calculations & Control Variable	Type of industry where the respondent performs their occupation

OCC	Independent Variable Calculations	Respondent's primary occupation
PERWT	Data Frequency Weights	Indicates how many persons are represented by a given sample
RACE	Control Variable	Respondent's race
SEX	Control Variable	Respondent's sex
YEAR	Categorization Variable	Year when the sample was taken

3.3 Dataset Preprocessing

To make the dataset ready for analysis, I preprocessed the dataset. The first step was to remove all rows that had a null or empty value. Some variables had numerical values that stood for a null or empty value. For example, for the variable INCWAGE, 9999999 stood for N/A. Therefore, I checked the documentation of each variable and removed rows according to each variable's specific codes. This step reduced the number of rows from 54,042,724 rows to 12,414,658 rows. Next, I multiplied INCWAGE which contains dollar values by the CPI index to make sure all dollar amounts are represented in 1999 inflation amounts.

Since my analysis involves analyzing the impact of tech companies, I need to categorize each row of the dataset as a person who works in tech or a person who works in non-tech. The industry column and the occupation column were utilized to determine whether the row is a data point for a person(s) who works at a tech company. Since the categorization of industries and the categorization of occupations changed multiple times between 2005 and 2020, I had to redetermine which industries and which occupations should categorize as "tech" each time the categorization changed.

To categorize the occupations in the occupations column as either tech or non-tech, I asked whether the occupation exists primarily inside a tech company. If the occupation satisfies the question, then I categorized the occupation as tech. While there are various occupations that are in the tech industry that do not exist primarily inside a tech company such as marketing, I formulated the question to be more constrained so that the data categorized as tech will have a higher chance of being data from someone who works at a tech company. For example, while marketing roles exist in a lot of tech companies, they do not primarily exist inside a tech company so if I included marketing, I would have possibly added data to the tech set that included people who do not work at a tech company.

Table 2: Names of all occupations (OCC) between 2005-and 2020 that was categorized as an occupation of a person working at a tech company

OCC code(s)	**Occupation Name**
0110	Computer and information system managers
10001, 1005	Computer and information research scientists
10001, 1006	Computer systems analysts
11102, 10007	Information security analysts
1010	Computer programmers
10201, 1021, 1020,	Software Developers
1022	Software quality assurance analysts and testers
11102, 1031, 1030	Web developers
10001, 1107, 1108,	Computer occupations, all other
10001, 1106	Computer network architects
1032	Web and digital interface designers
11102, 1050	Computer support specialists

1065, 1060	Database administrators and architects
11103, 1105	Network and computer systems administrators
1400	Computer Hardware Engineers
1410	Electrical and electronics engineers
1551	Electrical and electronic engineering technologists and technicians

To categorize industries as either tech or non-tech, I asked whether the industry is made up of primarily tech companies. If the industry satisfies the question, I categorized the industry as tech. Similar to the categorization of occupations, I formulated the question to be more conservative with which industries I categorized as aligned with tech.

Table 3: Names of all industries (IND) between 2005-and 2020 that were categorized as an occupation of a person working at a tech company

IND code(s)	**Industry Name**
3360, 3365	Computer and peripheral equipment manufacturing
3370	Communications, and audio and video equipment manufacturing
3380	Navigational, measuring, electromedical, and control instruments manufacturing
3390	Electronic component and product manufacturing, n.e.c.
5590	Electronic shopping
6490	Software publishers
6675, 6672	Internet publishing and broadcasting and web search portals
6680	Wired telecommunications carriers

6690	Telecommunications, except wired telecommunications carriers
6692	Internet service providers
6695	Data processing, hosting, and related services
7290	Architectural, engineering, and related services
7380	Computer systems design and related services
7390	Management, scientific, and technical consulting services

After choosing which industries and which occupations were categorized as tech companies, I filtered through the data and if both the occupation and the industry are categorized as tech, the row would be categorized as a datapoint for a person(s) who works in tech.

