Trade Costs, Supply Chains, and the Decline of the Heartland

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Abstract

This paper studies how changes in domestic trade costs can cause regions to decline. The agriculture-intensive states of the American Midwest (the "heartland") lost population relative to the rest of the country over the postwar period. I document that the price of shipping agricultural relative to manufactured goods fell considerably over this same period. To show how these two facts may be linked, I outline a simple version of a trade model and derive comparative statics of the price, production, and population effects of a decline in agricultural shipping costs. I validate the model's predictions by studying how a 1963 Supreme Court ruling that sharply reduced the cost of shipping wheat versus flour affected the flour milling industry. Finally, I calibrate a multi-sector, multi-location version of the model to the U.S. in 1950 and find that observed declines in agricultural trade costs can explain around 8% of the postwar population decline in the heartland.

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For the past 30 years, our population has also been growing and shifting. The result is exemplified in the vast areas of rural America emptying out of people and of promise...

— President Richard Nixon, State of the Union, 1970

1 Introduction

Over the past century, the spatial distribution of economic activity within many countries, especially the United States, has changed dramatically. These large shifts in where people live, where they work, and where goods are produced have welfare implications for people living in different places. Inevitably, people living in some regions end up better off than those in other regions. Why have some regions prospered while others have declined? What role have changes in trade costs within countries played in shaping these welfare gains and welfare losses across locations? To make progress on these questions, this paper examines a region over a period of significant decline: the agriculture-intensive states of the American Midwest (the "Heartland") over the postwar period.[1]

Between 1950 and 1980, the percent of the U.S. population living in Heartland states fell by 18%, from 9% to 7% (U.S. Census). By this measure, the Heartland fared worse than almost any other Census division.[2] Figure 1 maps the percentage change in the share of the national population living in each state between 1950 and 1980.[3] States colored in (darker) blue grew (more) while states in (darker) red shrunk (more).[4] The Heartland is outlined in black. Four Heartland states – the Dakotas plus Iowa and Nebraska – made up half of the top eight states in terms of relative population declines over the period. About one-third of all U.S. counties experienced net out-migration over the period; of

[1]I define the Heartland as the set of states in the Census' West North Central division which corresponds to the non-Rustbelt Midwestern states. The Midwest follows the U.S. Census classification. Following Alder, Lagakos and Ohanian (2014), I define the Rustbelt as: Illinois, Indiana, Michigan, New York, Ohio, Pennsylvania, West Virginia and Wisconsin. Thus, the non-Rustbelt Midwest includes Minnesota, Iowa, Missouri, the Dakotas, Nebraska, and Kansas

[2]There are nine Census divisions. The Middle Atlantic division experienced a percentage decline in relative population of about the same magnitude (18%).

[3]Figure A.1 plots percentage of the U.S. population living in each Census region in each year between 1900 and 2000. While there was a small decline in the Midwest's relative population preceding this period, it accelerated after the war.

[4]I focus here on state-level data because my eventual model calibration will be at the state level due to data constraints. However, the pattern is equally striking at the county level.

those, 35% were in the Heartland, even though the Heartland includes less than 20% of all U.S. counties.

The Heartland states are sometimes referred to as the "breadbasket" because they largely specialize in producing agricultural goods, especially bulk grains like wheat (Wishart (2004)).[5] In 1950, North Dakota and South Dakota led the nation as the states with the largest share of gross output coming from the agricultural sector while Iowa and Nebraska were close behind. Although Heartland states housed only 9% of the population in 1950, together they produced nearly a quarter of the nation's agricultural output. Population declines in these rural, agriculture-intensive areas received considerable policy attention during the period. President Nixon's 1970 State of the Union remarked on the need to "stem the migration to urban centers". This rural to urban migration also motivated the passage of the Rural Development Act of 1972, an early example of a place-based policy, which provided financial support to rural areas. Its stated purpose was to "foster a balanced national development" (Rural Development Act, 1972).

This paper proposes, studies, and quantifies the importance of a novel explanation for this decline of the American Heartland: changes in the structure of domestic trade costs.[6] Freight rates for bulk (agricultural) goods fell considerably relative to those for finished (manufactured) products beginning in the 1950s. To document this fact, I digitized records from the Interstate Commerce Commission (ICC), the regulatory body for freight transport during the period. The ICC annually published the *Freight Commodity Statistics*, from 1928 to 1980, in which it reported aggregate data on tons shipped and revenue earned by major rail carriers.[7] To measure shipping costs levied by shippers on producers, I compute the revenue per ton earned by railroad companies for shipments of goods from each commodity class.[8]

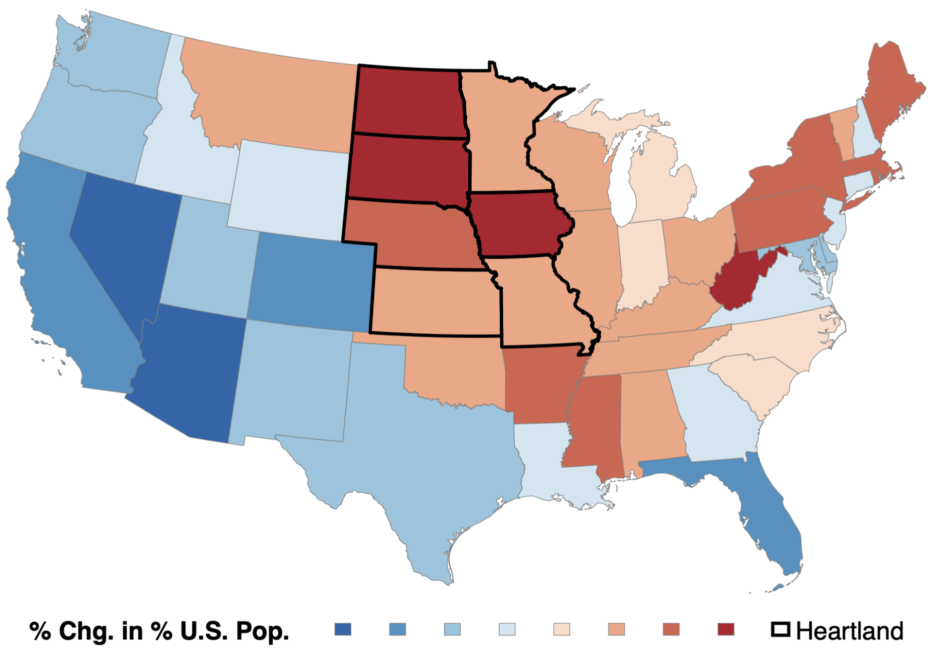
[5] Figure A.2 plots the percentage of exports in agriculture for each state.

[6] This hypothesis, that changes in the structure of trade costs within the postwar U.S. had important effects on the distribution of economic activity, received some attention among economists during the period. For example, see Meyer and Morton (1975) who wrote that, "[T]he lower freight rates for transporting bulk commodities than their fabricated equivalent commonly encourages manufacturers to substitute the transport of bulk commodities for the movement of the finished goods."

[7] Total revenue is the total payments made by producers to railroad shippers.

[8] Revenue per ton is a standard measure of shipping costs used in the literature; for example, see Hyslop and Dahl (1964). However, in addition to the tariff charged by shippers, revenue per ton may also reflect changes in the underlying distance shipped. I control for this using data on bilateral trade costs in Section

Figure 1: **The Postwar Decline of the Heartland, 1950 to 1980**



Note: This figure shows the percentage change in the share of the national population living in each state between 1950 and 1980. *Source:* U.S. Census, 1950 and 1980.

In Figure 2, I plot annual real revenue per ton earned by the railroads in each year, separately for agricultural goods and manufactured goods.[9] I find large declines in the shipping costs of agricultural relative to manufactured goods beginning in the postwar period.[10] Revenue per ton earned in these each of these two sectors was relatively constant until around 1955 at which point it began to fall sharply in the agricultural sector. By 1967, agricultural revenue per ton was nearly one third lower than manufacturing revenue per ton. Qualitative evidence suggests that most of this decline was driven by innovations in the shipment of bulk grain products; new types of rail cars, like the unit train and the covered hopper car, allowed railroads to significantly reduce the cost of service on these products particularly over long distances.[11]

4. Even conditional on distance, the decline in relative shipping costs is around one-third.

[9] Figure A.3 shows the same figure using data on Class I motor carriers (trucks), starting when these data become available in 1956.

[10] This figure uses aggregate data. When I quantify the model, I use data on revenue per ton earned by each state pair for each sector to show that this relative decline in shipping costs holds up to controlling for origin-destination fixed effects.

[11] These new technologies are discussed more in Section 3. Panel (a) of figure B.5 shows the covered

Figure 2: **Railroad Shipping Costs Over Time**

Note: This figure shows revenue per ton earned by Class I railroads in each year, separately for agricultural goods and manufactured goods. *Source:* Interstate Commerce Commission's *Freight Commodity Statistics*.

How could these changes in trade costs have caused relative population declines in the Heartland states? To explore the channels through which these two facts may be linked, I outline a simple, Armington model of trade between two locations with three sectors. Labor is mobile across locations, and sectors are connected to each other through input-output linkages. The mechanics of this simple model are at the heart of most trade models used in the literature. The key assumption I make is that one location has a comparative advantage in the production of agricultural goods and so it relies on imports of agricultural goods from other regions relatively less than the other location in the model. I use this model to derive analytic comparative statics describing the response of prices, production, firm locations, welfare, and population to a decline in the cost of trading agricultural goods.

The model highlights a key channel through which declines in agricultural goods can cause a population decline of the heartland: the input-output structure of the economy.

hopper car, which displaced box cars over this period, as shown in panel (b) of the same figure.

Agricultural goods are used by other sectors including food processing, textile mills, rubber and plastics industries, and apparel industries, as intermediate inputs (BEA, 1947). Initially, trade costs gave locations that specialized in the production of agricultural goods a comparative advantage in certain downstream sectors. But when it becomes relatively cheaper to acquire agricultural goods outside the heartland, agriculture-intensive locations' downstream comparative advantage is weakened and downstream firms move out of the agriculture-intensive location. Plus, there may be spillover effects from agriculture-intensive manufacturers to other firms through the input-ouput structure, as well as through external economies of scale in manufacturing.[12]

To show that this channel is operating in the data, I take advantage of a natural experiment that affected flour mills in 1963. Studying this natural experiment has a few key benefits. First, it allows me to narrow in on a single industry for which I have collected location-specific data on prices for goods, plants, firms, and trade in the upstream and downstream sectors. Most of these data are not systemically available for this time period for a broader set of industries. Second, it provides a setting with a clear and significant change in the cost of shipping the upstream, agricultural good relative to the downstream, manufactured good, that was caused by an unexpected change in regulation rather than by changes in patterns of demand or supply that may also affect prices and production patterns.

Before 1963, wheat and flour, which are flour mills' agricultural input good and final manufactured good respectively, were equally costly to ship via rail as a result of railroad regulation by the Interstate Commerce Commission. Rail car innovations in the late 1950s and early 1960s reduced the railroad cost of shipping bulk products, but regulation initially prevented railroads from lowering prices accordingly. In 1963, a Supreme Court ruling allowed railroads to significantly reduce the price of wheat shipments which allowed them to compete more effectively with barges. Other railroads soon followed, and the result was that the price of shipping wheat fell by about a third while the price of shipping flour remained the same. I document this fall in the relative cost of shipping wheat versus flour using an event study design.

[12]For example, as in the case of Bartelme et al. (2019).

I then use newly digitized data and two sources of variation generated by the Court's ruling to show how this change in shipping costs affected flour prices, production, and firm locations. To estimate the causal effects of the change in trade costs on outcomes, I use a differences-in-differences strategy. The first source of variation that I use is variation across time, before and after the ruling. The second source of variation is variation across locations, as flour mills that were initially located close to wheat production were relatively less affected by the change in trade costs since they did not initially rely heavily on the railroad for wheat shipping.

I find empirical support for the model's mechanisms using this setting. I find that, after the ruling, prices of wholesale flour, consumer flour, and bread rose in the Midwest, which is close to where wheat is produced, as compared with prices in cities and states farther away from where wheat is produced. Flour milling capacity and the number of mills fell in areas close to where wheat is produced following the change in shipping rates relative to areas further away. The relative decline in the number of flour mills in wheat-producing areas was driven by an exodus of relatively less productive mills. These results are consistent with the simple model's comparative statics.

Finally, building off of Caliendo et al. (2018), I extend the simple model to a multi-sector, multi-location model of trade between U.S. states. To capture the mechanism, the model includes labor mobility, trade costs that vary by sector, and input-output linkages between sectors. I include land as a fixed factor of production to correctly model the agricultural sector. I digitize data from 1950 on output and trade in order to calibrate the model. I use the model to ask how changes in agricultural trade costs, which I measure in the data, affected the distribution of the population across states. I find that this channel can explain around 8% of the postwar population decline in the heartland. Nearly half a million people would have remained in the Heartland had the structure of trade costs remained at its 1950 level.

This paper makes several contributions to the literature. First, the paper contributes to a broad literature in trade about how changes in trade costs affect different locations. Glaeser and Kohlhase (2004), Fajgelbaum and Redding (2022), Donaldson and Hornbeck (2016) and Donaldson (2016) among others all use historical settings to study how changes in trade costs shape the distribution of economic activity across locations within countries. Recent work by Costinot and Donaldson (2016) studies the gains from market integration within the U.S. Gollin and Rogerson (2010) study the impact of the transport network on rural to urban migration. Relative to these papers, this paper proposes and studies a new channel – the changing structure of domestic trade costs – to explain changes in economic activity across locations.

Second, by proposing and carefully quantifying a new explanation for the decline of the American Midwest, this paper contributes to a broad literature studying historical patterns of population and production in the United States. Long and Siu (2018) and Hornbeck (2012) study how the Dust Bowl contributed to out-migration in some Midwestern counties in the 1930s. Eckert and Peters (2018) study the spatial implications of structural change within the U.S. over the past century. Caselli and Coleman II (2001) study the contribution of structural transformation in explaining the convergence of incomes across regions in the U.S. Kim (1995) explores the changing spatial distribution of manufacturing in the U.S. Alder, Lagakos and Ohanian (2014) study how competitive pressure affected the postwar, manufacturing-intensive Rust Belt and Autor et al. (2014) study how exposure to import competition affected manufacturing-intensive locations since the 1990s. Finally, the particular population patterns I study are documented extensively, though without explanation, by Wilson (2009).

This paper also contributes to a growing body of literature, both theoretical and empirical, on supply chains and trade with input-output linkages. Caliendo and Parro (2015) and Caliendo et al. (2018) embed input-output linkages into a standard trade, Melitz (2003) style trade model. Recent theoretical work by Grossman and Helpman (2021), Antras, Fort and Tintelnot (2022), Antras and Helpman (2004) considers the effects of changes in upstream and downstream trade costs in a world connected by supply chains. This paper provides novel empirical evidence describing how downstream prices and production re-allocate in response to changes in upstream trade costs, and how this can affect population in the long run. While these mechanisms are at the heart of the models in all of these papers, there is limited evidence that they operate in the data which this paper provides. Relative to Cox (2021), I show how changes in trade costs allow supply chains can reallocate population across space.

Finally, this paper relates to work in agricultural economics on the flour milling industry over the postwar period. Kim et al. (2001), Nightingale (1967), Hyslop and Dahl (1964) and Harwood (1991) discuss the existence of the cost shock and speculate on its potential implications for the locations of flour mills. Babcock (1976) and Babcock, Cramer and Nelson (1985) use aggregate data to measure which regions will experience an increase in flour production in response to the shock. Relative to these papers, I use very granular, plant-level data on flour mills to credibly quantify the extent to which observed changes in trade costs affected prices and the locations of mills.

2 Simple Model and Testable Predictions

To explore the channels that link changes in the structure of trade costs with population declines, I outline a simple two-state, three-sector model. I use the model to derive comparative statics which I then test empirically.

2.1 Simple Model

In the initial equilibrium, there are two locations, New York, denoted as N, and Kansas, denoted as K. There are three sectors: an agricultural sector ("wheat", W), a manufacturing sector ("flour", F), and an outside manufactured good sector M. I assume that, initially, N imports more wheat from K than K imports from N, so $\pi^W_{NN} < \pi^W_{KK}$ where π^W_{in} is the share of wheat imported from i by n. This pattern will hold if, for example, K has a comparative advantage in the production of wheat as compared with N.[13] This pattern of comparative advantage is the key assumption that will drive the results.

Agents' Problem. In each location, there is a common component of utility across all

[13]Consistent with this assumption, there are strong patterns of comparative advantage in the production of agricultural goods across states in the U.S., with agricultural exports making up a particularly large share of the Heartland's exports. Figure A.2 shows the share of agricultural goods in each state's export bundle in 1949. Appendix proof 1 shows one set of parameters – that Kansas is sufficiently more productive in growing wheat than New York – that is consistent with this assumption.

agents in a location, plus an idiosyncratic component of utility associated with each agent. Agents have quasi-linear utility over a constant elasticity of substitution (CES) aggregator of flour, plus the outside good. The outside good is homogenous and freely traded. Because agents have CES utility over flour types from each location, agents love variety; thus, they want to consume flour from every location since each location is producing its own variety.[14] The elasticity of substitution of flour across origins is σ_F. Agents in a location i choose to buy flour from each location c^F_{ni} and the outside manufactured good from each location c^M_{ni} to solve:

$$\max_{c^F_{ni}, c^M_{ni}} \left[\sum_n c^M_{ni}\right] + \ln\left(\left[\sum_n (c^F_{ni})^{\frac{\sigma_F - 1}{\sigma_F}}\right]^{\frac{\sigma_F}{\sigma_F - 1}}\right)$$

subject to a budget constraint of $w_i = \sum_n p^M_{ni} c^M_{ni} + p^F_{ni} c^F_{ni}$. The common component of indirect utility is then $v_i = w_i + \ln\left(\frac{\sigma_F}{\sigma_F - 1}\right) - \ln\left(P^F_i\right) - \frac{\sigma_F}{\sigma_F - 1} P^F_i$.

The total indirect utility of a worker b in state i is $v^b_i = v_i + \epsilon^b_i$ where ϵ^b_i represents agent b's idiosyncratic preferences for location i. Agents choose to live in the state that gives them the largest indirect utility. Assuming that $\epsilon^b_n \sim$ *Gumbel* yields the share of agents living in state n:

$$\lambda_i = \frac{exp\left(w_i + \ln\left(\frac{\sigma_F}{\sigma_F - 1}\right) - \ln\left(P^F_i\right) - \frac{\sigma_F}{\sigma_F - 1} P^F_{n'}\right)}{\sum'_n exp\left(w_{n'} + \ln\left(\frac{\sigma_F}{\sigma_F - 1}\right) - \ln\left(P^F_{n'}\right) - \frac{\sigma_F}{\sigma_F - 1} P^F_{n'}\right)}$$

The number of people living in state i is $L_i = \lambda_i L$, where L is total population which I assume to be exogenous.

Production. Wheat is produced using labor, $Y^W_{it} = T^W_{it} L^W_{it}$. The outside good is also produced using labor, $Y^M_{it} = T^M_{it} L^M_{it}$. Flour is produced using a CES aggregator of wheat, $Y^F_{it} = T^F_{it}\left[\sum_n \left(c^W_{ni}\right)^{\frac{\sigma_W - 1}{\sigma_W}}\right]^{\frac{\sigma_W}{\sigma_W - 1}}$ where σ_W is the elasticity of wheat across origins.

[14]This, too, is not divorced from reality. Different regions specialize in different types of flour, often related to the type of wheat that is locally grown. For example, White Lily flour is generally associated with the Southern states because it is milled there, and is important in baking biscuits.

Prices. I assume that all markets are perfectly competitive and that wheat and flour are subject to sector-specific iceberg trade costs, τ^W_{in} and τ^F_{in} respectively. Thus, prices in each sector are $p^F_{in} = \tau^F_{in} p^F_{ii}$ and $p^W_{in} = \tau^W_{in} p^W_{ii}$ where p^j_{ii} is the price of producing goods from sector j in location i. Since the outside manufactured good is homogenous and freely traded, it is the numeraire good so its price is 1. Wages in each location will then be set based on productivity in this sector $w_n = T^M_i$ and thus are exogenously determined.

Extension with Heterogeneous Firms. While a causal link between declines in agricultural good trade costs and changes in the distribution of population does not require firms to be present, including firms in the model allows me to derive testable predictions governing what will happen to firm entry and average productivity of mills in different locations. The richness of my data will allow me to test these predictions. In this case, I assume monopolistic competition among flour mills, closely following Chaney (2008) and Krugman (1980). Each agent chooses c^M_{ni} and $c^F_{ni}(\omega)$ where $\omega \in \Omega$ is a flour variety to solve:

$$\max_{c^M_{ni}, c^F_{nit}(\omega)} \left[\sum_n c^M_{ni}\right] + \ln\left(\left(\sum_k \int_{\Omega_k} (c^F_{ki}(\omega))^{\frac{\sigma_F - 1}{\sigma_F}} d\omega\right)^{\frac{\sigma_F}{\sigma_F - 1}}\right)$$

$$\text{s.t.} \quad w_i = \sum_k \int_{\Omega_k} p^F_{ki}(\omega) c^F_{ki}(\omega) d\omega + \sum_n p^M_{ni} c^M_{ni}$$

From this maximization problem, I obtain the quantity demanded of each flour variety from agents in state i:

$$c^F_{ki}(\omega) = \left(p^F_{ki}(\omega)\right)^{-\sigma_F} \left(P^F_i\right)^{\sigma_F - 1} \tag{1}$$

In terms of production, each mill produces its own flour variety ω, though a variety is unique conditional on a firm's productivity, which I index as φ. Entry and exit of flour mills in each state are endogenous and depend on a zero profit condition. In each market there is some endogenously given mass of potential entrants, M_i and some share of them will end up entering the market. The number of firms operating in any period is then $M^*_i = M_i \cdot (1 - G(\varphi^*_i))$ where φ^*_i is the lowest level of firm productivity for which profits are non-negative, and G(.) is the distribution of firm productivities, which I will assume to be Parteo as in Chaney (2008).

