UNIVERSITY OF OREGON

A Study on The Impact of the US-China Trade War on County Level US Housing Prices

by

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undergraduate theses course

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Abstract

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During Donald Trump's first presidential term, the United States launched a trade war with China, marked by a series of escalating tariffs on goods exchanged between the two countries. A growing body of research has examined the impact of these trade policies across various sectors of the U.S. economy. One notable study, "The Consumption Response to Trade War Shocks: Evidence from the US-China Trade War" by Michael E. Waugh, analyzes the effect of the trade war on county-level consumption, using automobile sales as a proxy. Drawing on Waugh's methodological framework, this paper investigates the potential effects of the trade war on the U.S. housing market, a sector that has experienced sustained price growth over the past few decades. I assess whether the tariffs imposed on Chinese imports during the trade war affected housing prices at the county level. To do so, I estimate a fixed-effects regression model that includes time and regional fixed effects and controls for local economic conditions via county-level employment rates. This empirical strategy aims to isolate the causal impact of trade policy shocks on housing market outcomes. Given that the trade war unfolded in successive rounds, this study focuses on the cumulative effects of tariff implementation, beginning in early 2018 and concluding in the fall of that year. The analysis uses data spanning from early 2017 through late 2019, allowing for the examination of both pre and post-shock housing market responses.

Contents

Chapter 1

Introduction

This paper examines the impact of the U.S.–China trade war (2017–2019) on U.S. housing prices. During this period, the United States imposed tariffs on more than 360 billion dollars worth of Chinese goods, while China retaliated with tariffs on 110 billion dollars worth of U.S. exports. These trade disruptions affected various industries, employment levels, and local economic conditions, which in turn may have influenced housing markets. Housing prices, often used as indicators of economic well-being and quality of life, provide a valuable lens for assessing the broader effects of trade-induced economic shocks. These tariffs imposed by the Trump administration inspired a plethora of studies on the tariffs and their effects on both the US and global economy. For instance, Waugh (2019) investigates the consumption response to trade shocks by analyzing automobile sales at the county level using a difference-in-differences framework. Waugh finds that there are large effects on a county's consuming power, dropping around 3.8 percentage points when moving from the bottom to the top quartile in counties affected by the tariffs. Similarly, Fajgelbaum et al. (2019) explore the short-run effects of the shift toward trade protectionism in their study The Return to Protectionism, highlighting how U.S. tariff policies disrupted supply chains and regional economies after decades of encouraging free trade. They find that the tariffs costed consumers of imported products around 50.8 billion USD per annum. Amiti et al (2019) finds that nearly 100 percent of the tariff costs where passed onto US consumers and importers. Furthermore, they found that imports fell 25-30% on tariffed goods. The primary motivation for this research is to identify key factors driving increases in housing prices. Over the past several decades, the United States has experienced substantial growth in housing costs, creating significant economic and social challenges. Given the broad economic effects of tariffs documented in existing literature, examining their potential impact on the housing market represents a valuable area of inquiry. This paper investigates whether U.S. tariffs

have measurable effects on American housing prices and, if so, identifies the mechanisms through which these effects occur.

Chapter 2

Data

The data I used is a combination of Zillow Housing Data ranging from 2017 to 2019 in tandem with government data for county level population by the year and monthly employment levels. I then combine that with the tariff level indicators provided by Mike Waugh on his US-China Trade War Tracker

2.1 Housing Data

The housing data used for this analysis is sourced from the Zillow Research Data website, covering the period from 2017 to 2019 at the county level. The dataset specifically utilizes Zillow Home Value Index (ZHVI) values, which measure typical home values by reflecting properties in the 35th to 65th percentile range. Detailed methodology for ZHVI calculations can be found at the Zillow Home Value Index Methodology website. Zillow data was selected over government sources due to its superior county-level coverage. Government data lacks information for numerous individual counties, as illustrated in the comparative visualization in the Appendix. While state-level trends show comparable patterns between government and Zillow data (insert comparison numbers), county-level comparisons reveal significant discrepancies, primarily attributable to the government data's limited county coverage. As shown in Figure 2.1, most counties experienced moderate housing price increases between 2017 and 2019. The most substantial growth occurred in Wexford County, MI, with a 67.91% increase, followed by Pocahontas County, IA (40.66%), Crawford County, IL (38.52%), Hooker County, NE (37.18%), and Greeley County, NE (36.66%). Conversely, 110 counties experienced declining housing prices, with Perry County, IL recording the largest decrease at 26.46%. The values in Figure 2.1 represent unweighted percentage changes in housing prices, calculated as the relative percentage change between 2017 and 2019 at the county level.

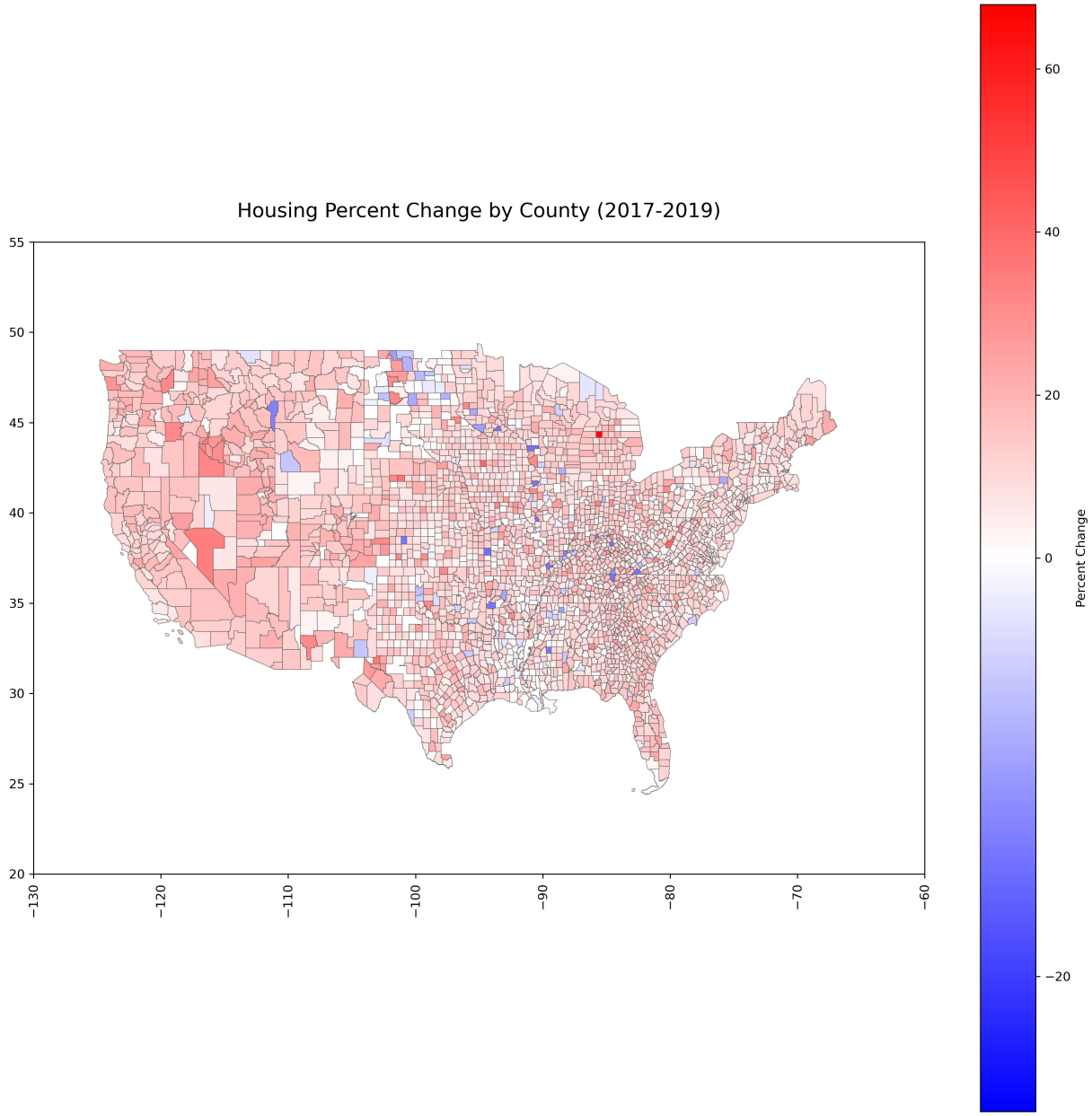

FIGURE 2.1: 2017 to 2019 Percentage Housing Price Change by County

2.2 Population Data

The population data used in this study was sourced from the U.S. Census Bureau. This dataset provides yearly county-level population estimates calculated using a cohort-component method derived from the demographic balancing equation: Population base + births - deaths + migration. The Population Estimates Program regularly revises and updates the entire time series from July 1, 2010 (the anchor date) through July 1 of the current year. For this analysis, I utilize the annual population values for each county throughout the study period.

