Essays on the Distributional Effects of Globalization

by

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This dissertation studies the implications of globalization using theoretical, empirical, and structural estimation techniques. I investigate heterogeneity in the effects of import tariffs, implications for estimating structural gravity equations with discrete good varieties, and geographical impacts of trade on inequality.

In my first chapter, titled "Trade Policy and the Decline of the Labor Share", I analyze the impact of tariffs on US imports that are used as inputs to manufacturing on labor market outcomes. I develop theoretical predictions using a model of final goods production in which firms combine labor, capital, and intermediate inputs. Utilizing changes in tariff rates, input-output tables, and local employment in the input sector, I develop a sector- and state-specific measure of exposure to tariffs in input markets. I estimate the effect of input market tariff exposure on labor market outcomes with a three-way fixed effects regression. An increase in tariff exposure is associated with increases in employment and wages; however, due to larger increases in output the labor share of output declines.

In my second chapter, titled "Gravity and the Law of Large Numbers", my coauthor and I examine the implications of uncertainty in gravity models of trade due to the violation of the Law of Large Numbers (LLN) that we document in the data. When the number of available technologies (or traded goods) is finite and the LLN does not hold, the variance of the stochastic component in gravity models is large, which leads to the poor goodness of fit of gravity models and high uncer-

tainty in comparative statics results. We offer a procedure that specifies counterfactual predictions in terms of distributions rather than point estimates and helps to account for such uncertainty.

In my third chapter, titled "Trade and Inequality: Evidence from the United States", I examine the effects of globalization on regional inequality. I directly measure import and export shares for US states and develop a geography based instrument to quantify the causal effect of trade on income inequality. I decompose income inequality between and within urban and rural counties and estimate a 2 stage least squares model. I find little evidence of a relationship between trade and inequality measured broadly. Further, I find little evidence that trade and globalization are driving an urban-rural wage premium nor inequality within urban and rural counties.

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Chapter 1

Introduction

The rise of globalization during the late twentieth and early twenty-first century has significant economic, social, and political implications. The objective of this dissertation is to further the understanding of the economic implications of increasing trade, globalization, and the associated public policy response. A secondary objective of this dissertation is to expand upon the identification, estimation, and modeling techniques used to evaluate the effects of international trade and globalization.

In chapter 2 I examine the effects of U.S tariff policy on the inputs to production. I construct a measure of exposure to tariffs in input markets that is specific to state and manufacturing sector pairs. Leveraging this identification I use an empirical model to quantify the effects of changes in input market tariffs on the distribution of revenues to labor and capital. Further, I decompose the distribution of revenue to labor into separate components consisting of wages and employment. I show that as a result of changes in input market tariffs during the period from 2008 to 2019, including increases in tariffs during 2018 and 2019, that final goods sectors and states which experience an increase in tariff exposure increase their usage of labor and capital, which leads to an increase in final output. However, I show that capital investment as a share of output increases signifgicantly, while the labor share of output decreases due to a relatively larger increase in output relative to wages and employment.

In chapter 3 I investigate an assumption regarding the amount of tradeable goods between countries that are a feature of quantitative economic models. As a result of a law of large numbers assumption, structural gravity models may be solved analytically to quantify the changes in economic welfare resulting from increasing globalization and changes in trade policy. In practice, the amount of goods traded between countries is finite; by relaxing this assumption and solving gravity models computationally I show that the fit of the fundamental model is weak when a small number of goods are produced and traded. Further, to account for this poor fit a procedure to generate confidence intervals, rather than point estimates, for the welfare gains from trade is developed and tested using data on trade between 215 countries in 2006.

In chapter 4 I build upon methods used to quantify the effect of trade on income across countries to quantify the effect of trade on the distribution of income within regions. Using microdata on wages within U.S states and data on imports and exports to and from states I evaluate the effect of trade on inequality using an instrument for predicted trade. The instrument is constructed by leveraging variation in the elasticity of trade relative to sea and air distances between state-country pairs to predict aggregate import and export flows. Armed with this empirical framework, I find that there is little evidence of a link between trade and wage inequality during the period from 2008 to 2019. This result contrasts with previous results which show a positive link between globalization and inequlaity. These previous results typically leverage cross-country variation whereas I rely on variation within U.S states over time; further, my results reflect slowing growth in income inequality following the great recession.

Chapter 2

Trade Policy and the Decline of the Labor Share

2.1 Introduction

In the twenty-first century the decline of manufacturing employment and wages has been well documented by economists (see e.g Pierce and Schott 2016, Autor Dorn and Hanson 2013) and has drawn much attention from policymakers in the developed world. In the manufacturing sector, the replacement of labor with capital via automation, low-skilled labor with high-skill labor via job polarization, and high wage labor with low wage labor from abroad via offshoring have each been scrutinized as factors in explaining this decline. Broadly speaking, this decline has coincided with a decline in the share of national income flowing to labor across all sectors in the form of wages, salaries, and other benefits. Further, policymakers concerned with a variety of issues such as job creation, rising inequality, and national security have brought attention to this pattern of declining fortunes for workers in the manufacturing sector. Specifically, among other policies such as subsidies for firms and industries and the renegotiation of NAFTA, the US has recently introduced increases in bilateral tariffs as part of a broader pattern of increased protectionism.

This chapter builds upon a partial equilibrium framework to study the effect of input tariffs on labor market outcomes. Specifically, I use a model featuring a two-tier CES production function consisting of three inputs to production. At the highest tier firms producing goods for final consumption combine intermediate goods with all other factors of production that enter into value-added. In the second tier, value-added is a CES production function consisting of labor and a fixed factor of production. Moreover, intermediate inputs are considered a CES aggregate of goods that are subject to trade costs. I use this model to derive predictions regarding the response to a change in the price of intermediate inputs. To take this model and predictions to the data I construct a novel measure of exposure to tariffs in input markets. I utilize national level input-output data and state level employment data to derive the amount of exposure to tariffs faced by sectors producing goods for final consumption. Further, I establish several assumptions necessary to empirically implement this model by estimating a three-way fixed effects model. I find that while wages, employment, and capital expenditure increase (decrease) in response to a rise (fall) in tariff exposure, the share of output flowing to labor declines with an elasticity of -0.062 while the share of output flowing to capital increases with an elasticity of 0.413.

A large strand of literature has documented the decline of the share of national income flowing to labor, particularly in the United States since the second half of the 20th century. Further, researchers and policymakers have devoted significant attention to uncovering and rectifying the causes of the decline. A closely related article by Autor et al. (2020) emphasizes the role of highly concentrated industries in driving down the share of output flowing to labor in the US while dismissing the role of globalization. Karabarbounis and Neiman (2014) emphasize the role of the declining relative price of capital globally in driving this decline. Related literature focuses on inequality and skill-biased changes in earnings, see Parro (2020), Krussel et al. (2000), Song et al. (2019), Helpman et al. (2017), and Caliendo, Dvorkin, and Parro (2019). To address the consequences of the decline of the labor share, a variety of policies addressing the taxation system, social safety net, reskilling, and the impacts of globalization have been introduced since the beginning of the 21st century.

In this chapter, I seek to analyze the impacts of one particular set of policies, increases in US import tariff rates after 2016, on a variety of labor market outcomes including the labor share.

Though tariffs are typically introduced by policymakers with the goal of protecting producers in output markets by reducing foreign competition, I leverage input-output and local employment data to quantify the effect of input market tariffs across a broad swath of manufacturing sectors. This approach, through the use of a national policy and employment in input industries, is able to leverage plausibly exogenous variation in input prices for final goods sectors at the state level to identify the effects of variations in price on labor market outcomes.

Additionally, I contribute to a broad strand of literature which has sought to empirically uncover the effects of globalization on labor markets in developed countries. Autor, Dorn, and Hanson (2013) empirically measure exposure to Chinese imports across US commuting zones to uncover local labor market effects. Pierce and Schott (2016) uncover similar effects at the plant-level while further accounting for input-output linkages. Further work by Acemoglu et al. (2020) connects trade to slow employment growth more broadly across the US. Extending these empirical studies to a European setting Branstetter et al. (2019) find significant negative labor market effects as a result of import competition in Portugal. Focusing on tariff increases in 2018, Amiti et al. (2019) study the effects of the protectionist policies which I evaluate; however, they focus on prices and welfare while I focus on labor market outcomes. Finally, Handley and Limao (2017) study the effects of globalization through the lens of trade policy uncertainty.

Lastly, measurement and the methodology documenting the decline of the labor share has drawn interest from a branch of the literature. Chari, Kehoe, and McGrattan (2007) develop a quantitative macroeconomic framework that embeds wedges for labor and investment to study US business cycles. Accounting for capitalization of intellectual property, Koh et al. (2020) argue that the decline of the labor share can be explained through changes in accounting methods. Elsby, Hobijn, and Sahin (2013) argue that while some of the decline in the labor share is a statistical artifact, exposure to trade within manufacturing sectors has also been a primary driver of the decline. An outline of the methods used to quantify the labor share and alternative measures are presented in

Krueger (1999). In my analysis I explicitly define the labor share in two ways; as the share of final sectoral output and as the share of value-added in the final goods sector.

This chapter makes two primary contributions to the literature. First, this chapter studies the effects of globalization and the associated policy response by studying inputs to production, instead of focusing on imports and exports or tariffs in output markets. I further focus my analysis across many manufacturing sectors and account for the input-output structure of the economy. Second, I construct a novel way of measuring exposure to tariffs in input markets across sectors and regions which allows me to exploit plausibly exogenous variation in tariff rates and local input industry employment.

My findings demonstrate that the labor share of output does decline following an increase in tariffs on inputs to production. This is primarily driven by an expansion of output at a faster rate than employment or wages. Increased prices in output markets cannot explain this expansion and the difference between highly concentrated sectors and more competitive sectors does little to shed light on this result. Instead, I find that increases in tariff exposure lead to significant increases in the share of final sector output flowing to capital expenditure. This finding suggests that while higher input prices may yield increases in production and sales in the domestic final goods sector; much of this increase results from increased capital investment rather than improvements in employment and wages for labor. Additionally, I find that the share of output flowing to labor in low-skill occupations significantly declines relative to the share of output flowing to highly skilled workers. Thus, this chapter provides evidence that increasing tariffs on inputs to production does little to protect workers more broadly, with workers in low-skilled occupations bearing a larger burden relative to highly-skilled workers.

The chapter proceeds as follows. In section II, I introduce my theoretical model and derive testable predictions. In section III, I discuss the data sources used in the analysis. In section IV, I establish a method for measuring exposure to tariffs in input markets and provide my empirical specification. In section V, I produce and discuss the results. Section VI concludes.

2.2 Theoretical Background

The economy consists of consumers located in location j. Utility of a representative consumer in state j is $U_j = log(C_j)$ where C_j is a CES aggregate of final good varieties produced in state j. There are S final good varieties produced by sector s. Consumers inelastically supply labor in j such that $\bar{L}_j$ is the total amount of labor supplied to firms in j. Consumer income consists of wage labor and the revenue generated by tariffs collected by the government and distributed equally among consumers across all locations.

Final goods firms produce non-tradeable goods for consumption in sector s and state j. Competitive firms operating in s produce goods using a two-tier nested CES production function with a fixed factor K_{sj}, intermediate goods, M_{sj}, and labor, L_{sj}. Labor is immobile across regions and fixed by $\bar{L}_j$; however, labor is perfectly mobile across sectors and industries. Intermediate goods are tradeable and produced by input industries i using unskilled labor. Intermediates that are sourced from abroad are subject to tariffs (τ_{ik}) and iceberg trade costs (κ_{jk}), $t_{ijk} = (1 + \tau_{ik})(1 + \kappa_{jk})$.

In order to flexibly allow for varying degrees of substitutability or complimentarity between inputs into production, consider a two-tier nested CES production function. Firms operating in sector s combine intermediates with an aggregate of all other factors of production as follows

$$Q_{sj} = A_{sj}\Big[\gamma_{sj}^{1/\zeta_s} VA_{sj}^{\frac{\zeta_s-1}{\zeta_s}} + (1-\gamma_{sj})^{1/\zeta_s} M_{sj}^{\frac{\zeta_s-1}{\zeta_s}}\Big]^{\frac{\zeta_s}{\zeta_s-1}} \tag{2.1}$$

M_{sj} is a CES aggregate of intermediate goods with constant elasticity of substitution μ.

$$M_{sj} = \Big[\sum_i \delta_{is}^{1/\mu} m_{isj}^{\frac{\mu-1}{\mu}}\Big]^{\frac{\mu}{\mu-1}} \tag{2.2}$$

VA_{sj} is a CES aggregate of all other inputs without a loss of generality. To fix ideas, I assume that the only other inputs to production are labor and capital. Each factor of production enters VA_{sj}

with constant elasticity of substitution ρ.

$$VA_{sj} = \Big[\alpha_{sj}^{1/\rho_s} L_{sj}^{\frac{\rho_s - 1}{\rho_s}} + (1-\alpha_{sj})^{1/\rho_s} K_{sj}^{\frac{\rho_s - 1}{\rho_s}}\Big]^{\frac{\rho_s}{\rho_s - 1}} \tag{2.3}$$

Intermediate inputs are assumed to be produced using a linear production technology in labor,

$$m_{ij} = A_{ij} L_{ij} \tag{2.4}$$

where A_{ij} is labor productivity in industry i in state j. I assume that intermediates are produced by monopolistically competitive firms in industry i. Thus, the price of intermediate inputs comes from the CES aggregate of foreign and domestically sourced intermediates

$$P_{sj}^{m} = \Big\{ \sum_i \delta_{is} p_{ij}^{\frac{1}{\mu}} + \sum_i \delta_{is} \Big[p_{ij}(1+\tau_{ik})(1+\kappa_{jk})\Big]^{\frac{1}{\mu}} \Big\}^{\frac{\mu}{\mu - 1}} \tag{2.5}$$

firms which source intermediate inputs from a foreign location face two types of trade costs. κ_{jk} is a standard iceberg trade cost which is paid when an input i is sourced from any location other than the home location. Tariffs are taxes collected by the national government when goods are sourced from foreign locations; $\tau_{ik} = 0$ for locations k which are other domestic regions. Workers are assumed perfectly mobile across sectors and industries but cannot move across locations. Labor markets are assumed to be perfectly competitive. Wages are then given by w_j . Firms rent capital at an exogenously determined rental rate, r_j. Intermediates are sourced from industry i from the lowest cost supplier inclusive of trade costs, p_{isj}. The unit cost function is given by

$$c_{sj} = w_j L_{sj} + r_j K_{sj} + (\sum_i \delta_{isj}^{1-\mu} p_{isj}^{1-\mu})^{\frac{1}{1-\mu}} M_{sj} \tag{2.6}$$

Firm's solve the following profit maximization problem

$$argmax \Pi_{sj} = P_{sj}^{f} Q_{sj} - w_j L_{sj} - r_j K_{sj} - (\sum_i \delta_{isj}^{1-\mu} p_{isj}^{1-\mu})^{\frac{1}{1-\mu}} M_{sj} \tag{2.7}$$

Solving the sector s firm's optimization problems yields an expression for the parameters defining the share of each input used in producing one unit of output. Recall from equation equation 2.1 that the intermediate share of production is defined by $1 - \gamma_{sj}$ and that the labor share of value added (see equation 2.3) is defined by α_{sj}. The labor share of output is given by the interaction of $\gamma_{sj}\alpha_{sj}$. Taking first order conditions and solving equation 2.7 yields the following expression for the labor share of output

$$\gamma_{sj}^{1/\zeta_s}\alpha_{sj}^{1/\rho_s} = (1-\gamma_{sj})^{1/\zeta_s} M_{sj}^{1/\mu-1/\zeta}\delta_{sj}^{1/\mu} m_{isj}^{-1/\mu} p_{isj}^{-1} VA_{sj}^{1/\zeta-1/\rho} L_{sj}^{1/\rho} w_{sj} \tag{2.8}$$

For the requisite derivations see the appendix.