The threshold level of productivity above which all firms enter, and below which no firms will enter, is the productivity for which profits in a market are equal to 0. Profits made by a firm with productivity φ in location i are given by:

$$\pi_i(\varphi) = \sum_j c_{ij}^F(\varphi)\left(\underbrace{\tilde{\tau}_{ij}^F \frac{\sigma_F}{\sigma_F - 1}\frac{P_i^W}{\varphi}}_{p_{ij}^F(\varphi)} - \underbrace{\tilde{\tau}_{ij}^F \frac{P_i^W}{\varphi}}_{MC_{ij}}\right) - w_i f_e$$

where f_e is the fixed cost of entry, denominated in wages, $MC_{ij} = \tilde{\tau}_{ij}^F \frac{P_i^W}{\varphi}$ is the marginal cost of production for a firm of productivity φ in state i to produce flour for state j, and $p_{ij}^F(\varphi) = \tilde{\tau}_{ij}^F \frac{\sigma_F}{\sigma_F - 1}\frac{P_i^W}{\varphi}$ is the price charged by firm φ in state i for flour in state j. There is no fixed cost of exporting; all firms that enter can export without paying an additional fixed cost. The zero profit condition yields a closed form solution for the cut-off value of productivity. All firms above this level will enter the market:

$$\varphi_n^{*F} = \left(\frac{(\sigma_F - 1)^{1-\sigma_F}\,\sigma_F^{\sigma_j} w_n f_n \left(c_n^F\right)^{\sigma_F - 1}}{\sum_i \left(\tau_{ni}^F\right)^{1-\sigma_F} Q_i^F (P_i^F)^{\sigma_F}}\right)^{\frac{1}{\sigma_F - 1}} \tag{2}$$

2.2 Testable Predictions

I express the model in changes, where $\hat{x} = \frac{x_{post}}{x_{pre}}$ and consider a decline in the cost of shipping the agricultural good, $\hat{\tau}^W < 1$, while holding all other exogenous variable constant.

Price effects. When the price of shipping wheat falls, flour prices fall everywhere because wheat is the only input to flour production and prices are set with perfect competition. Flour prices fall by more in New York than in Kansas; formally, $\hat{p}_{NN}^F < \hat{p}_{KK}^F < 1$. I provide a proof of this result in Theorem 1. This result is driven by the initial pattern of trade, generated by Kansas' agricultural comparative advantage, plus the fact that trade within a state is costless. Because Kansas has a comparative advantage in wheat production, Kansas is importing relatively less wheat from New York in the initial equilibrium than

New York is importing from Kansas. Thus, a larger share of wheat imports to New York are affected by the decline in shipping costs, so the price of importing wheat (and thus of producing flour) falls by more in New York than in Kansas.

A similar logic holds in the case of consumer flour prices: $\hat{P}_N^F < \hat{P}_K^F < 1$. Since demand is CES, agents are buying flour from all locations in the initial equilibrium. But since trade across states is costly, agents in New York are initially buying relatively more flour from New York in the initial equilibrium than agents in Kansas are buying from New York. Thus, flour becomes relatively cheaper for consumers to buy in New York than in Kansas which I show in Theorem 2. This is how the cost of living changes across locations as a result of changes in the costs of shipping agricultural goods.

Production effects. Because producer prices fall everywhere, demand for flour rises everywhere. However, demand rises by more in New York since the price of producing falls by more there; as a result, the production of flour rises more in New York than in Kansas, $\hat{Y}_N^F > \hat{Y}_K^F > 1$. The proof of this result is in Theorem 3.

Firm location effects. While my baseline model does not include firms, I turn to the version of the model with monopolistic competition to generate predictions of the effect of trade costs on firms. In this version of the model, because it becomes cheaper to produce flour everywhere and especially so in New York, the productivity threshold for firm entry falls by more in New York than it falls in Kansas. Thus, more flour milling firms enter in New York and the total number of firms in New York increases by more as well, as compared with Kansas, $\hat{M}_N^F > \hat{M}_K^F$. The proof of this result is in Theorem 5.

Productivity effects. Since the productivity entry threshold falls by more in New York, relatively less productive firms can enter the market there. Thus, the new, lower-productivity firms drag down the average productivity level in New York, so average productivity actually falls by more here than in Kansas: $\hat{\varphi}_N^* < \hat{\varphi}_K^*$, as per Theorem 4.

Decline of the heartland. Since wages are exogenous in this model, effects on welfare in this model operate through changes in the cost of living across locations. Since consumer prices of flour fall by more in New York, welfare increases by more in New York. Since relative population is linked to relative welfare, relative population thus rises there as well compared with Kansas. Since Kansas the relatively agriculture-intensive location here as is the Heartland, this effect is the "decline of the heartland". The proof of this result is in Theorem 6.

3 Empirical Case Study

To test whether these model predictions hold in the data, I study the flour milling industry following a sudden and sharp decline in the railroad cost of shipping wheat generated by the outcome of a Supreme Court case in 1963.

3.1 Historical Background

Before 1963, railroads charged identical rates for similar movements of flour and wheat (Babcock (1976), Babcock, Cramer and Nelson (1985), Harwood (1991), Held (1979), USDA (1964)). This was primarily due to regulation by the Interstate Commerce Commission (ICC), which, from its inception in 1887 until rail deregulation in 1980, controlled to a great extent how railroads could set prices. As noted by a 1963 article in the *Southwestern Miller*, a trade publication for the flour milling industry, "...the parity between rates of wheat and flour has long been in effect..." (The Southwestern Miller (1963)).

However, in the 1960s, new innovations in the shipment of bulk commodities including the covered hopper car and the unit train made it cheaper for railroads to ship bulk grains like wheat as compared with manufactured goods like flour.[15] Shipments of flour were unaffected by these innovations in part because shipments of wheat tend to be in much larger quantities than shipments of flour; bulk shipments lend themselves well to both covered hopper cars and unit trains whereas smaller shipments of more processed goods do not (USDA (1964)). In addition, hygiene requirements are much stricter among

[15]For example, see figure B.5.

shipments of flour which is a manufactured good as compared with wheat which is a raw material. This makes flour even more difficult to ship in vast quantities. A 1965 article in the *Minneapolis Tribune* quoting a railroad executive explains: "Unit trains for grain have meant streamlined, high-speed operation– rapid turnaround and high utilization of equipment that have kept profits up in spite of lower rates... No one has come to us with any kind of a similar development for flour. Simply, more grain can be moved faster, per car, than flour".

The Southern Railroad, one of the first to develop these new technologies, proposed new, lower rates on wheat to the ICC in 1962. By law, the ICC had seven months to either approve or deny the rate change. After seven months, no decision was made. In lieu of a ruling, the reduced rates were supposed to go into effect, but a competing barge company sued. They claimed the rates could not go into effect until the ICC had made a decision and that the new rates would "irreparably injure their [the barge company's] respective economic interests". In the meantime, the ICC required the Southern to keep its rates at the initial level. In 1963, the Supreme Court ruled in *Arrow Transportation v. Southern Railway Company* that the ICC didn't have the authority to prevent proposed rates going into effect since the decision period had lapsed (United States Court of Appeals (1962)).

Once the Southern was allowed to introduce the new technology and offer lower rates, other railroads followed. Importantly, this change in railroad rates was *not* generated by changes in producer locations or characteristics, and thus is plausibly exogenous to the outcomes I will study. Many trade publications, newspapers, and economists of the period took note of changing relative trade costs and speculated on its implications for the spatial distribution of the industry. For example, the cost shock was described succinctly in the 1964 USDA Farm Index (USDA (1964)):

> With recent changes in the grain rate structure, *it now costs more to ship grain products, including flour, by rail from some locations than it does raw grain*. As a result, some millers near the city bakeries and retail outlets for flour may have new transportation advantage over those located nearer the production areas.

Local newspapers reveal how Midwest flour millers felt about the changing rates. An article published on April 30, 1963 in *The Southwestern Miller* was titled "Kansas Millers Plea Against Peril to Trade", and stated that "the Southern Railway rate cuts would place Kansas flour at a disadvantage of as much as 43c per cwt in comparison to wheat" (The Southwestern Miller (1963)). On June 27, 1965, an article entitled "Minneapolis Mills Fight for Life, Blame Transit Rates" was published in the *Minneapolis Tribune* (1965). The article included the following quote, describing how Minneapolis millers feared for their viability given the advantage that millers closer to population centers would face after this change in relative shipping costs:[16]

> A growing controversy is raging over the issue of changing transportation rates which, the [Minneapolis] millers contend, *have given Eastern flour mills an overpowering competitive advantage over the Midwest*. They say they're hurt because a disparity between transportation rates on wheat and flour makes it cheaper to ship wheat east for milling and sale in the population centers than to mill it here and ship the flour to the big Eastern markets. *The chief target of milling industry criticism are railroad freight rates which until recently were about the same for wheat and flour...*

This is shipping rate change that I exploit to study the response of prices and downstream production locations to a change in the cost of shipping agricultural inputs relative to manufactured final goods.

3.2 Data

Flour mill locations, sizes, flour prices. To identify the changing distribution of flour mill locations, I digitized records on the locations, sizes, and ownership of U.S. flour mills from the *Northwestern Miller*, a trade publication that published an annual directory of all U.S. flour mills that I obtained from the published, *Sosland Publishing*. Figure B.3 shows two examples of what these directory entries look like. Given the address of each mill, I geocode mills to latitude and longitude coordinates. I then combine the coordinates with 2010 U.S. Census county boundaries to create a panel dataset of counties and years, with

[16] Emphasis is added.

variable including the total number of mills, the total number of mills that belonged to a multi-unit firm, and the total milling capacity. In addition, I use mill names and addresses to track plants over time and construct a dataset of mill entry and exit.[17]

Table A.4 shows annual summary statistics of these data. Some key trends emerge: over the time period, the total number of mills is falling, but total capacity is rising, so the average capacity of a mill is rising considerably over the period. The share of flour produced by the states that are top producers of wheat is also falling, and the share of mills that are owned by large corporations nearly doubles over the period. One drawback is that I do not observe actual production of each mill in each year; I only observe the mill's capacity which may be a noisy indicator of demand for that mill's flour since it is costly to adjust capacity.

I measure producer prices of flour at major markets from The *Southwestern Miller*, a trade publication that included averages of flour prices from local mills for a selection of major milling markets (The Southwestern Miller (1955)). Figure B.4 shows an example of the price listings for Kansas City. Data were published every week for many different varieties of flour. I use data from the last week in October for standard patent flour, except in the case of Portland, Oregon where the price of standard patent flour is never listed and instead I use family flour. Table A.5 shows average prices in 1963 and 1966 for each state in my sample, which I obtain either by using the price listings from a city in that state, or from averaging over cities (as in the case of Kansas). One drawback of these data is that they are only available for a small number of cities; in total, only ten states are represented. I measure the retail prices of flour and bread in a selection of different cities from the Bureau of Labor Statistics' *Retail Prices in U.S. Cities*.

Wheat Production and Prices. I obtain county-level data on wheat production and wheat yields from the United States Department of Agriculture (USDA) and the Census of Agriculture. 63% of wheat production in 1963 was produced in Midwestern states; 71% was produced by Midwestern states plus Montana and Idaho (USDA, 1963).

[17] I detail this matching process in B.3.1.

Transportation Network. I measure transport costs for agricultural products in 1950 among all pairs of counties. To using a map of the 1957 railroad network drawn by the Army Service Corps of Engineers that I have digitized.[18] To measure the cost of shipping agricultural products one ton-mile along this network, I use the reported revenue per ton-mile earned by Class I railroads in 1950 for Products of Agriculture (ICC, 1950).

Railroad Trade. I obtain data on railroad trade of wheat and flour between U.S. states and major regions from the Carload Waybill Sample Statistics. These data are a 1% sample of all terminated waybills, which are contracts between railroad companies and producers. Each observation in the data is of a commodity traded in a given year between an origin state or region and a destination state or region, and the data include the volume of goods traded as well as the revenue earned by the railroad on shipments along that route in that year. I have digitized state level data are available from 1958 through 1966. Region level data for five major regions in the U.S. are much coarser but are available for more years, 1950 through 1987, with some gaps.

3.3 Effects on Trade Costs

3.3.1 Empirical Strategy

I first quantify the extent to which the court's ruling affected the relative cost of shipping wheat versus flour. To do this, I use railroad trade data at the route-commodity-year level to estimate the following event study:

$$\ln\left(\frac{revenue_{odct}}{ton_{odct}}\right) = \sum_{y\neq 1963} \boldsymbol{\beta_y} \cdot 1(t=y)\cdot 1(c=\text{wheat}) + \gamma_{odc} + \gamma_{odt} + \gamma_{ot} + \gamma_{dt} + \epsilon_{odct} \qquad (3)$$

where o is an origin region, d is destination region, and $c \in (\text{wheat, flour})$ is a commodity. Standard errors are clustered at the route level, of which there are 25. $revenue_{odct}$ measures total payments from producers to railroad shippers for goods of commodity group c shipped along route od in year t. $tons_{odct}$ measures total tons of commodity c

[18]The original map is shown in Appendix Figure B.2.

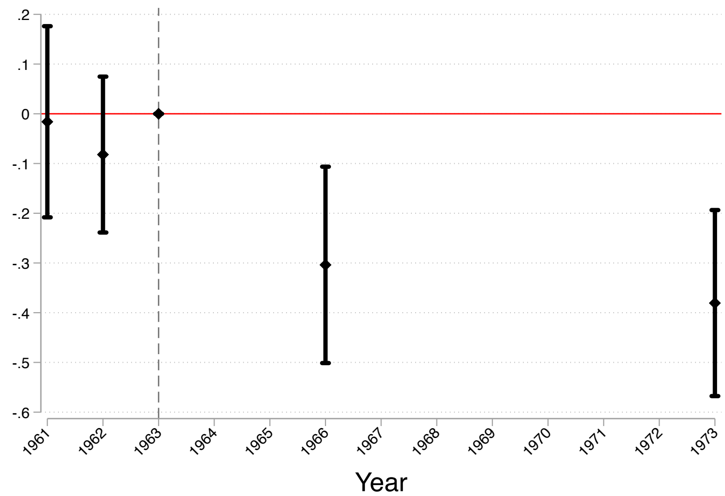
shipped by railroad companies in year t from o to d. Each event study coefficient $\boldsymbol{\beta_y}$ measures the relative cost of shipping wheat versus flour in year y relative to 1963, which is the last untreated year.

I attribute my estimates of $\boldsymbol{\beta_y}$ to the causal effect of the Supreme Court ruling. I assume that, had the ruling in 1963 not happened, the cost of shipping wheat relative to the cost of shipping flour would have remained constant over this period. I include various fixed effects control for factors other than the court's ruling that may influence the cost of shipping wheat relative to that of shipping flour. For example, changes in the compositional quality of wheat or flour being shipped, which would affect its value, could also affect the relative revenue per ton earned by the railroads. Assuming this effect is constant across routes, commodity-time fixed effects control for any such compositional changes. Similarly, origin-destination-commodity fixed effects control for any route and commodity-specific differences in the cost of shipping that do not vary over time. I also include origin-time and destination-time fixed effects.

3.3.2 Results

Figure 3 shows event study estimates of equation 3. While the cost of shipping wheat was not statistically different than the cost of shipping flour in 1961 and 1962, as these point estimates are small and not statistically different from zero, there is considerable wedge between the trade costs for the two commodities by 1966: the cost of shipping wheat has fallen by about 30% relative to the cost of shipping flour. This significant and sudden shift in shipping costs provides the ideal scenario to study how declines in agricultural good trade costs affect production across locations. Finally, I separately estimate equation 3 by commodity. Consistent with the story, the decline in relative trade costs is driven by a decline in the cost of shipping wheat, while the cost of shipping flour remained unchanged.

Figure 3: **Effects of the Ruling on Shipping Costs**



Note: This figure shows event study estimates of equation 3, in which I compare the revenue per ton earned by railroads, a measure of shipping costs, in shipping wheat versus flour each year, relative to the year of the Court's ruling.

3.4 Effects on prices, production, firms

How did flour prices, flour production, and flour mill locations evolve after this change in shipping costs? Figure 4 shows the relationship between initial proximity to wheat and flour mill locations. Each county is colored based on its wheat market access which is the inverse distance-weighted average of wheat production in all surrounding counties.[19] Dark orange and red counties are closer to wheat-producing locations; Each black dot represents a county with at least one flour mill in the indicated year; dots are sized by the number of mills in that county. Comparing 1961 (the top panel, corresponding to the last pre-shock year for which I have data) to 1975 and 1985, many (but not all) of the mills in North Dakota, Montana, and Kansas have closed. Many new mills are instead closer to population centers including New York Cities, New Orleans, Tampa, and Jacksonville. While these maps are suggestive, I estimate difference-in-differences models to quantify the effects.

[19]This measure is defined formally in Equation 5.

3.4.1 Empirical Strategy

To estimate the causal effects of changes in agricultural shipping costs on outcomes, I take advantage of two sources of variation. First, I take advantage of variation across time induced by the Supreme Court ruling, comparing outcomes before and after 1963. Second, I take advantage of variation across locations. Places close to where wheat is produced initially relied less on the railroad for shipping wheat than places far from where wheat is produced. For example, a flour mill in New York is far from wheat production and thus must import wheat from the Midwest while a mill in Kansas is close to wheat production and instead exports finished flour, rather than importing wheat.

Effects on prices. I first measure how prices of flour and bread evolved differently in the Midwest, where wheat is produced, versus in other places. I use a differences-in-differences specification. My estimating equation is:

$$\log\left(price_{it}\right) = \sum_{y \neq 1963}^{T} \beta_y \cdot 1(y = t) \cdot 1(i \in Midwest) + \gamma_t + \gamma_i + \epsilon_{it} \tag{4}$$

where i is a city and t is a year. The identifying assumption is that, in lieu of changes in trade costs, prices would have evolved in the same way in locations within the Midwest as compared with locations outside the Midwest.

Each event study coefficient β_y measures the difference in prices in the Midwest in year y relative to 1963, versus outside the Midwest. If the predictions of Section 2 hold, then we would expect to prices to fall by more outside the Midwest (or, in other words, rise in the Midwest relative to other locations), so $\beta_y > 0$ for $y > 1963$. There should be no difference in the evolution of prices in the Midwest versus in other locations, in which case $\beta_y = 0$ for $y > 1963$.

Effects on production and firms. When looking at production and mill locations, I have data for every county, instead of for a selection of cities as in the case of price data. This allows me to construct a continuous measure of exposure to the change in wheat shipping costs. I measure each location's "wheat market access" $WMA_{i,1959}$ before the shock:

$$WMA_{i,1959} = \sum_n (\tau_{ni}^W)^{1-\sigma_W} \cdot Y_{n,1959}^W \tag{5}$$

where $Y_{n,1959}^W$ is production of wheat in bushels in 1959 and τ_{ni}^W is the iceberg cost of shipping wheat from n to i. σ_W determines the distance decay; I estimate this parameter to be 13.7 using trade data as described in Section 4. My main empirical specification is:

$$y_{it} = \sum_{y \neq 1961}^{T} \beta_y \cdot 1(y = t) \cdot \log(WMA_{i,1963}) + \gamma_t + \gamma_i + \epsilon_{it} \tag{6}$$

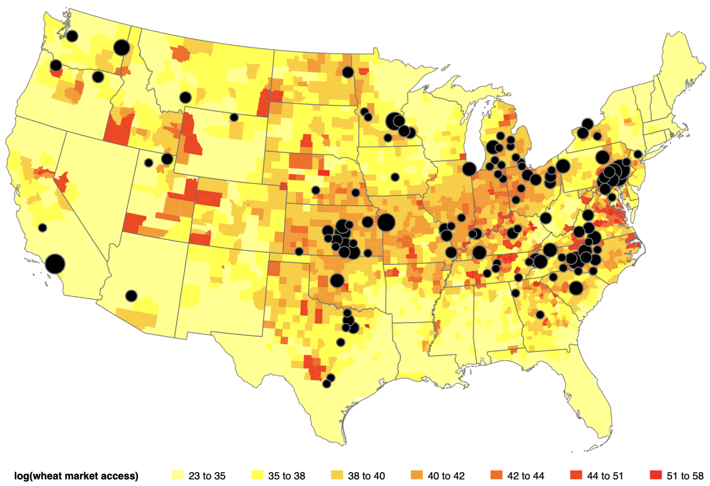
where i is a location, which will be either a county or a city, and t is a year.[20] The first difference is the difference between the pre-1963 and post-1963 periods while the second difference is that between counties that are relatively better or worse producers of wheat. My coefficients of interest are each β_y. I omit the last pre-treatment year for which I observe data (1961), so each estimated coefficient is relative to the 1961 level. Standard errors are clustered at the county-level, of which there are around 3,000.

Similarly to the price regressions, my identifying assumption is that, in lieu of changes in trade costs (i.e., if the Supreme Court had ruled in favor of Arrow Transportation Co. and the new rates had not gone into effect), flour prices, mill locations, and production would have evolved similarly across locations regardless of that location's initial specialization in wheat production. The event study nature of these regressions allows me to test, to some extent, this assumption. If this assumption holds, then we would expect there to be no difference in outcomes across locations prior to the change in trade costs after controlling for year and location fixed effects. In later sections, I will also include a series of robustness checks to control for alternative explanations of my results.