2.3 Employment Data

As a control for this model, I use local county-level employment data from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW). The QCEW provides comprehensive labor market data at the county level across the United States, broken down by sector and month. This dataset is primarily derived from employment and wage information reported to U.S. Unemployment Insurance programs, covering approximately 97 percent of all wage and salary civilian employment nationwide. Although the QCEW offers various employment measures across individual sectors, for the purposes of this study, I utilize only the aggregate employment measure as a control variable within the model.

2.4 Tariff Data

The Tariff Data used for this analysis is sourced from Michael Waugh's US-China Trade War Tracker. The values are produced by a trade weighted average between the associated tariff values on NAICS products within each county. Figure 2.2 illustrates the percentage change between 2017 and 2019 by county using this data from Waugh's dataset.

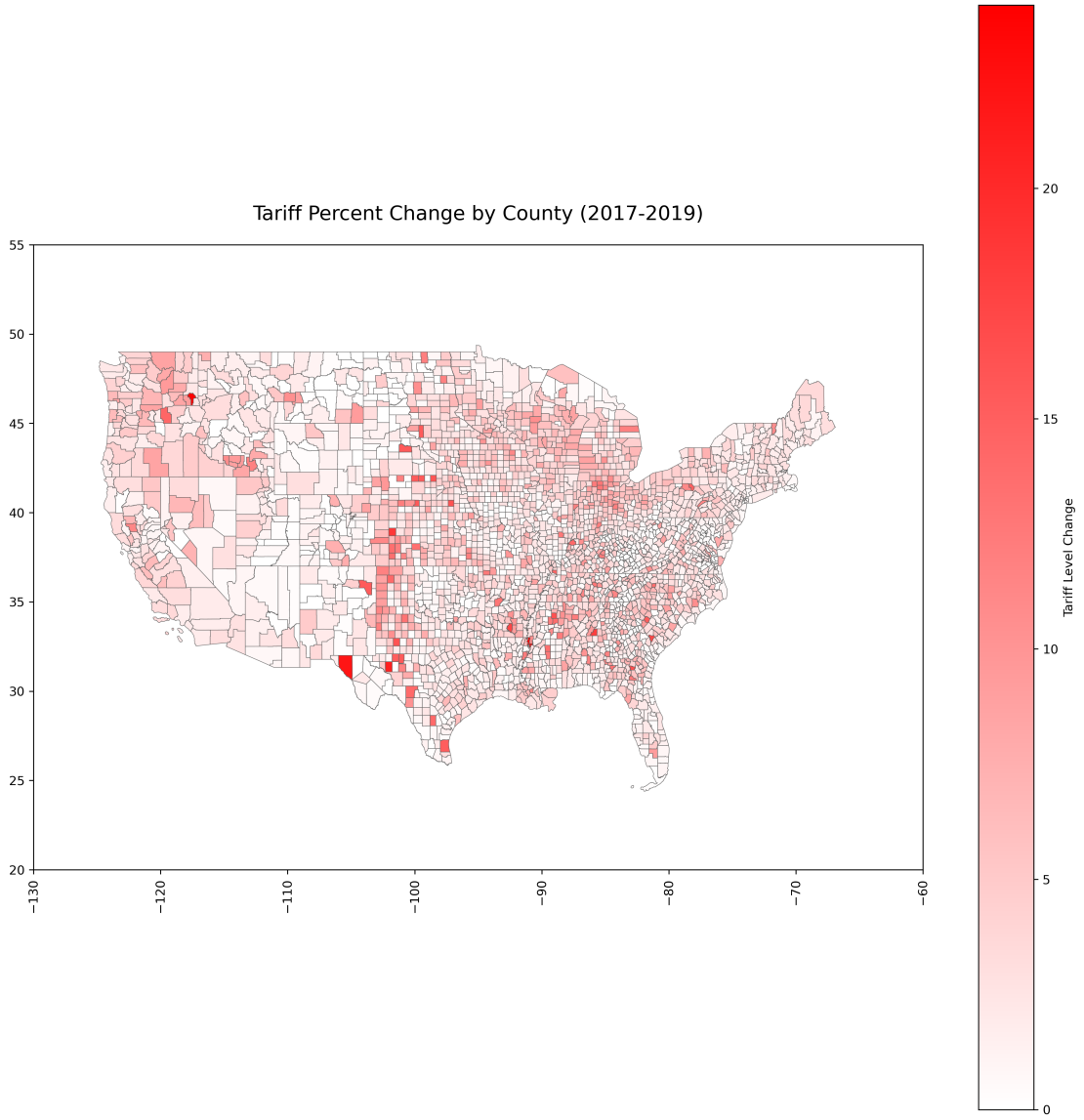

FIGURE 2.2: 2017 to 2019 Percentage Tariff Level Changes by County

As seen in figure 2.2, the majority of the US experienced a low to mid level change in tariff levels.

Chapter 3

Housing Prices and US Protectionist Tariffs

This section explores the effects of US Protectionist Tariffs on housing prices. This covers visualization between

3.1 Difference in Difference Visualization

This section visualizes the housing price differences between counties that experienced the largest tariff changes versus those with the smallest changes. The analysis compares the extremes (second-lowest quartile Q2 vs. lowest quartile Q1) to highlight potential tariff impact patterns.

The methodology calculates county-level tariff changes between January 2017 and December 2019, then classifies counties into quartiles based on tariff change magnitude. The graph shows the differential between second-lowest-impact (Q2) and lowest-impact (Q1) counties, with annotations marking key trade war events and pre/post-tariff average price levels. With the X axis being the date and the Y axis being the log difference between mean housing prices for the two quartiles.

The resulting visualization reveals how housing markets in differently-affected regions diverged following major trade policy actions, providing insight into potential causal relationships between trade policy and local housing markets.

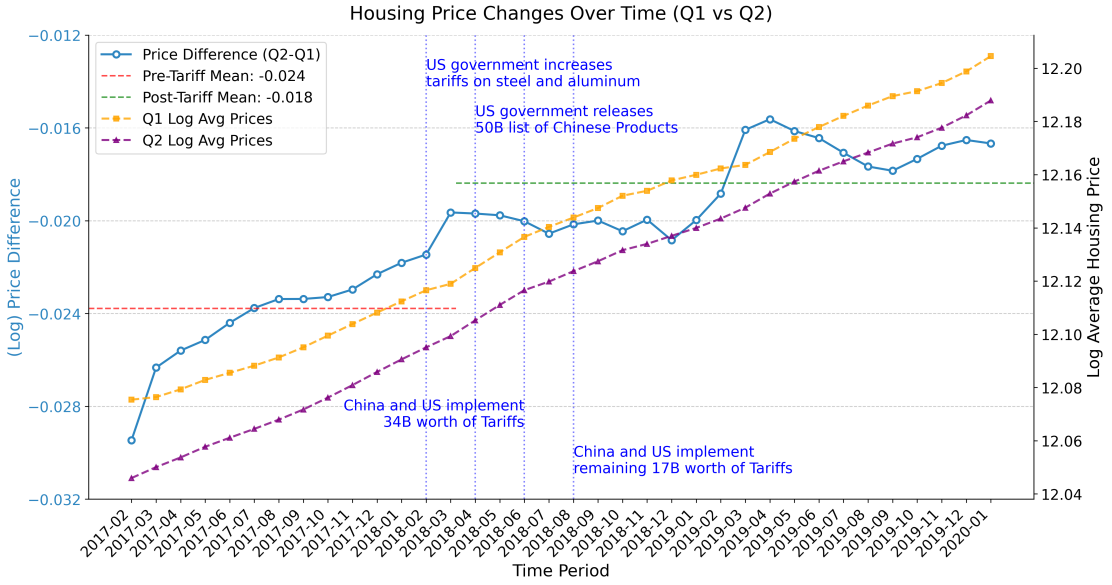

FIGURE 3.1: Difference in Housing Prices Between Top and Bottom Quartiles of Counties affected by Tariffs

The mean price difference between the most and least affected counties shows a sharp decline following the initial tariff implementation, as illustrated in Figure 3.1. Furthermore, around 6 months after the final stage of the trade war, the difference between the two quartiles nears 0 before increasing again in the following months.

