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COVID-19 and County-Level Economic Impacts: Analyzing Heterogeneity in the State of California

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COVID-19 AND COUNTY-LEVEL ECONOMIC IMPACTS: ANALYZING HETEROGENEITY IN THE STATE OF CALIFORNIA

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in

APPLIED ECONOMICS AND FINANCE

by

Riley K. Lewis

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Abstract

COVID-19 and County-Level Economic Impacts: Analyzing Heterogeneity in the State of California

by

Riley K. Lewis

The COVID-19 pandemic has caused widespread economic destruction throughout the state of California. In this paper, I use employment and small business data from the Opportunity Insights Economic tracker combined with income and industry sector from the national census and BLS to explore the relationship between median county income, industry distribution, and changes in small business revenue and employment levels over the course of the pandemic. While my findings regarding industry distribution were inconclusive, I found a negative relationship between county median income and changes in employment, as well as a negative relationship between small business revenue and county median income. I conclude my paper by putting forth some potential causal hypotheses.

Part I

Thesis

0.1 Introduction

The COVID-19 pandemic has touched almost every area of the economy, often with substantially heterogeneous effects. Existing literature focuses largely on the differing economic impacts based on demographic factors such as race and gender. I chose to search for heterogeneity in changes in small business revenue and employment levels, and to find a relationship between said changes and county-level median income and industry makeup. Searching for the aforementioned relationships will be a valuable contribution to the literature, because if locations are affected differently based on income, decision makers can make more efficient choices, and allocate aid to the areas that will receive the maximum benefit.

This paper is intended to be primarily descriptive analysis of the heterogeneous changes in small business revenue and employment as a result of COVID-19 at a county level in the state of California, and an attempt to relate said changes to county-level employment and income data. To perform this analysis, I sourced county-level data on changes small business revenue and employment, and aggregated said data with information from the BLS and BEA, constructing a dataset that presents county-level changes in employment and small business revenue alongside data on employment, income, and small business industry composition. I begin with a time-series analysis, which shows that employment and small business revenue fell sharply shortly after the shelter-in-place order took effect, and made a small recovery before leveling out somewhat. I then estimate models for county-level differences in these outcome variables based on factors such as county median income and industry.

Previous literature has found substantial evidence of heterogeneity. Using data from the CPS, Montenovo et. All found that job loss was larger in occupations that require more interpersonal contact and that cannot be preformed remotely. Along with this, some of the more protected jobs during the early months are associated with higher income and job security in normal times, suggests that the pandemic increased existing disparities. Re-employment from initial loss was broadly proportional across ethnic groups except for African Americans, but substantial unexplained differences remain among employed groups(Montenovo, Jiang, Lozano). Lee, Park, and Shin sourced data from the CPS to examine heterogeneity along multiple demographic axes. They found that the initial negative impact on employment was larger for women, minorities, the less-educated, and the young, and that leisure and hospitality suffered the most out of any industries. Interestingly, the differential impacts along gender, education, and age were only present in the short term. (Lee,Park, Shin). Dr. Fairlie utilized data from the April 2020 wave of the CPS to chart early impacts of the pandemic on small business. He found that losses were widespread, and African American, Asian, female, and Latinx small business owners experienced above-average negative impacts. Some of the larger negative impact may be due to differences in industry compositions, as modeling indicates.(Fairlie). Bloom et. all partnered with Strip, a payments processing provider, to design and execute a survey to asses the impact of COVID-19 on small businesses. They found significant heterogeneity, with smaller offline firms experiencing sales drops over 40 percent compared to less than 10 percent for larger, more virtual firms. Along demographic lines, the authors found that female and African American owners experienced larger drops in sales as well. (Bloom, Fletcher, & Yeh). Overall, there is strong evidence of heterogeneous impacts along economic lines, with smaller and lower income individuals and businesses being more affected than larger or more affluent ones.

I hypothesize a positive relationship between county median income and changes in employment/small business revenue, and a positive relationship between proportional employment in essential industries and said outcomes after augmenting my median income model with said industry shares. Previous evidence suggests that lower-income individuals suffered more negative employment impacts (Acs, Gregory, Karpman), and extrapolating those results from the individual level to the county level is reasonable. Sectors such as agriculture, utilities, caregiving, and government are very much essential, and counties with a higher proportion of employment and businesses in these sectors should see a smaller impact as a result. I test this hypothesis by running a set of regressions, first my outcomes of interest against median income alone, then by median income plus job sectors. The second set of specifications will allow me to evaluate my hypothesis while controlling for industry share, which is a potentially major confound. The paper concludes by proposing some potential causal hypotheses and research designs. I aim to contribute to the ongoing dialogue around policy decisions regarding recovery in the wake of the pandemic.

0.2 Data

The OIET, or Opportunity Insights Economic Tracker, is a public-private partnership that processes data from private firms and repackages said data in a publicly available format. The database and accompanying paper are available on the OIET Github. I have used 2 data files from the OIET, focusing on employment and small businesses.The data is broken down at national, state, county, and city levels, with slightly different formatting to account for qualitative differences in each kind of data.