The use of intermediate inputs by the final goods sector is determined by share parameters δ_{isj} and the constant elasticity of substitution μ. The final goods sector in a given location will source intermediate inputs from the lowest cost supplier of a given variety. The price of variety i which enters the unit cost function is thus a function of transport costs, the wage paid by producers of i in a location k, and the industry-location specific productivity. I assume that the final goods sector consists of many firms purchasing goods from monopolistically competitive input industries at competitive prices. Thus, the price of a given intermediate variety is

$$p_{ij} = \min\{p_{ij}^F, p_{ij}^H\} \tag{2.9}$$

where

$$p_{ij}^F = \frac{\mu}{\mu-1} w_{ik}(\tau_{ijk}+1)(1+\kappa_{jk})/A_{ik} \forall k \neq j \tag{2.10}$$

$$p_{ij}^H = \frac{\mu}{\mu-1} w_{ij}/A_{ij} \tag{2.11}$$

Recall, the aggregate price of intermediate goods used by s in j is as follows

$$P_{sj}^m = \Big[\sum_{i\in I^H} \delta_{is} p_{ij}^{H\frac{1}{\mu}} + \sum_{i\in I^F} \delta_{is} p_{ij}^{F\frac{1}{\mu}}\Big]^{\frac{\mu}{\mu-1}} \tag{2.12}$$

the composite price of intermediates is thus a function of the costs of inputs and the trade costs incurred by sourcing inputs from abroad. Sectors which source a greater proportion of inputs from abroad face larger swings in the composite intermediate price compared to a sector with a greater proportion of domestic inputs.

Under equation 2.12, final goods sectors which source a greater proportion of inputs from abroad will face larger changes in the aggregate price of intermediates when faced with a change in tariff policy. This insight is critical for forming a variety of testable predictions. For the sake of convenience when referring to a change in the price of intermediate inputs I assume that this arises from a change in trade costs based on variation in tariff rates. This implies additional assumptions regarding A_{ij} and δ_{is}; specifically I assume that relative productivity across input industries within states are constant through time which follows from the assumption of a perfectly competitive labor market. Additionally, I assume that the shares of intermediate inputs purchased by the final goods sector is constant through time. Though this assumption is strong, as it is reasonable to expect that when relative tariffs change final goods firms may alter their mix of input goods with cheaper and substitutable varieties. I will show below that this would bias my empirical results towards zero.

Following the production structure outlined above, in the first-tier CES production function a change in the price of intermediates faced by a firm located in j operating in sector s will result in a change in the value-added share of output. This change in γ_s is dependent on ζ_{sj}, the elasticity of substitution between value-added and intermediates sourced from input industries. Sectors which have outsourced a significant amount of their production process, are mainly focused on assembly of final goods, or are reliant to a significant degree on foreign rather than domestic suppliers would be expected to reduce output and value-added as a result of an increase in the price of intermediates. Alternatively, sectors in which firms have implemented a production process where workers and the fixed factor both produce intermediate inputs and assemble final goods, near-shored production along the value chain, or rely primarily on domestic suppliers would be expected to reduce their use of intermediates and increase value-added and output as a result of an increase in the price of intermediate inputs. More formally,

Proposition 1. *Firms operating in sector s and location j with $\zeta_{sj} < 0$, an increase in P^m_{sj} yields the following;* $\frac{dQ_{sj}}{dP^m_{sj}} < 0$ *and* $\frac{dVA_{sj}}{dP^m_{sj}} < 0$

Further, the effect of a change in the price of intermediate inputs on labor market outcomes can be analyzed. Specifically, the labor share of output is captured by the parameter $\alpha_{sj}\gamma_{sj}$ and the labor share of value added is captured by parameter α_{sj}. The change in the share of revenue and value-added flowing to labor is dependent on the elasticity of substitution between labor and intermediates and that between labor and capital. Specifically, a change in the price of intermediates will alter the share of revenue flowing to the factors of production used in generating value-added in a location j by sector s. Further, the elasticity of substitution between and relative prices of labor and capital will determine the proportion of value-added flowing to labor.

There are two cases to consider; one in which sectors increase output as a result of an increase in the price of intermediate inputs, and the opposite case in which, faced with an increase in input prices the final goods sector contracts and reduces output. In the first case, the labor share of output may increase following an increase in the price of intermediates due to low reliance on intermediate inputs as outlined above which results in a sector-state gaining a cost advantage, resulting in an expansion of output and employment of labor. Alternatively, the labor share may decline if these conditions hold true, yet capital and labor are highly substitutable and the cost of capital relative to labor is low. In the second case, the labor share of output may increase following an increase in the price of intermediates because the firms that decrease output as a result of this price increase may cut output while maintaining the same level of wages and employment or switching away from intermediates towards a more labor-intensive but less productive mix of inputs. Conversely, the labor share may fall as a result of high substitutability between labor and capital and a relatively low cost of capital. In each case where the labor share falls, the labor share of value-added will fall more quickly than the labor share of output.

The above intuition is captured more formally by the following proposition.

Proposition 2. *Firms operating in sector s and location j with $\zeta_{sj} > 0$, $\frac{d\gamma_{sj}\alpha_{sj}}{dP^m_{sj}} > 0$ if $\rho_s >> 0$ or γ_{sj} is small. Firms operating in sector s and location j with $\zeta_{sj} < 0$, $\frac{d\gamma_{sj}\alpha_{sj}}{dP^m_{sj}} > 0$ if $\rho_s < 0$ or $\frac{dVA_{sj}}{dP^m_{sj}} < \frac{dQ_{sj}}{dP^m_{sj}}$*

In sum, firms in final goods sectors choose a mix of labor, the fixed factor of production, and intermediate goods to produce final output under a process governed by ζ_{sj}, ρ_s, and γ_{sj}. When firms experience a change in the price of intermediate goods they alter their mix of inputs based on these three parameters which also yields a change in value added and output. After the change in output and the mix of inputs used, the share of output that flows to each input has been altered by the initial price change.

2.2.1 Extension: Heterogeneous Labor-Augmenting Productivity

In the baseline framework I have remained agnostic about the role of productivity in determining the response of the labor share to changes in intermediate input prices. Similar to Demirer (2022), I now introduce the term χ^x_{sj} which denotes the labor-augmenting productivity of a firm x operating in final goods sector s and state j. By introducing this additional productivity parameter I enrich the baseline model in two ways; first I now allow heterogeneity across sectors and states in labor productivity into the model and allow for within sector-state firm heterogeneity. I now derive theoretical predictions regarding changes in labor market outcomes as a result of changes in input tariffs while accounting for several new mechanisms. First, I can now test for heterogeneous effects on the basis of labor productivity and skill across sectors and states. Second, I am able to account for entry and exit of firms which yields heterogeneous market concentration in the final goods sector as an explanation for my results.

I first follow Demirer (2022) in incorporating labor augmenting productivity into the original production structure by modifying equation 2.3.

$$VA^x_{sj} = \Big[\alpha_{sj}^{1/\rho_s}\{\chi^x_{sj}L_{sj}\}^{\frac{\rho_s-1}{\rho_s}} + (1-\alpha_{sj})^{1/\rho_s}K_{sj}^{\frac{\rho_s-1}{\rho_s}}\Big]^{\frac{\rho_s}{\rho_s-1}} \tag{2.13}$$

Now, equation 2.1 can be rewritten as a firm-specific production function.

$$Q^x_{sj} = A_{sj}\Big[\gamma_{sj}^{1/\zeta_s}VA_{sj}^{x\frac{\zeta_s-1}{\zeta_s}} + (1-\gamma_{sj})^{1/\zeta_s}M_{sj}^{\frac{\zeta_s-1}{\zeta_s}}\Big]^{\frac{\zeta_s}{\zeta_s-1}} \tag{2.14}$$

To introduce firm-specific heterogeneity into the model I follow the finite-firm case outlined by Eaton, Kortum, and Sotelo (2012). Firm-specific productivity is a Poisson random variable drawn from the distribution governed by the parameter $\mu^X_{sj}(\chi) = T_{sj}\chi^{-\theta}$. Further, firms now produce under the following heterogeneous unit cost function

$$c^x_{sj} = \frac{w_jL_{sj}}{\chi^x_{sj}} + r_jK_{sj} + (\sum_i \delta_{isj}^{1-\mu}p_{isj}^{1-\mu})^{\frac{1}{1-\mu}}M_{sj} \tag{2.15}$$

It is convenient to rank and denote firms from least to highest cost, $c^{(1)}_{sj} < c^{(2)}_{sj} < c^{(3)}_{sj}$.... Under these assumptions the total number of final goods firms producing in sector s and state j with unit cost $c^x_{sj} < \bar{c}$ is also a realization of a Poisson random variable with parameter $\mu_{sj}^{c^x_{sj}}(\bar{c}) = \Phi_{sj}\bar{c}^{\theta}$ where

$$\Phi_{sj} = \sum_n \Phi_{sjn}\Phi_{sjn} = T_{sj}c_{sj}^{x^{-\theta}} \tag{2.16}$$

With all potential firms entering and producing in sector s and state j ordered by increasing unit-cost I can now determine the number of firms that actually enter the market.

A two-step process determines firm entry and profits. In the second stage, all firms that have chosen to enter the market partake in Cournot competition as follows. First, each firm is faced with the following profit maximization problem

$$argmax\Pi^x_{sj} = P^f_{sj}q^x_{sj} - c - sj^x q^x_{sj} \tag{2.17}$$

Under CES preferences for final goods, the final goods price index can be defined as follows

$$P^f_j = (\sum_s \lambda_s P_{sj}^{f\frac{1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \tag{2.18}$$

The CES demand for the final good variety produced by sector s is

$$P_{sj}^{f} = \frac{\lambda_{sj}}{Q_{sj}^{\frac{1}{\sigma}}} \frac{w_j \bar{L}_j}{P_j^f}^{\frac{1}{\sigma}} \tag{2.19}$$

Substituting equation 2.19 into equation 2.17 and solving for the Cournot equilibrium yields the following demand for q_{sj}

$$q_{sj} = c_{sj}^{x^{-}\sigma} \lambda_{sj}^{\sigma} w_j \bar{L}_j P_j^{f^{-1}} \tag{2.20}$$

Substituting equation 2.20 into equation 2.17 yields the following expression for firm profits

$$\Pi_{sj}^{f} = c_{sj}^{x^{-\sigma}} \lambda_{sj}^{\sigma} w_j \bar{L}_j - c_{sj}^{x^{1-\sigma}} \lambda_{sj}^{\sigma} w_j \bar{L}_j P_j^{f^{-1}} \tag{2.21}$$

The solution to the second stage of the firm's problem yields the expected result. Increased firm entry acts through the term P_j^f to reduce demand for each firm's final good, thus reducing profits. The firms with the lowest costs generate larger profits and capture greater market share. Thus, denoting $x+1$ as the next most profitable firm to enter the market, the following condition holds

$$\Pi_{sj}^{f^{(x)}} > \Pi_{sj}^{f^{(x+1)}} \tag{2.22}$$

In stage 1 of the firm's problem, firm's sequentially choose whether or not to enter the market under the zero-profit condition $\Pi_{sj}^{f(X+1)} < 0$, where firm X is the last firm that profitably enters the market.

Conditional on entry into the market and the solution to the Cournot problem, firm's choose the mix of intermediates, labor, and the fixed factor of production. As in the baseline model, taking first order conditions and solving equation 2.17 yields a new expression for the labor share accounting for firm-specific labor augmenting productivity

$$\gamma_{sj}^{1/\zeta_s} \alpha_{sj}^{1/\rho_s} = (1-\gamma_{sj})^{1/\zeta_s} M_{sj}^{1/\mu - 1/\zeta} \delta_{sj}^{1/\mu} m_{isj}^{-1/\mu} p_{isj}^{-1} V A_{sj}^{1/\zeta - 1/\rho} \chi_{sj}^{x^{\frac{\rho-1}{\rho}}} L_{sj}^{1/\rho} w_{sj} \tag{2.23}$$

For the requisite derivations see the appendix.

Now, there are offsetting effects. On the one hand, firms employing highly productive workers substitute away from intermediate inputs to labor to take advantage of relatively larger labor productivity. On the other hand, for a fixed level of output a smaller labor force can be employed relative to less productive firms producing the same output. This intuition is captured through the following logic; a larger χ^n_{sj} increases $\gamma_{sj}\alpha_{sj}$ while simultaneously decreasing L_{sj} for a fixed Q_{sj}, which has a second order effect of lowering $\gamma_{sj}\alpha_{sj}$. This yields an ambiguous result with respect to changes in the relative price of inputs on the basis of the relative productivity of the final goods sector.

Further, the dynamics of firm entry under heterogeneous productivity can yield heterogeneous final goods market concentration across sectors and locations. Highly productive firms capture a larger share of market demand, leaving smaller demand and smaller profits for less productive firms. Moreover, the entry of highly productive firms with low labor costs implies a higher productivity cutoff for market entry, yielding higher concentration in more productive sectors. At the sector-state level, sectors in which a small share of highly productive firms crowd out less productive firms can be characterized by a smaller share of output flowing to labor. Essentially, less productive firms which hire a relatively large share of labor to produce a disproportionately small share of output either leave or never enter the market, thus reducing the labor share across the sector. This provides an explanation for the second order effects outlined above outweighing the increase of $\gamma_{sj}\alpha_{sj}$ from a larger χ^n_{sj}.

Now, armed with the explanation outlined above a change in the price of intermediate goods may be analyzed. In the following I denote s' as a final goods sector which features X' firms relative to sector s in which X firms enter the market, where $X' < X$. Sector s' features fewer, but more productive firms than sector s, thus I refer to sector s' as highly concentrated relative to sector s. When faced with an increase (decrease) in the price of intermediates, firms in s' will decrease (increase) the amount of labor in their mix of inputs to a larger degree than firms in s. This is a direct result of relatively higher labor augmented productivity; if the price of intermediates falls then relatively more productive firms are reluctant to switch away from labor while in the reverse case the rise in the price of intermediate goods leads to a reduction in output (see proposition 1). As a result, when reducing output since labor is a relatively more productive input, firms in s' will disproportionately reduce the share of output flowing to labor relative to the intermediate and capital shares. An alternative interpretation, in the case under which labor augmenting productivity is worker-specific, the intuition outlined above can be used to argue that when switching away from (to) labor, firms respond by retaining workers who are highly productive while reducing (increasing) employment and wages of low productivity workers.

I express the intuition above in the following theoretical prediction.

Proposition 3. *Sector s' features X' firms, sector s features X firms where $X' < X$. When faced with $dP_{sj} < 0$, then $\frac{d\gamma_{sj}\alpha_{sj}}{dP^m_{sj}} < \frac{d\gamma_{s'j}\alpha_{s'j}}{dP^m_{sj}}$ if $\chi^X_{sj} < \chi^{X'}_{s'j}$. When faced with $dP_{sj} > 0$, then $\frac{d\gamma_{sj}\alpha_{sj}}{dP^m_{sj}} < \frac{d\gamma_{s'j}\alpha_{s'j}}{dP^m_{sj}}$ if $\chi^X_{sj} < \chi^{X'}_{s'j}$ and $\frac{dQ_{sj}}{dP^m_{sj}} < 0$.*

To summarize, now allowing for heterogenous productivity across firms and firm entry I have derived several predictions about relative changes in the mix of inputs used for production. The preceding propositions describe heterogeneity in labor market outcomes resulting from changes in intermediate goods prices on the basis of concentration in the final goods sector.