It is important to note that the gap between top and bottom quartiles begins to contract more rapidly starting in March 2019—approximately six months after the trade war's final phase—which could possibly be attributed to exogenous factors, consequently pulls up the post-initial tariff mean.

3.2 Bubble Plot Visualization

Figure 3.2 illustrates the relationship between percentage changes in housing prices and percentile point changes in tariffs. For example, a change from a 5 percent to a 15 percent tariff on a county's goods results in a 10 percentage point increase in tariffs. The size of each point represents the county's population in 2017.

While many bubbles are clustered together and difficult to distinguish individually, several patterns emerge. Notably, few large counties experienced high percentile point changes in tariffs. However, a substantial number of large counties experienced low tariff percentile point changes while still showing high percentage increases in housing prices.

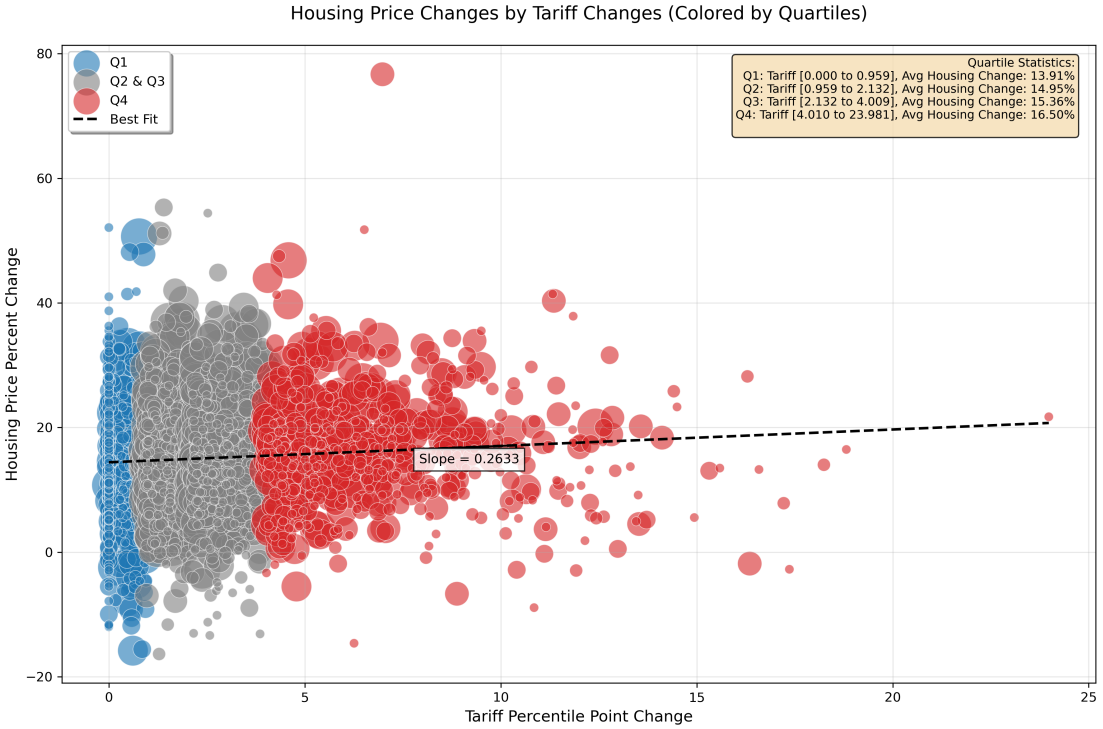

FIGURE 3.2: Housing Price Percent Changes by Tariff Percentile Point Change

Figure 3.2 also displays a line of best fit across the varied distribution of housing price changes, with a slope of 0.2633. While this does not represent a strong upward trend, it demonstrates a systematic positive relationship between protectionist tariff level increases and housing price increases.

There is a notable outlier county within the scatter plot: Wexford County, Michigan, which experienced a significantly higher change in housing prices compared to the rest of the United States. The potential effects of this county and other outliers on the line of best fit are covered in the robustness check in the appendix.

Chapter 4

Formal Regression Analysis

4.1 Base Regression

This section presents a formal regression analysis examining the relationship between tariff levels and housing prices. The empirical model employed is:

$$\Delta \log H_{c,t} = \beta_0 + \beta_1 \Delta \text{Tariff}_{c,t} + \gamma_c + \gamma_t + X_{ct} + \epsilon_{c,t} \tag{4.1}$$

where $\Delta \log H_{c,t}$ represents the 12-month log difference in housing prices for county c at time t; β_0 is the intercept; β_1 captures the effect of 12-month changes in county-level tariffs on housing price growth; γ_c and γ_t denote county and time fixed effects, respectively; X_{ct} controls for the 12-month change in employment; and $\epsilon_{c,t}$ is the error term.

Table 4.1: Effect of Tariff Changes on 12-Month Housing Price Changes

	(1)	(2)	(3)	(4)	(5)	(6)
Tariff	0.001***	0.000	0.004***	0.005***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Employment		0.000		0.156***		-0.035***
		(0.000)		(0.006)		(0.005)
Fixed Effects:						
County	N	N	N	N	Y	Y
Time	N	N	Y	Y	Y	Y
Population Weight	N	Y	Y	Y	Y	Y
Observations	61410	61410	61410	61410	61410	61410
R-squared	0.002	0.000	0.061	0.073	0.647	0.648

Table 4.1 presents the regression results across six model specifications. Model 1, which conducts an unweighted raw regression of tariff changes on housing price changes, unsurprisingly produces no significant correlation between the two variables. Models 2 through 6 are weighted by county population from the initial year of each interval (for example, the 2017-2018 difference is weighted by 2017 population levels). Notably, all weighted models demonstrate statistical significance at the 1% level, with the exception of Model 2 (the simple weighted regression), which yields a correlation coefficient of zero. Models 5 and 6 incorporate both county and time fixed effects. Despite the removal and subsequent reintroduction of employment as a control variable between these specifications, the coefficient estimate remains stable. Across Models 3 through 6, the coefficient consistently hovers around 0.004 and maintains statistical significance at the 1% level, suggesting a robust relationship between tariff changes and housing price growth.

Figure 4.1 visualizes the estimated tariff effects on housing prices using 12-month differences. A notable decline occurs around February 2017-2018, preceding the first wave of tariff implementations. This timing suggests that external factors, rather than tariffs themselves, likely drove this initial drop. In subsequent periods, the estimated tariff effects exhibit a markedly different pattern. While the magnitude of changes is less dramatic than the February decline, the effects predominantly remain positive, with distinct peaks occurring in September 2017-2018, January 2018-2019, and August 2018-2019. Importantly, these peaks align temporally with the implementation timeline of various tariff measures, providing evidence that tariffs did indeed influence county-level housing prices during this period.