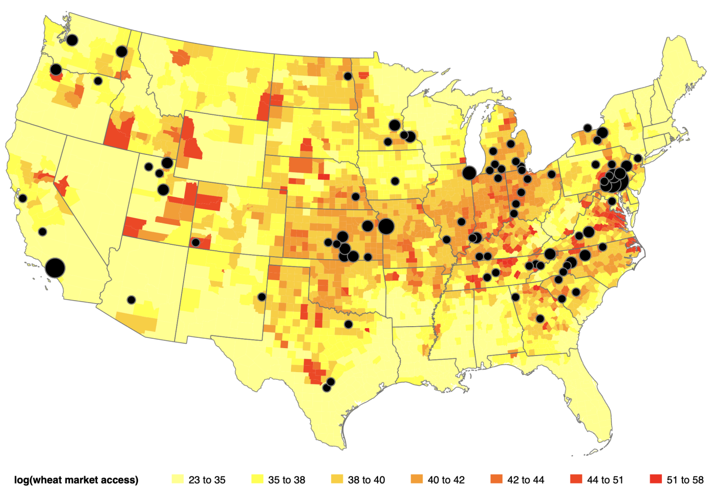
[20] In robustness checks, I estimate the differences-in-differences version of this specification, which is: $y_{it} = \beta \cdot 1(t > 1963) \cdot \log(WMA_{i,1963}) + \gamma_t + \gamma_i + \epsilon_{it}$.

Figure 4: **Flour Mill Locations and Capacity**

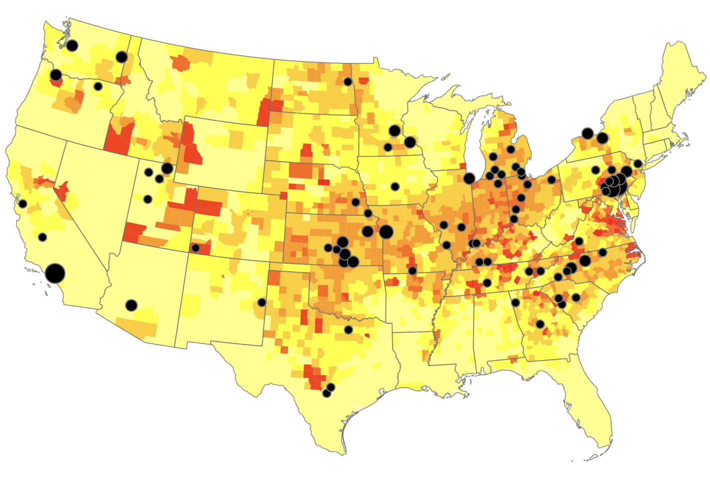
(a) 1961



(b) 1975



(c) 1985



Note: Each black dot represents the centroid of a county with at least one flour mill in the indicated year, with the size of the centroid scaled by the number of mills in that county. The background shading represent access to wheat in 1959, as measured by wheat market access in equation 5, with shades tending towards red representing areas closer to wheat production areas. *Source:* The Northwestern Miller, Army Map Service Map of U.S. Railroads (1957), and the Census of Agriculture (1959).

3.4.2 Results

Prices. Figure 5 plots event study estimates of equation 4. In panel (a), the outcome variable of interest is $log(p_{ii}^F)$, the log of the producer price of flour. I find that the producer price of flour rises in the Midwest compared to other locations by about 3% in the first year following the decline in trade costs. Three years later, the price remains about 7% higher in the Midwest relative to the rest of the country, even though there were no differential trends in flour prices between the Midwest and the rest of the country prior to 1963. In panel (b), the outcome variable of interest is $log(P_i^F)$, the log of the consumer price of flour. Here, I find a similar result as in the case of producer prices: by 1965, two years after the change in trade costs, consumer prices of flour have risen by about 6% and remain at that lower level for the decade. Panel (c) looks at bread prices and finds an effect of around 10%.[21]

Production. Figure 6 plots event study estimates of equation 6. In Panel (a), the outcome variable is the number of mills in each county in each year. I omit the year 1961, which is the last year for which I observe data before the 1963 ruling.[22] To get a sense of the magnitudes, consider that in 1961, the average county had 0.17 flour mills. The estimated coefficient for 1975 is around -0.01. Thus, moving from a 25th percentile wheat access location (far from wheat) to a 75th percentile wheat access location (close to wheat), which is a difference of about five log points, is associated with a decline of -0.05 mills, or about 30% of the mean.

In Panel (b), I look at the total capacity of mills. Because there are many zeros, I use an inverse hyperbolic sine transformation which allows me to preserve the zeros. The pattern of changes in capacity following 1961 is almost the same as in the case of the number of mills. By 1975, flour milling capacity is about 20% lower when moving from a location with a 25th percentile wheat access location to a 75th percentile wheat access location. In Panel (c), I look at the log of the average mill size where mill size is milling

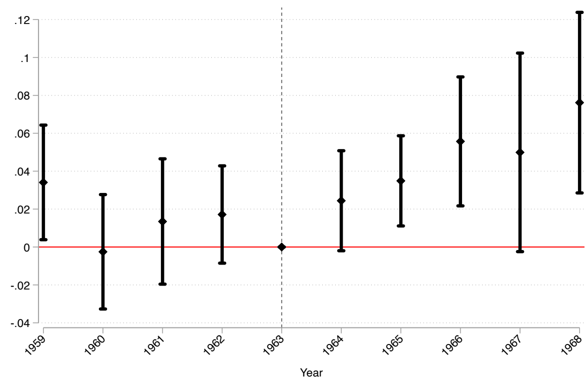
[21]Bread pricing reflects the price of flour sold to bakers, which may be priced differently than flour sold in grocery stores.

[22]While I use OLS here, I use Poisson and Logit (with an indicator for whether there is a least one mill) models in robustness checks.

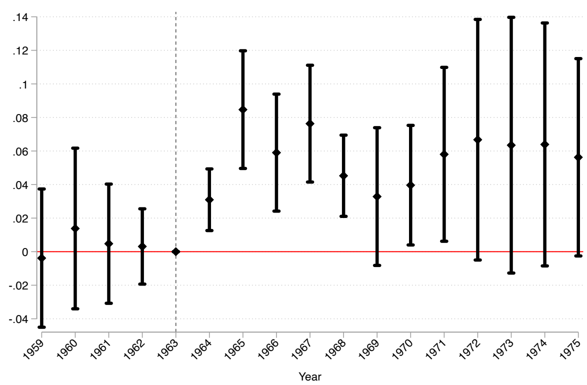
capacity in a county divided by the number of mills in that county. There appears to be no differential change in mill size by location, suggesting that changes in milling capacity are driven by changes in the number of mils, not by changes in mill sizes.

Figure 5: **Effects of Shipping Cost Changes on Flour and Bread Prices**

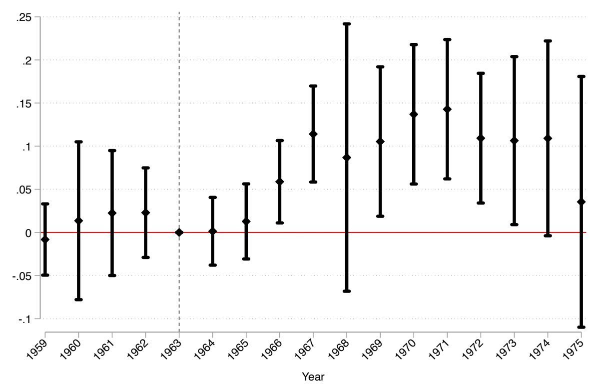
(a) Flour producer prices



(b) Flour consumer prices



(c) Bread consumer prices



Note: These figures show event study estimates of equation 6. Each point estimate is the relative difference each year in prices in Midwestern cities relative to non-Midwestern cities.

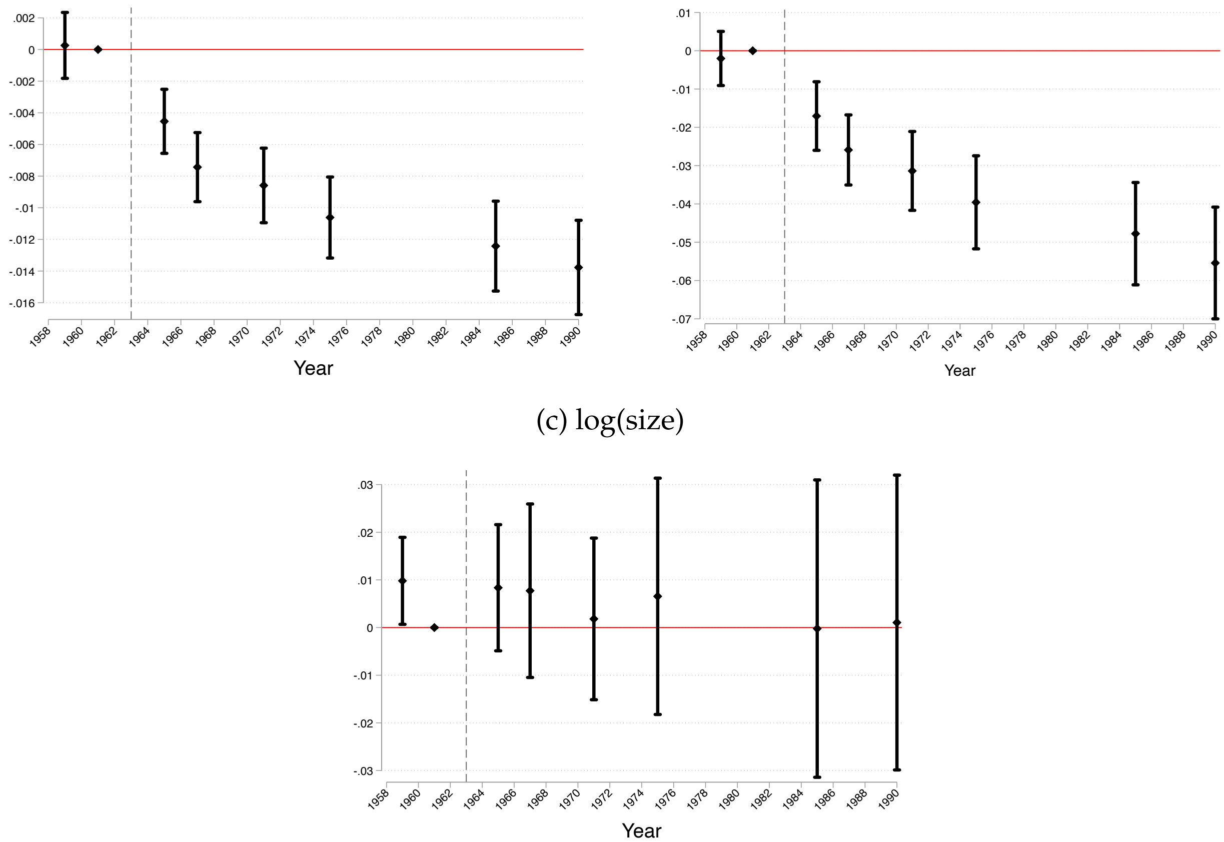
In Figure 7, I look at outcomes related to the firms version of the model. While I do not directly observe firm productivity, I estimate how the changes in trade costs differently affected plants that were initially part of multi-unit firms versus those that were initially stand-alone plants. For example, all of General Mills' plants would be considered as part of a multi-unit firm. I separately estimate the event study for single-unit plants and multi-unit plants, or plants that are part of larger firms. I find that the effect on the number of firms is completely driven by a decline in the number of single-unit plants in initially

Figure 6: **Effects of Shipping Cost Changes on Flour Mills**

(a) Number of mills

(b) $sinh^{-1}$ (Flour milling capacity)

(c) log(size)



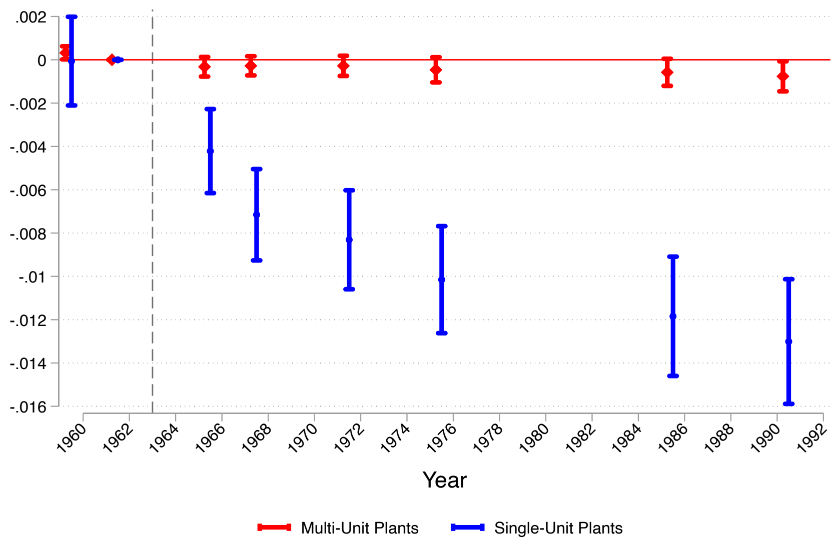
Note: These figures show event study estimates of equation 6. Each point estimate is the relative difference each year in the outcome variable, based on a location's initial access to wheat production.

wheat-intensive locations.

Robustness. I consider some alternative explanations for these results, and address each in turn. Tables A.1 and A.2 show these robustness checks for the number of mills outcome variable and the flour milling capacity outcome variable respectively. Column (1) shows the baseline difference-in-differences estimate corresponding to the event study regressions in equation 6 and I add additional controls in each subsequent column.

To control for state-level policies that may have changed across years, for example, any tax policies that may have incentivized firms to locate in a certain state, I include state by year fixed effects in Column (2). Another concern is that technology was increasing the

Figure 7: **Effects of Shipping Cost Changes on Multi- & Single-Unit Mills**



Note: This figure show event study estimates of equation 6 where the outcome is either the number of mills that are were part of multi-unit plants (in red) and the number of mills that are part of single-unit plants (in blue) in the last year before the change in trade costs, or in their year of entry, whichever is earlier.

returns in scale; in fact, the average size of mills grew considerably over this period (see Table A.4). This could vary across counties depending on the initial distribution of mills: for example, a county with smaller mills initially may see a relative decline in the number of mills not due to changes in trade costs, but due to the changing returns to operating a large mill. To account for this, column (3) adds county by year linear time trends to the baseline specification.

An additional explanation of these patterns is that because mills were becoming larger, they required more labor, and thus moved closer to cities where labor may have been more easily available. While the labor share of flour milling output is small, making this story unlikely, I include dummy variables for each year interacted with a county's initial population, thus allowing the impact of population on the location of mills to vary over time in Column (4).[23]

Another possibility is that demand for U.S. flour is increasing from the rest of the

[23] In 1947, Flour and meal products' wage and salary share of total output was 4.7% (Census of Manufacturers).

world, in which case it may be becoming increasingly attractive for flour mills to locate near coasts and ports. Since the coasts are far from where wheat is grown, wheat-intensive areas locations would become relatively less attractive. To control for this possibility, I introduce dummy variables for each year interacted with the distance of that county to the coast of the U.S. an additional covariates into my main regression. This allows the impact of being close to a port to vary by year, as the level effect of a county's proximity to the port will be absorbed by the county fixed effect. These results are in column (5).

Finally, I consider some additional measures of initial proximity to wheat. I use the Global Agro-Ecological Zones data to measure the potential wheat yield in each location, given the climate and soil conditions. In this case, I simply replace the quantity of wheat production in equation 5 with the potential yield. I do the same using the wheat yield in each county, where yield is computed as the ratio of wheat bushels harvested to the wheat acreage planted based on the Census of Agriculture.

I also consider robustness to the functional form choice of my empirical specification. My main results are OLS estimates. In the case of the number of mills, the outcome variable is a count variable. However, the vast majority (98%) of county-year observations have either zero or one mill. Thus, my regression in this case is, in practice, nearly a linear probability model. I consider both Poisson models, a linear probability model, and a logit model. Table A.3 shows these estimates for both the number of mills and the wheat flour capacity.

4 Quantification

How important were these trade cost changes in shaping the distribution of the U.S. population? This section outlines and calibrates a full, quantitative model of intranational trade, which I use to asses the extent to which declining agricultural trade costs can explain the population decline of the heartland states over this period. Relative to the simple model, this full model has two key advantages. The first advantage is that it allows me to quantify the importance of changes in trade costs in shaping the distribution of population in the U.S. over the period. The second advantage is that it relaxes assumptions I made in the simple model and allows for endogenous changes in wages and rental rates.

The model set up closely follows Caliendo and Parro (2015) and Caliendo et al. (2018), and includes a few key ingredients required to capture the mechanism. First, there are input-output linkages across sectors. Second, labor is mobile across states. Third, trade costs vary by sector. Finally, to appropriately model the agricultural sector, land is an input to production.

4.1 Model Setup

Agents' problem. In each location n, a representative agent chooses consumption of goods C_n^j from each sector j to maximize their utility subject to a budget constraint:

$$\max u(C_n) = \Pi_{k=1}^{K} \left(C_n^k\right)^{\alpha_n^k} \text{ where } \sum_{k=1}^{K} \alpha_n^j = 1 \text{ subject to } I_n = \sum_{j=1} P_n^j C_n^j$$

where $I_n = w_n + r_n \ell_n / L_n + D_n$ is per-capita income in location n and α_n^k is the share of total income spent on products in sector k. w_n is the wage in location n, r_n is the rental rate of land in n, ℓ_n is the endowment of land in n, and D_n is the trade deficit which will be defined later.

This problem yields demand functions of $C_n^k = \frac{\alpha_n^k I_n}{P_n^k}$ and an indirect utility function: $v_n = I_n \Pi_{k=1}^{K} \left(\frac{\alpha_n^k}{P_n^k}\right)^{\alpha_n^k}$. v_n is the common component of utility of agents living in a location n. In addition, there is an idiosyncratic component of utility, such that indirect utility of a worker b living in location n is given by $v_n^b = v_n + \epsilon_n^b$, where $\epsilon_n^b \sim Gumbell(0, \epsilon)$, as in Eckert and Peters (2018). From this, I derive the share of agents living in each location n as $\lambda_n = \frac{exp(\epsilon \cdot v_n)}{\sum_{n'} exp\left(\epsilon \cdot v_{n'}\right)}$. The population of each location is given by $L_n = \lambda_n L$. Labor and land are both freely mobile across sectors within a location and not subject to any frictions; hence, there will only be a single wage and rental rate in each location.

Intermediate goods. A continuum of intermediate goods $\omega^j \in [0, 1]$ is produced in each sector j. A firm producing good ω^j in sector j in location n combines land, labor and materials via a Cobb-Douglas production function:

$$q_n^j = z_n^j(\omega^j)\left(\left(l_n^j(\omega^j)\right)^{1-\delta_n^j}\left(L_n^j(\omega^j)\right)^{\delta_n^j}\right)^{\gamma_n^j}\prod_p^K\left(m_n^{p,j}(\omega^j)\right)^{\gamma_n^{p,j}} \tag{7}$$

where $l_n^j(\omega^j)$ is land, $L_n^j(\omega^j)$ is labor, $m_n^{p,j}(\omega^j)$ are composite intermediate goods from sector p used in the production of intermediate good ω^j. γ_n^j is the share of value added in total output for sector j. $\gamma_n^{p,j}$ is the share of sector j total output in location n that comes from sector p such that $\sum_{p=1}^K \gamma_n^{p,j} = 1-\gamma_n^j$. Given this production function, the unit cost of goods from sector k in location n is $p_n^j(\omega^j) = c_n^j / z_n^j(\omega^j)$ where:

$$c_n^j = \Gamma_n^j \cdot (w_n^{1-\delta_n^j} r_n^{\delta_n^j})^{\gamma_n^j}\prod_{p=1}^K\left(P_n^p\right)^{\gamma_n^{p,j}}$$

where $\Gamma_n^j = \gamma_n^j\left(\left((\delta_n^j)^{-\delta_n^j}\cdot(1-\delta_n^j)^{\delta_n^j-1}\right)\right)^{-\gamma_n^j}\cdot\prod_p^K\left(\gamma^{p,j}\right)^{-\gamma^{p,j}}$. The productivity of each intermediate good producer $z_n^j(\omega^j)$ is distributed Frechet with location parameter T_n^j and shape parameter θ^j.

Composite goods. Following Caliendo and Parro (2015), composite good producers in each sector purchase intermediate goods from each firm producing varieties ω^k within that sector. They substitute across goods within a sector with elasticity of substitution σ^k to bundle goods into Q_n^k.

$$Q_n^k = \left[\int r_n^k(\omega^k)^{1-1/\sigma_k} d\omega^j\right]^{\sigma_k/(\sigma_k-1)} \tag{8}$$

where $r_n^k(\omega^k)$ is the demand of intermediate goods ω^k from the lowest cost supplier across all possible origins. These composite goods are then used as materials or as final consumption. Composite good producers have the following demand for good ω^k:

$$r_n^k(\omega^k) = \left(\frac{p_n^k(\omega^k)}{P_n^k}\right)^{-\sigma_k} Q_n^k \tag{9}$$

where P_n^k is the unit price of the composite intermediate good:

$$P_n^k = \left[\int p_n^k(\omega^k)^{1-\sigma_k} d\omega_k\right]^{\frac{1}{1-\sigma_k}} = \left[\sum_i T_i^k \left(c_i^k \tau_{in}^k\right)^{-\theta_k}\right]^{\frac{1}{-\theta_k}} \tag{10}$$

where the second equality follows since the price realized for each good in each sector is the lowest price available from all locations: $p_n^k(\omega^k) = \min_i \left[\frac{c_i^k \tau_{in}^j}{z_i^k(\omega^k)}\right]$ where τ_{in}^j is the amount of a good from sector j shipped from i to n that must be shipped for one unit to arrive. Total expenditure on sector j goods in n is given by $X_n^j = P_n^j Q_n^j$.