2.3 Data Sources

In this section I provide an outline of the data sources and sample construction.

I construct a dataset consisting of state-sector observations across the United States spanning from 2008 to 2019. I utilize the Survey of Manufactures conducted by the US Census to collect data on the value of shipments and receipts for services, number of employees, total annual payroll, total capital expenditure, and total cost of materials. This data is further supplemented in 2012 and

2017 by the Economic Census. I combine this with state-level data on employment which comes from the annual County Business Patterns. Further, I use sector-level import data for NAICS 3- and 4-digit sectors which is obtained from the USA Trade database.

National level data on the use of commodities by industry are gathered from the Bureau of Economic Analysis Input-Output Accounts. Specifically, I utilize the 2012 Commodity Industry Input-Output Table, the 2012 Use of Commodities by Industry table, and the Use of Imported Commodities by Industry table. I collect national-level tariff data on HS-8 products on an annual basis from the USITC. Additionally, I gather industry-level pricing data from the Bureau of Labor Statistics. Lastly, I obtain industry concentration data for 3- and 4-digit sectors from the 2017 Economic Census.

	Mean	Standard Deviation
Labor Share	20.57	24.45
Output (billion$)	6.35	13.91
Intermediates (billion$)	3.78	10.14
Wage bill (billion$)	0.798	1.86
$tariff_{sjt}$	0.091	0.225

Table 2.1: Summary statistics for the main sample.

I obtain state-level employment and occupation data from the BLS Occupational Wage and Employment Statistics. This data is used to measure wages by occupations which are defined as routine (low-skilled) and non-routine (high-skilled) following Autor and Dorn (2013) and Dvorkin and Shell (2017). Further, I gather data on state-level unionization rates in private manufacturing from the Union Membership and Coverage Database. Finally, I obtain data on NAICS sector-state specific imports spanning the entire sample from the USA Trade database.

I construct an unbalanced panel of state-sector observations across the time period from 2008 to 2019 at the NAICS 3-digit level. I supplement this with an additional sample of 4-digit sectors; however, due to data confidentiality and a lack of establishments in some states this is also an

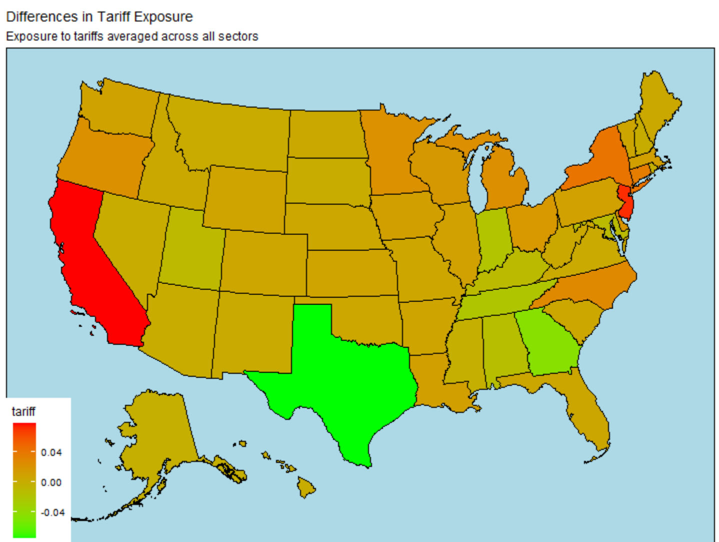


Figure 2.1: *Mean difference in tariff exposure across states between 2008 and 2019.*

unbalanced panel. I report the mean and standard deviation for the main outcome variables and the measure of tariff exposure in table 2.1. Supplementing this, I also provide a summary of the change in tariff exposure, averaged across each final goods sector for each state in figure 2.1.

2.4 Empirical Framework

I use variation in tariff rates across intermediate inputs, states, and time to identify changes in prices of intermediates. The measure of tariff exposure that I derive below follows from Lake and Liu (2022), though instead of commuting zones I measure tariff exposure at the state level. Further, Dix-Carniero and Kovak (2017) also leverage regional employment data in Brazil to capture trade liberalization, though they do not account for input-output linkages. Lastly, Flaaen and Pierce (2019) construct a measure of increases in input tariffs for naics 6 digit industries using BEA input-output accounts without allowing for regional variation. Ideally, the precise mix of intermediate inputs purchased by firms in each sector, state, and year could be observed in the data. However, I only observe total spending on intermediate inputs at this level of observation. To identify changes in the price of intermediates I make several assumptions and construct a measure of tariff exposure for each final goods sector s in state j in year t. For notational convenience I supress the time subscript below.

I first assume that intermediate goods industries across locations have access to the same technology and that relative productivity growth in these industries is constant across locations. Under this assumption, input industry i produces a share of all intermediate goods produced in state j equivalent to input industry i's share of employment in state j.

$$\frac{M_{ij}}{\sum_i M_{ij}} = \frac{L_{ij}}{\sum_i L_{ij}} \tag{2.24}$$

Define M_j as the total intermediates produced in j ($M_j \equiv \sum_i M_{ij}$). Under a balanced trade assumption for all regions j then the following must hold

$$M_j = \sum_s M_{sj} \tag{2.25}$$

By rearranging equation 2.24 it is possible to solve for M_{ij}. This will be used to compute relative price changes faced by the final goods sector across states. To compute these changes, first start with the cost for final goods sector s to produce a unit of output, given by (equation 2.6). The change in price of intermediates, P^m_{sj} that results from a change in trade costs is dependent on the degree to which firms in sector s and state j rely on foreign intermediate inputs. I then make several assumptions; first, final goods producers in j will source intermediates from suppliers based in j before purchasing intermediates from abroad. Second, μ is sufficiently large such that final goods producer in sector s do not respond to a change in the price of an intermediate input by substituting to an alternative intermediate. This is a strong assumption that can be revisited. Third, labor markets are perfectly competitive within states; labor is immobile across j and perfectly mobile across s and i. Lastly, I assume that in the short-run the fixed factor of production K is unchanged after a change in the price of intermediates.

Next, I define M^H_{sj} as the CES aggregate consisting of all intermediates purchased from local intermediate goods producers. Further, define M_{ij} and M^H_{ij} as the supply of intermediates available in j and the supply of intermediates produced in j, respectively. To study the effect of changes in intermediate goods prices on the share of output flowing to labor in the final goods sector the main variable of interest is P^m_{sj}. Specifically, I am interested in changes in this composite price resulting from a change in trade costs. With knowledge of M_{sj}, specifically M^H_{sj}, it is possible to calculate the amount of intermediates used by sector s which are produced in the home region. Further, I have information on national level input requirements used to produce output in s from the Input-Output Accounts.

The price of intermediate inputs, on the other hand, are not readily available. Using previous assumptions I can construct a proxy for the amount of intermediate i which is produced in j. First, I solve for M_{ij} by rearranging equation 2.24.

$$M_{ij}^H = \frac{L_{ij} \sum_i M_{ij}^H}{\sum_i L_{ij}} \tag{2.26}$$

By using previous assumptions; I can infer the amount of intermediate i produced in j by taking the share of employment used to produce i as a proportion of total j employment. Further, I can use data on the total value of intermediate goods purchased by sector s in j to calculate the value of requirement i for each final goods sector s. This s-j specific input requirement is calculated as follows

$$M_{ij} = r_{is} M_{sj} \tag{2.27}$$

where r_{is} is taken from the input-output data and serves as a proxy for δ_{is}. I can exploit the difference between the amount of i required by s in j and the amount of i produced in j to measure exposure to price swings as a result of tariffs. This requires the strong assumption that there is no relative change in wages paid to workers or in productivity across locations. This implies that changes in trade costs are driving any change in P_{sj}^m faced by the final goods sector. Further, I assume that changes in trade costs are primarily driven by tariffs; over the time period from 2008 to 2019 there are no significant improvements in technology that drastically reduce trade costs.

Following these assumptions, I can calculate the requirements for foreign inputs of sector s in j.

$$M_{ij}^F = \begin{cases} M_{ij} - M_{ij}^H, M_{ij}^H \leq M_{ij}^F \\ 0, M_{ij}^H > M_{ij}^F \end{cases} \tag{2.28}$$

For each sector, state, and year I can calculate exposure to tariffs by finding M_{ij}^F as a proportion of M_{sj}. I define τ_i as the ad-valorem tariff placed on input i at the national level. The tariff faced by sector s in j can be expressed as

$$tariff_{sj} = \sum_i (1 + \tau_i) \frac{M_{ij}^F}{M_{sj}} \tag{2.29}$$

Under assumptions of no relative changes in wages, productivity, and trade costs outside of tariffs, I can infer year over year changes in P^m_{sj} from changes in $tariff_{sj}$. Exploiting this variation over time I can estimate the effect of a change in price of intermediate goods used by sector s in j on the share of output flowing to labor. Estimating the elasticity of employment, wages, and the labor share with respect to changes in the price of intermediates allows me to characterize the degree of complimentarity or substitutability between intermediates and labor.

Exploiting variation over time in tariffs faced by the final goods sector to estimate the effect of a change in the price of intermediate inputs on labor market outcomes requires several assumptions. First, conditional on covariates and included fixed effects, there is no correlation between the error term and labor market outcomes. An additional assumption is that when there is a change in the tariff rate faced by the final goods sector this is actually the tariff rate that is paid. For example, if firms in the final goods sector change to another variety of inputs or source them from another country to avoid paying the tariff, this assumption could be violated. However, in this scenario the final goods sector is generally attempting to pay a lower price for intermediate inputs, so in the case of an increase in tariffs this measurement error would bias results towards zero. In the case that tariff rates are lowered, there is no reason to expect that firms would attempt to avoid paying a lower tariff rate. Lastly, I make a strong assumption that while firms may face tariffs in input markets they are simultaneously not responding to tariffs in output markets. For example, a final goods producer of cars which faces an increase in steel tariffs simultaneously with an increase in tariffs on cars is not changing its mix of inputs based on an increase in competitiveness in the output market.

I then run a three-way fixed effects model to estimate the effect of a change in tariffs faced by sector s in the intermediate goods market on output, employment, wages, and the share of output which flows to labor. I measure the labor share in two ways; as the share of employee compensation in the form of wages and salaries in proportion to the total value of shipments and receipts as well as in proportion to value-added. I study naics manufacturing sectors and use data at both the 3- and 4-digit level. I rely on changes over time in exposure to tariffs for each industry-state observation. This can be driven by either changes in actual tariffs applied to HS-8 products that are used as inputs to production or changes in M_{ij}^H, the amount of inputs that are supplied locally. I run the following estimating equation

$$log(Y_{j,s,t}) = \alpha_0 + \beta log(tariff_{j,s,t}) + X_{j,s,t} + \gamma_j + \gamma_s + \gamma_t + \epsilon r, s, t \tag{2.30}$$

γ_j is a state fixed effect, γ_s is a final sector fixed effect, and γ_t is a year fixed effect. In all of my results I cluster standard errors at the state level. When the labor share is the outcome variable it is scaled by 100 before taking a logarithm. I control for GDP, population, unemployment rates, and union membership rates in the private manufacturing sector. Further, I disentangle input tariffs from tariffs in output markets by controlling for state-industry specific output tariffs. To construct this variable I interact $(1 + \tau_i)$ with the sector's share of manufacturing imports flowing into each state. Most covariates, with the exception of my control for output tariffs, are observed at the state level. These covariates address several concerns regarding omitted variable bias. For example, heterogeneous growth in incomes and population across states and time could potentially bias the results related to final output and employment. While controlling for the unemployment rate may introduce concerns about endogeneity with respect to outcomes related to employment, it should be reiterated that employment in each state-sector observation is small relative to total state employment and that the main reason for including this control is to account for tightness in labor markets which may influence changes in wages as a result of changes in labor demand. Lastly, it is important to account for the fact that while the final goods sector may be altering its mix of inputs in response to input tariffs, they are likely simultaneously responding to changes in protection in the output market as well. I do remove controls from the primary specification and include the results from this check in the appendix.

Lastly, to empirically test proposition 3 I first split my sample by final goods sector into highly concentrated and non-highly concentrated sectors. At the naics 3 digit level, I choose an HHI of 110 as the cutoff; sectors which have a larger HHI are considered highly concentrated. By choosing this cutoff I ensure that roughly half of my sample is classified as highly concentrated (10 naics 3 sectors) and non-highly concentrated (11 naics 3 sectors). I rely on the 2007 Economic Census to obtain the market concentration data for each sector. I then run 2.30 separately for each subsample to test for heterogeneous labor market outcomes resulting from higher costs in intermediate input markets. Concluding this heterogeneity test, I run a Wald test for the equality of coefficients on β for each subsample.

2.5 Results and Discussion

I begin by reporting estimates of 2.30 in table 2.2. In the first two columns the outcome variables are the value-added share of output and the intermediate input share of final output. In columns 3 and 4 I extend the results to the labor share of output and the capital expenditure share of output. The estimates of β from 2.30 are found in the first row of each table.

Examining the relationship between input market tariff exposure and intermediate use, there is scant evidence that final goods sectors alter the share of intermediate input usage. However, given that increased tariff exposure implies higher costs of using intermediates from the same source or switching to a more expensive source of intermediate inputs, these results suggest that the quantity of intermediate goods used is either held constant or decreases to account for these higher costs. Similarly, there is an non-significant change in the value-added share of output. Regardless, when examining two components of value-added, the labor share and capital expenditure shares, I find significant changes in the input mix used by the final goods sector. Specifically, I find evidence of a decrease in the mix of labor and an increase in capital investment in response to increased input market tariff exposure.

To investigate my initial results related to the mix of inputs used I decompose the labor

Table 2.2: Response of Input Shares

	(1)	(2)	(3)	(4)
	γ_{sj}	$1-\gamma_{sj}$	$\gamma_{sj}\alpha_{sj}$	$(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	-0.021	0.016	-0.062**	0.413***
	(0.014)	(0.014)	(0.026)	(0.054)
GDP	0.050	-0.112**	-0.264	0.406
	(0.090)	(0.054)	(0.191)	(0.351)
Unemployment	0.044*	-0.008	-0.042	-0.026
	(0.023)	(0.016)	(0.051)	(0.085)
Population	-0.062	0.126	0.300	-0.318
	(0.186)	(0.158)	(0.288)	(0.696)
Unionization	-0.003	0.004	0.007	0.012
	(0.005)	(0.005)	(0.009)	(0.024)
Output Tariff	-0.204	0.114	-0.297	1.475***
	(0.129)	(0.118)	(0.331)	(0.387)
N	9402	9366	10054	8667
R^2	0.5472	0.5186	0.6071	0.7431

Standard errors in parentheses are clustered at the state level.