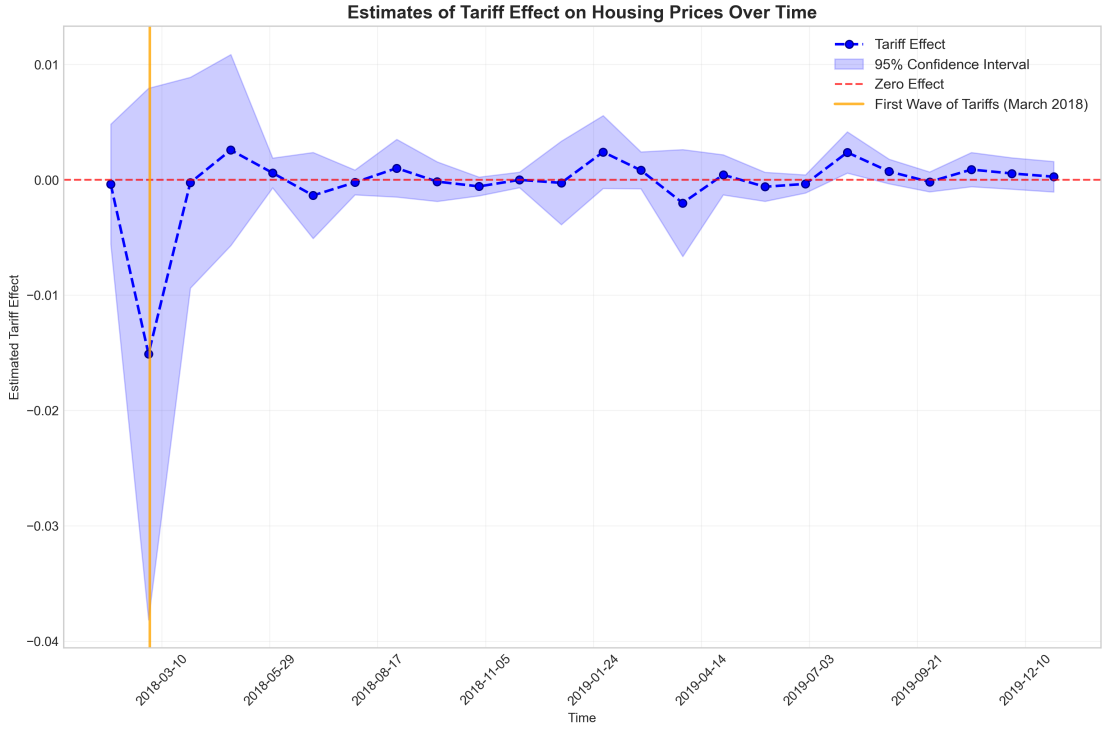

FIGURE 4.1: Estimated Tariff Effects

4.2 Quartile Regressions

In this section, I have run the same regression as I did in the previous section after separating the data points by tariff quartiles. Figures 4.2 to 4.5 illustrate the results.

Figure 4.2 shows the results from the regression on the counties least affected by the tariffs. As seen in the table, through column 5, there appears to be a strong relationship between changes in tariff levels and changes in housing prices, with column 4 showing a coefficient of .037 which is far higher than the .004 found in the larger regression. However, once county fixed effects are introduced, the relationship drops off significantly to .001, which is not even statistically significant at the 1 percent level.

TABLE 4.2: Effect of Tariff Changes on 12-Month Housing Price Changes - Q1 (Least Affected - Lowest Tariff Increase)

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Tariff	-0.007***	-0.020***	0.039***	0.037***	0.002	0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Δ Log Employment				0.234***		-0.011
				(0.010)		(0.009)
Fixed Effects:						
County	N	N	N	N	Y	Y
Time	N	N	Y	Y	Y	Y
Population Weight	N	Y	Y	Y	Y	Y
Observations	13833	13833	13833	13833	13833	13833
R-squared	0.001	0.011	0.087	0.121	0.663	0.663

Tables 4.3 and 4.4 cover the two middle quartiles. Both tables exhibit results closer to those of the larger regression, with coefficients that approximate the .004 produced by the larger regression and remain statistically significant at the one percent level. Notably, the final result from Table 4.2 (Q1) appears to place significantly lower weight on log employment compared to the two middle quartiles, with Q2 showing a much more significant coefficient of -.097 compared to the -.011 produced by Q1.

TABLE 4.3: Effect of Tariff Changes on 12-Month Housing Price Changes - Q2 (Low-Medium Tariff Increase)

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Tariff	0.002**	-0.015***	0.004***	0.005***	0.003**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δ Log Employment				0.114***		-0.097***
				(0.013)		(0.014)
Fixed Effects:						
County	N	N	N	N	Y	Y
Time	N	N	Y	Y	Y	Y
Population Weight	N	Y	Y	Y	Y	Y
Observations	15634	15634	15634	15634	15634	15634
R-squared	0.000	0.044	0.083	0.088	0.641	0.642

TABLE 4.4: Effect of Tariff Changes on 12-Month Housing Price Changes - Q3 (Medium-High Tariff Increase)

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Tariff	-0.001*	-0.002***	0.006***	0.006***	0.001***	0.001***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Δ Log Employment				0.120***		-0.041***
				(0.011)		(0.010)
Fixed Effects:						
County	N	N	N	N	Y	Y
Time	N	N	Y	Y	Y	Y
Population Weight	N	Y	Y	Y	Y	Y
Observations	16362	16362	16362	16362	16362	16362
R-squared	0.000	0.005	0.031	0.037	0.683	0.683

Table 4.5 illustrates the results of the final regression. The most striking observation is that there appears to be little to no relationship between the tariffs and changes in housing prices. This finding is unexpected, as one would anticipate that counties experiencing the most severe effects of the tariffs would also experience the largest swings in housing prices.

TABLE 4.5: Effect of Tariff Changes on 12-Month Housing Price Changes - Q4 (Most Affected - Highest Tariff Increase)

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Tariff	-0.000**	-0.000	0.000	0.000**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ Log Employment				0.110***		-0.008
				(0.010)		(0.009)
Fixed Effects:						
County	N	N	N	N	Y	Y
Time	N	N	Y	Y	Y	Y
Population Weight	N	Y	Y	Y	Y	Y
Observations	15581	15581	15581	15581	15581	15581
R-squared	0.000	0.000	0.008	0.016	0.595	0.595

Chapter 5

Conclusion

While this paper was able to establish a relationship between tariffs and US housing prices, it opens up various topics for further investigation. There are obviously many unique attributes associated with counties that would play a significant role in determining housing prices. Furthermore, while markets like stocks are observably very responsive to events like tariffs, large investments like housing that are determined by many more factors may not necessarily respond as quickly or to the same degree. As cited by Waugh when writing his paper, the trade war has continued to escalate, with President Trump's recent actions imposing large-scale tariffs on the majority of the US's major trading partners. The data that can be drawn from this trade war in the following years will likely produce more concrete results that further identify the relationship between tariffs and housing price changes, as the wave of tariffs is of a much stronger magnitude than previous ones.

The conclusions drawn from this paper are that while housing markets do not appear to suffer large direct increases in housing prices, there is a clear correlation between counties that have high rates of tariffs and increased housing price levels within the studied time period.

Appendix A

Figures and Tables

The heatmap below visualizes the government data for county level housing prices. As observable in the figure, the majority of counties in the US are lacking data for housing prices.

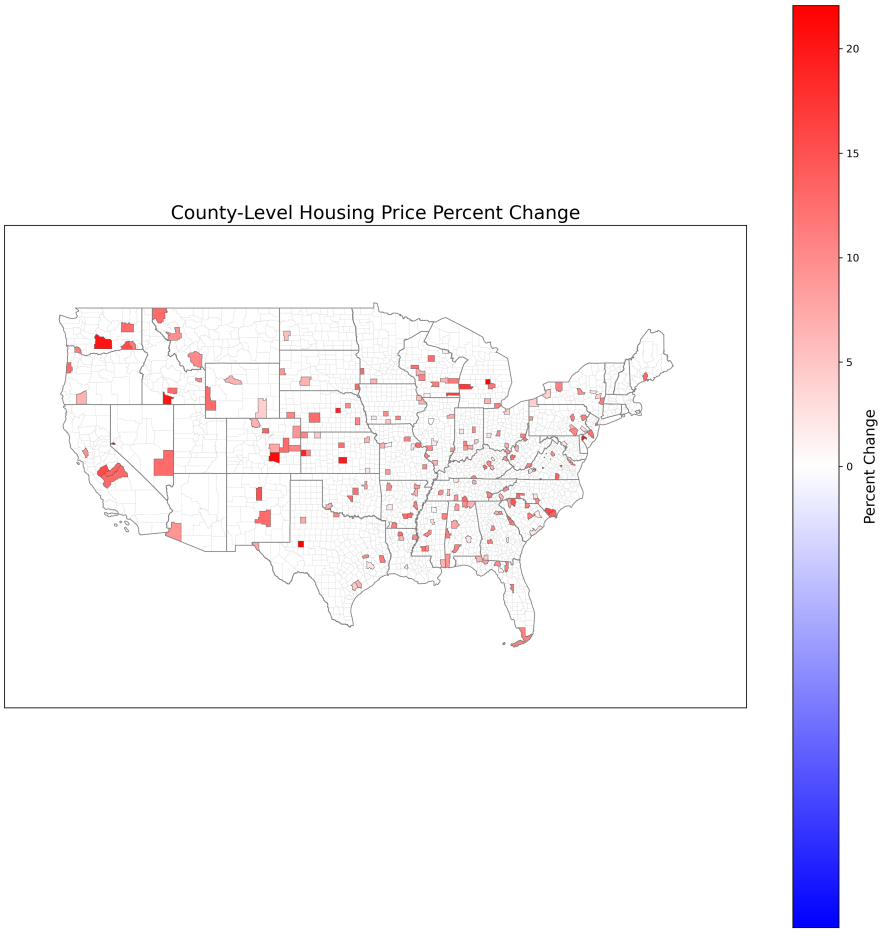

FIGURE A.1: 2017 to 2019 Percentage Housing Level Changes by County Government Data