The remaining rows that were not categorized as tech are all considered "non-tech" and I further categorized the "non-tech" rows as either people who work in a nontradable industry or tradable industry using the industry column. I categorized the non-tech rows as either non tradable or tradeable because my analysis looks at the impact on the local economy and tradable sectors sell their goods and services outside of the local economy. Therefore, the tradable sector is largely unaffected by the potential increase in spending from tech employees so the wages of tech employees do not get passed on to employees of the tradable sector. Since the categorization of industries changed multiple times between 2005 and 2020, I had to also redetermine which industries should be categorized as non-tradable and which industries should be categorized as tradable each time the categorization changed.

Since the industries have industry categories which accurately represent the industries categorized underneath it, I sorted the industries as non-tradable or tradable based on the industry categories. I went through each industry category and determined if the industry category is tradable or non tradable based on whether the majority of the industries in the category make goods and services for the local economy. Therefore, all industries under the same industry category were sorted the same. The industry categories that I categorized as nontradable are:

Agriculture, Forestry, Fishing and Hunting, Mining, Manufacturing, Wholesale Trade, and Armed Forces.

The last step of the dataset preprocessing was to create the independent variable for my regressions. The independent variable in my regression is the number of tech employees in each city in each year. To make the independent variable, I iterated through the rows categorized as tech and for each city and each year, I summed the person weights.

4. MODEL

I built multiple regression models to evaluate the impact that tech company growth has on wages in the local economy. In all of the models, both the regressors and the dependent variable are log-transformed to impose linearity between the variables. All of the models also perform weighted regressions to account for the different number of respondents that each row of data has according to the variable PERWT (person weight).

4.1 Model 1

Model 1 is the most simplified model and performs paneled OLS regression. Model 1 can be expressed as:

$$w_{rmt} log(wage_{rmt}) = \beta_0 + w_{rmt}\beta_1 log(T^T_{mt}) + \varepsilon_{rmt}$$

In the equation above, T^T_{mt} refers to the total number of people working at a tech company in metropolitan area *m* at time *t* for each year between 2005 and 2020 (inclusive). $wage_{rmt}$ represents the wages of respondent r who resides in metropolitan area m at time t and works in the non-tech sector. I only look at the wages of people in the non-tech sector since I'm analyzing the impact of tech companies on wages outside of the tech sector. w_{rmt} refers to the weight of respondent *r* who resides in metropolitan area *m* at time *t*. The coefficient β_1 can be interpreted as how much a percent change in $log(T^T_{mt})$ changes the $log(wage_{rmt})$. Therefore a 1% change in $log(T^T_{mt})$ will cause a β_1% change in $log(wage_{rmt})$.

Model 1 contains substantial omitted variable bias. Uniform changes in both year and metropolitan area are not accounted for and there are other numerous variables that impact the dependent variable that are not accounted for in the model. In addition, the different impact that non-tradable and tradable industries have on the local economy is also not accounted for. If there are omitted variables that are positively correlated with the number of tech companies and wages, this might lead to an overestimation of β_1.

4.2 Model 2

In Model 2, I decrease the omitted variable bias by adding a dummy variable for nontradable industries and an interaction variable between the number of tech companies and nontradable industries. Model 2 is expressed as:

$$w_{rmt} log(wage_{rmt}) = \beta_0 + w_{rmt}(\beta_1 log(T^T_{mt}) + \beta_2 NT_{rmt} + \beta_3 log(T^T_{mt}) NT_{rmt}) + \varepsilon_{rmt}$$

In this equation, NT_{rmt} represents is a dummy variable that represents whether respondent *r* who lives in metropolitan area *m* at time *t* works in a nontradable industry. Therefore, a positive β_2 would indicate that workers in the nontradable industry have higher wages than workers in the tradable industry while a negative β_2 would indicate that workers in the nontradable industry have lower wages than workers in the tradable industry. Since the number of tech workers at metropolitan area *m* at time *t* influences whether a person works in a non-tradable sector, I added the interaction term $log(T^T_{mt}) NT_{rmt}$. β_3 can be interpreted as the increase in effectiveness of $log(T^T_{mt})$ for each unit increase in NT_{rmt} and vice versa. Therefore, if β_3 is positive, it would imply that the higher the $log(T^T_{mt})$, the greater the effect that NT_{rmt} has on wages and vice versa. If β_3 is negative, it would imply that the higher the $log(T^T_{mt})$, the less the effect that NT_{rmt} has on wages and vice versa.