The employment dataset is a composite of data sourced from Paychex, Intuit, Earnin, and Kronos. Firm-level payroll data is sourced from Paychex and Intuit, while worker-level data on employment comes from Earnin, and firm-level time sheet data is sourced from Kronos. The dataset begins coverage on January 15th 2020 and is still currently being updated. Sourcing data from payroll management systems provides more granularity and possibly a better representation of the current state of labor than unemployment claims alone, as it takes into account workers that have lost their position and not filed claims, or other similar situations that prevent accurate representation of employment changes. The dataset includes multiple breakdowns, including income categories and industry. The employment series is a composite, and the authors applied two different masking methods to Paychex and Earnin. For the Paychex series, tracking and dropping high sensitivity cells to avoid the introduction of new Paychex clients distorting the data was done by selecting influential cells that recorded more than 50 percent employment growth and dropped said cells.

Womply, a high-tech local commerce platform, provided data on small business revenue over the course of the pandemic. The dataset tracks percent change in revenue, controlling for seasonality and indexed to January 2020. Womply again provides multiple breakdowns, both by income and by industry, focusing on similar high, middle, and low income categories as well as NAICS supersector. Small businesses are defined as businesses with an annual revenue below the SBA's thresholds. Thresholds vary by number of employees, with maximums ranging from 100-1500 depending on industry. The data has been restricted to firms with 30 or more transactions in a quarter and more than one transaction in 2 out of 3 months. Womply excludes firms outside double the interquartile range of annual firm revenue calculated within the sample, and imputes values for cells that contain fewer than 3 merchants. The OEIT filters any series with more than 25 percent of revenue coming from cells containing one or two merchants, or less than 250,000 in revenue during January 2020.

For demographic and employment/business sector data, I compiled the 2019 data from the BLS, National Census, and BEA. I extracted county level median income from the national census and overall employment by NAICS sector from the BLS. To interpolate county-level small business sector composition, I selected county-level employment data by NAICS sector from the BEA limited to businesses under 50 employees, and divided that number by the total number of employees at businesses that have less than 50 employees. I then merged demographic and employment/business sector data with the employment and small business revenue from the OIET, and collapsed the dataset on county. This produces an average difference in small business revenue and employment per county from June 1st 2020 to late October 2021. Data Dictionary (Sourced from OIET, BLS, BEA, and Census)

Employment

• emp.combined: Percent change in net employment for all workers, indexed to January 4-31 2020

Small Business Revenue

- revenue.all: Percent change in net revenue for small businesses, calculated as a seven-day moving average, seasonally adjusted, and indexed to January 4-31 2020

Misc:

- date: The date observed, YYYY-MM-DD format

- countyfips: county 4 digit FIPS code

Regressors:

- Median.Household.Income..2019:County-level median household income in 2019 from the National Census

- LogInc: Logged median household income, constructed via logging Median.Household.Income..2019

- Agriculture: Proportion of the labor pool engaged in agriculture, ranging from 0-1. Sourced from the BLS for my employment dataset, and the BEA for interpolating small business composition.

- Utilities: Proportion of the labor pool engaged in utility-related labor, such as power generation or water treatment, ranging from 0-1. Sourced from the BLS for my employment dataset, and the BEA for interpolating small business composition.

- Retail.trade: Proportion of the labor pool engaged in retail trade, ranging from 0-1. Sourced from the BLS for my employment dataset, and the BEA for interpolating small business composition.

- Caregiving: Proportion of the labor pool engaged in healthcare and caregiving, ranging from 0-1. Sourced from the BLS for my employment dataset, and the BEA for interpolating small business composition.

- Government.Enterprises: Proportion of the labor pool engaged in government enterprises, ranging from 0-1. Sourced from the BLS for my employment dataset, and the BEA for interpolating small business composition.

- State.and.Local: Proportion of the labor pool directly employed by the state or local government, ranging from 0-1. Sourced from the BLS for my employment dataset, and the BEA for interpolating small business composition.

- sbRetail: The proportion of a county's total population that is employed at retail businesses with less than 50 employees.

Tables 1 and 2 present summary statistics for the datasets I have constructed for employment and small business revenue,respectively. Simply based on observing means and standard deviations, there's a high degree of variance in both outcomes at the county level, but on average, both employment and small business revenue have seen negative negative changes throughout the pandemic. Employment and business sector summary statistics are more challenging to interpret, as inter-county differences are significantly higher, which makes interpreting the means less useful. Median income, or the natural log thereof, presents similarly high differences across counties.

0.3 Methods

I utilized RStudio and several packages to complete and present my analysis, including ggplot2, tidyr, and xtable, which are all available freely online through CRAN. Data manipulation was handled primarily via Tidyverse and Collapse, and figures were generated via ggplot2 and ggcorrplot respectively.

I started by creating time series figures tracking daily changes in employment (Figure A.1) and small business revenue (Figure A.2), and then using the insight from said figure to specify my figures and regressions intended for more rigorous analysis. As my time-series summaries demonstrate, there appears to be a large initial drop around the first shelter-in-place order, then a gradual recovery. Small businesses, at their lowest, experienced a nearly 50 percent drop in revenue. A small recovery was made through the beginning of summer, but revenue remained around 30 percent lower through January 2021. Californian employment fared slightly better, with an initial drop of nearly 20 percent, and partial recovery to levels a little under 10 percent less than pre-pandemic. Nearly a year later, both small business revenue and employment have still seen significant and sustained negative impacts as a result of the pandemic.