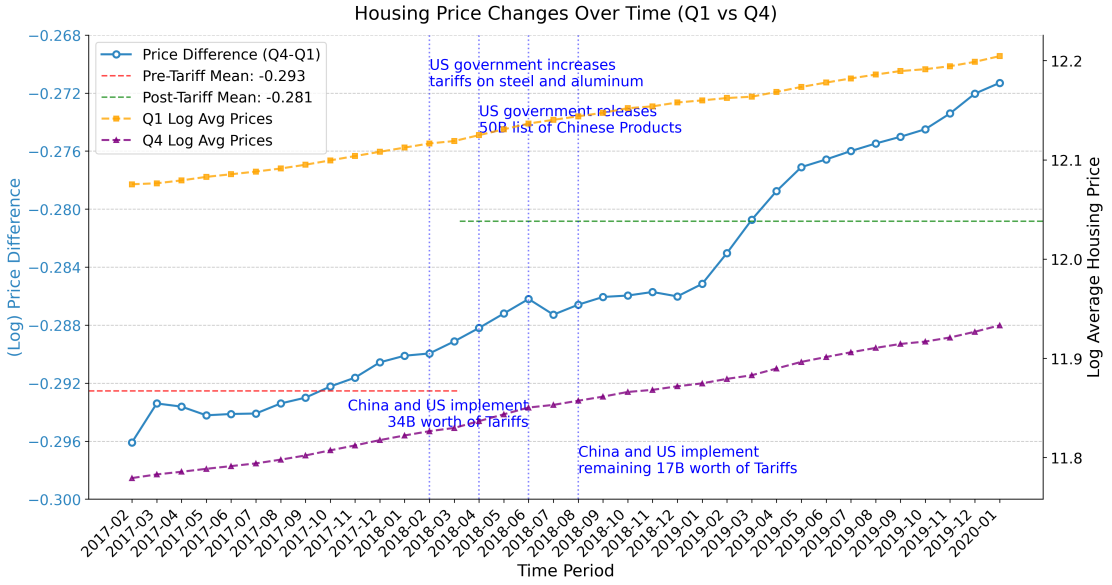

FIGURE A.2: Housing Price Changes Q1 to Q2

Figure A.2 displays housing price line plots comparing different quartile pairs over time. The figure shows that the price gap between Q1 (lowest quartile) and Q4 (highest quartile) narrowed significantly throughout the examined period. There is a notable increase in the rate of change around six months after the tariffs were implemented. While not directly comparable to the sharp spike seen in Figure 3.1 comparing Q1 and Q2, this likely indicates a shock in the housing market independent of the tariff effects. A notable feature of this graph is the absence of the extreme spikes and dips observable in other figures, with the rate of change in the difference between the two quartiles remaining relatively constant throughout the entire time period.

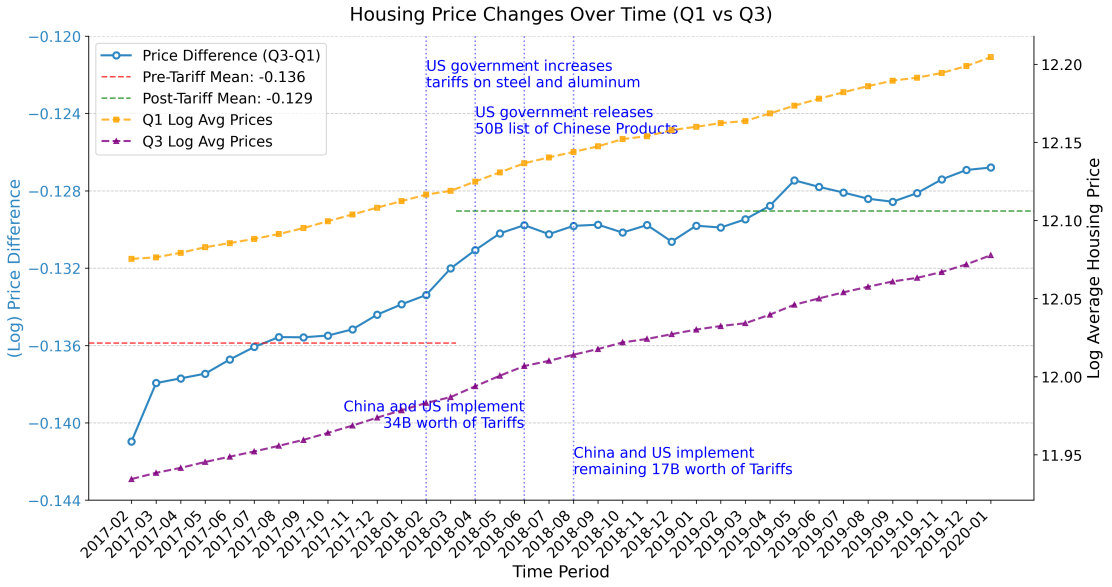

FIGURE A.3: Housing Price Changes Q1 to Q3

Figure A.3 observes similar behavior to figure A.2, with spikes in the decrease in housing price difference with a generally smaller difference between the two quartiles, However, as displayed in the plot, there was a bigger difference between the two quartiles' mean housing prices.

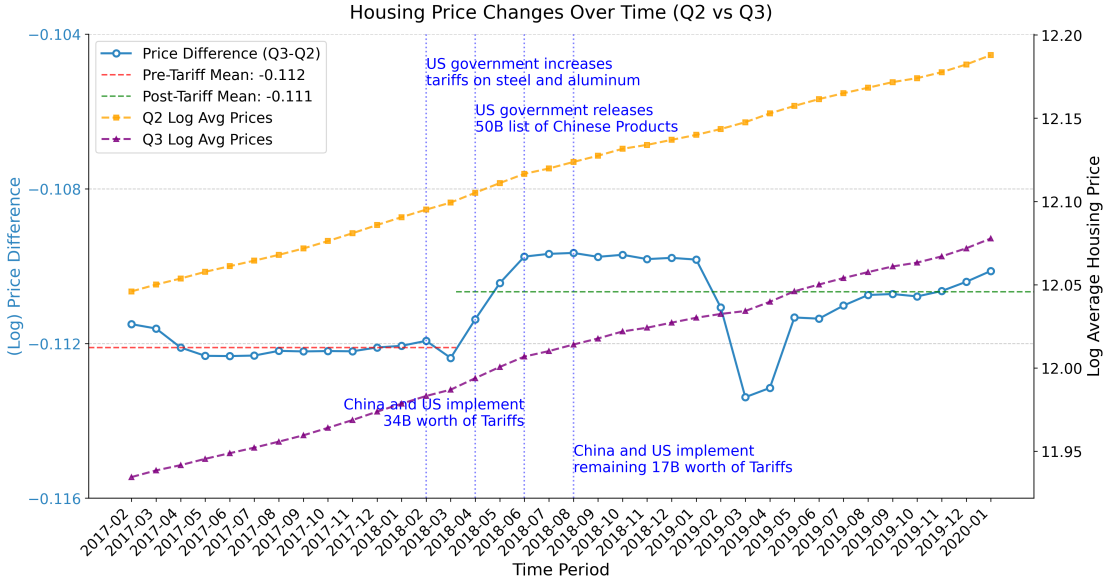

FIGURE A.4: Housing Price Changes Q2 to Q3

Figure A.4 compares quartiles 2 and 3 of housing prices. While the different scales on the two axes make it difficult to observe the individual fluctuations in each quartile's mean housing prices, these movements are correlated with the major peaks and valleys shown in the price difference between the quartiles.

Figure A.5 displays the mean values of all quartiles side by side, as well as the overall mean values. Counties within Q4 (highest tariffs) have significantly lower average housing prices than counties in the other three quartiles, with Q1 and Q2 showing the highest and most similar housing price levels. All quartiles exhibited a similar rate of change.