Trade. Trade flows along a route in in sector j are defined as $X_{ni}^j = \pi_{ni}^j \cdot X_n^j$, where:

$$\pi_{in}^j = \frac{T_i^j \left(c_i^j \tau_{in}^j\right)^{-\theta^j}}{\sum_m T_m^j \left(c_m^j \tau_{mn}^j\right)^{-\theta^j}} \tag{11}$$

Goods market clearing. Total spending on goods from a sector j in a location n must be the total amount spent on final good consumption, plus demand for goods from that sector for all firms in that location for use as intermediate goods:

$$X_n^j = \alpha_n^j I_n + \sum_k \gamma_n^{j,k} Y_n^k \tag{12}$$

Land & labor market clearing. Land used in production equals land available in each location, $\sum_j l_n^j = l_n$. Labor supply equals labor demand everywhere, $L_n = \sum_j L_n^j$.

Trade imbalances. Since there are significant imbalances in trade between U.S. states, I allow for such imbalances in the model. The trade deficit for each states is total imports, minus total exports:

$$D_n = \sum_j \sum_i X_{ni}^j - \sum_j \sum_i X_{in}^j$$

4.2 Calibration

To calibrate the model, I express all variables in changes where $\hat{x} = x'/x$.[24] The model has $N = 48$ locations, representing each of the contiguous U.S. states, and $J = 24$ sectors. These sectors, which include 16 manufacturing sectors, 6 non-tradable sectors, and 2 raw material sectors. This set of sectors was chosen based on data availability.[25] The initial period of the model is set to 1950 and the post period is 1980.

4.2.1 Trade, Production, and Parameters

Trade. In the model, outcomes critically depend on trade patterns between states in the initial equilibrium. To measure these patterns, I use data on railroad trade between each pair of states for each sector from the Carload Waybill Sample Statistics in 1949. I created a crosswalk to match CWSS sectors, which use an old style of commodity classifications, to the modern commodity groupings used in my model based on the descriptions of each.[26] CWSS commodity classifications are fairly disaggregated relative to the model's sector categories: for example, CWSS sectors include "soap compounds" (mapped to the chemical products sector) and "sugar" (mapped to food and kindred products sector).

There are two main challenges with this dataset. First, many origin-destination-sector pairs don't appear in the data, suggesting zero trade flows. Some fraction of these zeros may not be "true zeros"; instead there may be small amounts of trade that are not captured in the 1% sample. In fact, some states that are listed in the Census of Manufacturers as producing goods from a given sector may appear as in the trade data as not producing any goods from that sector. Using this raw data would thus introduce considerable noise

[24] Appendix C.4 lists the set of equations that characterize the equilibrium of the model in changes.

[25] The sectors are: Food or kindred products and tobacco; Textille mill products; Apparel, leather, finished textile products; Lumber or wood products; Furniture or fixture; Pulp, paper, or allied products; Chemical or allied products; Petroleum or coal products; Rubber or plastics products; Clay, concrete, glass, or stone products; Primary metal products; Fabricated metal products; Machinery, excluding electrical; Electrical machinery, equipment, supplies; Transportation equipment; Miscellaneous products or manufacturing; Construction, wholesale and retail trade; Finance, insurance, real estate; Transportation, communications, utilities; Arts, recreation, accommodation, repair; Education, legal, health; Other services; Agriculture products; Mining products.

[26] This is trivial the case of agricultural goods and mining products, as trade is reported for these aggregate categories. However, I need to separately observe trade patterns for each manufactured good sector to calibrate the model.

into my calibration. The second challenge is that I do not observe value shipped; instead, I observe revenue earned and tons shipped along each route. As a result, I cannot directly compute the value of trade between each location for each sector.

To address both of these issues, I measure gross output by sector and state from other sources, as I describe below. I then use the trade data to measure the share of exports from each origin state that are shipped to each destination. To address the sampling issue, I do not use the raw data. Instead, I use a Poisson model to estimate the share exported from each origin to each destination. I estimate, separately by sector:

$$\lambda^j_{in} = \gamma^j_i \cdot exp\left(\beta_0 + \beta_1 \cdot \log(distance_{in}) + \sum_l \beta_l \cdot X^l_{in}\right)$$

where λ^j_{in} is the share of sector j goods produced in i exported to n. $distance_{in}$ is the railroad distance between i and n and X^l_{in} is the lth covariate. I then use these estimated coefficients to compute predicted export shares. The Poisson model is consistent with the model: it will never predict that there will be zero trade flows between two locations. I use the predicted export shares in my calibration. Observing export shares, predicted from the trade data, and the total value of exports for each state and sector allows me to compute the total value shipped between each pair of locations for each sector.

In addition to distance, I use a number of different covariates to predict export flows. I use an indicator for whether that observation corresponds to a state shipping to itself, $1(i = n)$. I use an indicator for whether the destination is a coastal state, and for whether the origin and destination are both coastal states. Finally, to capture the size of the market in the destination state, I use demand for goods from that sector in the destination n.

Figure A.5b shows the correlation between the estimated export shares and the export shares that I observe in the data. Figure A.5a shows the relationship between that share of total imports that each state imports from itself and that state's initial specialization in agriculture, in both the model and the data. Importantly, import shares match this pattern of specialization: states that specialize in agricultural production import relatively larger shares of agricultural goods from themselves.

Gross output, value added, land shares, IO linkages. I measure input-output linkages across all sectors $\gamma^{k,j}$ as well as each manufacturing sector's share of value added in total output γ^j from the Bureau of Economic Analysis Input-Output table in 1950.[27] To measure gross output for each location and sector Y_i^j, I rely on a number of different sources. First, I digitize state-level data on value added by each manufacturing sector from the Census of Manufacturers (CMF, 1947).[28] When a sector has a small presence in a state, value added is not be separately reported for that sector in that state. Instead, all remaining value added is reported in a single category ("All other major industry groups"). I allocate this remaining amount to the remaining sectors that are not separately listed based on the employment share of each omitted sector in the total employment of all unlisted sectors.[29] I then use each sector's value added share of output from the BEA I-O table to convert value added, measured from the CMF, to gross output: $Y_i^j = \frac{VA_i^j}{\gamma^j}$ for every manufactured sector.. I also use the CMF to measure each state's share of manufacturing wages in manufacturing value added and assume that $\delta_n^j = \delta_n$ for every manufactured sector.

For the agricultural sector, I measure value added and gross output (total value of agricultural production) in 1949 by state from the USDA's Economic Research Service report on value added. I measure the agricultural value added share as $\gamma_n^{Ag} = VA_n^{Ag}/Y_n^{Ag}$. It is very high on average, around 75%, ranging from around 45-50% in Delaware and New Hampshire to above 95% in North Carolina and North Dakota.[30] I measure the share of wages in value added δ_n^j by dividing the total amount spent on hired labor and employee compensation by total value added for each state. I measure value added,

[27]These values are not disaggregated by state, so I assume that γ_n^j for manufacturing sectors and $\gamma_n^{k,j} = \gamma^{k,j}$ for all sectors.

[28]Ideally, I would measure gross output as the total value of shipments. However, the total value of shipments is not reported at the two-digit sector level for each state. There were concerns about double counting shipments between firms within the same two-digit category. While the total value of shipments is reported at the four digit industry code, using these figures would require the digitization of many hundreds of additional figures.

[29]Given this assumption the only state-sector pairs with zero gross output are those with zero value added and zero employment. Because this requires granular data on employment by sector, I rely on the 1940 U.S. Census which is available for all sectors instead of the 1950 U.S. Census which has not been fully released yet.

[30]Most of the intermediate inputs used in agricultural sector are from the agricultural sector, and include feed purchases, seed purchases, livestock purchase, plus a small amount of manufactured inputs like electricity, fertilizer, fuel, and pesticides (USDA).

gross output, and wage payments for the mining sector from the 1954 Census of Mineral Industries. The average value added share of output is also quite high, around 75%, ranging from 52% (Nevada) to 88% (California).

I measure non-tradable gross output using a combination of two data sources. First, I measure national gross output for each non tradable sector from the BEA IO table. I then measure the share of output in each sector that is produced in each state based on each state's share of national employment in that sector, and use that to compute total output in each state for each tradable sector. I impose that $\gamma_n^j = 1, \delta_n^j = 1 \forall j \in NT$.

The data and methodology described above allow me to measure total gross output for each state and sector; however, because my model is a closed economy, I need to measure output in each state and tradable sector destined for *domestic* use. I adjust for the amount of gross output that each state and sector exports abroad by using the U.S. Department of Commerce 1966 "State Export Origin Series". It reports, for each state and manufacturing sector, total exports and total gross production in 1966. I use this to compute the share of production that is exported, and subtract this amount from gross output. Data are also provided for each state for agricultural products. For mining, there is no state-specific data, so I measure the aggregate percent of mining product shipments that are exported (5%) from U.S. Department of Commerce 1958 report on "U.S. Commodity Exports and Imports as Related to Output".[31]

Productivity dispersion. I measure the dispersion of productivity within each sector θ_j from the trade data and equation 11. I assume that trade costs take the form $\tau_{od}^j = raildist_{od}^{\kappa} \cdot X$ where X is a constant.[32] Using Poisson to handle the large quantity of zeros in the raw trade data, I estimate:

$$\pi_{in}^j = \gamma_i^j \cdot \gamma_n^j \cdot exp\left(\beta^j \cdot \log(raildist_{in}) + \epsilon_{in}^j\right) \tag{13}$$

where $\beta^j = \kappa \cdot \theta^j$ and $raildist_{ij}$ is the railroad distance in miles between i and j as com-

[31] Both of these reports are "one-off" and exist only for the years listed here; I assume that export patterns were similar over the 1950-1966 period.

[32] This constant will not affect the estimation of each θ_j here, but will become important later on.

Table 1: **Estimates of Trade Elasticities**

Sector	$\hat{\theta}^j$
Food or kindred products and tobacco	$7.48(0.45)^{***}$
Textille mill products	$0.52(1.45)$
Apparel, leather, finished textile products	$0.97(1.55)$
Lumber or wood products	$9.93(0.54)^{***}$
Furniture or fixtures	$6.35(0.60)^{***}$
Pulp, paper, or allied products	$7.87(0.53)^{***}$
Chemical or allied products	$9.30(0.64)^{***}$
Petroleum or coal products	$18.58(0.62)^{***}$
Rubber or plastics products	$4.30(1.09)^{***}$
Clay, concrete, glass, or stone products	$19.31(0.63)^{***}$
Primary metal products	$4.62(1.76)^{***}$
Fabricated metal products	$11.18(0.49)^{***}$
Machinery, excluding electrical	$4.38(0.55)^{***}$
Electrical machinery, equipment, supplies	$2.91(1.13)^{***}$
Transportation equipment	$8.73(0.73)^{***}$
Miscellaneous products or manufacturing	$18.50(1.11)^{***}$
Agriculture products	$13.78(0.47)^{***}$
Mining products	$16.86(0.54)^{***}$
Median	8.30

Note: This table shows estimates of $\hat{\theta}^j$ from estimating equation 13 with Carload Waybill Sample Statistics data, and railroad distances measured from the 1957 rail network. I set $\delta = 0.169$ from Donaldson (2016), and report $\hat{\theta}^j = -\hat{\beta}^j/\eta$.

puted using the 1957 railroad network. I measure κ, the elasticity of trade costs with respect to distance, as $\kappa = 0.169$ from Donaldson (2016). Table 1 shows estimates of θ^j for each sector. The median value is 8.3, which falls well within the range of conventional estimates.[33] Precisely estimated values range from 2.91 (electrical machinery) to 18.5 (miscellaneous products).[34] I assign the median value of 8.3 as the elasticities for the non-tradable sectors.

Final Consumption Shares. Following Caliendo and Parro (2015), I solve for each sector's share in final consumption in each state, α_n^j to satisfy the goods market clearing condition in equation 12 in the initial equilibrium. Figure A.4a shows the median expenditure share across states for each sector.

Other Parameters. I measure total employment and the share of workers in each state

[33]For example, Eaton and Kortum (2002) also estimate a value of around 8.

[34]Estimates for textile mill products and apparel are very small and nosily measured. In my calibration, I assign the median value of θ^j to these sectors.

and state from the 1950 U.S. Census. I measure the land area of each state $land_n$ from the Census of Agriculture. I compute the initial rental rate on land as $r_n = \frac{\sum_j Y_n^j \gamma_n^j (1-\delta_n^j)}{\ell_n}$. Similarly, wages are $w_n = \frac{\sum_j Y_n^j \gamma_n^j \delta_n^j}{L_n}$. Finally, the elasticity of mobility across locations is critical to determining how population will change across places. I set $\epsilon = 2.38$, as estimated in the context of the historical United States by Eckert and Peters (2018).

4.2.2 Quantifying changes in trade costs

The key inputs to the model are bilateral changes in agricultural trade costs. To measure these, I first measure agricultural trade costs between states in the initial equilibrium. I assume that trade costs between each pair of locations are given by $\tau_{in}^{Ag} = raildist_{in}^{\kappa} \cdot X$ where $raildist_{in}$ is the railroad distance between locations i and n, and X is a constant. I solve for the constant, X, using data on revenue earned, tons shipped, railroad distance, and costs of goods at the origin, as described in Section C.4.3.

Then, I estimate changes in trade costs by collecting data on revenue per ton mile earned by railroads across each pair of states for agricultural goods and manufactured goods in 1988, which is the first year of bilateral, state-to-state railroad trade data that is available after 1966. I estimate:

$$\Delta_{1949-1988} \log\left(\frac{revenue_{odc}}{tons_{odc}}\right) = \gamma_{od} + \beta_1 \cdot 1(c \in \text{Ag Good}) + \epsilon_{odc} \tag{14}$$

Results of estimating equation 14 are in Table 2. In column (1), all observations are weighted equally; in column (2), I weight observations by the log of the tonnage of that commodity shipped along that route in 1949. I find that overall, revenue per ton earned on agricultural products fell by roughly 33% (unweighted) to 37% (weighted). I use these differences-in-differences point estimates to estimate the average change in revenue per ton earned along each location:

$$\hat{\hat{\tau}}_{in}^{Ag} = \frac{1 + 0.63 \cdot \tau_{in,1950}^{Ag}}{1 + \tau_{in,1950}^{Ag}} \tag{15}$$

Figure A.6 shows $\hat{\hat{\tau}}_{in}^{Ag}$ for each pair of states. I assume that there are no changes in trade

Table 2: **Changes in Agricultural Shipping Costs, 1949-1988**

	Δ log(revenue per ton)	
	(1)	(2)
1(c$\in$ agricultural)	-0.329***	-0.367***
	(0.0438)	(0.0426)
N	1600	1600
Weighted	No	Yes
FE	Route	Route

Note: This table shows estimates of equation 14 using data from the 1949 and 1988 Carload Waybill Sample Statistics. Column (1) shows unweighted estimates; in column (2), I weight observations by the volume of trade along the route in 1949. Bulk agricultural goods include soybeans, wheat, corn, sorghum, oats, barley and rye, and rice. Standard errors clustered at the route level are reported in parentheses.

costs for shipments within states.[35]

4.3 Results

Changes in population. I use the model to compute the change in each state's share of the U.S. population given these declines in the costs of shipping agricultural goods. Figure 8 shows resulting the distribution of changes in population across states. To measure the extent to which the model can explain the observed population decline of the heartland, I construct the model and data implied change in the heartland's share of population between 1950 and 1980:

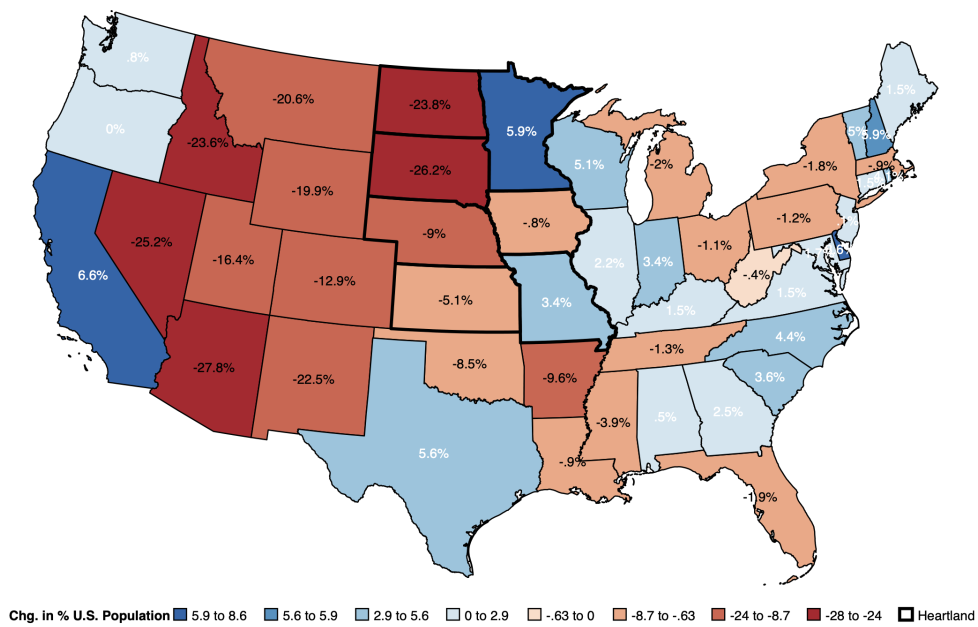
$$\hat{s}^v = \underbrace{\frac{\sum_n 1(n \in heartland) \cdot \hat{l}_n^v \cdot l_n}{\sum \hat{l}_n^v \cdot l_n}}_{\text{Heartland's share in 1980}} \Bigg/ \underbrace{\frac{\sum_n 1(n \in heartland) \cdot l_n}{\sum l_n}}_{\text{Heartland's share in 1950}} \tag{16}$$

for $v \in (model, data)$ where l_n is the population state n in 1950 as measured in the data and $\hat{l}_n^v$ is the change in state n's population in either the model or data. To compute the percentage of $\hat{s}^{data}$ that can be explained by the model, I construct $\frac{\hat{s}^{model}}{\hat{s}^{data}} \cdot 100$. I find that

[35] In a robustness check, I measure within-state trade costs based on the average distance between each pair of counties within the state and allow such changes to occur, based on equation 15. However, there is limited data to measure the extent to which trade between states occurs via rail; as these are shorter distances, goods may be more likely to be transported via trucks. Thus, this case in which I assume no changes in trade costs within states, is the most conservative choice.

the observed decline in trade costs for agricultural products can explain around 8% of population declines in the heartland.

Figure 8: **Estimated Population Changes Across States**



Note: This figure shows model-predicted changes in relative population in each state, corresponding to the baseline parameterization of the model.

Consistent with the intuition of the simple model, the mechanism operates by reducing population in locations that initially specialized in agriculture. Figure 9 shows the relationship between each state's initial specialization in agriculture, as measured by the percentage of employment in agriculture in 1950, and the log of the change in relative population between 1950 and 1980.[36] Panel (a) shows the relationship in the data and panel (b) shows the relationship as generated by the model. In both, there is a negative relationship between initial agriculture specialization and the change in relative population, with the most agriculture-intensive locations losing relatively more people.

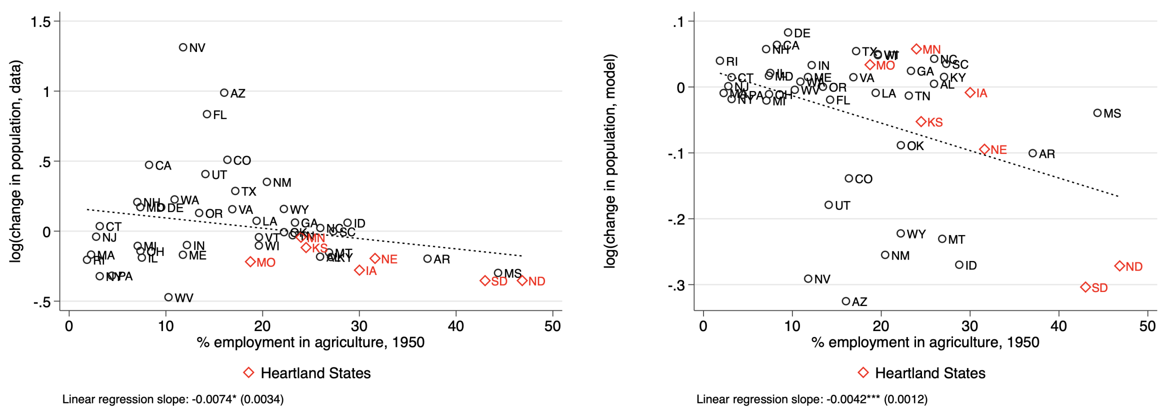
In the data, the relationship is only marginally significant overall as some locations that are initially moderately intensive in agriculture, such as Florida, Arizona, and Nevada, saw large increases in relative population over this period. Nevertheless, there is a strong

[36] This is computed for state n as $\log\left(\frac{s_n^{1980}}{s_n^{1950}}\right)$ where $s_n^t = \frac{pop_n^t}{\sum_i pop_n^t}$.

association between these two variables among the seven heartland states with the most agriculture intensive – the Dakotas, Iowa, and Nebraska – losing more relative population. Using the model, I find that declines in agricultural shipping costs generate a similar pattern in the model. While there is no strong correlation overall between the model and data generated changes in population, the correlation is strong among the heartland states (77%) as the model captures the observed relative population declines of these states.[37]

Figure 9: **Population Changes and Initial Specialization in Agriculture**

(a) **Data** (b) **Model**



Note: These figures plot, along the x-axis, the percentage of employment in agriculture in each state in 1950 and along the y-axis, the change in population as computed in the data in Panel (a) and in the model in Panel (b). The line is the best linear fit, the slope of which is reported below the figure.