To examine heterogeneity relating to factors like income or job sector, I use county-level data on growth in employment and small business revenue as my outcome variables. Since the outcomes are already in percentage terms relative to Jan. 2020, I could in principle use a single day from the county data. However, to boost power and representativeness of the sample, I use the full sample of daily observations from June first 2020 to October fifteenth and collapse to a cross-section of mean changes to smooth out any potential single-day anomalies. When estimating models, I cluster standard errors on county to avoid auto correlation inherent to time series as well.

I began with the county-level revenue data from the OIET, which presents small business revenue as a percent change indexed to January 2020 at a daily frequency. As an example, a 20 percent decrease in revenue would be represented as "-.2" in the data. Next, I took a subset of the data from June first onward, and collapsed the subset on county, producing an average difference in small business revenue from June 1st to late October 2021. I then merged county-level median income from the 2019 census, and logged it, which allowed me to create my first regression specification:

$$SBrevenue = B_0 + B_1 LogInc$$

This regression specification allows me to explore my initial hypothesis, that lower income counties would see a larger negative impact on small business revenue. I expect to see a positive relationship as more affluent counties likely have more of an economic surplus at baseline, which would make them more able to weather sudden shocks with little change in day-to-day spending or consumption. In this model, B_1 represents the effect of a 1 percent change in income on county-level small business revenue. Fundamentally, I'm attempting to estimate the income elasticity of small business revenue at the county level in the state of California. I augmented my regression by drawing employment data from businesses with under 50 employees from the BEA, and manipulated the sector-level data to give me county level employment proportions by sector by dividing each sector-level employment observation by the total number of workers employed by businesses with less than 50 employees in each county. I then created correlation matrices for employment (Figure A.3) and small business industry sectors (Figure A.4), and found that industries broadly considered essential such as agriculture, retail trade, utilities, medical and in-home caregiving, and government employment present a negative relationship with county median income. Considering the relationship showcased by the correlation matrix, I expect that including these new regressors in my original specification would reduce the magnitude of the coefficient on median income, as I would expect the negative correlation I added the aforementioned proportional employment variables to my regression, which is now

$$SBrevenue = B_0 + B_1 LogInc + \beta_2 Agriculture + B_3 Utilities + \beta_4 Retail.Trade + B_5 Caregiving$$

Both regressions present potential issues with auto-correlation of standard errors, as it's likely that counties close to each other face similar issues or possibly even influence the small business makeup or revenue of each other, so I decided to cluster my standard errors by county. This augmented regression, now controlling for industry distribution, presents a relationship between income and and small business revenue with less omitted variable bias.

My process of investigation regarding the COVID-19-related impacts on employment followed a similar process to my efforts on small business revenue. I drew county-level employment data from the OIET, which is again presented as a change relative to January 2020 at a daily frequency. I again limited my observations to after June first, and collapsed the panel on county, which gave me a county-level average of the employment difference from June first onward. I merged the same county-level median income from the 2019 national census, logged it, and specified my first regression as

$$Employment = B_0 + \beta_1 LogInc$$

Initially, I hypothesized that employment in lower-income areas would be more severely impacted, as lower income areas are already intuitively more vulnerable to systemic shocks such as a pandemic-induced recession. Interestingly, the results of my initial regression did not support that hypothesis, so I created a correlation matrix similar to the one I used for small business revenue, taking employment statistic by county from the BLS, transforming them into county-level proportions broken out by industry, and examining the relationship between industry and county-level median income. The relationships I found between overall employment and median income are similar to the relationships I found between small business sectors and median income, and as a result, I included agriculture, utilities, retail trade, care giving, government enterprises, and state/local government. The only real additions that differentiate this selection are the ones administrated by the state, as the government is not a small business. My augmented regression is specified as :

$Employment = B_0 + \beta_1 LogInc + \beta_3 Agriculture + B_4 Utilities + \beta_5 Retail + \beta_6 Gov.Enterprises + \beta_7 State.and.Local$

0.4 Results

The results I found were quite different from my hypothesis. A negative and at least marginally significant coefficient on income seems counter-intuitive, even after accounting for the differences in industry composition between counties. The impacts on small businesses were of significantly larger magnitude than on employment. Both regressions can be interpreted as a sort of median income elasticity specification, as the both the explanatory and outcome variables have been logged. Starting with my univariate employment model (Table A.3), my initial coefficient on *Loginc* is -0.0419, and a p-value of 0.0519, which is marginally significant. While this relationship, especially in terms of elasticity, seems small, we're dealing with county-level numbers, where a percent change can mean hundreds or even thousands out of jobs. Moving to my second employment specification (Table A.4), we see the inclusion of essential employment sectors actually increased the magnitude of the coefficient on *Loginc*. All of my sector variables aren't of statistical significance, but *Loginc* has an estimated beta of -0.1118, and a p-score of 0.0364, more than doubling in magnitude and now highly statistically significant. My regressions for small business revenue and *Loginc* show similar results, with my first univariate model (Table A.5) presenting an estimate of -0.1685 and a p-score of .0024. I'm interpreting this as small business revenues being more sensitive to county median income over the course of the pandemic than employment, which isn't super surprising to me. After adding essential business sectors to my regression (Table A.6), we see an increase in magnitude of the coefficient on *Loginc*, to -0.1924, and a p value of 0.0437, remaining highly significant. None of my included employment sector variables are of statistical significance, but *agriculture* and *retail.trade* present negative coefficients, while *utilities* and *caregiving* are positive. Interestingly, it appears that small business revenue is more sensitive than employment with regards to differing county median incomes, and controlling for county-level industry composition actually increases the magnitude of the sensitivity. This demonstrates a statistically and economically significant negative relationship between small business revenue/overall employment and county median income.