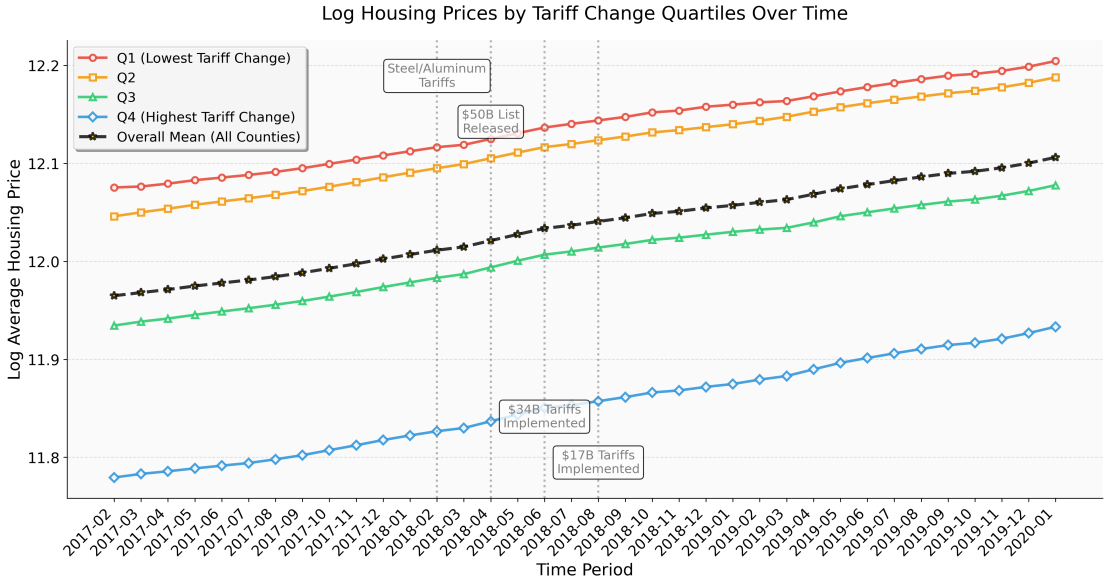

FIGURE A.5: All Quartiles Housing Mean

Figure A.6 displays the mean housing prices of each quartile once again, but they are normalized at the start date. As shown in the graph, counties with the lowest tariffs experienced the lowest increase in housing prices, while those in the most affected quartile experienced notably higher levels of increase in housing prices.

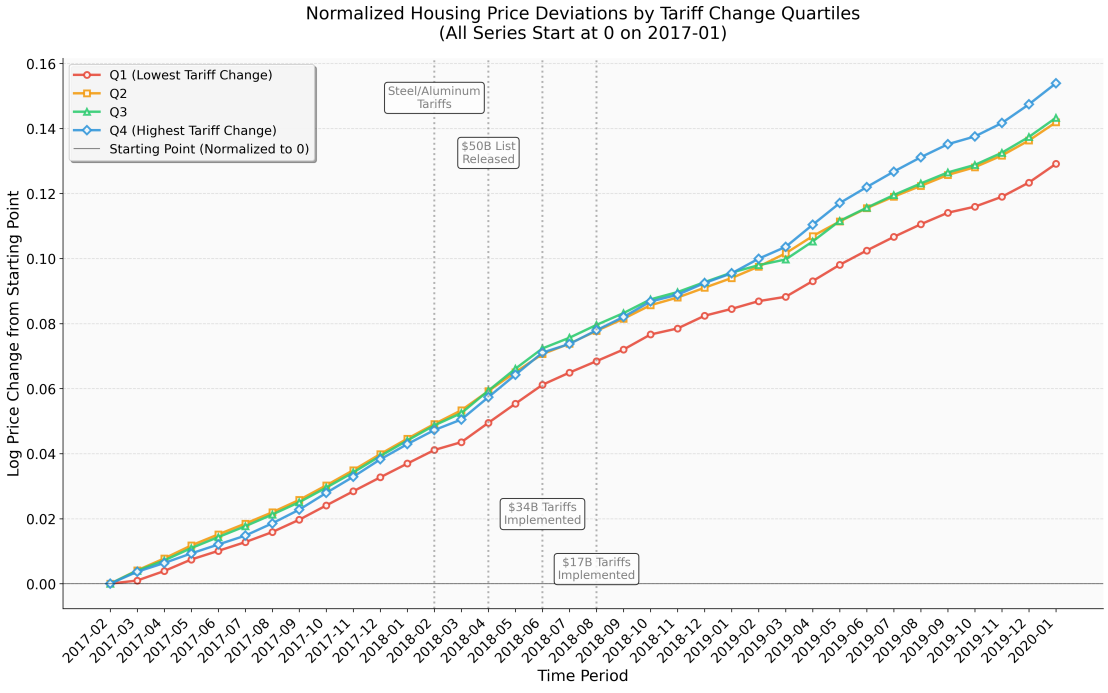

FIGURE A.6: Normalized Housing Quartile Housing Changes

Figures A.7-A.9 illustrate the relationship between state political bias and housing price changes at the county level. Each bubble's size corresponds to the number of votes cast

in that county. The trend lines represent different regression models: LOWESS (locally weighted scatterplot smoothing), fourth-degree polynomial, and quadratic, respectively.