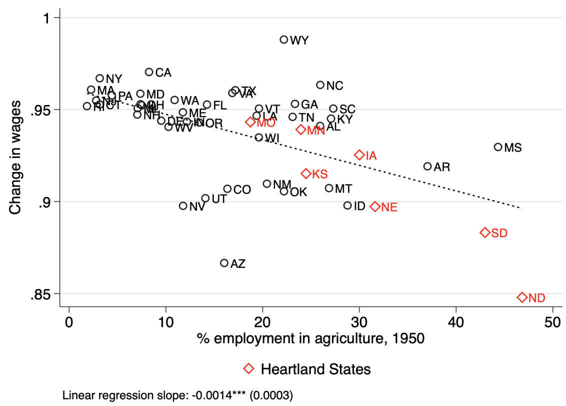
Mechanisms. Figure 10 shows how changes in wages and rental rates vary as a function of a location's initial specialization in agriculture. Because land is a fixed factor, and the demand for agricultural products is rising, the rental rate of land rises by more in more agriculture-intensive locations. Wages, however, move in the opposite direction, as these locations become less attractive and people move out, taking with them the consumption of non-tradable goods which are very labor intensive. Figure 11 shows how the composition of gross output in each state changes. In Panel (a), I plot each state's change in agriculture's share of gross output while Panel (b) plots each state's change in

[37]This is as expected. The model, which incorporates only a single mechanism occurring over a 30 year period, cannot explain population changes across all states, but can correctly replicate the population decline in the most agriculture-intensive states.

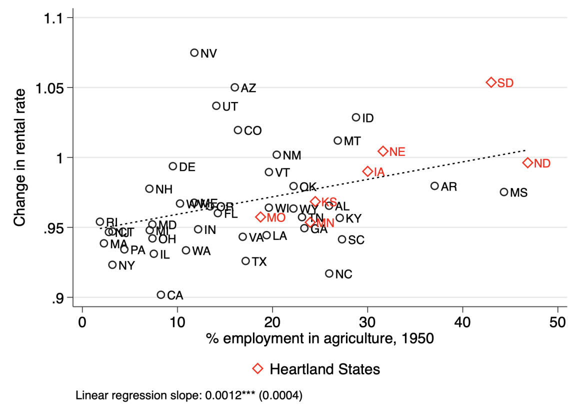
non-tradables' share of gross output. Places that were initially intensive in agriculture actually become *more* agriculture-intensive intensive, as demand for agricultural goods in these places rises. In Panel (b), we see that agriculture-intensive areas are losing non-tradable output.

Figure 10: **Effects on Factor Prices**

(a) **Wages**



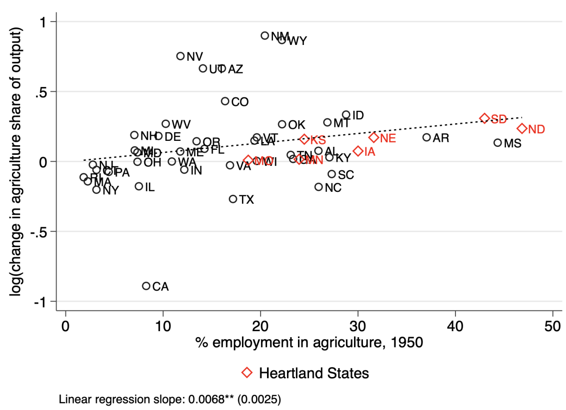
(b) **Rental Rates**



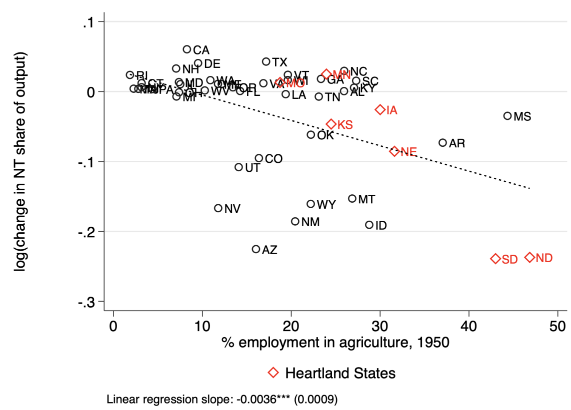
Note: These figures plot, along the x-axis, the percentage of employment in agriculture in each state in 1950 and along the y-axis, the wages in Panel (a) and in rental rates in Panel (b). The line is the best linear fit, the slope of which is reported below the figure.

Figure 11: **Effects on Sectoral Composition of Gross Output**

(a) **Agriculture**



(b) **Non-Tradables**



Note: These figures plot, along the x-axis, the percentage of employment in agriculture in each state in 1950 and along the y-axis, the change in agriculture's share of gross output in Panel (a) and the change in the non-traded share of gross output in Panel (b). The line is the best linear fit, the slope of which is reported below the figure.

5 Conclusion

This paper studies the link between the structure of domestic trade costs across commodities and the spatial distribution of the population within countries. I use a historical setting – the American Heartland over the postwar period – to document that changes in the costs of shipping certain commodities relative to others can have substantial implications for the relative welfare of people living in different regions. I argue that rail car innovations in the U.S. over this period, which affected only bulk commodities, drove down the cost of shipping agricultural goods relative to manufactured goods and reduced the population of America's agriculture-intensive areas.

I used a simple model to explore the channels through which this could have occurred. I find that reductions in agricultural shipping costs reduce prices by more in locations farther away from where agricultural goods are produced, making other locations relatively more attractive for manufacturing production as well as for buying food. To show that this mechanism is operating in the data, I study flour mills following a sudden, significant, and exogenously generated reduction in the cost of shipping wheat versus flour. Consistent with the model's predictions, I find that this change in trade costs reduced flour and bread prices by more outside of the agricultural Heartland, and that flour milling firms entered at higher rates in locations more distant from the agricultural Heartland. Finally, I specify and calibrate a model of trade between U.S. states in 1950 and find that these changes in trade costs played a considerable role in explaining the population decline of the Heartland.

My findings suggest that how tariffs differ across commodities, and in particular how they differ between upstream and downstream goods, plays an important role in shaping the long run spatial distribution of economic activity. This was certainly the case in postwar America. As the world becomes increasingly connected via supply chains and policymakers differently apply tariffs on upstream and downstream goods, the distribution of economic activity may change substantially.

References

Alder, Simeon, David Lagakos, and Lee Ohanian. 2014. "Competitive pressure and the decline of the Rust Belt: A macroeconomic analysis." National Bureau of Economic Research.

Antras, Pol, and Elhanan Helpman. 2004. "Global sourcing." *Journal of political Economy*, 112(3): 552–580.

Antras, Pol, Teresa Fort, and Felix Tintelnot. 2022. "Trade Policy and Global Sourcing: An Efficiency Rationale for Tariff Escalation." *University of Chicago, Becker Friedman Institute for Economics Working Paper*, , (2022-89).

Autor, David H, David Dorn, Gordon H Hanson, and Jae Song. 2014. "Trade adjustment: Worker-level evidence." *The Quarterly Journal of Economics*, 129(4): 1799–1860.

Babcock, Michael. 1976. "An Empirical Locational Analysis Of The Wheat Flour Milling Industry." *The Review of Regional Studies*, 6(3): 11–18.

Babcock, Michael, Gail Cramer, and William Nelson. 1985. "The Impact of Transportation Rates on the Location of the Wheat Flour Milling Industry." *Agribusiness*, 1(1): 61–71.

Bartelme, Dominick G, Arnaud Costinot, Dave Donaldson, and Andres Rodriguez-Clare. 2019. "The textbook case for industrial policy: Theory meets data." National Bureau of Economic Research.

Caliendo, Lorenzo, and Fernando Parro. 2015. "Estimates of the Trade and Welfare Effects of NAFTA." *The Review of Economic Studies*, 82(1): 1–44.

Caliendo, Lorenzo, Fernando Parro, Esteban Rossi-Hansberg, and Pierre-Daniel Sarte. 2018. "The impact of regional and sectoral productivity changes on the US economy." *The Review of economic studies*, 85(4): 2042–2096.

Caselli, Francesco, and Wilbur John Coleman II. 2001. "The US structural transformation and regional convergence: A reinterpretation." *Journal of political Economy*, 109(3): 584–616.

Chaney, Thomas. 2008. "Distorted gravity: the intensive and extensive margins of international trade." *American Economic Review*, 98(4): 1707–21.

Costinot, Arnaud, and Dave Donaldson. 2016. "How large are the gains from economic integration? Theory and evidence from US agriculture, 1880-1997." National Bureau of Economic Research.

Cox, Lydia. 2021. "The Long-Term Impact of Steel Tariffs on US Manufacturing." mimeo, Harvard University.

Donaldson, Dave. 2016. "Railroads of the Raj: Estimating the Impact of Transportation Infrastructure." *American Economic Review*, 108(4): 899–934.

Donaldson, Dave, and Richard Hornbeck. 2016. "Railroads and American Growth: A "Market Access" Approach." *Quarterly Journal of Economics*, 799–858.

Eaton, Jonathan, and Samuel Kortum. 2002. "Technology, geography, and trade." *Econometrica*, 70(5): 1741–1779.

Eckert, Fabian, and Michael Peters. 2018. "Spatial structural change." *Unpublished Manuscript*.

Fajgelbaum, Pablo, and Stephen Redding. 2022. "Trade, Structural Transformation and Development: Evidence from Argentina 1869-1914." *NBER Working Paper Series*, 130(5).

Glaeser, Edward L, and Janet E Kohlhase. 2004. "Cities, regions and the decline of transport costs." In *fifty years of regional science*. 197–228. Springer.

Gollin, Douglas, and Richard Rogerson. 2010. "Agriculture, Roads, and Economic Development in Uganda." *NBER Working Paper Series*.

Grossman, Gene, and Elhanan Helpman. 2021. "When Tariffs Disrupt Global Supply Chains."

Harwood, Joy. 1991. "U.S. Flour Milling on the Rise." *Food Research and Policy*, 34–38.

Held, Walter G. 1979. "U.S. Wheat Industry." *USDA Agricultural Economic Report*, , (32).

Hornbeck, Richard. 2012. "The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe." *American Economic Review*, 102(4): 1477–1507.

Hyslop, J.D., and R. P. Dahl. 1964. "The Effect of Changes in Transportation Costs on Minnesota Wheat Flour Millers and Oilseed Processors." *University of Minnesota Agricultural Experiment Station*, 3–11.

Kim, C.S., C. Hallahan, G. Schaible, and G. Schluter. 2001. "Economic Analysis of the Changing Structure of the U.S. Flour Milling Industry." *Agribusiness*, 17(1): 161–171.

Kim, Sukkoo. 1995. "Expansion of Markets and the Geographic Distribution of Economic Activities: The Trends in U. S. Regional Manufacturing Structure, 1860–1987*." *The Quarterly Journal of Economics*, 110(4): 881–908.

Krugman, Paul. 1980. "Scale economies, product differentiation, and the pattern of trade." *The American Economic Review*, 70(5): 950–959.

Long, Jason, and Henry Siu. 2018. "Refugees from Dust and Shrinking Land: Tracking the Dust Bowl Migrants." *The Journal of Economic History*, 78(4): 1001–1033.

Melitz, Marc. 2003. "The Impact of Transportation Rates on the Location of the Wheat Flour Milling Industry." *Econometrica*, 71(6): 1695–1725.

Meyer, John R., and Alexander L. Morton. 1975. "The U.S. Railroad Industry in the Post-World War II Period: A Profile." In *Explorations in Economic Research, Volume 2, number 4*. *NBER Chapters*, 449–501. National Bureau of Economic Research, Inc.

Minneapolis Mills Fight for Life, Blame Transit Rates. 1965. "Minneapolis Mills Fight for Life, Blame Transit Rates." *Minneapolis Tribune*.

Nightingale, Edmund. 1967. "Some Effects of Recent Changes in the Railway Grain-Rate Structure on Interregional Competition and Regional Development." In *Transportation Problems and Policies in the Trans-Missouri West.* , ed. Jack Ottoson and Howard Davidson, 105–168. University of Nebraska Press.

The Northwestern Miller. 1959. "List of U.S. Flour Mills." *The Northwestern Miller*.

The Northwestern Miller. 1961. "List of U.S. Flour Mills." *The Northwestern Miller*.

The Northwestern Miller. 1967. "List of U.S. Flour Mills." *The Northwestern Miller*.

The Northwestern Miller. 1975. "List of U.S. Flour Mills." *The Northwestern Miller*.

The Northwestern Miller. 1985. "List of U.S. Flour Mills." *The Northwestern Miller*.

The Northwestern Miller. 1990. "List of U.S. Flour Mills." *The Northwestern Miller*.

The Southwestern Miller. 1955. "The Southwestern Miller."

The Southwestern Miller. 1963. "Kansas Millers Plea Against Peril to Trade." *The Southwestern Miller*.

United States Court of Appeals, Fifth District. 1962. "Arrow Transportation Co. v. Southern Ry. Co."

USDA. 1964. *The Farm Index: 1964 World Report.* Economic Research Service.

Wilson, Steven. 2009. "Population Dynamics of the Great Plains: 1950 to 2007." *Current Population Reports*.

Wishart, David J. 2004. *Encyclopedia of the great plains.* U of Nebraska Press.

World Trade Organization. 2004. *World Trade Report*.

A Tables and Figures

A.1 Tables

Table A.1: **Number of Mills Robustness Checks: Controls & Exposure Measure**

	Dependent variable: Number of Flour Mills						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$1(t > 1963) \times log(WMA_i), baseline$	-0.00969***	-0.00310*	-0.00469***	-0.00999***	-0.00962***		
	(0.00112)	(0.00135)	(0.00114)	(0.00115)	(0.00110)		
$1(t > 1963) \times log(WMA_i), GAEZ$						-0.00393**	
						(0.00127)	
$1(t > 1963) \times log(WMA_i), yield$							-0.00947***
							(0.00109)
N	24856	24856	24856	24856	24848	24856	24856
County FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
State $\times$ year	✗	✓	✗	✗	✗	✗	✗
County Time Trends	✗	✗	✓	✗	✗	✗	✗
Population	✗	✗	✗	✓	✗	✗	✗
Distance to coast	✗	✗	✗	✗	✓	✗	✗

Note: This table shows robustness checks corresponding to estimating Equation 6 with a post indicator for all years after the trade cost shock in 1963. Column (1) shows the baseline result. Column (2) adds state by year fixed effects. Column (3) allows each county to follow its own time trend. Column (4) includes the baseline population level interacted with an indicator variable for each year. Column (5) does the same with the distance of that county to the coastline. Column (6) uses a different measure of exposure; instead of using wheat production when computing WMA_i, I use wheat yields. Column (7) uses GAEZ's wheat suitability index as the measure of wheat productivity when computing WMA_i.

Table A.2: **Milling Capacity Robustness Checks: Controls & Exposure Measure**

	Dependent variable: $sinh^{-1}$ (Flour milling capacity)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$1(t > 1963) \times log(WMA_i), baseline$	-0.0352***	-0.0111^{+}	-0.0139**	-0.0351***	-0.0352***		
	(0.00519)	(0.00644)	(0.00534)	(0.00519)	(0.00517)		
$1(t > 1963) \times log(WMA_i), GAEZ$						-0.0121*	
						(0.00589)	
$1(t > 1963) \times log(WMA_i), yield$							-0.0344***
							(0.00514)
N	24856	24856	24856	24856	24848	24856	24856
County FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
State $\times$ year	✗	✓	✗	✗	✗	✗	✗
County Time Trends	✗	✗	✓	✗	✗	✗	✗
Population	✗	✗	✗	✓	✗	✗	✗
Distance to coast	✗	✗	✗	✗	✓	✗	✗

Note: This table shows robustness checks corresponding to estimating Equation 6 with a post indicator for all years after the trade cost shock in 1963. Column (1) shows the baseline result. Column (2) adds state by year fixed effects. Column (3) allows each county to follow its own time trend. Column (4) includes the baseline population level interacted with an indicator variable for each year. Column (5) does the same with the distance of that county to the coastline. Column (6) uses a different measure of exposure; instead of using wheat production when computing WMA_i, I use wheat yields. Column (7) uses GAEZ's wheat suitability index as the measure of wheat productivity when computing WMA_i.

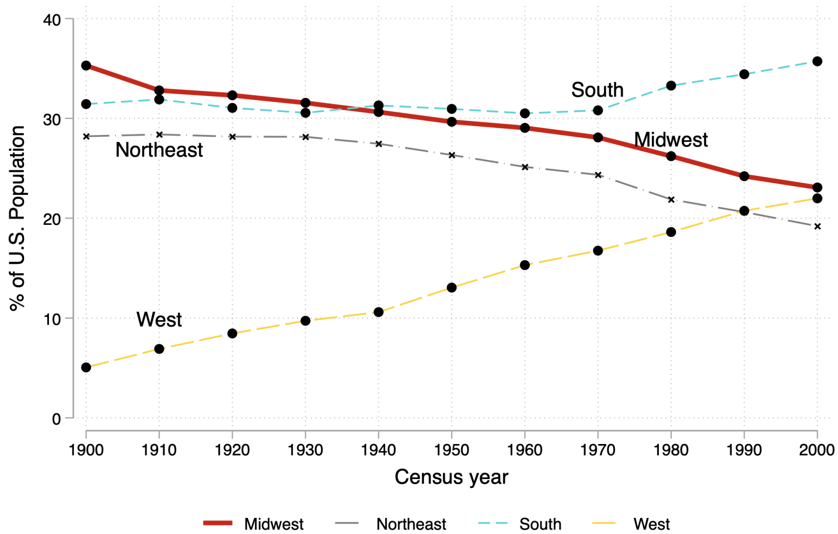
Table A.3: **Robustness Checks: Functional Form**

	Number of Flour Mills				Wheat Flour Capacity		
	(1) OLS	(2) PPML	(3) OLS, $1(n \geq 0)$	(4) Logit, $1(n \geq 0)$	(5) OLS, sin^{-1}	(6) OLS	(7) PPML
$1(t > 1963) \times log(WMA_i), baseline$	-0.00969***	-0.0199	-0.00578***	-0.152***	-0.0352***	-3.524	-0.0195
	(0.00112)	(0.0140)	(0.000786)	(0.0366)	(0.00519)	(2.859)	(0.0187)
N	24856	3800	24856	2800	24856	24856	3800
County FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓

Note: This table shows robustness checks corresponding to estimating Equation 6 with a post indicator for all years after the trade cost shock in 1963.

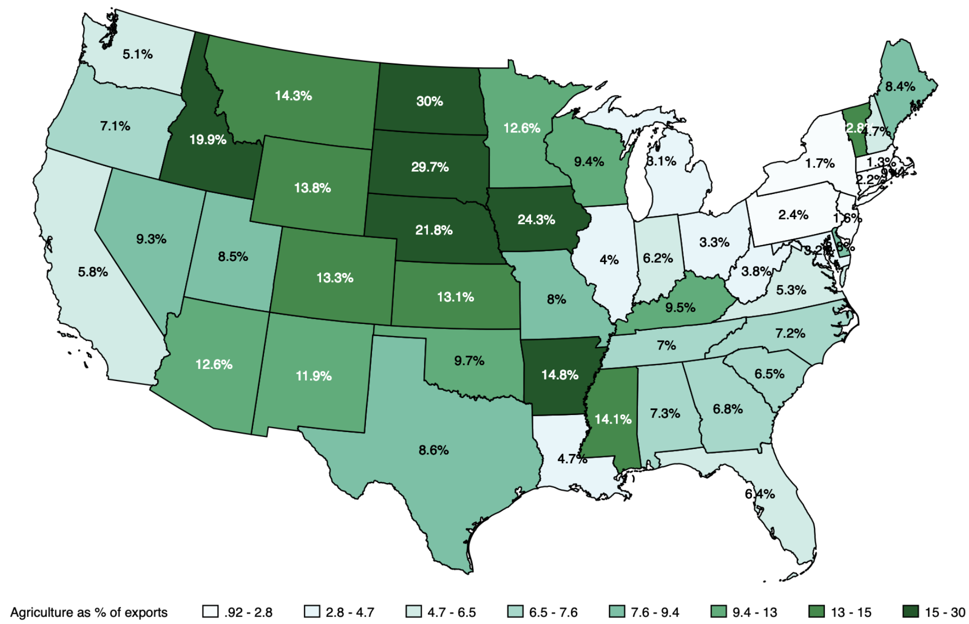
A.2 Figures

Figure A.1: **Distribution of U.S. Population Across Regions, Since 1900**



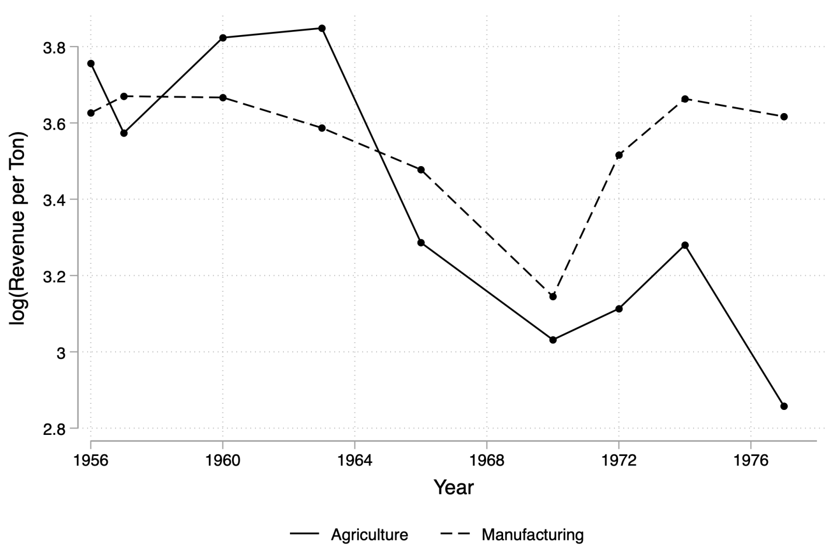
Note: This figure shows the percentage of the U.S. population living in each region in each year. Within a year, the sum of values across the four regions is 100. Regions are defined based on U.S. Census designations. *Source*: Decennial U.S. Census.