0.5 Conclusion

Interestingly, I found an inverse relationship between county median income and changes in small business revenue, even after controlling for industry sector. As this study is primarily intended to be descriptive, I'm not going to pursue any kind of rigorous causal analysis, but I will put forth some hypotheses and potential research designs to expand upon my findings. One root cause could be bias present with the data. Womply is a high-tech business intelligence platform for small businesses, and I would expect smaller/lower income firms have less of a use case for it. It's possible that the higher impact in in higher income areas presented in the data is a result of omission bias. Another potential cause for the relationship I've found is a material difference in business composition between small businesses in high income and low income areas. Small businesses in low income areas are largely in four sectors: construction, professional services, trade, and healthcare (Kugler). All four of those industries are somewhat essential, and theoretically less exposed to pandemic-related economic impacts. Also it's likely that lower income areas have less businesses which revolve around non-essential goods. Just allegorically, businesses in Santa Cruz such as the make-your-own candle lounge closed due to the pandemic while others such as my local corner store suffered minimally.

I also found an inverse relationship between county median income and changes in employment, also after controlling for job sector. This also isn't congruent with my initial hypothesis, but my correlation matrix median income and industries leads me to hypothesize that a higher proportion of jobs in lower-income counties fall into the "essential" category, such as retail trade, construction, etc. This is supported by previous literature on the subject from , and using data from the CPS to confirm and support this relationship would be a valuable next step. Another potential cause for this difference could be material differences in types of employment, e.g. undocumented workers or other unofficially employed individuals. Said labor is part of the so-called "shadow economy", which is extremely challenging to find data on. Reporting on job losses of segments that were never officially recorded in the first place wouldn't really fall within the scope of the data I utilized. Overall, my results were somewhat unexpected, and it would be interesting to see what kind of further work appears on this subject as time goes on. We're not even really post-crisis yet, and while a significant amount of economic research has been done regarding the pandemic, it will likely take years before we fully realize the scope and scale of the impacts.

0.6 Further Work

Utilizing data from the CPS and SBA, it would be possible to examine small businesses in higher or lower income areas at an individual level and gain a clearer understanding of their material differences. Individual and firm-level data would provide finer detail and possibly even allow for some causal conclusions to be drawn. Ideally, I'd like to survey employees and small business proprietors in lower income areas to increase the volume of data available for analysis as well. It's an under-observed segment according to the small business paper I read, and augmenting that body of material would benefit research beyond my own. Getting into contact with smaller businesses, especially those operating in a somewhat unofficial capacity, would be challenging. Creating a rapport and dialogue with said small businesses and employees could be a valuable way to generate data and gain a more holistic understanding of how the pandemic has affected less visible areas of the economy. Active community engagement, while not directly beneficial to quantitative analysis, would be an important step towards building trust with segments that are notoriously difficult to survey accurately. Working with and learning from the people and communities we study, and taking an approach to data collection that involves more community and citizen science will likely prove beneficial in situations where traditional sources of data are found to be lacking.

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Appendix A

Tables and figures

My time series figures demonstrate an initial steep drop for both employment and small business revenue at the state level, then a correction, with employment recovering signfiicantly more than small business revenue.

I chose to represent my correlation matrices graphically instead of just as a table. Each box is labeled as well as color coded with the given variable's correlation with county median income.

The graphical representations of my univariate regressions demonstrate a negative relationship with median county income for both outcomes of interest.