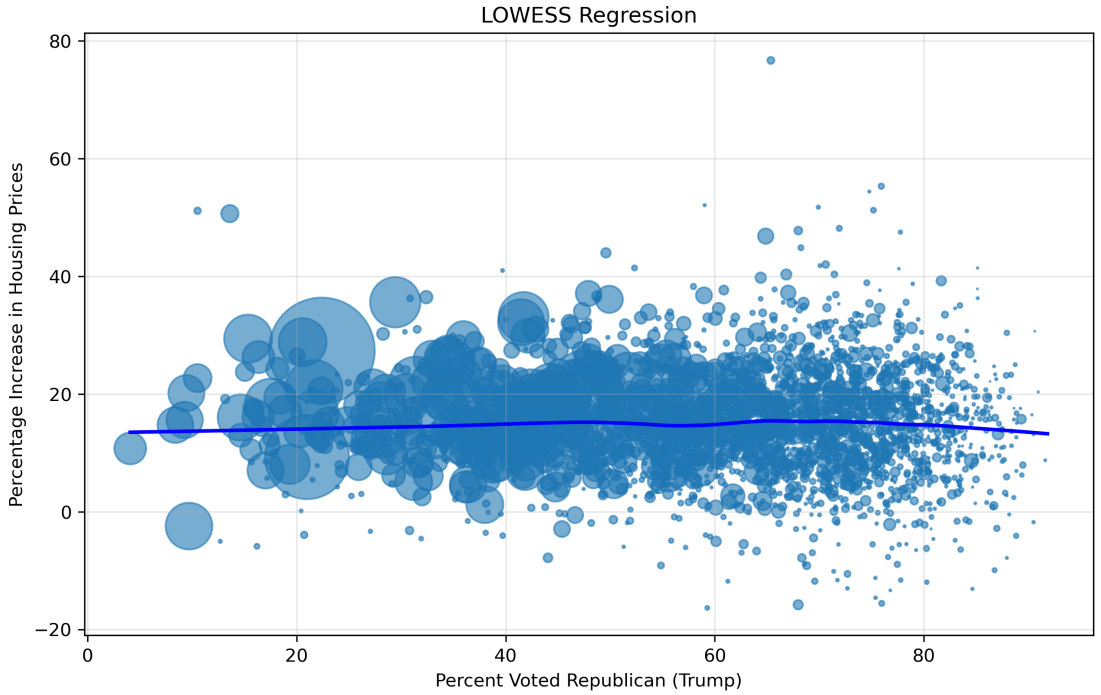

FIGURE A.7: Voting Patterns by County LOWESS

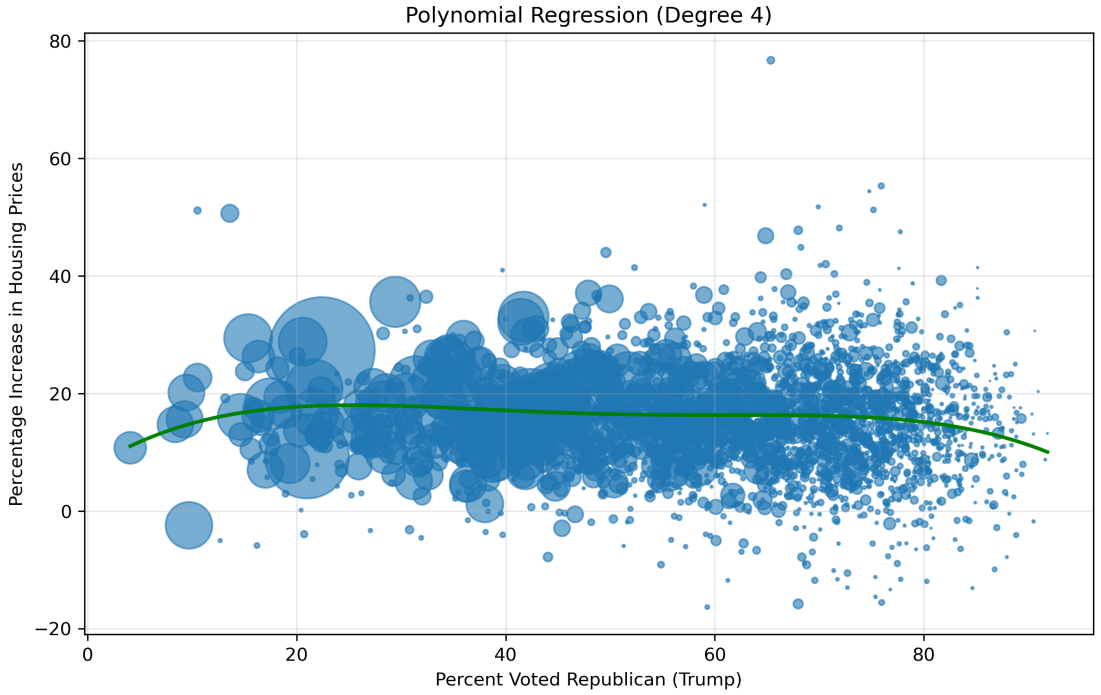

FIGURE A.8: Voting Patterns by County Polynomial

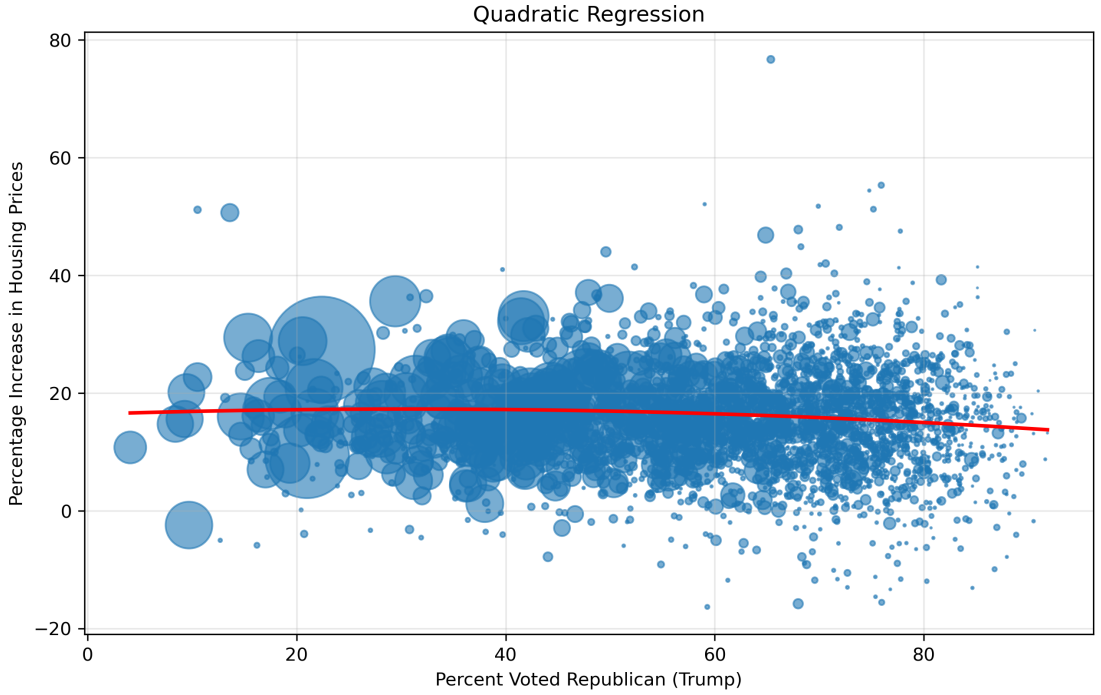

FIGURE A.9: Voting Patterns by County Quadratic

As shown in the graphs, all the methods of regression produce similar lines of best fit that indicate that there is not a strong correlation between the political stance of a county and the change in housing price levels. However, there is a noticeable dip on both ends of the lines in all three plots indicating that counties with strong political stances seemed to experience lower levels of housing price increases. Figure A.10 displays counties grouped into 10 percent bins based on their political preferences in the election. The plot reveals the pattern observed in previous figures: highly politically skewed counties experienced lower levels of housing price increases, while most counties saw approximately 15 percent increases in housing prices. Counties in the 20-40 percent range experienced around 18 percent increases in housing price levels.

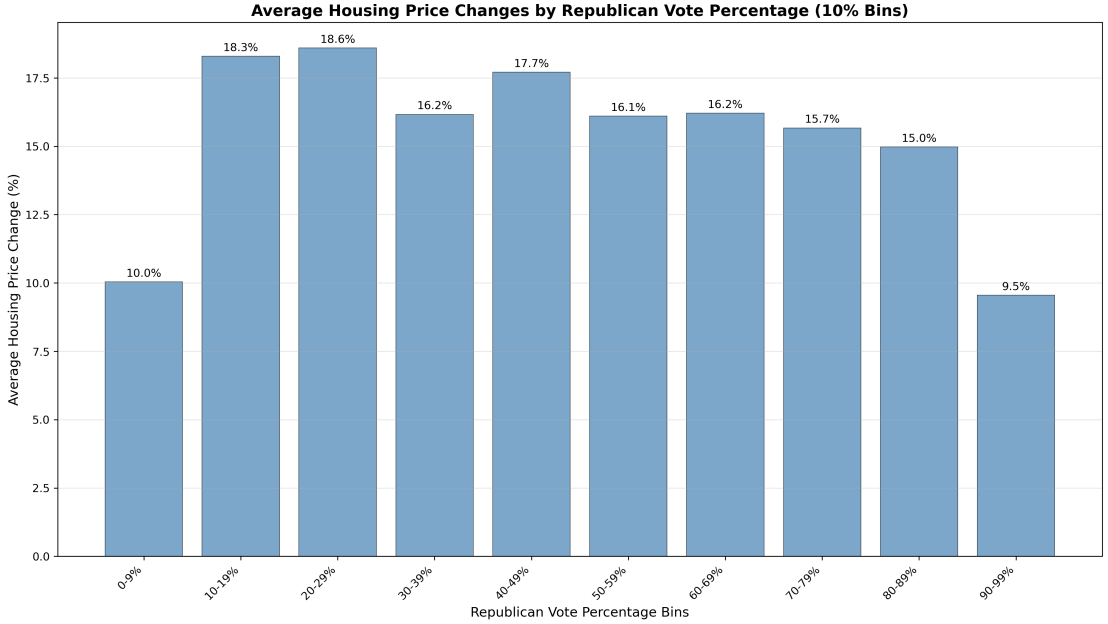

FIGURE A.10: Binned Voting Patterns Relation with Housing Prices

Appendix B

Robustness Check

This section examines the robustness of the best-fit line in the quartile scatter plot presented in Chapter 3. Figure B.1 shows the relationship after applying 1% Winsorization to the dataset, while Figure B.2 presents the same analysis with 5% Winsorization applied. The regression coefficients in both winsorized plots fall within one standard error (0.058049) of the original estimate, and the data patterns remain consistent across all three specifications. These results confirm the **reliability** and **stability** of the original findings.