* $p < .1$, ** $p < .05$, *** $p < .001$

Notes This table presents results for the baseline specification with the elasticity of input shares with respect to input market tariff exposure as the outcome of interest. In columns 1 and 2 I use value-added and intermediate purchases as a share of final sales, respectively as an outcome variable. In columns 3 and 4 I evaluate two components of value-added; the total payments, wages, and salaries of workers as a share of final sales and the share of final sales devoted to capital expenditure.

share into wages and total employment in final goods sectors and estimate the relationship between changes in output as a result of increasing input tariffs. I report these baseline estimates of 2.30 in table 2.3. The outcome variables of interest are wages, employment, output, the labor share of output ($\gamma_{sj}\alpha_{sj}$), the labor share of value-added (α_{sj}), and the capital expenditure share of output ($(1-\gamma_{sj})\alpha_{sj}$). The estimates of β from 2.30 are found in the first row of each table.

In my baseline results I find a significant negative relationship between exposure to tariffs and the labor share of output. The results suggest that a 1 percent increase in exposure to tariffs on intermediate inputs is associated with a 0.062 percent decrease in the labor share of output. However, wages and employment are positively related to exposure to input tariffs. The decline in the labor share is thus primarily driven by a faster increase in output that is associated with increased tariff exposure. There are several possible explanations for this result; one that I investigate in table 2.4 is the role of pricing power in driving changes in the value of output and wages. I use industry level producer price indices to deflate the value of output and the consumer price index at the national level to deflate total wages. I otherwise run the same specifications from table 2.3.

After deflating for producer prices in the final goods sector the results and conclusions, for the most part, remain unchanged. Allowing for heterogeneous price increases across sectors does little to change the relationship between tariff exposure in input markets and the value of final output (0.567 vs 0.569 percent increase). This implies that the increase in the value of output is primarily a quantity effect, firms in the final goods sector are increasing the quantity of goods produced, perhaps by increasing production of intermediate inputs locally.

An alternative explanation is that highly concentrated industries are driving the results. Autor et al. (2020) conclude that superstar firms, operating in highly concentrated industries, have been a driving force behind the decline of the labor share, independent of globalization. One hypothesis is firms operating in highly concentrated sectors, when faced with an increase in input prices, rather

Table 2.3: Baseline Specification

	(1) Total Wages	(2) Employment	(3) Output	(4) $\gamma_{sj}\alpha_{sj}$	(5) α_{sj}	(6) $(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	0.348***	0.306***	0.451***	-0.062**	-0.023	0.413***
	(0.059)	(0.060)	(0.057)	(0.026)	(0.029)	(0.054)
GDP	0.170	0.089	0.957**	-0.264	-0.267	0.406
	(0.230)	(0.218)	(0.338)	(0.191)	(0.195)	(0.351)
Unemployment	-0.087*	-0.087*	0.026	-0.042	-0.070	-0.026
	(0.047)	(0.046)	(0.083)	(0.051)	(0.051)	(0.085)
Population	0.362	0.314	-0.798	0.300	0.413	-0.318
	(0.361)	(0.353)	(0.519)	(0.288)	(0.329)	(0.696)
Unionization	-0.015	-0.011	-0.010	0.007	0.009	0.012
	(0.009)	(0.008)	(0.015)	(0.009)	(0.015)	(0.024)
Output Tariff	1.813***	1.603***	1.635**	-0.297	-0.166	1.475***
	(0.472)	(0.445)	(0.541)	(0.331)	(0.270)	(0.387)
N	11135	11135	10115	10054	9770	8667
R^2	0.8419	0.8480	0.8031	0.6071	0.4635	0.7431

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

Notes This table presents results for the baseline specification and the full sample. Columns 1 through 3 provide a decomposition of the labor share. Columns 1 and 2 enter the numerator; total wages is the average per worker wages, salaries, and other payments to workers across all firms operating in a sector, state, and year. Employment is the number of workers employed by firms operating in a state, sector, and year. Output is the reported value of sales for each sector, state, and year. Column 4 reports results for the labor share as a proportion of total sales, while column 5 reports results for the labor share as a proportion of total sales less the cost of intermediate inputs. Column 6 reports results with for the outcome as the capital share of final sales.

Table 2.4: Baseline Specification Deflated by Price Indices

	(1) Total Wages	(2) Output	(3) $\gamma_{sj}\alpha_{sj}$	(4) α_{sj}	(5) $(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	0.348***	0.457***	-0.067**	-0.0278	0.450***
	(0.059)	(0.057)	(0.026)	(0.029)	(0.065)
GDP	0.170	0.973**	-0.280	-0.273	0.130
	(0.230)	(0.337)	(0.188)	(0.196)	(0.265)
Unemployment	-0.087*	0.024	-0.041	-0.071	0.022
	(0.047)	(0.083)	(0.051)	(0.050)	(0.095)
Population	0.362	-0.832	0.334	0.450	0.008
	(0.361)	(0.514)	(0.288)	(0.328)	(0.652)
Unionization	-0.015	-0.011	0.008	0.009	-0.027
	(0.009)	(0.015)	(0.009)	(0.014)	(0.031)
Output Tariff	1.813***	1.594**	-0.255	-0.118	1.812***
	(0.472)	(0.534)	(0.324)	(0.267)	(0.419)
N	11135	10115	10054	9770	9111
R^2	0.8431	0.8048	0.5546	0.3971	0.7718

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

Notes This table reproduces the results from the baseline specification while deflating the value of output by the national level, industry specific Producer Price Index. Further, average per worker wages are deflated by the national level CPI. This robustness check is designed to account for the potential of increased pricing power in output markets and to ensure that nominal wage growth is not influencing the results.

than passing these on to the final consumer instead offer lower wages or require longer work hours without an increase in wage. I test for this by splitting my sample into two subsamples; consisting of final goods sectors that are highly concentrated and those that are not. I use data from the 2017 Economic Census, which includes sector level HHI data. I define the cutoff for a sector to be highly concentrated by requiring an HHI larger than 110. This allows for roughly half of the final goods sectors to be considered highly concentrated. I re-run the baseline specification for the high concentration and low concentration subsamples, with results presented in tables 2.5 and 2.6, respectively.

From the results, I have shown that sectors that are considered highly concentrated do experience slower employment and average wage growth, and experience a larger decrease in the labor share after experiencing an increase in tariff exposure, relative to sectors that exhibit low levels of concentration. Regardless, I run a Wald test for equality of coefficients and fail to reject the hypothesis of equal coefficients. Though highly concentrated industries may hire workers with different levels of productivity, face lower costs of capital expenditure, or rely less on intermediate inputs to begin with, I do not find compelling evidence that sectors featuring fewer and larger firms are substantial in explaining my findings.

Lastly, I conduct a heterogeneity check by re-running my baseline specification; however, I now run this on the labor share of high and low skilled workers, respectively. I use the definitions by Dvorkin and Shell (2017) to classify occupations as high and low skilled then use state level wage-occupation data to impute employment levels by state, sector, and skill level. The results from this specification are found in table 2.7.

These results indicate that the wages and employment of low-skilled occupations in manufacturing sectors are much more negatively impacted by higher tariffs in input markets. When these sectors face increased costs in intermediate input markets, they appear to be expanding output not by raising wages and employment in low-skill occupations but instead relying on high-skill, and

Table 2.5: High Concentration Subsample

	(1) Total Wages	(2) Employment	(3) Output	(4) $\gamma_{sj}\alpha_{sj}$	(5) α_{sj}	(6) $(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	0.284**	0.252**	0.395***	-0.050	-0.024	0.376***
	(0.092)	(0.088)	(0.094)	(0.054)	(0.063)	(0.084)
GDP	0.443	0.321	1.805**	-0.752**	-0.904**	0.780
	(0.374)	(0.373)	(0.537)	(0.232)	(0.277)	(0.576)
Unemployment	-0.063	-0.066	0.049	-0.045	-0.096	-0.033
	(0.089)	(0.085)	(0.114)	(0.074)	(0.099)	(0.140)
Population	-0.209	-0.288	-2.116**	0.793	0.790	-1.273
	(0.756)	(0.719)	(0.898)	(0.488)	(0.630)	(1.284)
Unionization	-0.017	-0.017	0.0002	0.009	0.004	0.002
	(0.019)	(0.017)	(0.036)	(0.019)	(0.024)	(0.041)
Output Tariff	2.126**	1.804**	1.959**	-0.420	-0.216	1.661**
	(0.677)	(0.585)	(0.763)	(0.491)	(0.421)	(0.544)
N	4981	4981	4384	4342	4167	3598
R^2	0.8184	0.8168	0.7625	0.5913	0.4594	0.7132

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

Notes This table reproduces the baseline specification for the sub-sample of final goods sectors I classify as highly concentrated, featuring an HHI greater than 110. This includes the following NAICS sectors; 312, 313, 314, 316, 322, 324, 325, 331, 334, 336.

Table 2.6: Low Concentration Subsample

	(1) Total Wages	(2) Employment	(3) Output	(4) $\gamma_{sj}\alpha_{sj}$	(5) α_{sj}	(6) $(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	0.388***	0.338***	0.486***	-0.096***	-0.043*	0.426***
	(0.052)	(0.052)	(0.058)	(0.027)	(0.025)	(0.063)
GDP	0.073	-0.042	0.427	0.022	0.131	0.240
	(0.330)	(0.280)	(0.261)	(0.208)	(0.166)	(0.351)
Unemployment	-0.114**	-0.112**	-0.027	-0.010	-0.040	-0.062
	(0.045)	(0.041)	(0.086)	(0.065)	(0.051)	(0.099)
Population	0.698*	0.774**	0.216	0.140	0.265	0.202
	(0.385)	(0.357)	(0.504)	(0.340)	(0.374)	(0.662)
Unionization	-0.007	0.001	-0.009	0.012	0.011	0.023
	(0.011)	(0.010)	(0.014)	(0.010)	(0.012)	(0.033)
Output Tariff	1.394**	1.473**	1.156**	-0.0968	-0.0446	1.025**
	(0.566)	(0.571)	(0.428)	(0.311)	(0.249)	(0.347)
N	6154	6154	5731	5712	5603	5069
R^2	0.8840	0.8854	0.8764	0.6318	0.4937	0.8096

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .001$

Notes This table reproduces the baseline specification for the sub-sample of final goods sectors I classify as low concentration, featuring an HHI smaller than 110. This includes the following NAICS sectors; 311, 315, 321, 323, 326, 327, 332, 333, 335, 337, 339.

Table 2.7: Baseline Specification With Skill-Biased Labor Share

	(1) Labor Share (Low)	(2) Labor Share (High)
$tariff_{sjt}$	-0.332***	0.0595
	(0.0400)	(0.0393)
N	10067	10067
R^2	0.7370	0.5856

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

Notes This table presents results from running the baseline specification, further subdividing the labor share into the share flowing to high-skill and low-skill occupations. High- and low-skill is defined as non-routine and routine occupations according to Dvorkin and Shell (2017). The labor share is defined as the sector-state-specific high- and low-skill average wage multiplied by high- and low-skill employment, respectively. In the denominator I use sector-state-specific total sales. The specification is run with all controls; however, I suppress the results for the control variables.

perhaps more productive workers. This result also demonstrates that when faced with increased input prices, workers in low-skilled occupations appear to bear a greater burden of the relative decline in the usage of labor.

As a robustness check, I run two specifications; the baseline and a specification with time and state-sector fixed effects on 4 digit rather than 3 digit NAICS sectors. When running the baseline specification on 4 digit sectors the coefficients do decrease in magnitude; however, the main conclusion remains unchanged. With the interacted fixed effects, the significance on the coefficient for the labor share of output disappears. The results for this robustness check can be found in the appendix.

2.6 Conclusion

In this chapter I have explored the effects of a policy response to increased globalization on labor markets. I have linked increases in US tariffs on intermediate imports to a decline in wages and employment relative to output of final goods industries. Using a three-way fixed effects model with a novel measure of exposure to input tariffs I have found that, though wages and employment are rising despite these tariffs, they do not match the simultaneous expansion in output of final goods, thus a decline in the labor share is associated with an increase in input tariffs. Though prices of final goods and high concentration do not explain this decline, I do find that there is significant heterogeneity in the effects of tariffs on high and low skilled workers.

Chapter 3

Gravity and the Law of Large Numbers

3.1 Introduction

The gravity model is, perhaps, the most widely used empirical tool in international economics. The reasons behind its success include a parsimonious specification, minimal data requirements, and good empirical fit. Yet surprisingly little is known about how much we can trust the predictions of gravity models and what factors influence the accuracy of comparative statics results that rely on deterministic methods to quantify trade outcomes.

We show that such methods critically rely on an unrealistic assumption of the Trade Law of Large Numbers (LLN) which states that the number of distinct technologies that can be used to produce traded goods goes to infinity. The assumption leads to a continuous probabilistic representation of technology such that trade flows can be expressed via a deterministic gravity equation that is log-linear in exporter-, importer-specific and bilateral components.[1] In reality, however, the number of technologies is finite, which yields a gravity equation that includes a structural stochastic error that is unrelated to the fundamental gravity forces. We demonstrate that this error is quantitatively important and contributes to explaining the differences in the goodness of fit of gravity models across different economic sectors.

[1] This holds for most models of international trade (see Eaton and Kortum, 2002**a**; Melitz, 2003**a**) and equivalently for most migration/spatial models, e.g., see Anderson (2011).

Our structural interpretation of the error term helps develop a theoretically consistent procedure that characterizes counterfactual predictions of gravity models as distributions rather than point estimates.[2] We build a simple guide for practitioners on how to put theory-consistent bounds on gravity comparative statics results with minimal data requirements.

3.2 Discrete Gravity and the LLN

To emphasize how departures from the LLN affect the gravity equation, we focus on a discrete gravity model with a finite number of technologies in the spirit of Eaton and Kortum (2010) and Jonathan Eaton, Samuel S. Kortum and Sebastian Sotelo (2012**b**). Our results, however, also apply to continuous models.

There are I countries and S sectors. Let N^s denote the total number of different technologies available to produce varieties in sector s that country i can export to j subject to trade cost, T_{ij}. The number of goods produced with a technology below $\bar{z}$ that i offers to j is distributed as follows:

$$N_{ij}^s \sim \text{Poisson}\left(e^{\alpha \ln(F_i^s) - \beta \ln(C_i^s) - \beta \ln(T_{ij}^s)}\ \bar{z}\right), \tag{3.1}$$

where F_i^s captures country i productivity fundamentals, C_i^s reflects production costs. Parameters α and β measure the relative factor importance in determining the distribution of N_{ij}^s. The total number of goods in sector s consumed in j can be specified as $N^s = \sum_k N_{kj}^s$ and by properties of the Poisson distribution the conditional distribution is as follows:

$$N_{ij}^s \sim \text{Multinomial}\left(N^s, \frac{e^{\alpha \ln(F_i^s) - \beta \ln(C_i^s) - \beta \ln(T_{ij}^s)}}{\sum_k e^{\alpha \ln(F_k^s) - \beta \ln(C_k^s) - \beta \ln(T_{kj}^s)}}\right). \tag{3.2}$$

The ratio of realized N_{ij}^s to N^s gives the expression for trade shares:

[2] Hence, this chapter relates to works that use gravity-type models for counterfactual analysis (e.g., see Anderson, 2011; Costinot and Rodriguez-Clare, 2014; Head and Mayer, 2014) and quantify uncertainty in the gains from trade as in Ossa (2015).

$$\pi_{ij}^s = \frac{N_{ij}^s}{N^s}. \tag{3.3}$$

The LLN states that as N^s goes to infinity, realization, π_{ij}^s, converges in probability to the event probability parameters of the Multinomial distribution:

$$\pi_{ij}^s \xrightarrow{p} e^{\alpha \ln(F_i^s) - \beta \ln(C_i^s) - \beta \ln(T_{ij}^s) - \ln(M_j^s)} \text{ , where } M_j^s = \sum_k F_k^{s\alpha}(C_k^s T_{kj}^s)^{-\beta}. \tag{3.4}$$

However, when N^s is finite and the LLN does not hold, π_{ij}^s deviates from $e^{\alpha \ln(F_i^s) - \beta \ln(C_i^s) - \beta \ln(T_{ij}^s) - \ln(M_j^s)}$ by the stochastic term ϵ_{ij}^s:

$$\pi_{ij}^s = e^{\alpha \ln(F_i^s) - \beta \ln(C_i^s) - \beta \ln(T_{ij}^s) - \ln(M_j^s)} + \epsilon_{ij}^s. \tag{3.5}$$

Equation (3.5) suggests two insights. First, observed π_{ij}^s should be viewed as a draw from a Multinomial distribution with parameters defined by the trade gravity forces. Second, the absolute value and variance of ϵ_{ij}^s is finite and decreasing in N^s. This offers two testable implications for trade gravity:

(i) The size of ϵ_{ij}^s is decreasing in N^s.