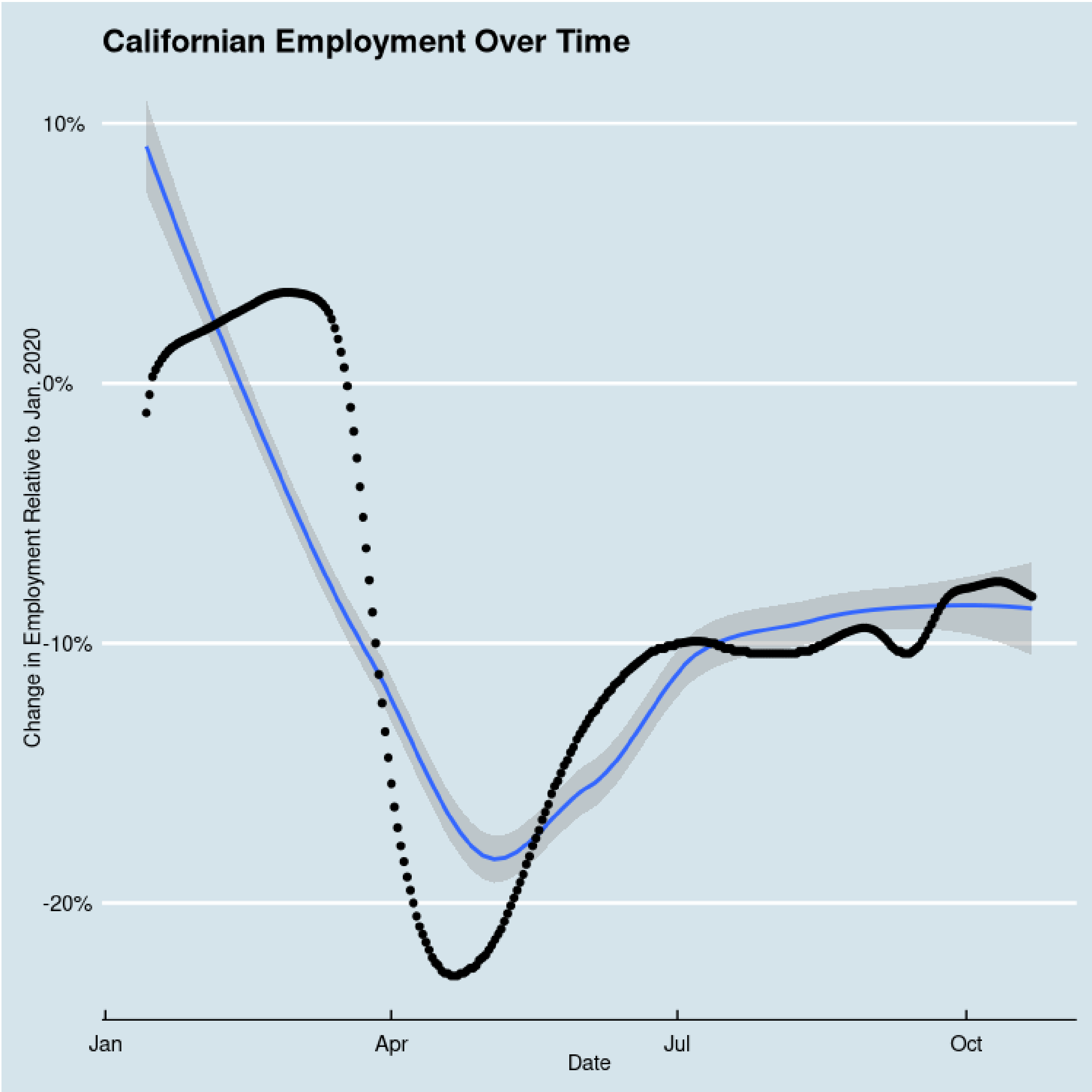

Figure A.1: State-Level Employment Time Series

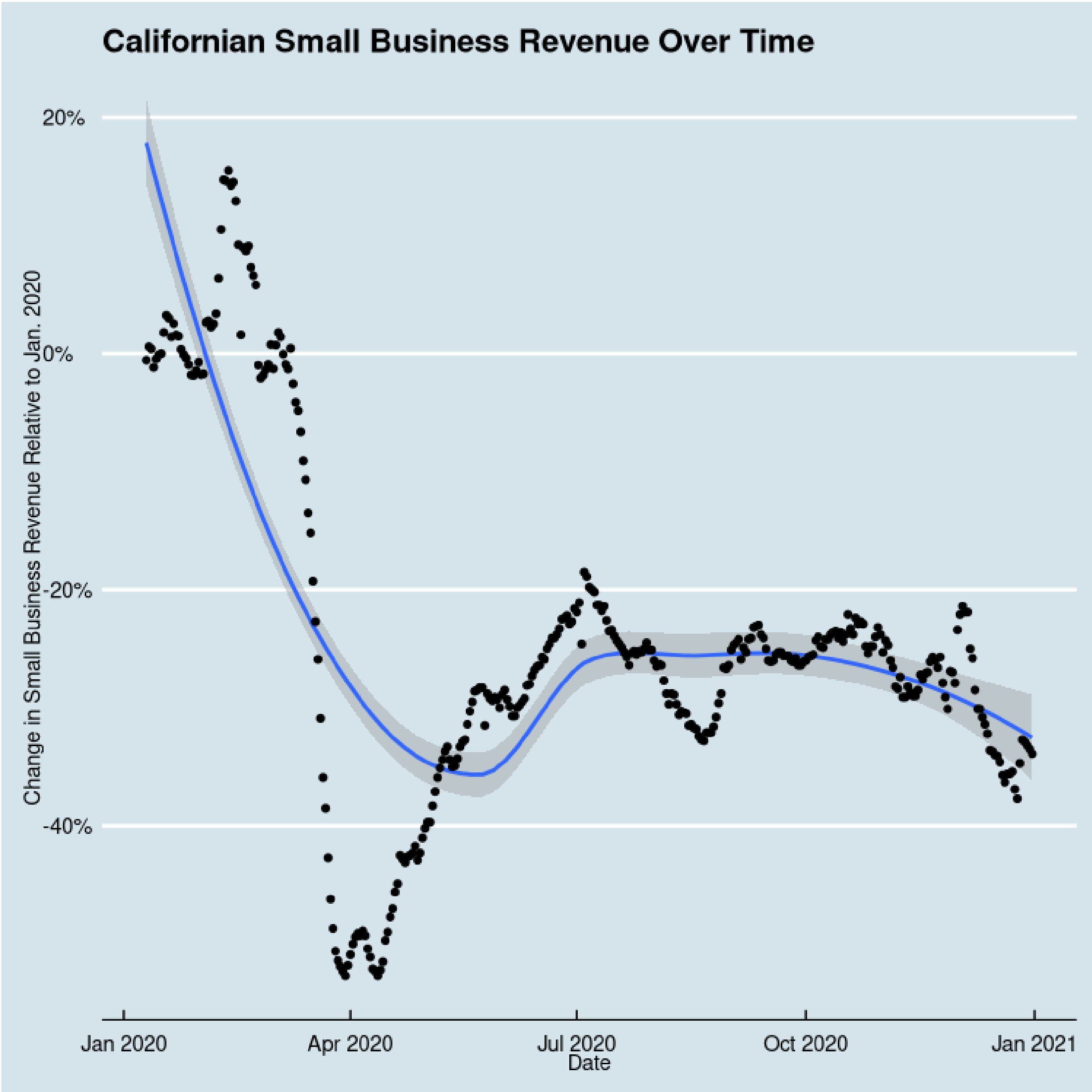

Figure A.2: State-Level Small Business Revenue Time Series

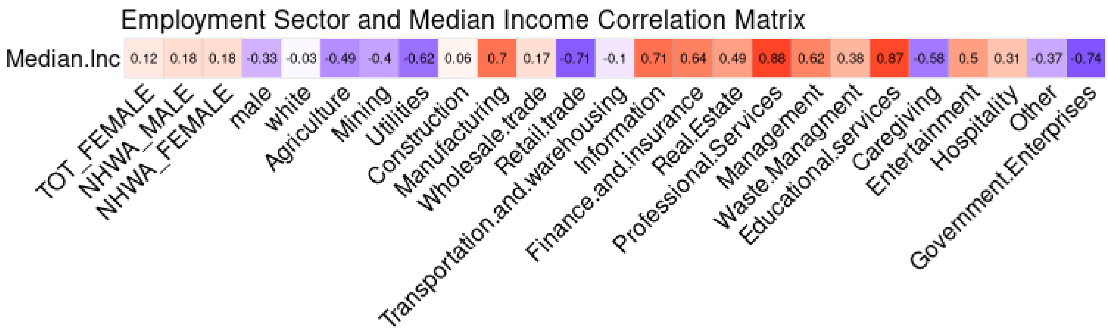

Figure A.3: Employment and Median Income Correlation Matrix

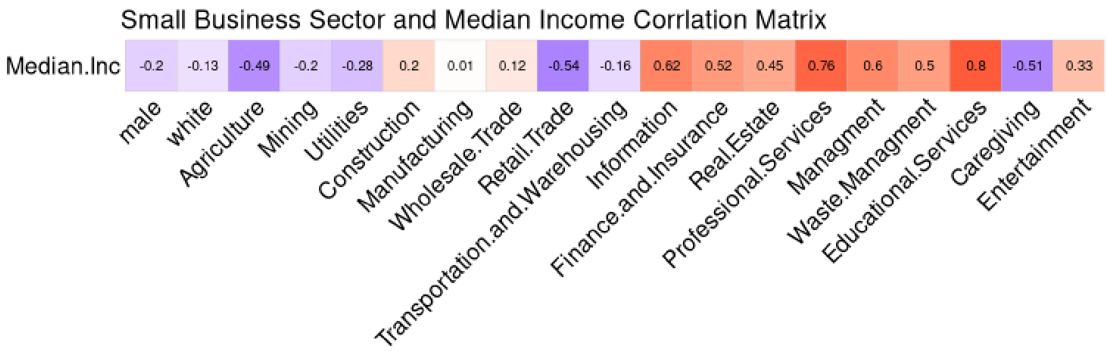

Figure A.4: Small Business Sector and Median Income Correlation Matrix

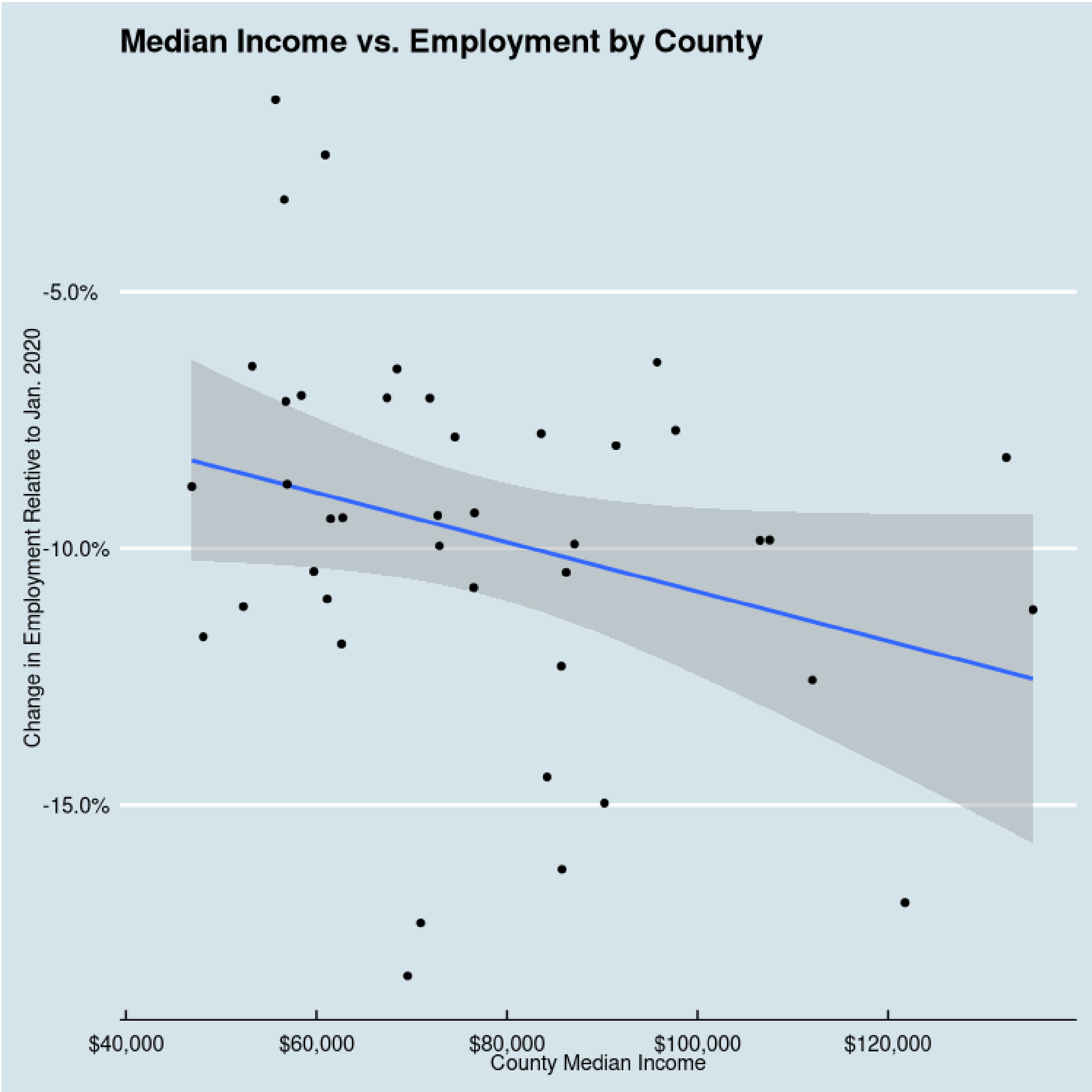

Figure A.5: Univariate OLS for Employment

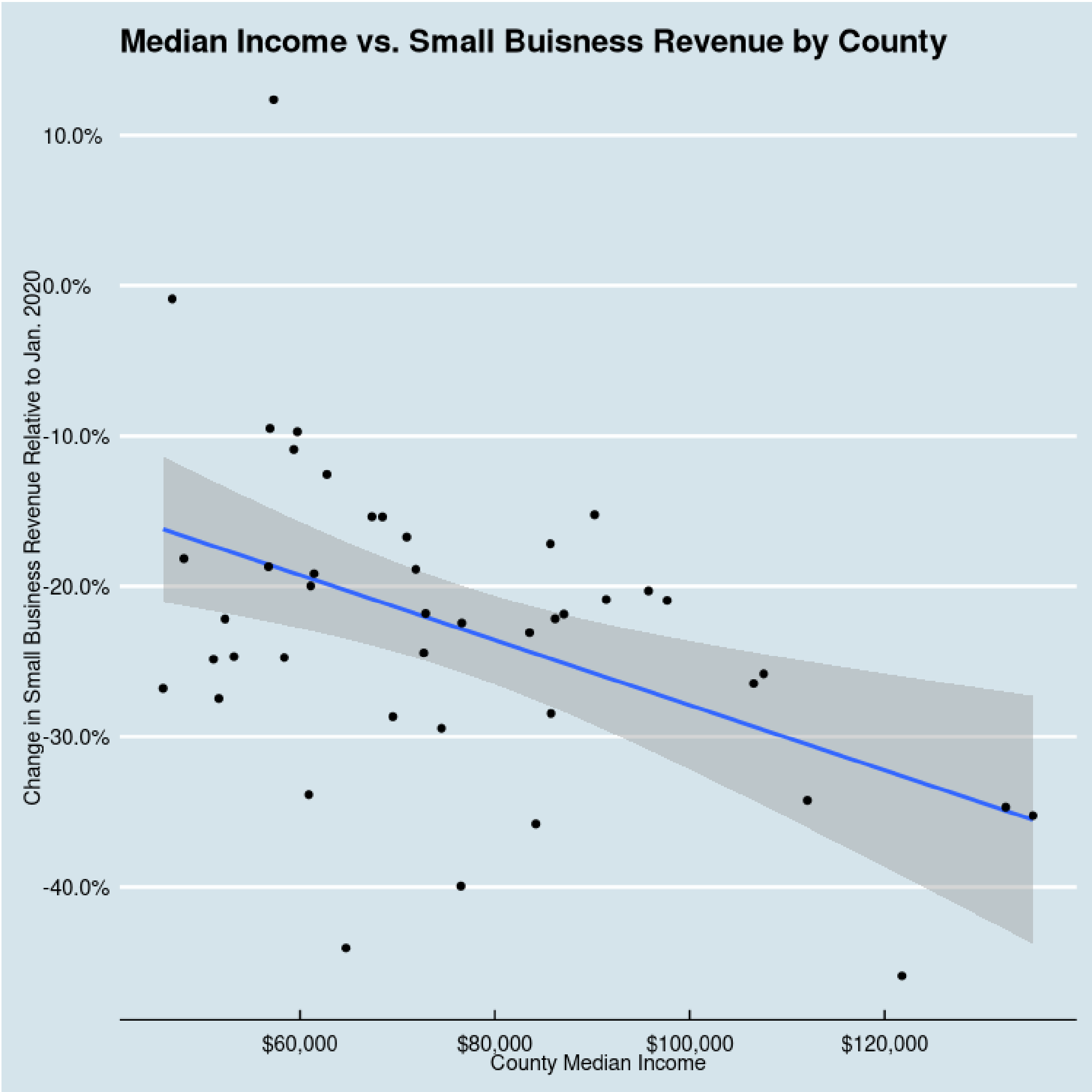

Figure A.6: Univariate OLS for SB Revenue

	Variable	Mean	SD
1	emp_combined	-0.09	0.08
2	Agriculture	0.02	0.04
3	Mining	0.00	0.01
4	Utilities	0.00	0.00
5	Construction	0.06	0.02
6	Manufacturing	0.05	0.02
7	Wholesale.trade	0.03	0.01
8	Retail.trade	0.09	0.02