In Model 2, β_1 should be a more accurate estimation since the impact of nontradable industries are accounted for. Therefore, the standard error should decrease. However, Model 2 still does not completely eliminate omitted variable bias since there are still other variables that are not accounted for.

4.3 Model 3

In Model 3, I decrease one source of omitted variable bias by adding year-fixed effects which control for factors that change yearly that are common to all metro areas in a given year. Model 3 is expressed as:

$$w_{rmt} log(wage_{rmt}) = \beta_0 + w_{rmt}(\beta_1 log(T^T_{mt}) + \beta_2 NT_{rmt} + \beta_3 log(T^T_{mt})NT_{rmt} + FE_t) + \varepsilon_{rmt}$$

In this equation, FE_t represents a vector of year fixed effect dummy variables. Therefore, the dummy variable trap occurs. The dummy variable trap occurs since one dummy variable in FE_t can be predicted using all other dummy variables which creates multicollinearity. Therefore, when creating FE_t through the function pd.get_dummies(), I passed in the parameter drop_first=True into the function which removes the first dummy variable. Removing one of the dummy variables removes the problem of multicollinearity.

In Model 3, β_1 is more accurate since year fixed effects are accounted for. This should cause the standard error to decrease since the year fixed effects are accounting for some of the variance that existed in the data. However, Model 3 still does not completely eliminate omitted variable bias since there are other variables that are not accounted for such as metro area fixed effects.

4.4 Model 4

In Model 4, I decrease another source of omitted variable bias by adding metro area fixed effects which controls for factors that change wage in metro areas over time. Model 4 is expressed as:

$$w_{rmt} log(wage_{rmt}) = \beta_0 + w_{rmt}(\beta_1 log(T^T_{mt}) + \beta_2 NT_{rmt} + \beta_3 log(T^T_{mt})NT_{rmt} + FE_t + FE_m) + \varepsilon_{rmt}$$

In this equation, FE_m represents a vector of metro area fixed effect dummy variables. Similarly to Model 3, the dummy variable trap occurs. Therefore, when I'm creating FE_m Through the function pd.get_dummies(), I complete the same steps of passing in the parameter drop_first=True into the function to remove the first dummy variable which removes the problem of multicollinearity.

This model further eliminates omitted variable bias by incorporating metro area fixed effects. Therefore, most likely, the standard error will most likely further decrease and the R-squared value will most likely further increase since the metro area fixed effects account for more of the variance and so the model is more accurately fitted to the data. However, bias still exists in the model since there are many different additional variables that impact wage that is not in the model.

4.5 Model 5

Model 5 introduces controlled variables to account for other factors that impact wages beyond the number of people in tech. The control variables that I introduce are respondent-related variables and they are age, education, sex, race, and industry. Model 5 is expressed as:

$$w_{rmt} log(wage_{rmt}) = \beta_0 + w_{rmt}(\beta_1 log(T^T_{mt}) + \beta_2 NT_{rmt} + \beta_3 log(T^T_{mt}) NT_{rmt} + FE_t + FE_m + \beta_4 C_{rmt}) + \varepsilon_{rmt}$$

In this equation, C_{rmt} is a combined variable that represents all of the control variables stated above. In this model, the control variables, sex, race, and industry, are dummy variables. β_4 represents the correlation between all of the control variables and $w_{rmt} log(wage_{rmt})$. By introducing respondent-related variables, we are able to account for other variables involving the respondent that impacts their wage outside of the number of people in the tech industry and the number of people in the non-tech industry. Multiple hypotheses are introduced with the control variables. For the age variable, the hypothesis is that people’s income generally grows with age. For the education variable, the hypothesis is that people’s income is larger if they have a higher level of educational attainment. For the sex variable, males are generally paid more than females. For the race variable, minorities are generally paid less than other races. For the industry variable, certain industries make more money than other industries. If the control variables are statistically significant, then the standard error should decrease and the R-squared value should increase since bias will be reduced by adding additional variables that account for the variance in the data. However, there will still be omitted variable bias since there are so many factors that impact a person's wage. Some of those factors are difficult to measure and there isn't data on all of the variables that impact a person's wage. Examples include personal values on money, family financial pressures, and size of personal network.