(ii) The goodness of fit of the gravity model is poorer in sectors with relatively low N^s.

3.3 Data and Estimation

To test predictions (i) and (ii), we need a measure of N^s, which in theory captures the number of available technologies. This measure must be detailed and based on a harmonized system to be comparable across countries. We use the 10-digit Harmonized System ($HS10$) to define a granular technology belonging to N^s. This classification is the most detailed encompassing system that is used to denote product categories in trade data in the United States.[3] Each technology can be used to produce a finite number of goods in s such that each country may import $HS10$ from several sources.

We assign each $HS10$ variety to SITC 2-digit sector s and count how many fall within each s. Next, we estimate the gravity equation in (3.5) separately for each sector s:

$$\pi_{ij}^{s} = e^{\ln(X_i^s) - \beta \ln(T_{ij}^s) - \ln(M_j^s)} + \epsilon_{ij}^{s}, \tag{3.6}$$

where is- and js-specific terms are captured by fixed effects and bilateral frictions $\ln(T_{ij}^s)$ are parameterized:

$$\beta \ln(T_{ij}^s) = \gamma^s \ln(\text{distance}_{ij}) + \mu^s \text{language}_{ij} + \eta^s \text{contiguity}_{ij}, \tag{3.7}$$

where language_{ij} and contiguity_{ij} are indicator functions for a common language and border, respectively.[4] Consistent with the specification in Equation (3.5) and following the arguments in Santos Silva and Tenreyro (2006), Fally (2015), and Sotelo (2019), we employ Poisson Pseudo Maximum Likelihood. For each sector, we record two statistics:

$$RSS^s = \sum_{i,j} \left(\pi_{ij}^s - \overline{\pi}_{ij}^s\right)^2 \text{ and } PR^s = 1 - \frac{var(\pi_{ij}^s - \overline{\pi}_{ij}^s)}{var(\pi_{ij}^s)} \text{ for } i \neq j, \tag{3.8}$$

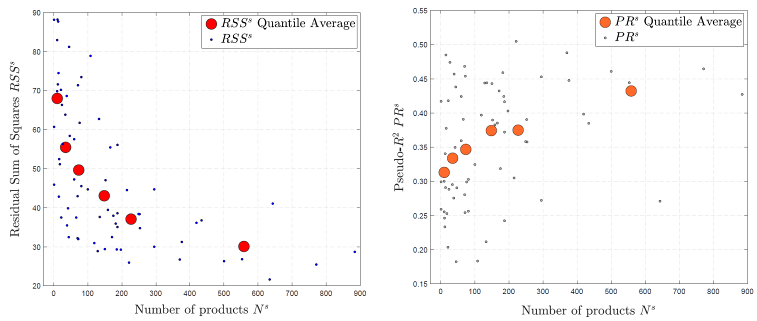
where $\overline{\pi}_{ij}^s$ are fitted values from Equation (3.6) that capture fundamental gravity forces; RSS^s is the residual sum of squares that captures the absolute size of the error terms in sector s; PR^s is one minus the share of variance of the error term in the total variance, which is interpreted

[3]We use the list of all recorded $HS10$ products during 1989 - 2006 from Robert C. Feenstra, John Romalis and Peter K. Schott (2002).

[4]Bilateral trade data is from COMTRADE and gravity variabales are from CEPII. The data cover 215 countries in 2006.

as Pseudo-R^2. We present the results for 68 sectors in Figure 3.1. In the left panel, we report RSS^s for each sector as well as average results for six quantiles defined according to N^s. In the right panel, we demonstrate that Pseudo-R^2 increases in N^s. Together, the results show that the predictions (i) and (ii) stated in Section 3.2 hold in the data.

Figure 3.1: Residual Sum of Squares & Pseudo-R^2 (SITC2 2-DIGIT)



3.4 Counterfactual Predictions as Distributions

Current quantitative approaches used for counterfactual analysis (see Dekle, Eaton and Kortum, 2007; Caliendo and Parro, 2015; Ossa, 2015) often referred to as *hat algebra* treat π_{ij} as deterministic and assume the LLN. Our results suggest that these approaches are problematic when the variance of ϵ_{ij} is high. We propose an alternative method of specifying counterfactual predictions when the LLN does not hold.

We use data from the World Input-Output Database for 2006, which includes 40 countries plus the Rest of the World, 16 manufacturing sectors and 1 service sector. We calculate the number of varieties N^s for each WIOD sector. For details refer to the Appendix. We modify the *hat algebra* approach against the backdrop of a neoclassical multi-sector model of international trade with input-output linkages as in Caliendo and Parro (2015) and calculate the gains from trade from a 10% reduction in bilateral trade costs. The idea of the proposed procedure is to account for uncertainty in the realization of π_{ij}^s due to ϵ_{ij} via simulations. It consists of three steps:

[1] Estimate the gravity equation and calculate fitted values $\overline{\pi}_{ij}^s$.

[2] Draw 100 samples of N_{ij}^s from the Multinomial(N^s, $\overline{\pi}_{ij}^s$) and calculate realization $\pi_{ij}^s = \dfrac{N_{ij}^s}{N^s}$

[3] Conditional on the realization π_{ij}^s, use the model to solve for the counterfactual equilibrium using standard *hat algebra* approach and calculate the welfare gains.

[4] Use 100 simulation results to characterize the distribution of the welfare gains from trade.

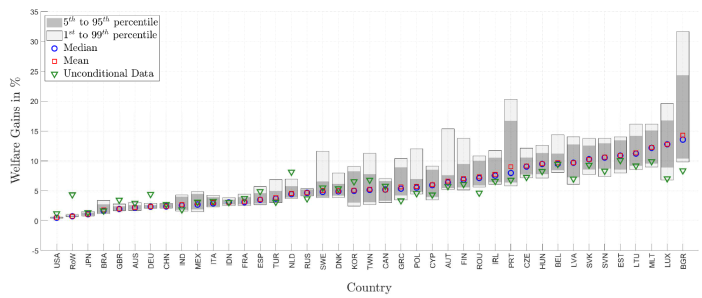
We briefly sketch the model in changes below. Let a' denote the counterfactual value of an arbitrary variable a and $\widehat{a}$ – the relative change $\widehat{a} = a'/a$. Then, given the counterfactual change in trade costs, $\widehat{T}_{ij}^s$, we solve the following system:

$$
\begin{aligned}
\widehat{C}_i^s &= \widehat{W}_i^{\gamma_i^s} \left(\prod_{s'} (\widehat{P}_i^s)^{\nu_i^{s's}} \right)^{1-\gamma_i^s}, \\
\widehat{P}_j^s &= \left(\sum_k \pi_{kj}^s (\widehat{C}_k^s)^{-\beta^s} (\widehat{T}_{kj}^s)^{-\beta^s} \right)^{-\frac{1}{\beta^s}}, \\
Y_i^{s\prime} &= \sum_{s'} \nu_i^{s's} \sum_k \pi_{ik}^s{}' Y_k^{s\prime} + \alpha_i^s (\widehat{W}_i (W_i L_i) + D_i), \\
\pi_{ij}^s{}' &= \pi_{ij}^s \left(\frac{\widehat{C}_k^s \widehat{T}_{kj}^s}{\widehat{P}_j^s} \right)^{-\beta^s} \\
Y_i^{s\prime} &= \sum_{s'} \nu_i^{s's} \sum_k \pi_{ik}^s{}' Y_k^{s\prime} + \alpha_i^s (\widehat{W}_i (W_i L_i) + D_i),
\end{aligned}
$$

where γ_i^s and $\nu_i^{s's}$ are the value added shares and input-output shares that producers in i in sector s source from s', respectively; β^s is the sectoral trade elasticity parameter from Caliendo and Parro (2015); α_i^s is the Cobb-Douglas consumption share; D_i is the deficit constant; $L_i W_i$ is total value added. All variables and parameters are calibrated using data from WIOD.

We characterize the distribution of the gains from trade in Figure 3.2 by reporting the mean as $\bigcirc$, median as $\square$, and conventional deterministic gains as $\triangledown$. We also report the intervals between the 1^{st} and 99^{th} percentiles and between the 5^{th} and 95^{th} percentiles. Our results suggest that accounting for ϵ_{ij} is important. For example, while Ireland and Portugal have similar median gains of roughly 8%, the 5^{th} and 95^{th} percentiles of the gains for the two countries are $\{6.4\%, 10.5\%\}$ and $\{6.4\%, 16.6\%\}$, respectively. For certain countries, e.g., Germany and Bulgaria, the estimates based on conventional *hat algebra* fall outside of the $1^{st} - 99^{th}$ interval. This suggests that they are not explained by the respective economic fundamentals but rather occur because the LLN does not hold.

Figure 3.2: Distribution of the Welfare Gains from Trade



Our estimates provide lower bound of the dispersion in the gains as there are other sources of the stochastic error terms in gravity such as mismeasurement of trade costs (see Novy, 2013; Egger and Nigai, 2015; Agnosteva, Anderson and Yotov, 2019) or other fundamentals (see Anderson and Yotov, 2010, 2012) and misspecification of the functional form (see Henderson and Millimet, 2008; Redding and Weinstein, 2019).

3.5 Conclusion

This chapter offers a novel explanation for why the goodness of fit of the gravity model of trade is heterogeneous across sectors. We show that when the LLN does not hold and the number of available technologies is finite, the gravity model has a structural stochastic component that is unrelated to the trade gravity forces. We confirm quantitative importance of this component in the data and develop a procedure to account for it in comparative statics exercises.

Chapter 4

Trade and Regional Inequality: Evidence From U.S States

4.1 Introduction

The growth of income and wealth inequality during the twenty-first century draws significant attention from economists and policymakers alike. Further, this period has been characterized by decreases in the costs of exchanging goods and increasing globalization leading to increases in importing and exporting. These patterns of trade and globalization have shaped economic outcomes such as employment, health, and welfare at both a national and local level. Recent studies have explored the relationship between trade and inequality using both international cross-sections and firm-level data within countries. This chapter adds to an emerging literature which analyzes the regional effects of trade on inequality by using city-level data within the United States to identify the association, document heterogeneity across cities, and investigate mechanisms.

In this chapter I explore the relationship between regional inequality and trade in the United States. I characterize inequality within U.S states using generalized entropy indices and specify a panel data fixed effects model to quantify the relationship. Further, I develop a geography based instrument to establish causality, and examine the mechanisms which shape this relationship.

In my preferred specification I quantify the effect of an increase in state level export, import, and trade shares on a variety of measures of inequality, including the Theil index, Gini coefficient, and wage distribution percentiles. The Theil index belongs to the class of generalized entropy indices which generally characterize the ”degree of disorder” of information within a sample. I take advantage of the decompositional properties of the Theil index to show that urban-rural inequality does not drive my results.

During the period from 2008 to 2019, I document little evidence that suggests there is a relationship between trade and inequality within U.S states. I do find evidence that increases in trade and imports as a share of GDP reduce wages at the 75th and 95th percentiles of the wage distribution; however, there is no significant effect on the Theil index and a marginally significant decrease in the Gini coefficient. I leverage differences in air and sea distance trade elasticities over time to develop a geography based instrument for predicted trade. I run a two-stage least squares specification to test for a causal effect of trade on inequality and find no evidence that increases in trade, imports, or exports as a share of GDP lead to a decline in inequality or a change in the wage distribution. I further test for a relationship by regressing the Theil index on lagged trade shares and continue to document no significant relationship between trade and inequality, which suggests that intertemporal transmission of trade shocks to the wage distribution does not explain my result.

Establishing that there is little evidence for a causal link between trade and aggregate inequality at the state level; I next test for a link between trade and urban-rural inequality within states. i classify counties as urban and rural and leverage the decompositional properties of the Theil index to compute inequality within urban and rural counties in each state. Further, the Theil index can also measure inequality between urban and rural counties; I supplement this measure by calculating the average urban-rural wage differential. I replicate the panel fixed effects model and the two-stage least squares model and again find little evidence that import, export, nor trade shares are associated or causally linked with urban-rural wage differences or within urban and rural wage inequality.

This chapter contributes to a literature which explores the heterogenous effects of trade on income (Feyrer 2019) and inequality (Helpman et al. 2017). My thesis extends this literature by studying the effects of trade within states, rather than across countries or within firms. I further contribute by merging this with a literature studying local distributional outcomes (Gaubert 2018) and characterizing the relationship between trade and inequality over time and within states of heterogeneous size.

Additionally, I contribute to a literature which documents reduced-form evidence of the impacts of trade on local economic outcomes in the US. Autor et al. (2013) find evidence of Chinese import exposure increasing manufacturing unemployment and decreasing earnings. At the firm level the relationship between exporting and a variety of outcomes such as human capital formation (Atkin 2016) and employment volatility (Kurz and Senses 2016) has been documented by this literature. I extend this literature which typically focuses on wages, employment, and labor force participation by specifically focusing on wage inequality. This literature highlights the uneven distribution of the gains from trade across regions while I analyze the gains from trade as they are distributed within regions.

In contrast with the literature which finds a positive causal relationship between trade and inequality using cross-sectional variation, I find scant evidence that globalization and inequality are linked at the state level following the great recession. This result is most likely explained by a deceleration of growth in income inequality; at the national level growth in wage inequality has slowed relative to the period prior to 2008. The chapter proceeds as follows. In section II, I introduce my data sources and define the primary methods of measuring wage inequality. In section III, I establish a method for estimating the relationship between trade and inequality within states using a panel fixed effects model and construct an instrument to test for a causal effect. In section IV I produce and discuss the results. Section V concludes.

4.2 Data

In this section I provide details of the data I use for the empirical analysis. I gather data on trade, inequality, geography, and covariates at the state-year level.

State-level import and export data is obtained from the USA trade database. For the primary specification I use aggregate imports and exports as a share of GDP. To construct my instrument I use data on imports and exports by country-state pairs.

I construct state level measures of inequality using individual wage data from the American Community Survey and limiting my sample to those categorized as employed, unemployed, or not in the labor force. For some measures I further drop observations with zero income. From the data I compute standard measures of inequality such as the Gini index and the ratio of income at the 90th percentile to the 10th percentile. Additionally, I gather measures derived from generalized entropy, which generally characterizes the disorder of a system. In this context, the share of total income in a city of any given person is interpreted as a probability, which can be summed across the population and used as a point of comparison. The Theil index is a special case of a generalized entropy index, further measures such as the mean log deviation and the coefficient of variation are also special cases. In following previous literature and to take advantage of the ability to decompose my measure of inequality into sub-groups, which is a property of all entropy indices, I use the Theil index in my preferred specification.