9	Transportation.and.warehousing	0.05	0.03
10	Information	0.02	0.02
11	Finance.and.insurance	0.04	0.01
12	Real.Estate	0.05	0.01
13	Professional.Services	0.07	0.04
14	Management	0.01	0.00
15	Waste.Managment	0.06	0.01
16	Educational.services	0.02	0.01
17	Caregiving	0.12	0.03
18	Entertainment	0.02	0.01
19	Hospitality	0.07	0.01
20	Other	0.06	0.01
21	Government.Enterprises	0.13	0.04
22	Federal.civilian	0.01	0.01
23	Military	0.01	0.01
24	State.and.local	0.11	0.04
25	State.government	0.02	0.02
26	Local.government	0.09	0.03
27	sbretail	0.06	0.09
28	LogInc	11.13	.27

Table A.1: Employment Dataset Summary Statistics

	Variable	Mean	SD
1	revenue_all	-0.23	0.20
2	Agriculture	0.08	0.09
3	Mining	0.00	0.01
4	Utilities	0.01	0.01
5	Construction	0.07	0.02
6	Manufacturing	0.09	0.05
7	Wholesale.Trade	0.04	0.01
8	Retail.Trade	0.12	0.03
9	Transportation.and.Warehousing	0.04	0.03
10	Information	0.02	0.03
11	Finance.and.Insurance	0.03	0.01
12	Real.Estate	0.02	0.01
13	Professional.Services	0.06	0.04
14	Managment	0.01	0.01
15	Waste.Managment	0.06	0.02
16	Educational.Services	0.01	0.01
17	Caregiving	0.17	0.05
18	Entertainment	0.02	0.01
19	Hospitality	0.12	0.03
20	Other	0.04	0.01
21	LogInc	11.13	.27

Table A.2: Small Business Dataset Summary Statistics

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.3730	0.2348	1.59	0.1202
loginc	-0.0419	0.0209	-2.00	0.0519

Table A.3: Regression of Employment on Median Income

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.2785	0.6048	2.11	0.0517
loginc	-0.1118	0.0487	-2.30	0.0364
Agriculture	-0.2106	0.2491	-0.85	0.4112
Utilities	0.1804	4.2059	0.04	0.9664
Retail.trade	-0.0641	0.5604	-0.11	0.9105
Caregiving	-0.3617	0.4862	-0.74	0.4683
Government.Enterprises	-0.2371	0.3849	-0.62	0.5471
State.and.local	-0.2158	0.4658	-0.46	0.6498

Table A.4: Regression of Employment on Median Income and Job Sector

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.6603	0.5838	2.84	0.0068
loginc	-0.1685	0.0521	-3.23	0.0024

Table A.5: Regression of Small Business Revenue on Median Income

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2.0541	1.1552	1.78	0.0834
loginc	-0.1974	0.0946	-2.09	0.0437
Agriculture	-0.1398	0.2368	-0.59	0.5586
Utilities	3.0565	2.7151	1.13	0.2673
Retail.Trade	-1.1817	0.9838	-1.20	0.2371
Caregiving	0.3729	0.4484	0.83	0.4109

Table A.6: Regression of Small Business Revenue on Median Income and Business Sector