Figure A.2: **Agricultural Goods as a Percentage of Gross Output, by State (1950)**



Note: This figure shows percentage of each state's export (defined as tradable output) from the agricultural sector in the initial period. *Source*: USDA (1949), Census of Manufacturers (1947), Census of Mining (1954) and author's calculations.

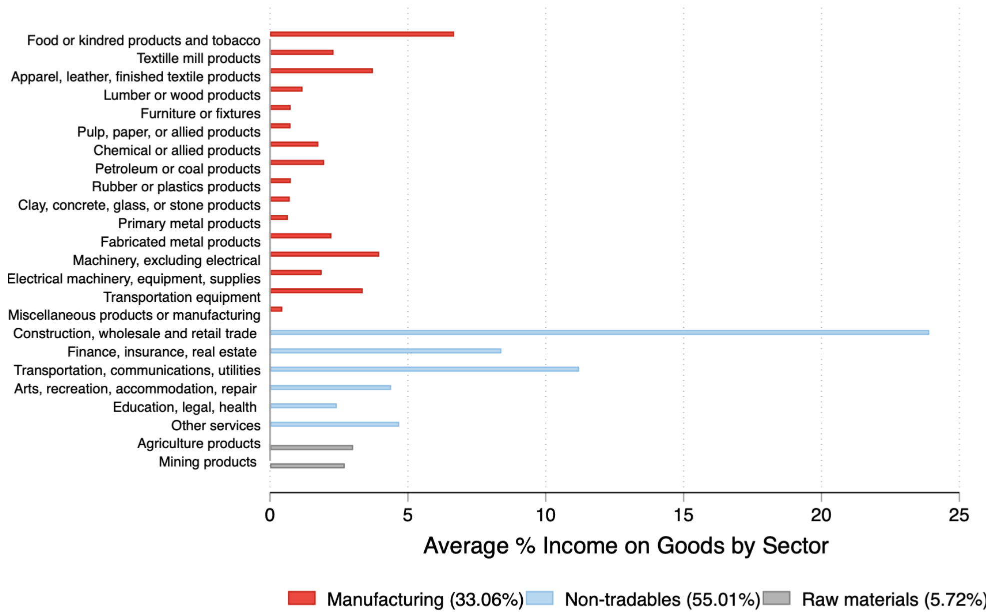
Figure A.3: **Annual Revenue Per Ton Earned, Motor Carriers**



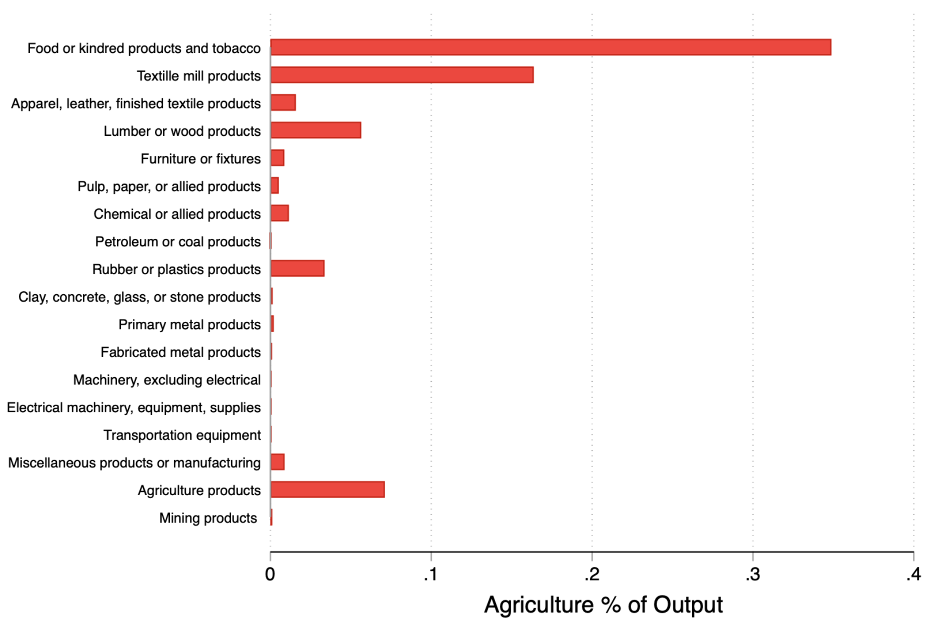
Note: This figure shows annual revenue per ton earned by Class I motor carriers from agricultural goods and manufactured goods using data from the Interstate Commerce Commission's *Freight Commodity Statistics*.

Figure A.4: **Key Model Inputs**

(a) **Sectoral Expenditure Shares**



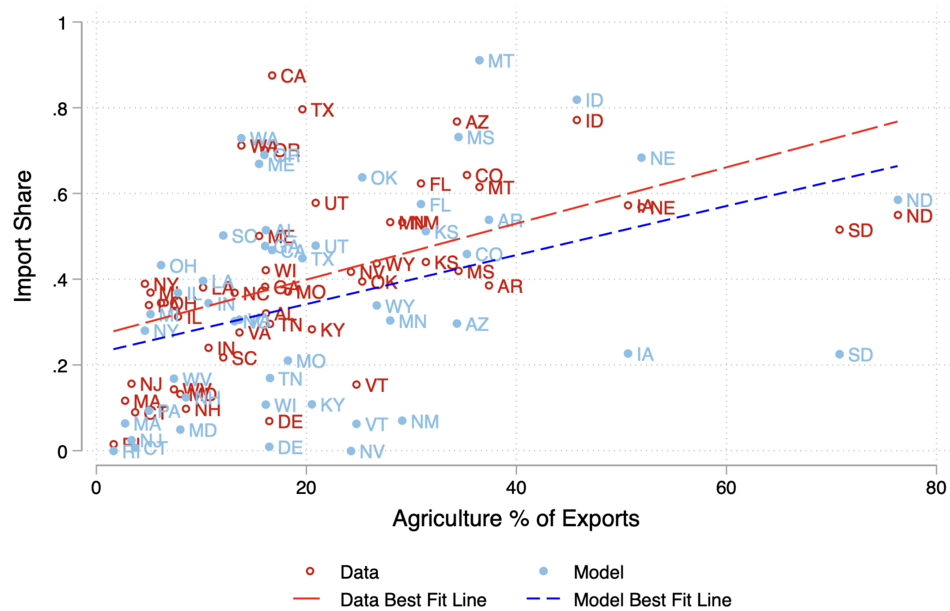
(b) **Agriculture Share of Total Output by Sector**



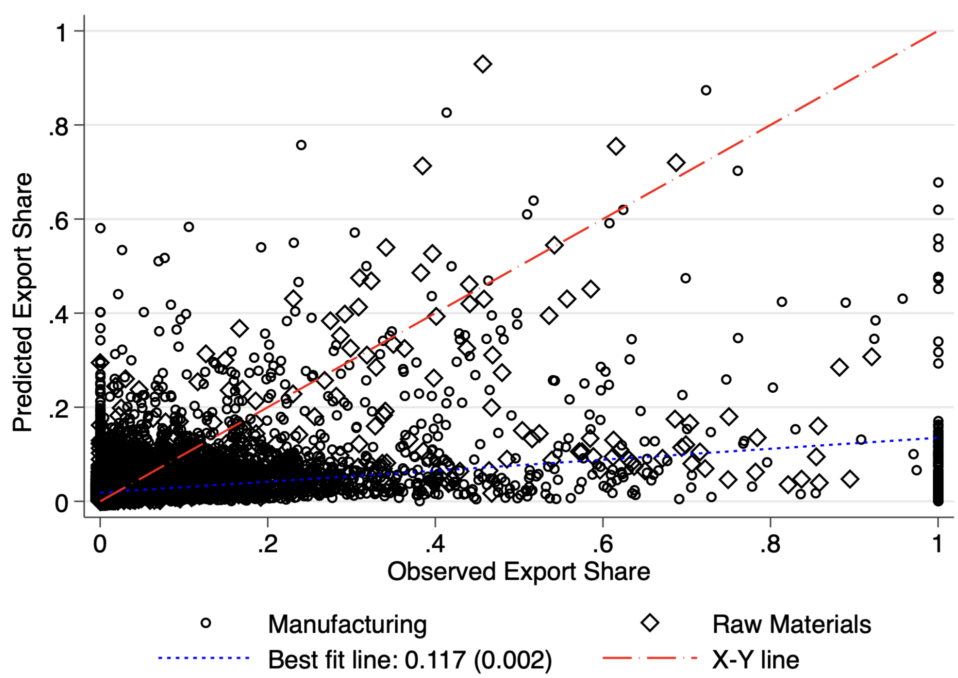
Note: Panel (a) shows the median percentage of final expenditure spent on goods from each sector across all 48 states, as computed from equation 12 and data as described in Section 4. Panel (b) shows the agricultural sector's share of final output for each sector, as computed from the 1949 BLS input-output table. *Source*: USDA, Census of Manufacturers (1947), Census of Mining (1954) and author's calculations.

Figure A.5: **Agriculture Specialization and Own-Import Shares**

(a) **Predicted and Observed Own-Import Shares**

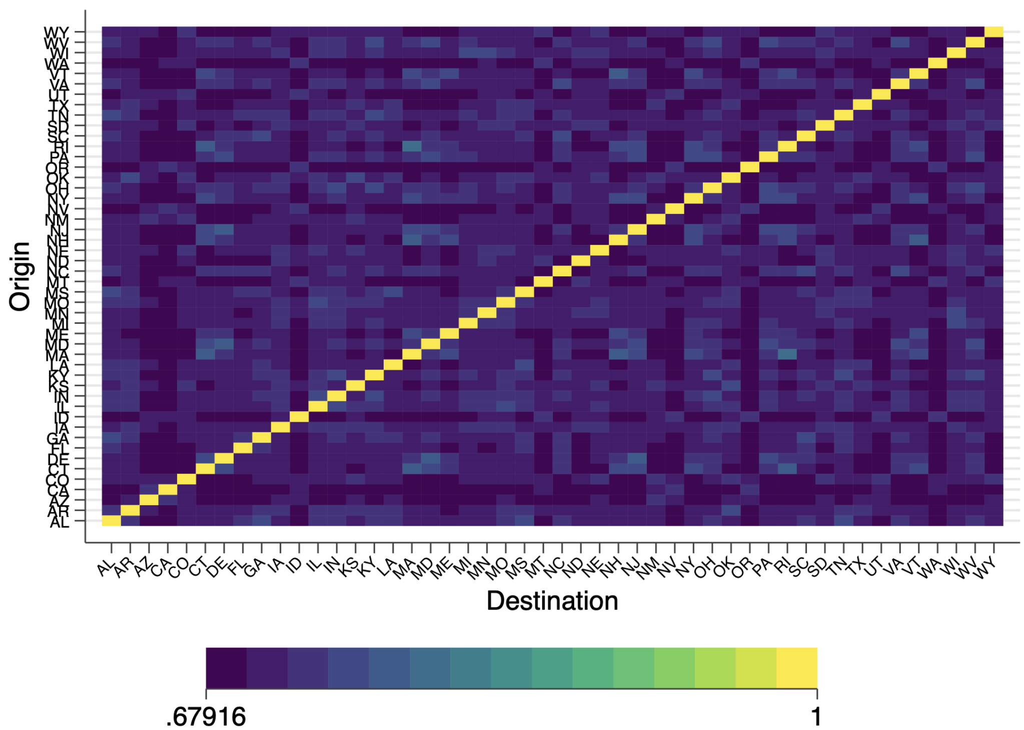


(b) **Predicted and Observed Export Shares**



Note: Panel (a) shows the correlation between each state's own import shares for agricultural goods and that state's agricultural percentage of exports in 1950. Panel (b) shows the relationship between export shares are observed in the data (on the x-axis) and the predicted export shares that I use in the calibration of the data. *Source*: Carload Waybill Sample Statistics (1949), USDA, Census of Manufacturers (1947), Census of Mining (1954) and author's calculations.

Figure A.6: **Changes in Trade Costs Across States**



Note: This figure shows changes in trade costs between each state as fed into the model, computed from equation 15. *Source:* Carload Waybill Sample Statistics and author's calculations.

B Data Appendix

B.1 Trade Data

I compile data on trade separately between U.S. states and regions from the Interstate Commerce Commission. The advantage to the region level data is that it more complete, while some state to state pairs are omitted if trade flows are too low. For the quantitative model, I use data on state to state trade flows. In addition to these data, I obtain aggregate data on railroad revenue earned and tons shipped in each year from the Freight Commodity Statistics, which cover Class I railroads.[1] The sampling process includes selecting all waybills, which are contracts between producers and shippers, with numbers ending in 1. This sampling procedure is supposed to result in an unbiased, representative sample of one percent of total traffic, according to the Interstate Commerce Commission.

Figure B.1: **Example of Carload Waybill Sample Statistics, State-to-State Trade Data**

Traffic Data Averages for Specified Units of Carload Traffic with Supporting Detail, by Commodity Class,
Computed from audited Waybills Representing 1 Percent of Carload Traffic Terminated by Class I Railways during the year 1956

State-to-State Movement	Carloads	Tons (2000 lbs.)	Revenue (Dollars)	Short-line ton-miles	Short-line car-miles	Avg. tons per car	Avg. Short-line Haul per ton	Avg. Short-line Haul per car	Average revenue per 100 lbs. ¢	Average revenue per car $	Average revenue per S.L. car mile ¢	Average revenue per S.L. ton mile ¢
940 MAN AND MISC												
MIC TO IDA	1	23	1505	42400	1845	23	1843	1845	327	1505	82	3.55
MIC TO ILL	354	10568	99861	3421900	112062	30	324	317	47	282	89	2.92
MIC TO IND	217	6786	60678	1885700	66266	31	278	305	45	280	92	3.22
MIC TO IOW	26	820	10625	408800	13001	32	499	500	65	409	82	2.60
MIC TO KAN	71	1492	38238	1018600	48198	21	683	679	128	539	79	3.75
MIC TO KY	98	2548	31239	918900	34750	26	361	355	61	319	90	3.40
MIC TO LA	25	416	11488	434400	25986	17	1044	1039	138	460	44	2.64
MIC TO MAI	13	311	7115	304900	13052	24	980	1004	114	547	55	2.33
MIC TO MD	69	1931	28409	1219000	43806	28	631	635	74	412	65	2.33
MIC TO MAS	184	3339	69237	2485200	135652	18	744	737	104	376	51	2.79
MIC TO MIC	1246	46866	147146	3528800	94112	38	75	76	16	118	156	4.17
MIC TO MIN	88	1825	32460	944000	47608	21	517	541	89	369	68	3.44
MIC TO MIS	8	125	3844	114700	7235	16	918	904	154	481	53	3.35
MIC TO MO	246	5054	103370	3048500	147227	21	603	598	102	420	70	3.39
MIC TO MON	6	127	5732	188100	9297	21	1481	1550	226	955	62	3.05
MIC TO NEB	7	130	2742	98200	5315	19	755	759	105	392	52	2.79
MIC TO NEV	1	9	602	19300	2142	9	2144	2142	334	602	28	3.12
MIC TO N H	6	153	2067	118500	4603	26	775	767	68	345	45	1.74
MIC TO N J	409	8112	164679	5435300	268194	20	670	656	102	403	61	3.03
MIC TO N M	4	58	3103	83600	5688	15	1441	1422	268	776	55	3.71
MIC TO N Y	491	10307	161712	4952000	254685	21	480	519	78	329	63	3.27
MIC TO N C	31	628	13787	501900	24953	20	799	805	110	445	55	2.75
MIC TO N D	4	55	1886	43200	3140	14	785	785	171	472	60	4.37
MIC TO OHI	452	16533	112966	3443100	97465	37	208	216	34	250	116	3.28

Note: This figure shows a sample of the state to state trade data that I used to estimate changes in trade costs over time, as well as to calibrate the quantitative model in Section 2. *Source: Carload Waybill Sample Statistics.*

B.2 Railroad Network

I obtained high resolution images of a 1957 Army Corps of Engineers Railroad Map of the United States from Stanford University Libraries, which was then hand-digitized

[1]Class I railroads are the largest railroad companies; generally, it includes all railroad companies with annual revenues exceeding a given threshold.

onto a Lambert Conic projection. I use this to measure railroad distances between the centroids of each county as in Section 3 and each state as in Section 4.

Figure B.2: **Sample of 1957 Army Corps of Engineers Railroad Map**

Note: This shows the lower right hand corner of the 1957 railroad map that I have digitized and is used throughout the paper.

B.3 Flour Data

B.3.1 Mill Locations

I collected data on the location, capacity, and ownership of flour mills from the *Northwestern Miller*'s annual Directory of U.S. Flour mills, which was compiled and shipped to their subscribers. Figure B.3 gives an example of what these directories look like for two separate years (1985 and 1961 respectively). Figure A.4 shows summary statistics describing the key variables obtained from these directories. Over this period, the number of mills falls roughly in half but total capacity of all mills rises, due to an increasing average size of the remaining mills. To construct a county-level panel of mills, and to

Table A.4: **Flour Mill Summary Statistics**

Year	# Mills	Total Capacity	Avg. Size	Top 5 % Capacity	Top 15 % Capacity	% Big
1959	580	1072.15	1849	25.65	65.52	25.34
1961	553	1021.30	1847	23.64	60.81	25.32
1965	426	953.88	2239	22.46	60.80	25.12
1967	360	951.71	2644	21.90	60.48	28.33
1971	325	957.02	2945	20.86	59.12	28.00
1975	267	951.78	3565	19.52	59.54	34.46
1985	228	1102.62	4836	17.73	55.61	38.60
1990	207	1198.12	5788	17.49	54.09	43.00

Source: *The Northwestern Miller*. Note: Top 5 are the top 5 producers of wheat in 1963: Kansas, North Dakota, Texas, Oklahoma, and Washington which together accounted for 48% of total U.S. wheat production. Top 15 are the top 15 producers of wheat in 1963, which accounted for 75% of total wheat production. Total capacity is in 1,000 of cwt per day. Big indicates plants that were part of a multi-unit firm in their first year of entry

assign a wheat market access term to each mill, I use the listed location information and the OpenCageGeocode API in Python to match plants to latitude-longitude coordinates. I then map these coordinates to modern-day county FIPS codes. I identify unique plants over time based on the following algorithm. First, I sort the data by state, city plant name, and year. Then I check the following steps:

1. If the state, city, and name fields are the same over time and there are no duplicates of the year given the state-county-name, then this is a uniquely identified plant.

2. Suppose the state and city are the same, only one plant is listed, and there are no du-

Figure B.3: **Milling Directory Examples**

KANSAS

ARKANSAS CITY

***DIXIE-PORTLAND FLOUR MILLS, INC.** — Tyler and "L" Sts. Zip 67005. (316) 442-6200. Vice-president, general manager — Don R. Morris; Vice-president, quality control — D. Keith Ehmke; Plant superintendent — Ralph Broadrick.

Capacity: wheat flour 12,000 cwts; storage 2,100,-000 bus. **Brands:** see corporate listing. **RR:** MP.

***ADM MILLING CO. (The New Era Milling Co.)** — 309 W. Madison Ave., P.O. Box 958. Zip 67005. (316) 442-5500. President — Doug Goff; Director of products control — Robert F. Pudden.

Capacity: wheat flour 9,000 cwts; mill storage 1,-400,000 bus. **Brands:** see corporate listing.

KANSAS

ABILENE

The Abilene Flour Mills Co., 211 N.E. 3rd St. Capacity: Wheat flour, 3,900 cwt. Storage capacity, 4,700,000 bu.
Pres.—T. L. Welsh
Vice Pres.—R. B. Laing
Supt.—C. E. Huffman
Head Miller: Tex Prestridge
Chief Chemist—Paul W. Wesley

Note: Flour milling directory data...

plicates of the year given a state-city, but the plant name changes across years. Then I check whether there is a secondary owner listed that explains the name change. For example, if in 1971 the firm is listed as "Alabama Flour Mills" and as "Conagra" in 1975, but Conagra is listed as the secondary owner in 1971, then this is a unique plant observation (and reflects an acquisition by Conagra).

3. Suppose the state and city are the same, but many plants are listed, and names change throughout different years. If the addresses match across time, I use this to uniquely identify plants. If name changes can be connected through time with information listed on the secondary owner, then I use this to identify firms. If address information is incomplete across years, I use the firm sizes to differentiate across firms. For example, it is unlikely a plant quadrupled in size in a few years.