I control for several covariates which are likely to influence income inequality within a state. Using ACS microdata I measure the college-educated share, the median income, and the unemployment rate of each state. I use the IRS SOI migration database to construct net internal migration flows. I obtain GDP for each state from the BEA regional accounts and further use this data to construct exports and imports as a share of GDP for each state. Summary statistics are provided in table

	Mean	Standard Deviation
Theil Index	41.358	3.882
Gini Index	47.298	1.982
Exports (Share of GDP)	7.696	4.243
Imports (Share of GDP)	10.629	6.250
Trade (Share of GDP)	18.325	9.323
GDP (billion USD)	343.372	434.125

Table 4.1: Summary statistics for the main sample.

C.2.

Lastly, I construct a geography-based instrument to address concerns regarding endogeneity and reverse causality. I utilize data from Feyrer (2019) and the county-distance database to measure sea distance and I calculate great circle distance from the ten U.S airports with the largest volume of freight cargo in 2008 to foreign countries and combine this data with distance measurements from the county-distance database. I use the ports of New York and Los Angeles for the sea distance measurements and take the population-weighted center of each state to measure internal distance to the nearest ports and airports.

4.3 Empirical Framework

To identify the effect of state-level trade on inequality I estimate two reduced-form models; a panel fixed effects model and a two-stage least squares model. For the panel fixed effects model I collect observations at the state-year level over the period from 2008 to 2019. Running the panel fixed effects model with state fixed effects I characterize the evolution of a variety of wage inequality measures with changes in export, import, and total trade shares. Further, I run a lagged panel fixed effects regression to document the evolution of inequality in response to changes in trade shares. Lastly, I develop a geography-based instrument which I apply to identify a causal channel and address endogeneity and reverse-causality concerns in my baseline specification.

Identifying a relationship between trade and inequality at the country level, previous literature has typically relied on cross-sectional studies. However, this is less useful when examining the evolution of this relationship over time in addition to introducing concerns regarding omitted variable bias. Using a panel data fixed effects framework this relationship can be studied within a country at a regional level. In the United States this is natural to examine this relationship at the state level.

I run the panel fixed effects regressions in (4.1) through (4.3) which captures the relationship between trade and inequality over time within a state. In the main specification I estimate the effect of trade on the Theil index, a measure of wage inequality which belongs to the family of generalized entropy indices. I follow the related literature in using the Theil index as my dependent variable in addition to leveraging its decompositional properties to separate inequality into within and between sub-group components. For my robustness checks I replace the Theil index with a variety of other measures of inequality are used as my dependent variable, including the 90-10 and 75-25 percentile ratios, the Gini coefficient, and alternative generalized entropy indices. State and time-varying control variables are captured by the term X_{jt}. Lastly, I construct the measures of inequality from ACS data which is representative at the state level; thus I cluster my standard errors at the state-level.

$$Y_{jt} = \alpha + \beta EX_{jt} + X_{jt} + \delta_j + \delta_t + \epsilon_{jt} \tag{4.1}$$

$$Y_{jt} = \alpha + \gamma IMP_{jt} + X_{jt} + \delta_j + \delta_t + \epsilon_{jt} \tag{4.2}$$

$$Y_{jt} = \alpha + \beta TRADE_{jt} + X_{jt} + \delta_j + \delta_t + \epsilon_{jt} \tag{4.3}$$

Running (4.3) contemporaneously does not capture any dynamic effects nor does it provide any evidence for the direction of causality. To address this I run (4.3) with lagged trade shares. I use values for export shares, import shares, and covariates starting 6 years prior to the observed level of inequality. The lagged panel fixed effects model documents temporal variation in the effect of trade on inequality and provides preliminary evidence in support of or against the hypothesis that trade is driving patterns of wage inequality. In order to address concerns about the direction of causality and endogeneity I utilize a 2-stage instrumental variable approach.

4.3.1 Instruments

My baseline specification identifies an association between trade shares and wage inequality within states. This specification is limited in that it is difficult to ascertain a causal relationship between trade and inequality or if a causal effect is present, in which direction it runs. For example, one could argue that firms which frequently partake in importing and exporting deal with a significant degree of uncertainty regarding inputs to production or the demand in the final goods market. Firms dealing with a greater degree of uncertainty may be interested in locating their production in states where workers are ex-ante relatively homogenous and can be paid similar wages with little monitoring costs. Under this type of channel, states characterized by decreasing wage inequality may become more attractive to firms beginning to import and export or encourage trading firms to relocate production to a given state. Alternatively, one could argue firms which participate in importing and exporting are interested in hiring similarly skilled workers and paying them similar wages. Workers may respond by pursuing a level of education which matches that of the workers within their own state or they may migrate and sort geographically into states where workers have similar skills and abilities. If this type of channel is operating then the presence of firms which partake in trade is more likely to drive a decline in observed wage inequality.

I propose to address this and issues of endogeneity related to human capital formation and geographic sorting using an instrument. The specifications given by (4.5) and (4.6) present the IV specification. To address the endogeneity concerns outlined above and show that variation in trade exposure is driving changes in inequality I introduce an instrument which leverages differences in air and sea distance between state-country pairs to predict import and export shares. To construct the instrument I run (4.4) for each state and country pair. By collecting the residuals from (4.4) and summing across i when states are importing I can predict total imports; similarly for exports I sum the residuals from the regression when j states are exporting goods.

$$log(\frac{trade_{ijt}}{GDP_{jt}}) = \alpha + \beta_{1,t} log(SEA_{ij}) + \beta_{2,t} log(AIR_{ij}) + \delta_i + \delta_j + \delta_t + \epsilon_{ijt} \tag{4.4}$$

Once I have gathered predicted exports and imports I can also obtain predicted trade shares by summing across each value. I then run the following specification to estimate the effect of trade on inequality by using predicted trade as an instrument.

$$log(TRADE)_{jt}) = \zeta_0 + \zeta_1 Z_{jt} + \gamma_t + \delta_j + X_{jt} + \mu_{jt} \tag{4.5}$$

$$Y_{jt} = \alpha_0 + \beta\zeta_0 + \beta\zeta_1 Z_{jt} + X_{jt} + \gamma_t + \delta_j + \mu_{jt} \tag{4.6}$$

I will test this instrument for relevance in the first stage by regressing observed export and import shares on the constructed instrument. There is no way for me to explicitly test that the exclusion restriction for the geography-based instrument is satisfied. I address this concern by arguing that, conditional on my controls, that predicted trade on the basis of distance by mode of transport is not predictive of changes in the state level wage distribution. Since variation in my instrument is based on variation in geographic distance and country-state trade flows it is reasonable to expect that trade patterns influencing my instrument will be unrelated to inequality within US states.

4.4 Results

I present a variety of results primarily from running specification (4.3). In the following tables I take a logarithm of import, export, and trade shares. For the measures of inequality I standardize the Theil index and Gini coefficient and take logarithms of income percentiles. I begin by running a series of panel fixed effects models of inequality on trade shares (see table 4.2), export shares (see table 4.4), and import shares (see table 4.3) which are presented below.

The results suggest that there is weak evidence for a link between trade and inequality. The best evidence is found in the results for wage percentiles; I find a significant relationship between trade shares and the wage income at the 75th and 90th percentiles of the income distribution within states. Further, this relationship holds for import shares. For example, a 1 percent increase in a state's trade as a share of GDP is associated with a 0.023 percent decline in the wage at the 90th percentile of the income distribution. This is significant; however, armed with a precise estimate this change in the wage distribution is small and is reflected by a lack of a significant decrease in the Theil index. The transmission of trade to wage inequality may not be contemporaneous; to check for an intertemporal relationship I regress the standardized Theil index on lagged and forward lagged trade shares and present the results in appendix figure D.1. I continue to find little evidence of a relationship between trade and inequality under this specification.

In the aggregate there is little evidence to suggest that there is a strong relationship between trade and aggregate inequality within states. I now present results for the panel fixed effects model to test for a relationship between trade and urban-rural inequality. To measure urban-rural inequality I decompose the state level Theil index into within- urban and rural components and also use the wage difference between urban and rural counties as a measure of between-inequality. The results for this test are presented below in table 4.5.

The above results provide a further lack of evidence for a relationship between trade and

Table 4.2: Baseline Specification: Trade Shares

	(1) Theil	(2) Gini	(3) 90th	(4) 75th	(5) 50th	(6) 25th	(7) 10th
Trade Share	-0.232	-0.275*	-0.0230**	-0.0298**	-0.00596	0.0171	0.160
	(0.191)	(0.162)	(0.010)	(0.013)	(0.016)	(0.033)	(0.216)
Unemployment	-0.165	-0.026	0.013	0.008	-0.012	-0.135***	-0.915***
	(0.212)	(0.191)	(0.016)	(0.020)	(0.026)	(0.031)	(0.185)
GDP	-0.097	-0.128	0.194***	0.222***	0.262***	0.325**	2.020**
	(0.618)	(0.535)	(0.049)	(0.054)	(0.064)	(0.098)	(0.671)
College Share	-0.642	-0.509	0.205***	0.176**	0.305***	0.351**	1.714*
	(1.205)	(1.017)	(0.058)	(0.079)	(0.046)	(0.122)	(0.957)
High School Share	7.370	5.449	-0.192	0.0951	0.396	-0.135	-2.264
	(4.465)	(4.241)	(0.189)	(0.245)	(0.376)	(0.868)	(4.502)
N	600	600	600	600	600	600	469

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

This table presents results for the baseline panel fixed effects model. Trade as a share of GDP is a logarithm, the Theil index and Gini coefficient are standardized, and wage distribution percentiles are logarithms.

Table 4.3: Baseline Specification: Import Shares

	(1) Theil	(2) Gini	(3) 90th	(4) 75th	(5) 50th	(6) 25th	(7) 10th
Import Share	-0.190	-0.218	-0.022**	-0.028**	-0.012	0.004	0.001
	(0.160)	(0.132)	(0.006)	(0.009)	(0.012)	(0.028)	(0.136)
Unemployment	-0.201	-0.066	0.008	0.002	-0.014	-0.135***	-0.935***
	(0.215)	(0.197)	(0.014)	(0.017)	(0.025)	(0.032)	(0.182)
GDP	-0.056	-0.079	0.198***	0.227***	0.263***	0.322**	1.972**
	(0.615)	(0.542)	(0.046)	(0.050)	(0.061)	(0.099)	(0.642)
College Share	-0.655	-0.519	0.201**	0.172**	0.298***	0.344**	1.606*
	(1.187)	(1.000)	(0.060)	(0.081)	(0.045)	(0.119)	(0.949)
High School Share	6.964	4.938	-0.222	0.0557	0.410	-0.0723	-1.326
	(4.376)	(4.207)	(0.200)	(0.240)	(0.368)	(0.862)	(4.620)
N	600	600	600	600	600	600	469

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

This table presents results for the baseline panel fixed effects model. Imports as a share of GDP is a logarithm, the Theil index and Gini coefficient are standardized, and wage distribution percentiles are logarithms.

Table 4.4: Baseline Specification: Export Shares

	(1) Theil	(2) Gini	(3) 90th	(4) 75th	(5) 50th	(6) 25th	(7) 10th
Export Share	-0.077	-0.108	-0.004	-0.001	0.003	0.018	0.200
	(0.141)	(0.129)	(0.010)	(0.014)	(0.018)	(0.025)	(0.208)
Unemployment	-0.144	0.002	0.014	0.009	-0.012	-0.138***	-0.927***
	(0.214)	(0.198)	(0.015)	(0.018)	(0.024)	(0.033)	(0.181)
GDP	-0.094	-0.133	0.197***	0.228***	0.265***	0.331***	2.160**
	(0.650)	(0.569)	(0.052)	(0.056)	(0.067)	(0.094)	(0.634)
College Share	-0.538	-0.392	0.217***	0.194**	0.309***	0.348**	1.661*
	(1.185)	(1.004)	(0.059)	(0.082)	(0.047)	(0.129)	(0.953)
High School Share	6.754	4.808	-0.274	-0.0365	0.353	-0.155	-2.677
	(4.626)	(4.346)	(0.192)	(0.254)	(0.381)	(0.855)	(4.445)
N	600	600	600	600	600	600	469
R2							

Standard errors in parentheses are clustered at state level
* $p < .1$, ** $p < .05$, *** $p < .001$

This table presents results for the baseline panel fixed effects model. Exports as a share of GDP is a logarithm, the Theil index and Gini coefficient are standardized, and wage distribution percentiles are logarithms.

Table 4.5: Urban-Rural Inequality, Panel Fixed Effects

	(1) Theil (urban)	(2) Theil (Rural)	(3) Theil (urban)	(4) Theil (Rural)	(5) Theil (Urban)	(6) Theil (Rural)
Trade Share	-0.005	-0.022				
	(0.008)	(0.018)				
Import Share			-0.005	-0.015		
			(0.006)	(0.014)		
Export Share					0.002	-0.014
					(0.007)	(0.014)
Unemployment	-0.001	-0.016	-0.002	-0.019	-0.002	-0.013
	(0.009)	(0.021)	(0.009)	(0.0212)	(0.009)	(0.021)
GDP	-0.004	-0.054	-0.003	-0.051	-0.003	-0.058
	(0.024)	(0.049)	(0.023)	(0.049)	(0.024)	(0.051)
College Share	0.042	0.017	0.041	0.023	0.050	0.031
	(0.048)	(0.078)	(0.046)	(0.078)	(0.050)	(0.077)
High School Share	0.015	-0.341	0.007	-0.401	-0.027	-0.376
	(0.180)	(0.363)	(0.179)	(0.372)	(0.193)	(0.368)
N	600	600	600	600	600	600

Standard errors in parentheses are clustered at state level
* $p < .1$, ** $p < .05$, *** $p < .001$

This table presents results for the baseline panel fixed effects model. Exports, imports, and trade as a share of GDP is a logarithm, the Theil index and Gini coefficient are standardized, and wage distribution percentiles are logarithms. This table examines the relationship between trade and the within components of urban-rural inequality.

inequality, now measured as urban and rural inequality.

I now run a 2-stage least squares panel fixed effects model to address concerns about endogeneity and reverse causality. I begin by presenting results for the construction of the geography based instrument. In figures 4.1 and 4.2 I show the evolution of the trade elasticity over time with respect to sea distances and air distances. These intertemporal changes in trade elasticities generate variation in predicted trade which I use to instrument for observed trade. In table 4.6 I present the results from the first stage, where I regress observed trade shares on predicted trade shares.

Table 4.6: Instrument First Stage

	(1) Trade Share	(2) Trade Share
$\widehat{Trade}$	0.243**	0.246**
	(0.109)	(0.110)
Full Controls		X
N	600	600

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

This table presents results for the first stage of the two-stage least squares model. In column 1 I do not include controls and in columns 2 I include my full set of controls.

In the first stage I demonstrate that there is a statistically significant relationship between predicted trade shares and observed trade shares. Next, I move on to running the second stage and presenting the full results. In table 4.7 I run the model that is analogous to the results presented in 4.2. As a robustness check I remove all control variables and run the same two-stage least squares regression in appendix table D.1. In table 4.8 I again test for a relationship between trade and urban-rural inequality.