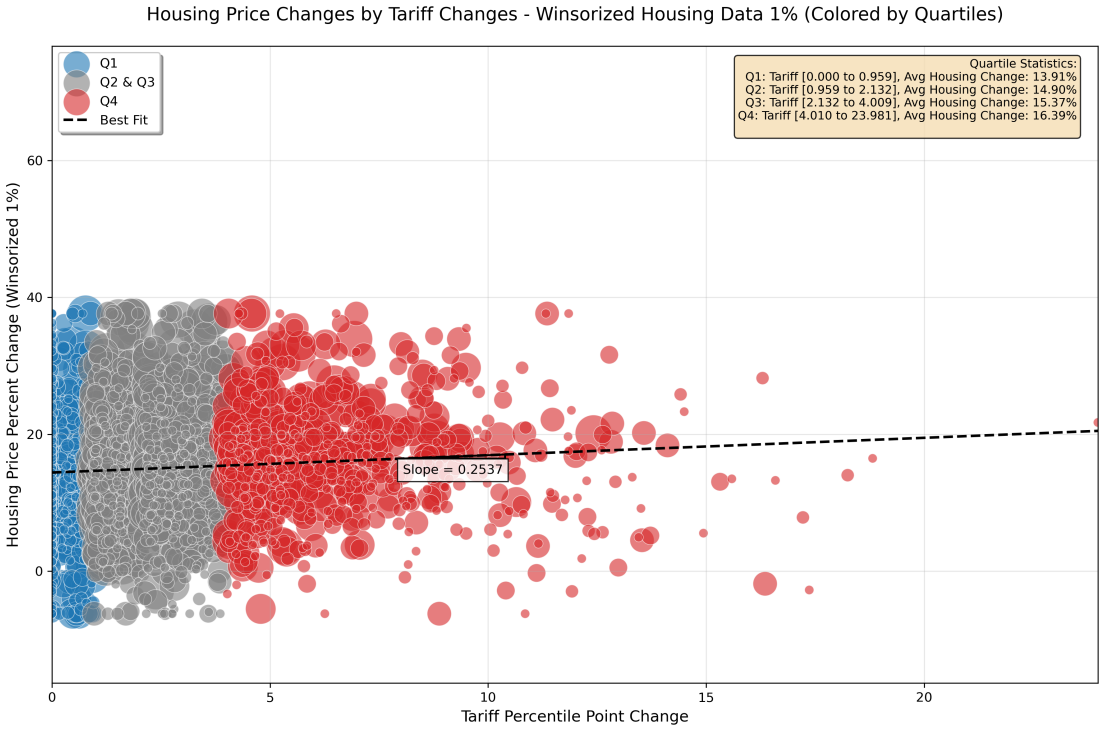

FIGURE B.1: Winsorized Quartile Scatterplot (1%)

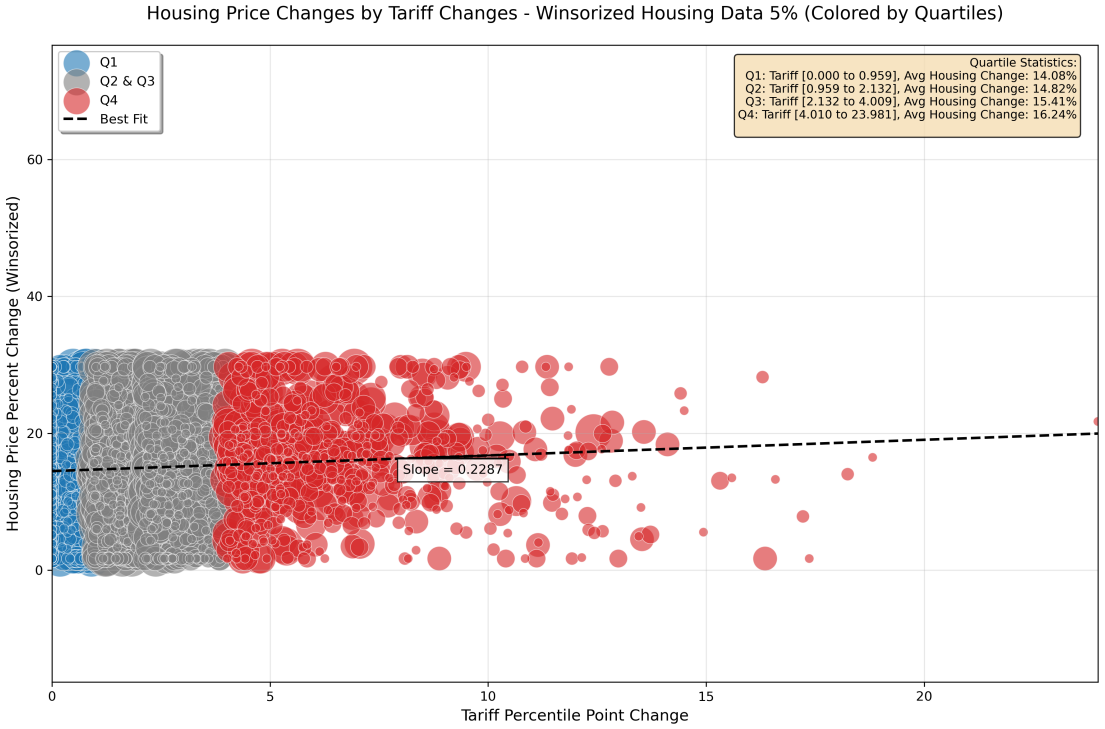

FIGURE B.2: Winsorized Quartile Scatterplot (5%)

Appendix C

Geographic Regression

This section examines the geographic relationship with housing prices. Following a similar approach to the quartile regression analysis, I separated counties by their respective regions within the United States. The analysis employs the U.S. Census Bureau's four-region classification system to categorize states geographically. The Northeast region comprises nine states: Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. The Midwest region includes twelve states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. The South region encompasses sixteen states and the District of Columbia: Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, West Virginia, and Washington D.C. Finally, the West region contains thirteen states: Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming.

Figure C.1 looks at the results of the respective regression for the Midwest. Similar to the general regression, columns 3 and 4 have higher coefficients which then go down after the introduction of the county fixed effect.

TABLE C.1: Effect of Tariff Changes on 12-Month Housing Price Changes - Midwest Region

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Tariff	0.002***	0.001***	0.005***	0.005***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ Log Employment				0.085***		-0.057***
				(0.011)		(0.009)
Fixed Effects:						
County	N	N	N	N	Y	Y
Time	N	N	Y	Y	Y	Y
Population Weight	N	Y	Y	Y	Y	Y
Observations	23378	23378	23378	23378	23378	23378
R-squared	0.008	0.003	0.040	0.043	0.682	0.682

Table C.2 displays the regression results for the Northeast. Unlike the Midwest and general regression, columns 1,2 and 3 produce negative coefficients. The regression then has a large jump in the values for columns 5 and 6, suggesting that the county identification plays a big role in controlling for variables.

TABLE C.2: Effect of Tariff Changes on 12-Month Housing Price Changes - Northeast Region

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Tariff	-0.004***	-0.006***	-0.001*	0.002***	0.008***	0.008***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δ Log Employment				0.338***		0.033
				(0.020)		(0.025)
Fixed Effects:						
County	N	N	N	N	Y	Y
Time	N	N	Y	Y	Y	Y
Population Weight	N	Y	Y	Y	Y	Y
Observations	4992	4992	4992	4992	4992	4992
R-squared	0.031	0.026	0.093	0.144	0.580	0.580

Tables C.4 and C.5 display the results for the South and West. Both regressions exhibited similar behaviors and values as the general regression, with the final produced coefficient being at .004.

TABLE C.3: Effect of Tariff Changes on 12-Month Housing Price Changes - South Region

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Tariff	0.001***	0.000**	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ Log Employment				0.032***		-0.049***
				(0.007)		(0.006)
Fixed Effects:						
County	N	N	N	N	Y	Y
Time	N	N	Y	Y	Y	Y
Population Weight	N	Y	Y	Y	Y	Y
Observations	26659	26659	26659	26659	26659	26659
R-squared	0.002	0.000	0.051	0.052	0.650	0.651

TABLE C.4: Effect of Tariff Changes on 12-Month Housing Price Changes - West Region

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Tariff	0.000	-0.004***	0.005***	0.006***	0.004***	0.004***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Δ Log Employment				0.475***		-0.044
				(0.025)		(0.028)
Fixed Effects:						
County	N	N	N	N	Y	Y
Time	N	N	Y	Y	Y	Y
Population Weight	N	Y	Y	Y	Y	Y
Observations	6381	6381	6381	6381	6381	6381
R-squared	0.000	0.010	0.174	0.218	0.630	0.630

References

[1] WAUGH, M. E. (2019): "The Consumption Response to Trade Shocks: Evidence from the US-China Trade War," Working Paper, New York University and NBER, December 2019.

[2] FAJGELBAUM, P. D., P. K. GOLDBERG, P. J. KENNEDY, AND A. K. KHANDELWAL (2019): "The Return to Protectionism," Working Paper 25638, National Bureau of Economic Research.

[3] AMITI, M., S. J. REDDING, AND D. E. WEINSTEIN (2019): "The Impact of the 2018 Tariffs on Prices and Welfare," Journal of Economic Perspectives, 33(4), 187-210.