B.3.2 Prices

Producer flour prices. I collected data on flour producer prices from a few different sources. My primary source is the *Southwestern Miller*, which published weekly flour prices from a sample of flour mills in each major flour market. Because these are prices reported by mills themselves where they are produced, I consider these to be producer prices. Table A.5 lists flour prices in 1962, the last year prior to the change, and 1966, several years after the shock for each location in the sample. I was not able to obtain

Figure B.4: ***Southwestern Miller* Flour Price Data**

* * *

KANSAS CITY FLOUR PRICE RANGE

Kansas City mills quoted hard winters, carlots, basis 100s paper, with comparisons for a year ago:

HARD WINTERS—	Nov. 23	Year Ago
Family patent, cottons.	\$8.00@8.10	\$7.60@7.70
Bakers' short patent....	5.75@5.80	5.60@5.65
Bakers' standard patent	5.65@5.70	5.50@5.55
Hard win.-Sprg. blend..	5.70@5.75	5.65@5.70
Fancy bakers' clear.....	4.80@4.85	4.90@4.95
1.0 ash, 13%	3.85@3.90	4.55@4.60

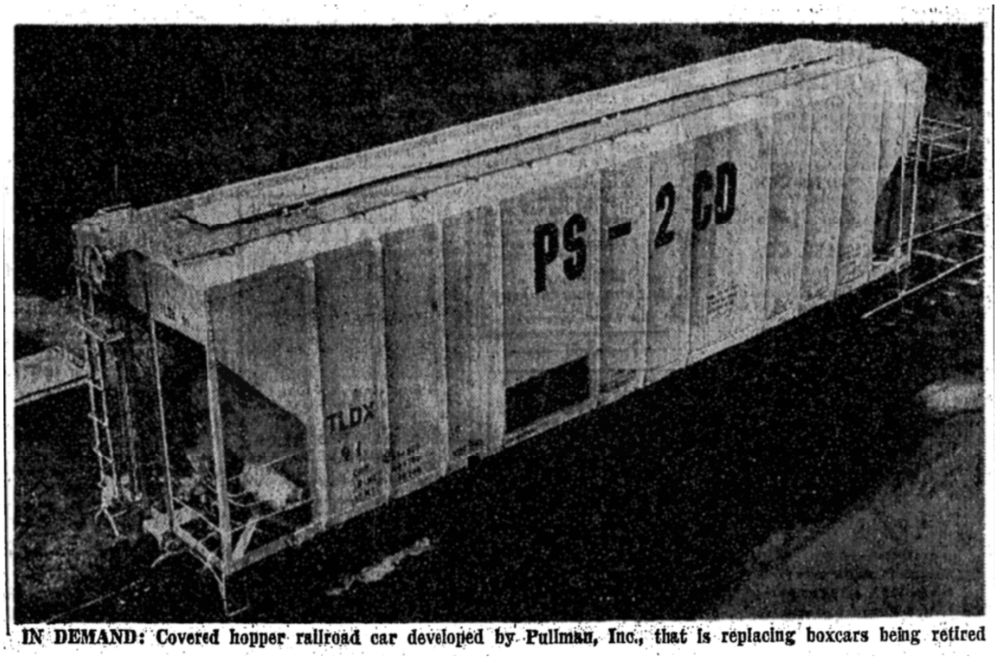
* * *

price data after 1968, so that is the last year in my sample. Minneapolis flour prices are not included in later years; thus, when that series ends, I use data on flour prices from Minneapolis mills from the USDA as part of the monthly "Wheat Situation" report.

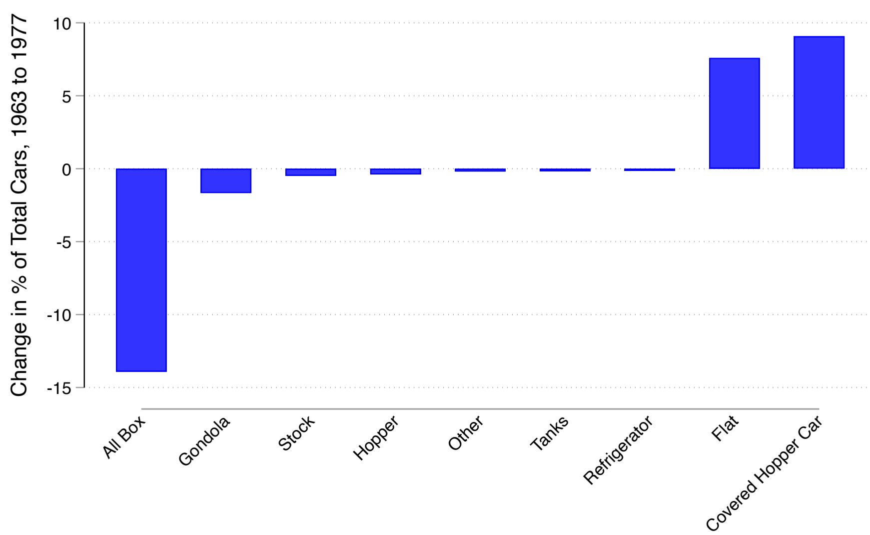
Consumer flour and bread prices. I digitized data on the annual price of wheat and flour for every city listed in the BLS's "Estimated Food Retail Prices by Cities". While the set of cities varies slightly over time, most years include around twenty cities. Table A.6 reports bread and flour prices for the set of cities in the sample for 1962 and 1964.

Figure B.5: **The Decline of the Box Car**

(a) Covered Hopper Car



(b) Changes in Rail Car Types, 1963-1977



Source: Bureau of Transport Economics and Statistics, Interstate Commerce Commission, 1979

Note: Panel (a) shows an image of a covered hopper car for transporting grain, from the New York Times (1964). Panel (b) shows the change in percentage of total cars represented by each rail car type, from the ICC (1979).

Table A.5: **Flour Producer Price Summary Statistics**

State	Cities	Flour Type	Price ($) 1962	Price ($) 1966	Price Ratio
Alabama	Birmingham	Standard Patent	21.90	21.02	0.96
Illinois	Chicago	Standard Patent	20.33	20.56	1.01
Kansas	Wichita, Salina, Arkansas City, Hutchinson	Standard Patent	20.92	21.13	1.01
Minnesota	Minneapolis	Standard Patent	21.82	22.48	1.03
Missouri	Kansas City	Standard Patent	20.92	21.13	1.01
Nebraska	Omaha	Standard Patent	19.42	20.09	1.03
New York	New York	Standard Patent	23.37	22.85	0.98
Oregon	Portland	Family	27.10	28.49	1.05
Pennsylvania	Pittsburgh	Standard Patent	21.98	19.66	0.89

Note: This table shows summary statistics of flour producer prices for each location in which I observe prices. This price data is used in Section 3 to estimate the effects of changes in upstream trade costs on downstream prices. *Source: Southwestern Miller* and BLS.

Table A.6: **Flour Consumer Price Summary Statistics**

State	City	Flour Price ($) 1962	Flour Price ($) 1964	Ratio	Bread Price ($) 1962	Bread Price ($) 1964	Ratio
Georgia	Atlanta	1.92	1.90	0.99	0.64	0.62	0.97
Maryland	Baltimore	1.83	1.88	1.03	0.68	0.75	1.10
Massachusetts	Boston	1.83	1.87	1.02	0.70	0.69	0.99
Illinois	Chicago	1.75	1.70	0.97	0.69	0.62	0.90
Ohio	Cincinnati	1.75	1.67	0.95	0.64	0.63	0.98
Ohio	Cleveland	1.78	1.69	0.95	0.67	0.68	1.01
Michigan	Detroit	1.70	1.68	0.99	0.61	0.56	0.92
Texas	Houston	1.87	1.87	1.00	0.55	0.57	1.04
Kansas	Kansas City	1.67	1.72	1.03	0.67	0.66	0.99
California	Los Angeles	2.02	1.85	0.92	0.88	0.92	1.05
Minnesota	Minneapolis	1.84	1.82	0.99	0.62	0.59	0.95
New York	New York	1.79	1.81	1.01	0.79	0.80	1.01
Pennsylvania	Philadelphia	1.86	1.77	0.95	0.74	0.72	0.97
Pennsylvania	Pittsburg	1.81	1.73	0.96	0.71	0.68	0.96
California	San Francisco	2.11	2.04	0.97	0.84	0.88	1.05
Washington	Seattle	2.12	2.07	0.98	0.80	0.80	1.00
Missouri	St Louis	1.78	1.79	1.01	0.65	0.63	0.97
District Of Columbia	Washington	1.92	1.95	1.02	0.67	0.65	0.97

Note: This table shows summary statistics of flour and bread consumer prices for each location in which I observe prices. This price data is used in Section 3 to estimate the effects of changes in upstream trade costs on downstream prices. Flour prices are for five pounds of wheat flour and bread prices are for one pound of bread. All prices are in 1985 dollars. *Source:* BLS, Estimated Retail Prices of Food in cities.

C Model Appendix

C.1 Model Setup

C.1.1 Flour Demand

Each agent chooses c_{ni}^F, c_{ni}^M to solve:

$$U(c_i^F, c_i^M) = c_i^M + \ln\left(c_i^F\right)$$

where:

$$c_i^F = \left[\sum_n (c_{ni}^F)^{\frac{\sigma_F - 1}{\sigma_F}}\right]^{\frac{\sigma_F}{\sigma_F - 1}} \text{ and } c_i^M = \left[\sum_n c_{ni}^M\right]$$

subject to a budget constraint of

$$w_i = \sum_n p_{ni}^M c_{ni}^M + p_{ni}^F c_{ni}^F$$

From this maximization problem we have demand functions for each variety of flour:

$$c_{ji}^F = p^M \left(p_{ji}^F\right)^{-\sigma_F} \frac{\sigma_F}{\sigma_F - 1} \left(P_i^F\right)^{\sigma_F - 1}$$

Then the total amount of spending on flour by state i is:

$$\sum_j p_{ji}^F c_{ji}^F = \sum_j p^M \left(p_{ji}^F\right)^{1-\sigma_F} \frac{\sigma_F}{\sigma_F - 1} \left(P_i^F\right)^{\sigma_F - 1} = p^M \frac{\sigma_F}{\sigma_F - 1}$$

This yields flour import shares – the share of flour imported to state i by state j – of:

$$\pi_{ji}^F = \frac{p_{ji}^F c_{ji}^F}{\sum_j p_{ji}^F c_{ji}^F} = \left(p_{ji}^F\right)^{1-\sigma_F} \left(P_i^F\right)^{\sigma_F - 1}$$

C.1.2 Indirect Utility

Next we want to find the indirect utility function in order to compute welfare. First sum over origins to find aggregate flour consumption:

$$c_i^F = \left[\sum_n \left(p^M \left(p_{ji}^F\right)^{-\sigma_F} \frac{\sigma_F}{\sigma_F - 1} \left(P_i^F\right)^{\sigma_F - 1} \right)^{\frac{\sigma_F - 1}{\sigma_F}} \right]^{\frac{\sigma_F}{\sigma_F - 1}} = \frac{p^M}{P_i^F} \frac{\sigma_F}{\sigma_F - 1}$$

Then to find c_i^M :

$$w_i = p^M c_i^M + \sum_n p_{ni}^F p^M \left(p_{ni}^F\right)^{-\sigma_F} \frac{\sigma_F}{\sigma_F - 1} \left(P_i^F\right)^{\sigma_F - 1}$$

$$c_i^M = \frac{w_i}{p^M} - \frac{\sigma_F}{\sigma_F - 1} \left(P_i^F\right)^{\sigma_F - 1} \sum_n \left(p_{ni}^F\right)^{1 - \sigma_F} = \frac{w_i}{p^M} - \frac{\sigma_F}{\sigma_F - 1} \left(P_i^F\right)^{\sigma_F - 1} \left(P_i^F\right)^{1 - \sigma_F} = \frac{w_i}{p^M} - \frac{\sigma_F}{(\sigma_F - 1)} P_i^F$$

Then, the indirect utility function for a single agents is given by (assuming income is sufficiently large):

$$V(P_i^F, I_i) = w_i + \ln\left(\frac{\sigma_F}{\sigma_F - 1}\right) - \ln\left(P_i^F\right) - \frac{\sigma_F}{\sigma_F - 1} P_i^F \tag{17}$$

C.1.3 Labor Mobility

Given the above indirect utility common across all agents in a location, and the assumption that indirect utility of a worker l in state i is $v_i^l = v_i + \epsilon_i^l$:

$$v_i^l = \left(w_i + \ln\left(\frac{\sigma_F}{\sigma_F - 1}\right) - \ln\left(P_i^F\right) - \frac{\sigma_F}{\sigma_F - 1} P_i^F \right) + \epsilon_n^l$$

Agents choose to live in the state that gives them the largest indirect utility. Assuming that $\epsilon_n^l \sim Gumbell$, the probability that an agent i chooses a state n is given by (or the share of agents living in state n):

$$\lambda_i = pr\left(v_i^l \geq \max_{n' \neq n} v_{n'}^l\right) = \frac{exp(v_i)}{\sum_{n'} exp(v_{n'})} = \frac{exp\left(w_i + \ln\left(\frac{\sigma_F}{\sigma_F - 1}\right) - \ln\left(P_i^F\right) - \frac{\sigma_F}{\sigma_F - 1} P_{n'}^F\right)}{\sum_n' exp\left(w_{n'} + \ln\left(\frac{\sigma_F}{\sigma_F - 1}\right) - \ln\left(P_{n'}^F\right) - \frac{\sigma_F}{\sigma_F - 1} P_{n'}^F\right)}$$

Given an exogenous level of the country's population size L, the number of people living in state i is: $L_i = \lambda_i L$

C.1.4 Flour Millers' Problem

Flour millers in state i choose the amount of wheat to import from each state j in order to minimize costs subject to a level of production:

$$\min_{c_{ni}^W} \sum_n p_{ni}^W c_{ni}^W \text{ s.t. } Y_{it}^F = T_{it}^F \left[\sum_n \left(c_{ni}^W \right)^{\frac{\sigma_W - 1}{\sigma_W}} \right]^{\frac{\sigma_W}{\sigma_W - 1}}$$

Then, the first order conditions are:

$$[c_{ni}^W] : p_{ni}^W - \lambda_{it} T_{it}^F \left[\sum_n \left(c_{ni}^W \right)^{\frac{\sigma_W - 1}{\sigma_W}} \right]^{\frac{1}{\sigma_W - 1}} \left(c_{ni}^W \right)^{-1/\sigma_W} = 0$$

Taking the ratio of first order conditions for different origins (holding i fixed):

$$\frac{p_{ni}^W}{p_{it}^W} = \left(\frac{c_{ni}^W}{c_{ji}^W} \right)^{-1/\sigma_W}$$

Solving for c_{ni}^W:

$$\left(\frac{p_{ni}^W}{p_{ji}^W} \right)^{-\sigma_W} c_{ji}^W = c_{ni}^W$$

Substituting this into the constraint:

$$\begin{aligned} Y_i^F = T_i^F \left[\sum_n \left(c_{ni}^W \right)^{\frac{\sigma_W - 1}{\sigma_W}} \right]^{\frac{\sigma_W}{\sigma_W - 1}} \quad &= T_i^F \left[\textstyle\sum_n \left(\frac{p_{ni}^W}{p_{ji}^W} \right)^{1-\sigma_W} \left(c_{ji}^W \right)^{\frac{\sigma_W - 1}{\sigma_W}} \right]^{\frac{\sigma_W}{\sigma_W - 1}} \\ &= T_i^F \left(p_{ji}^W \right)^{\sigma_W} c_{ji}^W \left[\textstyle\sum_n \left(p_{ni}^W \right)^{1-\sigma_W} \right]^{\frac{\sigma_W}{\sigma_W - 1}} \end{aligned}$$

Then, solving for consumption of wheat from state j in state i:

$$c_{ji}^W = \frac{Y_i^F}{T_i^F} \left(p_{ji}^W \right)^{-\sigma_W} \left(P_i^W \right)^{\sigma_W}$$

which means that total spending on wheat in state i is:

$$\sum_j p_{ji}^W c_{ji}^W = \frac{Y_i^F}{T_i^F} \left(P_i^W\right)^{\sigma_W} \sum_j \left(p_{ji}^W\right)^{1-\sigma_W} = \frac{Y_i^F}{T_i^F} P_i^W$$

Then the share of wheat imported from state j by state i, π_{ji}^W is:

$$\pi_{ji}^W = \frac{p_{ji}^W c_{ji}^W}{\frac{Y_i^F}{T_i^F} P_i^W} = \frac{\frac{Y_i^F}{T_i^F} \left(p_{ji}^W\right)^{1-\sigma_W} \left(P_i^W\right)^{\sigma_W}}{\frac{Y_i^F}{T_i^F} P_i^W} = \left(p_{ji}^W\right)^{1-\sigma_W} \left(P_i^W\right)^{\sigma_W - 1}$$

C.2 Proofs of Testable Predictions

C.2.1 Main Theorems

If $\pi_{NN}^W < \pi_{KK}^W$ and $\hat{\tau}^W < 1$, then the following theorems hold.

Theorem 1 (Flour producer price effect)**.** $\hat{p}_{NN}^F < \hat{p}_{KK}^F$

Proof.

$$\hat{p}_{NN}^F < \hat{p}_{KK}^F \iff \frac{\hat{P}_N^W}{\hat{T}_N^F} < \frac{\hat{P}_K^W}{\hat{T}_K^F} \iff \hat{P}_N^W < \hat{P}_K^W$$

Then note that:

$$\hat{\tau}^W < 1 \iff \left(\hat{\tau}^W\right)^{1-\sigma_W} > 1 \iff \pi_{NN}^W - \pi_{KK}^W > \left(\hat{\tau}^W\right)^{1-\sigma_W} (\pi_{NN}^W - \pi_{KK}^W)$$

since $\pi_{NN}^W - \pi_{KK}^W < 0$.

$$\iff \pi_{NN}^W - \pi_{KK}^W + \left(\hat{\tau}^W\right)^{1-\sigma_W} > \left(\hat{\tau}^W\right)^{1-\sigma_W} \pi_{NN}^W - \left(\hat{\tau}^W\right)^{1-\sigma_W} \pi_{KK}^W + \left(\hat{\tau}^W\right)^{1-\sigma_W}$$

$$\iff \pi_{NN}^W + (1 - \pi_{NN}^W) \left(\hat{\tau}^W\right)^{1-\sigma_W} > \pi_{KK}^W + (1 - \pi_{KK}^W) \left(\hat{\tau}^W\right)^{1-\sigma_W}$$

since $1 - \pi_{ii}^W = \pi_{ni}^W$:

$$\pi_{NN}^W + \pi_{KN}^W \left(\hat{\tau}^W\right)^{1-\sigma_W} > \pi_{KK}^W + \pi_{NK}^W \left(\hat{\tau}^W\right)^{1-\sigma_W}$$

$$\iff \left[\pi_{NN}^W + \pi_{KN}^W \left(\hat{\tau}^W\right)^{1-\sigma_W}\right]^{\frac{1}{1-\sigma_W}} < \left[\pi_{KK}^W + \pi_{NK}^W \left(\hat{\tau}^W\right)^{1-\sigma_W}\right]^{\frac{1}{1-\sigma_W}} \iff \hat{P}_N^W < \hat{P}_K^W$$

□

Theorem 2 (Flour consumer price effect)**.** If $\pi_{NN}^W < \pi_{KK}^W$ and $\hat{\tau}^W < 1$, then $\hat{P}_N^F < \hat{P}_K^F$.

Proof. Define $a = 1 - \sigma_F < 0$. By proposition (2),

$$\pi_{KK}^F > \pi_{KN}^F \iff \pi_{KK}^F > 1 - \pi_{NN}^F \iff \pi_{KK}^F + \pi_{NN}^F > 1$$

Then, applying proposition (3), $\hat{P}_N^W < \hat{P}_K^W \leq 1 \iff (\hat{P}_N^W)^a > (\hat{P}_K^W)^a \geq 1 \iff (\hat{P}_N^W)^a - (\hat{P}_K^W)^a > 0$,

$$\iff \pi_{NN}^F \left(\left(\hat{P}_N^W\right)^a - \left(\hat{P}_K^W\right)^a\right) + \pi_{KK}^F \left(\left(\hat{P}_N^W\right)^a - \left(\hat{P}_K^W\right)^a\right) > \left(\hat{P}_N^W\right)^a - \left(\hat{P}_K^W\right)^a$$

$$\iff \pi_{NN}^F \left(\left(\hat{P}_N^W\right)^a - \left(\hat{P}_K^W\right)^a\right) - \left(\hat{P}_N^W\right)^a > \pi_{KK}^F \left(\left(\hat{P}_K^W\right)^a - \left(\hat{P}_N^W\right)^a\right) - \left(\hat{P}_K^W\right)^a$$

$$\iff \pi_{NN}^F \left(\hat{P}_N^W\right)^a + (1 - \pi_{NN}^F) \left(\hat{P}_K^W\right)^a > \pi_{KK}^F \left(\hat{P}_K^W\right)^a + (1 - \pi_{KK}^F) \left(\hat{P}_N^W\right)^a$$

$$\iff \pi_{NN}^F \left(\hat{P}_N^W\right)^a + \pi_{KN}^F \left(\hat{P}_K^W\right)^a > \pi_{KK}^F \left(\hat{P}_K^W\right)^a + \pi_{NK}^F \left(\hat{P}_N^W\right)^a$$

$$\left[\pi_{NN}^F \left(\hat{P}_N^W\right)^a + \pi_{KN}^F \left(\hat{P}_K^W\right)^a\right]^{\frac{1}{1-\sigma_F}} < \left[\pi_{KK}^F \left(\hat{P}_K^W\right)^a + \pi_{NK}^F \left(\hat{P}_N^W\right)^a\right]^{\frac{1}{1-\sigma_F}} \leq 1 \iff \hat{P}_N^F < \hat{P}_K^F$$

□

Theorem 3 (Flour production effect)**.** $\hat{Y}_N > \hat{Y}_K^*$

Proof.

$$\hat{Y}_N^F > \hat{Y}_K^F \iff \lambda_{NN}\hat{c}_{NN}^F + (1 - \lambda_{NN})\hat{c}_{NK}^F > \lambda_{KK}\hat{c}_{KK}^F + (1 - \lambda_{KK})\hat{c}_{KN}^F$$

where $\lambda_{ni} = \frac{c_{ni}^F}{c_{ni}^F + c_{nn}^F}$ is the share of n's flour production shipped to i in the initial equilibirum.

$$\iff \lambda_{NN}(\hat{P}_N^W)^{-\sigma_F} \left(\hat{P}_N^F\right)^{\sigma_F - 1} + (1 - \lambda_{NN})(\hat{P}_N^W)^{-\sigma_F} \left(\hat{P}_K^F\right)^{\sigma_F - 1}$$

$$> \lambda_{KK}(\hat{P}_K^W)^{-\sigma_F} \left(\hat{P}_K^F\right)^{\sigma_F - 1} + (1 - \lambda_{KK})(\hat{P}_K^W)^{-\sigma_F} \left(\hat{P}_N^F\right)^{\sigma_F - 1}$$

From Proposition 3 we know that: $\hat{P}_N^W < \hat{P}_K^W$, and

$$\hat{P}_N^F < \hat{P}_K^F \iff \left[\pi_{NN}^F (\hat{P}_N^W)^{1-\sigma_F} + \pi_{KN}^F (\hat{P}_K^W)^{1-\sigma_F}\right]^{\frac{1}{1-\sigma_F}} < \left[\pi_{KK}^F (\hat{P}_K^W)^{1-\sigma_F} + \pi_{NK}^F (\hat{P}_N^W)^{1-\sigma_F}\right]^{\frac{1}{1-\sigma_F}}$$

so then it must be that $\hat{P}_N^W < \hat{P}_N^F < \hat{P}_K^F < \hat{P}_K^W$. We claim the following:

* $(\hat{P}_N^W)^{-\sigma_F} (\hat{P}_N^F)^{\sigma_F - 1} > (\hat{P}_K^W)^{-\sigma_F} (\hat{P}_K^F)^{\sigma_F - 1}$ which follows from the inequality, since $\frac{\hat{P}_N^W}{\hat{P}_N^F} < 1$ and $\frac{\hat{P}_K^W}{\hat{P}_K^F} > 1$
* $(\hat{P}_N^W)^{-\sigma_F} (\hat{P}_K^F)^{\sigma_F - 1} > (\hat{P}_K^W)^{-\sigma_F} (\hat{P}_N^F)^{\sigma_F - 1}$ which follows immediately.