Figure 4.1: *Sea distance coefficients over time.*

Figure 4.2: *Air distance coefficients over time.*

Table 4.7: 2-Stage Least Squares Specification: Baseline

	(1) Theil	(2) Gini	(3) 90th	(4) 75th	(5) 50th	(6) 25th	(7) 10th
Trade Share	-0.270	-0.357	-0.088*	-0.069	0.082	0.034	-1.170
	(0.629)	(0.570)	(0.053)	(0.047)	(0.073)	(0.102)	(0.967)
Unemployment	-0.173	-0.037	0.010	0.007	-0.006	-0.133***	-1.059***
	(0.200)	(0.176)	(0.018)	(0.020)	(0.023)	(0.029)	(0.226)
GDP	-0.292	-0.364	0.193***	0.236***	0.317***	0.372***	1.823**
	(0.633)	(0.536)	(0.058)	(0.058)	(0.058)	(0.103)	(0.717)
College Share	-0.680	-0.575	0.168**	0.155**	0.359***	0.364**	0.783
	(1.247)	(1.078)	(0.070)	(0.079)	(0.078)	(0.140)	(1.263)
High School Share	5.973	3.968	0.196	0.452	0.319	0.160	6.875
	(5.099)	(4.334)	(0.334)	(0.354)	(0.598)	(1.009)	(8.538)
N	600	600	600	600	600	600	469

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

This table presents results for the two-stage least squares model. The F-statistic is 4.939. Trade as a share of GDP is a logarithm, the Theil index and Gini coefficient are standardized, and wage distribution percentiles are logarithms.

Table 4.8: 2-Stage Least Squares Specification: Decomposition

	(1) Theil	(2) Wage Difference	(3) Theil (urban)	(4) Theil (rural)
Trade Share	-0.127	-0.018	-1.198	-1.396
	(0.704)	(0.218)	(0.893)	(1.575)
N	600	600	600	600

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

This table presents results for the two-stage least squares model. The F-statistic is 4.939. Trade as a share of GDP is a logarithm, and the Theil index is standardized. Controls are included in this regression and results are suppressed.

The Kleibergen-Paap F-statistic on each of these specifications is 4.939. Again, I find little evidence of a relationship between trade and inequality; however, the first stage is weakly identified.

4.5 Conclusion

This chapter has revisited the link between trade and inequality by focusing on regional inequality, specifically wage inequality within U.S states. Using a panel data fixed effects empirical model I demonstrate that there is scant evidence to suggest that there exists a relationship between trade and inequality at the state level. I do find small but significant compression of the wage distribution at the 90th and 75th percentiles; however, this relationship disappears when using the Theil index as an outcome. I develop an instrument based on geography and leverage country-state trade data to predict aggregate trade at the state-level; this approach does not uncover a causal link between trade and inequality. Last, I explore a more disaggregate measure of inequality, between urban and rural counties, and again find that there is no strong evidence of a relationship or causal link between trade and urban-rural inequality at the state level.

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Appendix A

Mathematical Derivations for Chapter 2

This appendix presents the solution to the final goods firm's problem. I use this to derive an analytical expression for the parameters governing the labor share.

The final good producer's problem is

$$argmax \Pi_{sj} = P^f_{sj} Q_{sj} - w_j L_{sj} - r_j K_{sj} - (\sum_i \delta_{isj}^{1-\mu} p_{isj}^{1-\mu})^{\frac{1}{1-\mu}} M_{sj} \tag{A.1}$$

Taking first order conditions yields the following;

$$\frac{d\Pi_{sj}}{dVA_{sj}} \frac{dVA_{sj}}{dL_{sj}} = A_{sj}^{\frac{\zeta-1}{\zeta}} Q_{sj}^{\frac{1}{\zeta}} \gamma_{sj}^{\frac{1}{\zeta}} VA_{sj}^{\frac{1}{\rho_s}-\frac{1}{\zeta}} \alpha_{sj}^{\frac{1}{\rho_s}} L_{sj}^{\frac{-1}{\rho_s}} = w_{sj} \tag{A.2}$$

$$\frac{d\Pi_{sj}}{dM_{sj}} \frac{dM_{sj}}{dm_{isj}} = P^f_{sj} A_{sj}^{\frac{\zeta-1}{\zeta}} Q_{sj}^{\frac{1}{\zeta}} (1-\gamma_{sj})^{\frac{1}{\zeta}} M_{sj}^{\frac{1}{\zeta}} [\sum_i \delta_{is}^{1/\mu} m_{isj}^{\frac{\mu-1}{\mu}}]^{\frac{\mu}{\mu-1}} \delta_{isj}^{\frac{1}{\mu}} m_{isj}^{\frac{-1}{\mu}} = p_{isj} \tag{A.3}$$

Solving the firm's optimization problem yields

$$(1-\gamma_{sj})^{\frac{1}{\zeta}} M_{sj}^{\frac{1}{\mu}-\frac{1}{\zeta} \delta_{isj}^{\frac{1}{\mu}} m_{isj}^{\frac{-1}{\mu}} p_{isj}^{-1}} = \gamma_{sj}^{\frac{1}{\zeta}} VA_{sj}^{\frac{1}{\rho_s}-\frac{1}{\zeta}} \alpha_{sj}^{\frac{1}{\rho_s}} L_{sj}^{\frac{-1}{\rho_s}} w_{sj}^{-1} \tag{A.4}$$

Rearranging the above equation yields the following expression for γ_{sj} and α_{sj}, the parameters which I use to define the labor share.

$$\gamma_{sj}^{\frac{1}{\zeta}} \alpha_{sj}^{\frac{1}{\rho_s}} = (1-\gamma_{sj})^{\frac{1}{\zeta}} M_{sj}^{\frac{1}{\mu}-\frac{1}{\zeta}} \delta_{isj}^{\frac{1}{\mu}} m_{isj}^{\frac{-1}{\mu}} p_{isj}^{-1} VA_{sj}^{\frac{1}{\zeta}-\frac{1}{\rho_s}} L_{sj}^{\frac{1}{\rho_s}} w_{sj} \tag{A.5}$$

In my extension of the model I introduce labor-augmenting productivity, firm entry, and Cournot competition. The firm's profit maximization problem, after substituting 2.15 and 2.19, is as follows

$$argmax\Pi_{sj} = \lambda_{sj}\frac{w_j\bar{L_j}}{P_j^f}^{\frac{1}{\sigma}}Q_{sj}^{\frac{\sigma-1}{\sigma}} - \Big[\frac{w_jL_{sj}}{\chi_{sj}^x} + r_jK_{sj} + (\sum_i \delta_{isj}^{1-\mu}p_{isj}^{1-\mu})^{\frac{1}{1-\mu}}M_{sj}\Big]q_{sj} \tag{A.6}$$

The first order conditions from above remain the same, except for the following modification.

$$\frac{d\Pi_{sj}}{dVA_{sj}}\frac{dVA_{sj}}{dL_{sj}} = A_{sj}^{\frac{\zeta-1}{\zeta}}Q_{sj}^{\frac{1}{\zeta}}\gamma_{sj}^{\frac{1}{\zeta}}VA_{sj}^{\frac{1}{\rho_s}-\frac{1}{\zeta}}\alpha_{sj}^{\frac{1}{\rho_s}}\chi_{sj}^{\frac{\rho_s-1}{\rho_s}}L_{sj}^{\frac{-1}{\rho_s}} = w_{sj} \tag{A.7}$$

The solution to the optimization problem is now

$$(1-\gamma_{sj})^{\frac{1}{\zeta}}M_{sj}^{\frac{1}{\mu}-\frac{1}{\zeta}\delta_{isj}^{\frac{1}{\mu}}m_{isj}^{\frac{-1}{\mu}}p_{isj}^{-1}} = \gamma_{sj}^{\frac{1}{\zeta}}VA_{sj}^{\frac{1}{\rho_s}-\frac{1}{\zeta}}\alpha_{sj}^{\frac{1}{\rho_s}}\chi_{sj}^{\frac{\rho_s-1}{\rho_s}}L_{sj}^{\frac{-1}{\rho_s}}w_{sj}^{-1} \tag{A.8}$$

I rearrange the above to write the following expression for the labor share

$$\gamma_{sj}^{\frac{1}{\zeta}}\alpha_{sj}^{\frac{1}{\rho_s}} = (1-\gamma_{sj})^{\frac{1}{\zeta}}M_{sj}^{\frac{1}{\mu}-\frac{1}{\zeta}}\delta_{isj}^{\frac{1}{\mu}}m_{isj}^{\frac{-1}{\mu}}p_{isj}^{-1}VA_{sj}^{\frac{1}{\zeta}-\frac{1}{\rho_s}}\chi_{sj}^{\frac{\rho_s-1}{\rho_s}}L_{sj}^{\frac{1}{\rho_s}}w_{sj} \tag{A.9}$$

Appendix B

Tables and Graphs for Chapter 2

In the following figure I replicate 2.1 for each naics 3 digit sector separately. In the tables below I replicate the baseline regressions for naics 4 digit sectors.

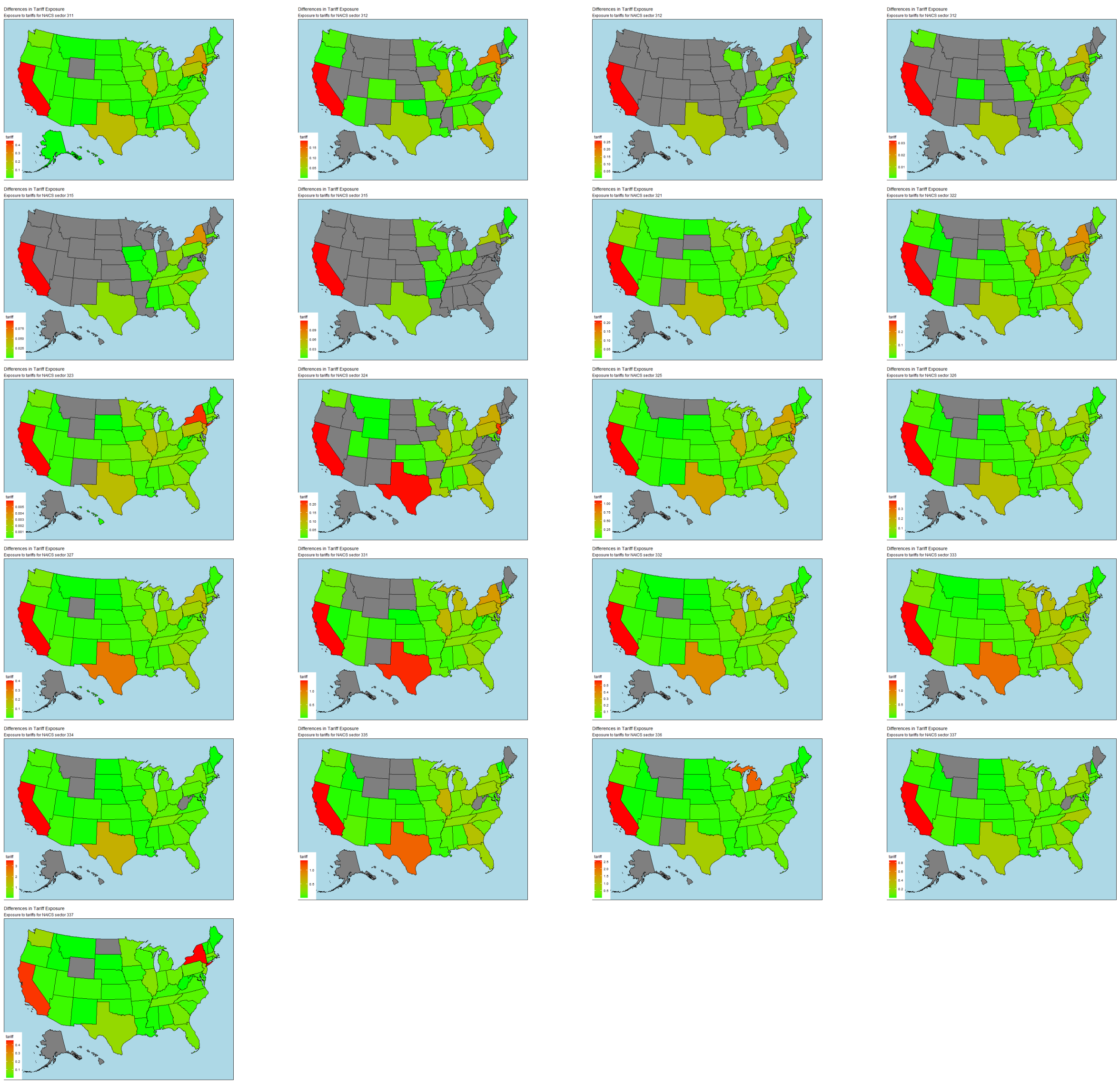

Figure B.1: Differences in tariff exposure for each naics 3 digit sector. Ordered left-to-right then top-down.

In addition to the earlier robustness checks, below I check for the sensitivity of the results to the removal of some of my controls. In the first table I remove all controls from the specification shown in table 2.3. In the following tables I remove one control to demonstrate that the results are not sensitive to each covariate's inclusion.

Table B.1: Baseline Specification

	(1) Total Wages	(2) Employment	(3) Output	(4) $\gamma_{sj}\alpha_{sj}$	(5) α_{sj}	(6) $(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	0.375***	0.330***	0.414***	-0.039**	-0.028**	0.401***
	(0.037)	(0.034)	(0.036)	(0.012)	(0.012)	(0.038)
GDP	0.374	0.328	1.087***	-0.310**	-0.210	0.384
	(0.300)	(0.269)	(0.251)	(0.127)	(0.142)	(0.337)
Unemployment	-0.191**	-0.184**	-0.124	-0.0153	0.00247	-0.176*
	(0.075)	(0.0652)	(0.076)	(0.043)	(0.039)	(0.010)
Population	0.283	0.165	-0.905	0.658**	0.273	-0.291
	(0.582)	(0.521)	(0.684)	(0.249)	(0.257)	(0.863)
Unionization	0.00780	0.00890	-0.00490	0.00976	0.00290	0.0283
	(0.015)	(0.014)	(0.020)	(0.009)	(0.010)	(0.029)
Output Tariff	2.463***	2.197***	2.795***	-0.195	-0.196	2.447***
	(0.480)	(0.435)	(0.460)	(0.310)	(0.281)	(0.391)
N	30622	30622	26463	25652	25329	21443
R2	0.684	0.702	0.657	0.479	0.304	0.583

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

Replication of table 1 for 4-digit NAICS final goods sectors.

Table B.2: High Concentration Subsample

	(1) Total Wages	(2) Employment	(3) Output	(4) $\gamma_{sj}\alpha_{sj}$	(5) α_{sj}	(6) $(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	0.390***	0.344***	0.435***	-0.042**	-0.028**	0.420***
	(0.040)	(0.036)	(0.039)	(0.014)	(0.013)	(0.040)
GDP	0.484	0.450	1.485***	-0.506**	-0.345*	0.700*
	(0.336)	(0.300)	(0.304)	(0.167)	(0.194)	(0.407)
Unemployment	-0.176**	-0.171**	-0.105	0.015	0.020	-0.132
	(0.080)	(0.070)	(0.088)	(0.048)	(0.049)	(0.132)
Population	0.156	0.0246	-1.349*	0.989***	0.500	-0.562
	(0.670)	(0.600)	(0.804)	(0.281)	(0.319)	(1.046)
Unionization	0.006	0.007	-0.006	0.008	-0.00	0.028
	(0.019)	(0.017)	(0.025)	(0.012)	(0.014)	(0.039)
Output Tariff	2.358***	2.073***	2.546***	-0.0956	-0.163	2.188***
	(0.513)	(0.456)	(0.504)	(0.349)	(0.311)	(0.398)
N	22502	22502	18961	18298	18029	15142
R2	0.654	0.669	0.636	0.476	0.302	0.570

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

Replication of table 3 for 4-digit NAICS final goods sectors.