5. RESULTS

5.1 Regression Outputs

Table : Wage Regressed on Number of People in Tech

	(1) logWage	(2) logWage	(3) logWage	(4) logWage	(5) logWage
log(Num of Tech Employees)	0.0533***	0.0338***	0.0336***	0.0336***	0.0337***
	(0.000)	(0.009)	(0.009)	(0.009)	(0.007)
Nontradable		1.2723***	1.2869***	1.2770***	1.2788***
		(0.083)	(0.083)	(0.083)	(0.082)
log(Num of Tech Employees) * Nontradable		0.0217**	0.0237***	0.0247***	0.0247***
		(0.009)	(0.009)	(0.009)	(0.009)
Age					0.0089***
					(3.81e-05)
Sex					-0.4175***
					(0.002)
R-squared	0.990	0.990	0.990	0.990	0.993
F-tests	1.223e+09	4.080e+08	6.805e+07	3.677e+07	4.491e+07
Controls	No	No	No	No	Yes
Year FE	No	No	Yes	Yes	Yes
Metro Area FE	No	No	No	Yes	Yes

Standard errors in parentheses

** p < 0.10, ** p < 0.05, *** p < 0.01*

5.2 Wages and Tech

The regression above shows that there is a statistically significant positive relationship between wage and the number of people that work in tech in all models. Model 1 shows that a 1% change in $log(T_{mt})$ leads to a 0.0533% change in $log(wage_{rmt})$. To find the how wages changes as T_{mt} changes according to model 1:

$$w_{rmt} log(wage_{rmt}) = \beta_0 + w_{rmt}.0533 \ log(T_{mt}) + \varepsilon_{rmt}$$

$$log(wage_{rmt}^{w_{rmt}}) = \beta_0 + log(T_{mt}^{.0533*w_{rmt}}) + \varepsilon_{rmt}$$

$$e^{log(wage_{rmt}^{w_{rmt}})} = e^{\beta_0 + log(T_{mt}^{.0533*w_{rmt}}) + \varepsilon_{rmt}}$$

$$wage_{rmt}^{w_{rmt}} = T_{mt}^{.0533*w_{rmt}} \left(e^{\beta_0 + \varepsilon_{rmt}}\right)$$

$$wage_{rmt} = T_{mt}^{.0533} \left(e^{\beta_0 + \varepsilon_{rmt}}\right)^{\frac{1}{w_{rmt}}}$$

$$\frac{dwage_{rmt}}{dT_{mt}} = .0533\, T_{mt}^{-0.9467} \left(e^{\beta_0 + \varepsilon_{rmt}}\right)^{\frac{1}{w_{rmt}}}$$

Since the exponent of T_{mt} is negative in the derivative, T_{mt} has a decreasing impact on the change in wage. In addition, since both the dependent and independent variables are log transformed, the proportional change in wage associated with a p percent increase in T_{mt} is equal to $e^{a\beta}$ where a = $log([100 + p]/100)$ and $\beta_1 = .0533$ from Model 1.

However, since Model 1 has a large amount of omitted variable bias, it is more valuable to analyze the other models since they account for other variables that are omitted in Model 1. Specifically, since Model 5 includes non-tradable sector information, fixed effects and controls, it is the most useful to use Model 5. The decrease of omitted variable bias in Model 5 compared to Model 1 is reflected in the slightly higher R-squared value of Model 5. In Model 5, the coefficient for the number of tech companies has decreased compared to Model 1 since variables that are positively correlated with both wages and the number of tech companies were omitted which causes the coefficient in Model 1 to be an overestimate.