Table B.3: Low Concentration Subsample

	(1) Total Wages	(2) Employment	(3) Output	(4) $\gamma_{sj}\alpha_{sj}$	(5) α_{sj}	(6) $(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	0.310***	0.277***	0.333***	-0.0228	-0.0178	0.334***
	(0.0694)	(0.0681)	(0.0727)	(0.0238)	(0.0217)	(0.0713)
GDP	0.0680	0.0194	0.0468	0.189	0.124	-0.541
	(0.354)	(0.341)	(0.341)	(0.180)	(0.163)	(0.484)
Unemployment	-0.240**	-0.232**	-0.237**	-0.0442	-0.0138	-0.308**
	(0.0995)	(0.0931)	(0.100)	(0.0771)	(0.0570)	(0.0951)
Population	0.506	0.406	-0.104	-0.141	-0.381	0.190
	(0.736)	(0.705)	(0.653)	(0.372)	(0.336)	(0.890)
Unionization	0.0135	0.0142	-0.0100	0.0152	0.0135	0.0138
	(0.0134)	(0.0121)	(0.0170)	(0.0116)	(0.0102)	(0.0329)
Output Tariff	2.476**	2.252**	3.018***	-0.502	-0.434	2.664**
	(0.771)	(0.672)	(0.823)	(0.419)	(0.435)	(1.306)
N	8120	8120	7502	7354	7300	6301
R2	0.799	0.806	0.763	0.369	0.245	0.671

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

Replication of table 4 for 4-digit NAICS final goods sectors.

Table B.4: Baseline Specification: No Controls

	(1) Total Wages	(2) Employment	(3) Output	(4) $\gamma_{sj}\alpha_{sj}$	(5) α_{sj}	(6) $(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	0.476***	0.418***	0.569***	-0.084***	-0.037	0.522***
	(0.049)	(0.047)	(0.054)	(0.023)	(0.024)	(0.058)
N	11135	11135	10115	10054	9770	8667
R^2	0.7626	0.8448	0.7996	0.6060	0.4630	0.8261

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

Notes This table presents results for the baseline specification and the full sample. This sensitivity check removes all control variables from specification 2.30.

Table B.5: Baseline Specification

	(1) Total Wages	(2) Employment	(3) Output	(4) $\gamma_{sj}\alpha_{sj}$	(5) α_{sj}	(6) $(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	0.347***	0.306***	0.450***	-0.062**	-0.023	0.412***
	(0.060)	(0.060)	(0.057)	(0.026)	(0.029)	(0.054)
Unemployment	-0.110**	-0.099**	-0.085	-0.011	-0.037	-0.071
	(0.055)	(0.048)	(0.098)	(0.057)	(0.056)	(0.078)
Population	0.562**	0.418	0.300	-0.002	0.114	0.133
	(0.250)	(0.256)	(0.417)	(0.245)	(0.243)	(0.551)
Unionization	-0.014	-0.011	-0.009	0.007	0.009	0.012
	(0.009)	(0.008)	(0.017)	(0.010)	(0.015)	(0.024)
Output Tariff	1.818***	1.605***	1.663**	-0.305	-0.173	1.488***
	(0.473)	(0.446)	(0.537)	(0.329)	(0.268)	(0.384)
N	11135	11135	10115	10054	9770	8667
R^2	0.7640	0.8480	0.8029	0.6070	0.4633	0.7431

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

Notes This table presents results for the baseline specification and the full sample. This sensitivity check removes the GDP control variable from specification 2.30.

Table B.6: Baseline Specification: No Unemployment

	(1) Total Wages	(2) Employment	(3) Output	(4) $\gamma_{sj}\alpha_{sj}$	(5) α_{sj}	(6) $(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	0.348***	0.306***	0.451***	-0.062**	-0.023	0.413***
	(0.059)	(0.060)	(0.057)	(0.026)	(0.029)	(0.054)
GDP	0.282	0.201	0.928**	-0.217	-0.187	0.433
	(0.238)	(0.216)	(0.347)	(0.196)	(0.197)	(0.325)
Population	0.276	0.227	-0.774	0.263	0.352	-0.337
	(0.363)	(0.346)	(0.541)	(0.304)	(0.347)	(0.689)
Unionization	-0.0155*	-0.012	-0.010	0.007	0.009	0.012
	(0.009)	(0.008)	(0.015)	(0.009)	(0.015)	(0.023)
Output Tariff	1.812***	1.602***	1.635**	-0.297	-0.167	1.474***
	(0.472)	(0.445)	(0.541)	(0.331)	(0.270)	(0.387)
N	11135	11135	10115	10054	9770	8667
R^2	0.7640	0.8480	0.8031	0.6071	0.4634	0.7431

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

Notes This table presents results for the baseline specification and the full sample. This sensitivity check removes the unemployment rate control variable from specification 2.30.

Table B.7: Baseline Specification: No Population

	(1) Total Wages	(2) Employment	(3) Output	(4) $\gamma_{sj}\alpha_{sj}$	(5) α_{sj}	(6) $(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	0.348***0.306***	0.450***	-0.062**	-0.023	0.412***	
	(0.059)	(0.059)	(0.057)	(0.026)	(0.029)	(0.054)
GDP	0.270	0.176	0.723**	-0.176	-0.150	0.315
	(0.176)	(0.170)	(0.262)	(0.160)	(0.144)	(0.279)
Unemployment	-0.078	-0.079*	0.007	-0.038	-0.060	-0.033
	(0.046)	(0.043)	(0.086)	(0.052)	(0.052)	(0.084)
Unionization	-0.016*	-0.012	-0.007	0.006	0.008	0.013
	(0.009)	(0.008)	(0.016)	(0.009)	(0.015)	(0.023)
Output Tariff	1.809***	1.599***	1.647**	-0.302	-0.172	1.480***
	(0.470)	(0.444)	(0.540)	(0.331)	(0.269)	(0.385)
N	11135	11135	10115	10054	9770	8667
R^2	0.7640	0.8480	0.8031	0.6071	0.4634	0.7431

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

Notes This table presents results for the baseline specification and the full sample. This sensitivity check removes the state population control variable from specification 2.30.

Table B.8: Baseline Specification: No Unionization

	(1) Total Wages	(2) Employment	(3) Output	(4) $\gamma_{sj}\alpha_{sj}$	(5) α_{sj}	(6) $(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	0.341***	0.299***	0.447***	-0.062**	-0.0241	0.413***
	(0.061)	(0.062)	(0.057)	(0.026)	(0.029)	(0.054)
GDP	0.142	0.066	0.948**	-0.266	-0.252	0.404
	(0.222)	(0.210)	(0.339)	(0.192)	(0.198)	(0.349)
Unemployment	-0.083*	-.084*	0.028	-0.040	-0.072	-0.025
	(0.047)	(0.045)	(0.083)	(0.051)	(0.051)	(0.085)
Population	0.427	0.365	-0.759	0.291	0.390	-0.319
	(0.358)	(0.348)	(0.521)	(0.285)	(0.327)	(0.689)
Output Tariff	1.846***	1.633***	1.642**	-0.296	-0.166	1.468***
	(0.481)	(0.456)	(0.540)	(0.331)	(0.268)	(0.386)
N	11135	11135	10115	10054	9770	8667
R^2	0.7642	0.8482	0.8028	0.6068	0.4636	0.7432

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

Notes This table presents results for the baseline specification and the full sample. This sensitivity check removes the state unionization rate control variable from specification 2.30.

Table B.9: Baseline Specification: No Output Tariff

	(1) Total Wages	(2) Employment	(3) Output	(4) $\gamma_{sj}\alpha_{sj}$	(5) α_{sj}	(6) $(1-\gamma_{sj})\alpha_{sj}$
$tariff_{sjt}$	0.479***	0.422***	0.570***	-0.084***	-0.036	0.521***
	(0.049)	(0.046)	(0.054)	(0.024)	(0.024)	(0.058)
GDP	0.345	0.243	1.140**	-0.297	-0.284	0.582
	(0.351)	(0.329)	(0.417)	(0.191)	(0.198)	(0.407)
Unemployment	-0.078	-0.078	0.029	-0.042	-0.070	-0.019
	(0.051)	(0.048)	(0.086)	(0.051)	(0.051)	(0.088)
Population	-0.022	-0.026	-1.164*	0.366	0.446	-0.650
	(0.475)	(0.457)	(0.634)	(0.298)	(0.328)	(0.756)
Unionization	-0.019*	-0.015	-0.011	0.007	0.010	0.014
	(0.011)	(0.009)	(0.018)	(0.009)	(0.014)	(0.026)
N	11135	11135	10115	10054	9770	8667
R^2	0.7626	0.8448	0.8003	0.6065	0.4632	0.7406

Standard errors in parentheses are clustered at state level

$^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .001$

Notes This table presents results for the baseline specification and the full sample. This sensitivity check removes the sector-state specific output tariff control variable from specification 2.30.

Appendix C

Data for Chapter 3

In the main text, we report the number of HS10 varieties in broad sectors. In Table C.1, we report the number of varieties in each of the narrow SITC sectors.

Table C.1: SITC2 (2-digit) & N^s

SITC2 (2-digit)	N^s	SITC2 (2-digit)	N^s	SITC2 (2-digit)	N^s	SITC2 (2-digit)	N^s
00	27	26	81	57	10	76	185
01	152	27	100	58	129	77	771
02	39	28	108	59	150	78	171
03	295	29	187	61	187	79	133
04	135	32	11	62	119	81	22
05	376	33	81	63	159	82	44
06	34	34	13	64	295	83	15
07	70	35	1	65	884	84	419
08	60	41	14	66	253	85	60
09	72	42	47	67	434	87	221
11	42	43	16	68	215	88	175
12	76	51	643	69	370	89	500
21	71	52	252	71	187	93	18
22	38	53	70	72	553	94	12
23	21	54	197	73	249	95	45
24	166	55	66	74	634	96	1
25	24	56	1	75	182	97	10

We report summary statistics in Table C.2:

Table C.2: Summary Statistics

variable	obs.	mean	std. dev.	min	max
Total Trade	46,010	237.71	3344.05	0	302310.50
Adjacency	46,010	0.01	0.11	0	1
Common Language	46,010	0.18	0.38	0	1
Distance	46,010	8549.28	4679.15	60.77	19888.66

In our empirical analysis, we use data for 215 countries with the following ISO codes:

ABW, AFG, AGO, AIA, ALB, AND, ANT, ARE, ARG, ARM, ATG, AUS, AUT, AZE, BDI, BEL, BEN, BFA, BGD, BGR, BHR, BHS, BIH, BLR, BLZ, BMU, BOL, BRA, BRB, BRN, BTN, BWA, CAF, CAN, CCK, CHE, CHL, CHN, CIV, CMR, COG, COK, COL, COM, CPV, CRI, CUB, CXR, CYM, CYP, CZE, DEU, DJI, DMA, DNK, DOM, DZA, ECU, EGY, ERI, ESH, ESP, EST, ETH, FIN, FJI, FLK, FRA, FRO, FSM, GAB, GBR, GEO, GHA, GIB, GIN, GMB, GNB, GNQ, GRC, GRD, GRL, GTM, GUY, HKG, HND, HRV, HTI, HUN, IDN, IND, IRL, IRN, IRQ, ISL, ISR, ITA, JAM, JOR, JPN, KAZ, KEN, KGZ, KHM, KIR, KNA, KOR, KWT, LAO, LBN, LBR, LBY, LCA, LKA, LSO, LTU, LUX, LVA, MAC, MAR, MDA, MDG, MDV, MEX, MHL, MKD, MLI, MLT, MMR, MNG, MNP, MOZ, MRT, MSR, MUS, MWI, MYS, NAM, NCL, NER, NFK, NGA, NIC, NIU, NLD, NOR, NPL, NRU, NZL, OMN, PAK, PAN, PCN, PER, PHL, PLW, PNG, POL, PRK, PRT, PRY, PYF, QAT, RUS, RWA, SAU, SDN, SEN, SGP, SHN, SLB, SLE, SLV, SMR, SOM, SPM, STP, SUR, SVK, SVN, SWE, SWZ, SYC, SYR, TCA, TCD, TGO, THA, TJK, TKL, TKM, TMP, TON, TTO, TUN, TUR, TUV, TZA, UGA, UKR, URY, USA, UZB, VCT, VEN, VGB, VNM, VUT, WLF, WSM, YEM, ZAF, ZAR, ZMB, ZWE.

Appendix D

Tables and Figures for Chapter 4

Table D.1: 2-Stage Least Squares Specification

	(1) Theil	(2) Gini	(3) 90th	(4) 75th	(5) 50th	(6) 25th	(7) 10th
Trade Share	-0.244	-0.450	-0.0506	-0.0201	0.173	0.215	-0.292
	(0.668)	(0.626)	(0.0528)	(0.0495)	(0.106)	(0.164)	(0.836)
N	600	600	600	600	600	600	469

Standard errors in parentheses are clustered at state level

* $p < .1$, ** $p < .05$, *** $p < .001$

This table presents results for the two-stage least squares model. The F-statistic is 5.321. Trade as a share of GDP is a logarithm, the Theil index and Gini coefficient are standardized, and wage distribution percentiles are logarithms.

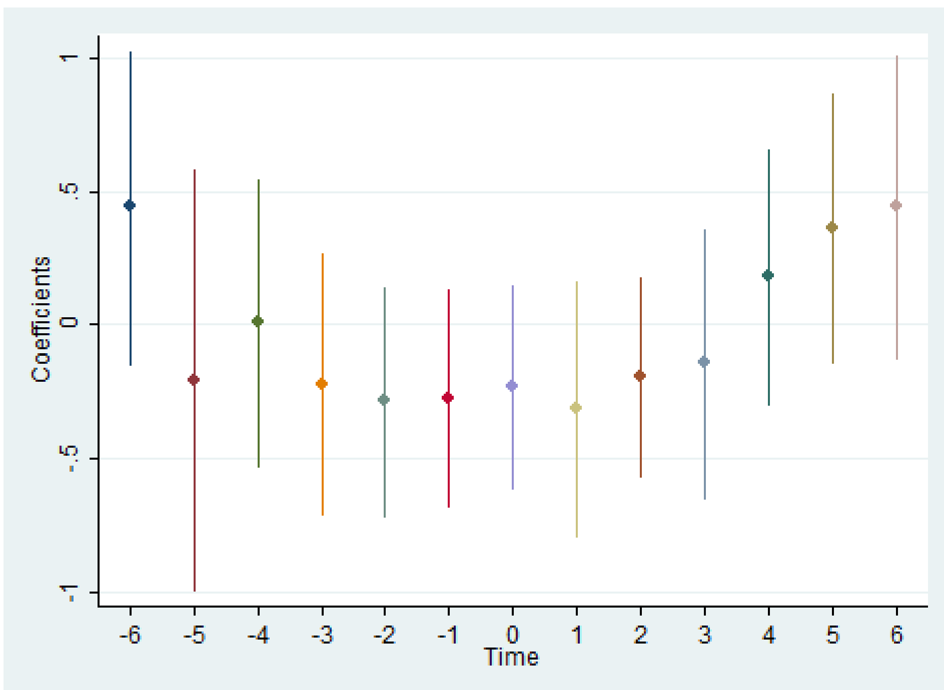

Figure D.1: *Coefficient plot of lagged trade shares regressed on the standardized Theil index.*