In Model 5, the coefficient for the number of tech companies remains statistically significant. The coefficient is 0.0337 and has a p-value of 0.007 which shows that the coefficient has a strong statistical significance. Since Model 5 has an interaction variable, the changes in $log(wage_{rmt})$ due to a change in $log(T_{mt})$ varies based on the whether the respondent r at metropolitan area m at time t works in a non-tradable or tradeable industry. If NT_{rmt} is 1, which means that the respondent works in the nontradable industry, the following equation simplification applies:

$$w_{rmt} log(wage_{rmt}) = \beta_0 + w_{rmt}\,(.0337 log(T_{mt}^{T}) + .0247 log(T_{mt}^{T}) NT_{rmt} + \ldots) + \varepsilon_{rmt}$$

$$w_{rmt} log(wage_{rmt}) = \beta_0 + w_{rmt}\,(.0337 log(T_{mt}^{T}) + .0247 log(T_{mt}^{T})(1) + \ldots) + \varepsilon_{rmt}$$

$$w_{rmt}log(wage_{rmt}) \ = \ \beta_0 + w_{rmt}(.0584log(T^T_{mt}) + \dots) + \varepsilon_{rmt}$$

Therefore, a 1% change in $log(T_{mt})$ leads to a 0.0584% change in $log(wage_{rmt})$ for those who work in the nontradable industry. If NT_{rmt} is 0, which means that the respondent works in the tradable industry, the following equation simplification applies:

$$w_{rmt}log(wage_{rmt}) \ = \ \beta_0 + w_{rmt}(.0337log(T^T_{mt}) \ +.0247log(T^T_{mt})NT_{rmt} + \dots) + \varepsilon_{rmt}$$

$$w_{rmt}log(wage_{rmt}) \ = \ \beta_0 + w_{rmt}(.0337log(T^T_{mt}) \ +.0247log(T^T_{mt})(0) + \dots) + \varepsilon_{rmt}$$

$$w_{rmt}log(wage_{rmt}) \ = \ \beta_0 + w_{rmt}(.0337log(T^T_{mt}) + \dots) + \varepsilon_{rmt}$$

Therefore, a 1% change in $log(T_{mt})$ leads to a 0.0337% change in $log(wage_{rmt})$ for those who work in the tradable industry. This conclusion shows that wages are more elastic to the growth of tech companies in the nontradable industry compared to the tradable industry. This shows that the growth of tech companies impacts the wages of those in the nontradable industry more since they are part of the local economy. Therefore, the increase in spending from tech employees is transferred to the wages of those in the non-tech nontradable industry.

5.3 Wages and Non-tradable vs Tradable Industries

In Model 2, I added a dummy variable that represents whether the respondent works in a nontradable industry and an interaction variable between the number of tech companies and the dummy variable.

Since the interaction variable is positive, that means that the wages are elastic to

s by adding a dummy variable for nontradable industries and an interaction variable between the number of tech companies and nontradable industries.

5.4 Control Variables

I only included age and education in my regression tables since all other control variables are dummy variables. Age and education are both statistically significant which implies that age is correlated to wage and education is correlated to wage. Education has a higher beta than the beta for age which means that increasing educational level has a larger impact on wage than increasing age. Essentially, increasing educational attainment by 1% correlates to a .1637% in wage. The beta value for age is .0159 which signifies that increasing age by 1% correlates to a .0159% increase in wage.

7. CONCLUSION

In this paper, I explored the relationship between the growth of tech companies, represented by the number of tech employees, and the local wages of non-tech residents. I found that there is a statistically significant positive correlation between the number of tech employees and the local wages of non-tech residents. This has significant policy implications since non-tech residents' wages benefit from the growth of tech companies in a metropolitan area. However, there are other factors that should be accounted for when making policy decisions on the topic of increasing the growth of tech companies. For example, if increasing the number of tech employees increases the cost of living in the local economy more than the increase in wages of non-tech employees, the benefit of the wage increase will be offset. Therefore, potential extensions of this research would be to look at factors that determine the cost of living such as groceries and rent and see how those factors are impacted by the number of tech companies. This research extension would give policymakers a better overview of how non-tech employees are impacted by the growth of tech companies and determine the best investments for their local economy.

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