Since our original inequality is a convex combination of these two conditions added together, we are done.

□

Theorem 4 (Pro-competitive effect). $\hat{\varphi}_N^* < \hat{\varphi}_K^*$

Proof. First, write φ_i^* in changes:

$$\hat{\varphi}_i^* = \hat{P}_i^W \left(\hat{w}_i \hat{f}_e\right)^{\frac{1}{\sigma_F - 1}} \left(\sum_j \lambda_{ij} (\hat{P}_j^F)^{\sigma_F - 1} \left(\hat{\tau}_{ij}^F\right)^{1-\sigma_F}\right)^{\frac{1}{1-\sigma_F}} = \hat{P}_i^W \left(\sum_j \lambda_{ij} (\hat{P}_j^F)^{\sigma_F - 1}\right)^{\frac{1}{1-\sigma_F}}$$

Then, proceed:

$$\begin{aligned}
\hat{\varphi}_N^* < \hat{\varphi}_K^* \iff & \left((\hat{P}_N^W)^{1-\sigma_F} \lambda_{NN} (\hat{P}_N^F)^{\sigma_F - 1} + (\hat{P}_N^W)^{1-\sigma_F} \lambda_{NK} (\hat{P}_K^F)^{\sigma_F - 1}\right)^{\frac{1}{1-\sigma_F}} \\
& < \left((\hat{P}_K^W)^{1-\sigma_F} \lambda_{KK} (\hat{P}_K^F)^{\sigma_F - 1} + (\hat{P}_K^W)^{1-\sigma_F} \lambda_{KN} (\hat{P}_N^F)^{\sigma_F - 1}\right)^{\frac{1}{1-\sigma_F}} \qquad (18) \\
\iff & (\hat{P}_N^W)^{1-\sigma_F} \lambda_{NN} (\hat{P}_N^F)^{\sigma_F - 1} + (\hat{P}_N^W)^{1-\sigma_F} (1 - \lambda_{NN}) (\hat{P}_K^F)^{\sigma_F - 1} \\
& > (\hat{P}_K^W)^{1-\sigma_F} \lambda_{KK} (\hat{P}_K^F)^{\sigma_F - 1} + (\hat{P}_K^W)^{1-\sigma_F} (1 - \lambda_{KK}) (\hat{P}_N^F)^{\sigma_F - 1} \qquad (19)
\end{aligned}$$

We know that $\hat{P}_N^W < \hat{P}_K^W$, and

$$\hat{P}_N^F < \hat{P}_K^F \iff \left[\pi_{NN}^F (\hat{P}_N^W)^{1-\sigma_F} + \pi_{KN}^F (\hat{P}_K^W)^{1-\sigma_F}\right]^{\frac{1}{1-\sigma_F}} < \left[\pi_{KK}^F (\hat{P}_K^W)^{1-\sigma_F} + \pi_{NK}^F (\hat{P}_N^W)^{1-\sigma_F}\right]^{\frac{1}{1-\sigma_F}}$$

so then it must be that $\hat{P}_N^W < \hat{P}_N^F < \hat{P}_K^F < \hat{P}_K^W$. We claim the following:

* $(\hat{P}^W_N)^{1-\sigma_F}(\hat{P}^F_N)^{\sigma_F-1} > (\hat{P}^W_K)^{1-\sigma_F}(\hat{P}^F_K)^{\sigma_F-1}$ which follows from the inequality, since $\frac{\hat{P}^W_N}{\hat{P}^F_N} < 1$ and $\frac{\hat{P}^W_K}{\hat{P}^F_K} > 1$
* $(\hat{P}^W_N)^{1-\sigma_F}(\hat{P}^F_K)^{\sigma_F-1} > (\hat{P}^W_K)^{1-\sigma_F}(\hat{P}^F_N)^{\sigma_F-1}$ which follows immediately.

Since the last expression is a convex combination of these two conditions added together, we are done.

□

Theorem 5 (Flour mill location effect)**.** $\hat{M}^*_N > \hat{M}^*_K$

Proof. $\hat{M}^*_N > \hat{M}^*_K \iff \hat{M}_N \frac{(1-G(\varphi'_N))}{(1-G(\varphi'_N)} > \hat{M}_K \frac{(1-G(\varphi'_K))}{(1-G(\varphi'_K)} \iff \frac{(1-G(\varphi_N\hat{\varphi}_N))}{(1-G(\varphi_N)} > \frac{(1-G(\varphi_K\hat{\varphi}_K))}{(1-G(\varphi_K)}$. If $G(.)$ is pareto, then $1-G(\varphi) = A^{\theta_i}\varphi^{\theta_i}$. Then we need to show that:

$$\iff \frac{A^{\theta_N}\varphi_N^{\theta_N}\hat{\varphi}_N^{-\theta_N}}{A^{\theta_N}\varphi_N^{-\theta_N}} > \frac{A^{\theta_K}\varphi_K^{-\theta_K}\hat{\varphi}_K^{-\theta_K}}{A^{\theta_K}\varphi_K^{-\theta_K}} \iff \hat{\varphi}_N^{-\theta_N} > \hat{\varphi}_K^{-\theta_K} \iff \hat{\varphi}_N < \hat{\varphi}_K$$

which we show in Theorem 4. □

Theorem 6 (Decline of the Heartland)**.** $\Delta v_N > \Delta v_K$ and $\hat{L}_N > \hat{L}_K$.

Proof, Welfare.

$$\Delta v_N > \Delta v_K \iff v'_N - v_N > v'_K - v_K \iff -\ln\left(\hat{P}^F_N\right) - \frac{\sigma_F}{\sigma_F-1}\Delta P^F_N > -\ln\left(\hat{P}^F_K\right) - \frac{\sigma_F}{\sigma_F-1}\Delta P^F_K$$

From Theorem 2 we know that $\hat{P}^F_N < \hat{P}^F_K \iff -\ln\left(\hat{P}^F_N\right) > -\ln\left(\hat{P}^F_K\right)$. Then $\pi^W_{NN} < \pi^W_{KK} \iff P^W_N > P^W_K \iff P^F_N > P^F_K, P^F_N > P^F_K \iff -P^F_N < -P^F_K$. By proposition 2, $\hat{P}^F_N < \hat{P}^F_K \iff \hat{P}^F_N - 1 < \hat{P}^F_K - 1 < 0$. Multiplying these together (since both are negative) yields,

$$-P^F_N(\hat{P}^F_N - 1) > -P^F_K(\hat{P}^F_K - 1)$$

Multiplying through by the positive constant $\frac{\sigma_F}{\sigma_F-1}$ and adding to our original condition yields the result. □

Proof, Population. $\hat{L}_N > \hat{L}_K \iff \frac{exp(v'_N-v_N)}{\lambda_N exp(v'_N-v_N)+(1-\lambda_N)exp(v'_K-v_K)} > \frac{exp(v'_K-v_K)}{\lambda_N exp(v'_N-v_N)+(1-\lambda_N)exp(v'_K-v_K)} \iff$ $exp(v'_N - v_N) > exp(v'_K - v_K)$ which is true by the above welfare result. □

C.2.2 Auxiliary Propositions

Proposition 1 (Primitives imply condition)**.** Suppose that $\frac{T_K^M}{T_N^M} < \frac{T_{\mathrm{K}}^W}{T_{\mathrm{N}}^W}$. Then, $\pi_{NN}^W < \pi_{KK}^W$.

Proof.

$$\pi_{NN}^W < \pi_{KK}^W \iff \frac{\left(w_N T_{\mathrm{N}}^W\right)^{\sigma_W - 1}}{\left(w_N T_{\mathrm{N}}^W\right)^{\sigma_W - 1} + (\tau^W)^{1-\sigma_W}\left(w_K T_{\mathrm{K}}^W\right)^{\sigma_W - 1}} < \frac{\left(w_K T_{\mathrm{K}}^W\right)^{\sigma_W - 1}}{\left(w_K T_{\mathrm{K}}^W\right)^{\sigma_W - 1} + (\tau^W)^{1-\sigma_W}\left(w_N T_{\mathrm{N}}^W\right)^{\sigma_W - 1}}$$

$$\iff \left(w_N T_{\mathrm{N}}^W\right)^{\sigma_W - 1}\left(\left(w_K T_{\mathrm{K}}^W\right)^{\sigma_W - 1} + \left(\tau^W\right)^{1-\sigma_W}\left(w_N T_{\mathrm{N}}^W\right)^{\sigma_W - 1}\right)$$

$$< \left(w_K T_{\mathrm{K}}^W\right)^{\sigma_W - 1}\left(\left(w_N T_{\mathrm{N}}^W\right)^{\sigma_W - 1} + \left(\tau^W\right)^{1-\sigma_W}\left(w_K T_{\mathrm{K}}^W\right)^{\sigma_W - 1}\right)$$

$$\iff \left(w_N T_{\mathrm{N}}^W\right)^{\sigma_W - 1}\left(\left(\tau^W\right)^{1-\sigma_W}\left(w_N T_{\mathrm{N}}^W\right)^{\sigma_W - 1}\right) < \left(w_K T_{\mathrm{K}}^W\right)^{\sigma_W - 1}\left(\left(\tau^W\right)^{1-\sigma_W}\left(w_K T_{\mathrm{K}}^W\right)^{\sigma_W - 1}\right)$$

$$\iff \left(w_N T_{\mathrm{N}}^W\right)^{2(\sigma_W - 1)} < \left(w_K T_{\mathrm{K}}^W\right)^{2(\sigma_W - 1)} \iff \left(w_N T_{\mathrm{N}}^W\right)^{\sigma_W - 1}$$

$$< \left(w_K T_{\mathrm{K}}^W\right)^{\sigma_W - 1} \iff w_N T_{\mathrm{N}}^W < w_K T_{\mathrm{K}}^W$$

Then, since $w_i = \frac{1}{T_i^M}$,

$$\iff \frac{1}{T_N^M} T_{\mathrm{N}}^W < \frac{1}{T_K^M} T_{\mathrm{K}}^W \iff \frac{T_K^M}{T_N^M} < \frac{T_{\mathrm{K}}^W}{T_{\mathrm{N}}^W}$$

which is true by assumption. □

Proposition 2. $\pi_{KK}^F > \pi_{KN}^F$

Proof. Denote $v_i = w_i^{\omega}(P_i^W)^{1-\omega}/T_i^F$.

$$\pi_{KK}^F > \pi_{KN}^F \iff \frac{v_K^{1-\sigma_F}}{v_K^{1-\sigma_F} + (\tau^F)^{1-\sigma_F} v_N^{1-\sigma_F}} > \frac{(\tau^F)^{1-\sigma_F} v_K^{1-\sigma_F}}{(\tau^F)^{1-\sigma_F} v_K^{1-\sigma_F} + \tau^F v_N^{1-\sigma_F}}$$

$$\iff \frac{1}{v_K^{1-\sigma_F} + (\tau^F)^{1-\sigma_F} v_N^{1-\sigma_F}} > \frac{(\tau^F)^{1-\sigma_F}}{(\tau^F)^{1-\sigma_F} v_K^{1-\sigma_F} + v_N^{1-\sigma_F}}$$

$$\iff (\tau^F)^{1-\sigma_F} v_K^{1-\sigma_F} + v_N^{1-\sigma_F} > \left(v_K^{1-\sigma_F} + (\tau^F)^{1-\sigma_F} v_N^{1-\sigma_F}\right)(\tau^F)^{1-\sigma_F}$$

$$\iff 1 > (\tau^F)^{1-\sigma_F} \iff 1 < \tau^F$$

which is true since trade is costly. □

Proposition 3. If $\pi^W_{NN} < \pi^W_{KK}$ and $\hat{\tau}^W < 1$, then $\hat{P}^W_N < \hat{P}^W_K$.

Proof.

$$\hat{\tau}^W < 1 \iff \left(\hat{\tau}^W\right)^{1-\sigma_W} > 1 \iff \pi^W_{NN} - \pi^W_{KK} > \left(\hat{\tau}^W\right)^{1-\sigma_W} (\pi^W_{NN} - \pi^W_{KK})$$

since $\pi^W_{NN} - \pi^W_{KK} < 0$.

$$\iff \pi^W_{NN} - \pi^W_{KK} + \left(\hat{\tau}^W\right)^{1-\sigma_W} > \left(\hat{\tau}^W\right)^{1-\sigma_W} \pi^W_{NN} - \left(\hat{\tau}^W\right)^{1-\sigma_W} \pi^W_{KK} + \left(\hat{\tau}^W\right)^{1-\sigma_W}$$

$$\iff \pi^W_{NN} + (1 - \pi^W_{NN}) \left(\hat{\tau}^W\right)^{1-\sigma_W} > \pi^W_{KK} + (1 - \pi^W_{KK}) \left(\hat{\tau}^W\right)^{1-\sigma_W}$$

since $1 - \pi^W_{ii} = \pi^W_{ni}$:

$$\pi^W_{NN} + \pi^W_{KN} \left(\hat{\tau}^W\right)^{1-\sigma_W} > \pi^W_{KK} + \pi^W_{NK} \left(\hat{\tau}^W\right)^{1-\sigma_W}$$

$$\iff \left[\pi^W_{NN} + \pi^W_{KN} \left(\hat{\tau}^W\right)^{1-\sigma_W}\right]^{\frac{1}{1-\sigma_W}} < \left[\pi^W_{KK} + \pi^W_{NK} \left(\hat{\tau}^W\right)^{1-\sigma_W}\right]^{\frac{1}{1-\sigma_W}} \iff \hat{P}^W_N < \hat{P}^W_K$$

□

C.3 Model in Changes: System of Equations

Given parameter estimates for σ_F and σ_W, changes in total population $\hat{L}$, changes in productivities $\hat{T}^F_i$, $\hat{T}^W_i$, and $\hat{T}^M_i$, changes in trade costs $\hat{\tau}^F_{ji}$, $\hat{\tau}^W_{ji}$, measures of the initial import shares for wheat and flour π^W_{ji}, π^F_{ji}, the initial export shares for wheat and flour Π^W_{ji}, Π^F_{ji}, population shares, λ_i and the initial price of flour, changes in allocations $\{\Delta v_i, \hat{\lambda}_i, \hat{L}_i, \hat{c}^F_{ni}, \hat{c}^W_{ni}, \hat{Y}^F_i, \hat{Y}^W_i\}$ and in prices $\{\hat{w}_i, \hat{p}^F_{ni}, \hat{p}^W_{ni}, \hat{P}^F_i, \hat{P}^W_i\}$ are given by:

$$\hat{w}_i = \hat{T}^M_i \tag{20}$$

$$\hat{p}^W_{ni} = \frac{\hat{w}_n}{\hat{T}^W_n} \hat{\tau}^W_{ni} \tag{21}$$

$$\hat{p}_{ij}^{F} = \frac{\hat{P}_i^W}{\hat{T}_i^F}\hat{\tau}_{ni}^{F} \quad (22)$$

$$\hat{P}_i^F = \left(\sum_n \pi_{ni}^F (\hat{p}_{ni}^F)^{1-\sigma_F}\right)^{\frac{1}{1-\sigma_F}} \quad (23)$$

$$\hat{P}_i^W = \left(\sum_n \pi_{ni}^W (\hat{p}_{ni}^W)^{1-\sigma_W}\right)^{\frac{1}{1-\sigma_W}} \quad (24)$$

$$\hat{L}_i = \hat{L}\hat{\lambda}_i \quad (25)$$

$$\hat{\lambda}_i = \frac{exp(\Delta v_i)}{\sum_n \lambda_n exp(\Delta v_n)} \quad (26)$$

$$\Delta v_i = \Delta w_i - \ln\left(\hat{P}_i^F\right) - \frac{\sigma_F}{\sigma_F - 1}\Delta P_i^F \quad (27)$$

$$\hat{Y}_i^F = \sum_j \hat{\tau}_{ij}^F \Pi_{ij}^F \hat{c}_{ij}^F \quad (28)$$

$$\hat{Y}_i^W = \sum_j \hat{\tau}_{ij}^W \Pi_{ij}^W \hat{c}_{ij}^W \quad (29)$$

$$\hat{c}_{ni}^W = \frac{\hat{Y}_i^F}{\hat{T}_i}\left(\hat{p}_{ji}^W\right)^{-\sigma_W}\left(\hat{P}_i^W\right)^{\sigma_W} \quad (30)$$

$$\hat{c}_{ji}^F = \left(\hat{p}_{ji}^F\right)^{-\sigma_F}\left(\hat{P}_i^F\right)^{\sigma_F - 1} \quad (31)$$

C.4 Quantitative Model

The baseline model is outlined in Section 4. Below I define an equilibrium in changes, where $\hat{x} = x'/x$.

C.4.1 System of Equations in Changes

Given parameters $\{\epsilon, \theta_j, \gamma_n^j, \gamma_n^{j,p}, \alpha_n^j, \delta_n^j\}$, data on $\{L_n, l_n, P_n, \lambda_n, w_n, r_n, D_n, \pi_{in}^j\}$, and changes in the exogenous variables $\{\hat{L}, \hat{\tau}_{ni}^k\}$, an equilibrium is a set of changes in allocations $\{\hat{v}_n, \hat{I}_n, \hat{c}_n^k, \hat{\pi}_{ni}^k, \hat{L}_n, X_n^{k'}, \hat{Y}_n^k, \hat{D}_n\}$ and prices $\{\hat{P}_n^k, \hat{w}_n, \hat{r}_n\}$ for a total of $6N + 4KN + KN^2$ unknowns that are defined by the following set of $6N + 4KN + KN^2$ equations:

$$N \qquad \hat{v}_n = \hat{I}_n \cdot \Pi_{k=1}^K \left(\hat{P}_n^k\right)^{-\alpha_n^k} \quad (32)$$

$$N \qquad I_n' = \hat{w}_n w_n + \frac{r_n \hat{r}_n l_n + D_n'}{L_n \hat{L}_n} \quad (33)$$

$$N \qquad \hat{L}_n = \hat{L}\frac{\hat{v}_n^{\epsilon}}{\sum_n \lambda_n \hat{v}_n^{\epsilon}} \quad (34)$$

$$N^2K \qquad \hat{\pi}_{in}^k = \frac{(\hat{\tau}_{in}^k \hat{c}_i^k)^{-\theta_k}}{\sum_i \pi_{in}^k (\hat{\tau}_{in}^k \hat{c}_i^k)^{-\theta_k}} \quad (35)$$

$$NK \qquad \hat{c}_n^j = \hat{w}_n^{\gamma^j} \hat{r}_n^{\delta_j} \prod_p^K \left(\hat{P}_n^p\right)^{\gamma^{p,j}} \quad (36)$$

$$NK \qquad X_n^{k'} = \alpha^k L_n \hat{L}_n I_n' + \sum_{j=1}^K \gamma_n^{k,j} \sum_{i=1}^N X_i^{j'} \pi_{in}^j \hat{\pi}_{in}^j \quad (37)$$

$$NK \qquad Y_n^k \hat{Y}_n^k = \sum_i X_i^{k'} \hat{\pi}_{ni}^k \pi_{ni}^{k'} \tag{38}$$

$$N \qquad D_n' = \sum_k \sum_i \pi_{in}^k \hat{\pi}_{in}^k X_n^{k'} - \sum_k \sum_i \hat{\pi}_{ni}^k X_i^{k'} \pi_{ni}^k \tag{39}$$

$$N \qquad \hat{w}_n w_n \hat{L}_n L_n = \sum_j \omega_n^j \gamma_n^j Y_n^{j'} \tag{40}$$

$$N \qquad \hat{r}_n r_n l_n = \sum_j (1 - \omega_n^j) \gamma_n^j Y_n^{j'} \tag{41}$$

$$NK \qquad \hat{P}_n^k = \left[\sum_i \pi_{in}^k \left(\hat{c}_i^k \hat{\tau}_{in}^k \right)^{-\theta_k} \right]^{\frac{1}{-\theta_k}} \tag{42}$$

C.4.2 Solving the Model

I solve the model using Python's optimization routines and the following algorithm:

1. Guess values for wages $\hat{w}_n$, rents $\hat{r}_n$, population $\hat{L}_n$, prices, $\hat{P}_n^j$, and spending X_n^j.
2. Given the guess for prices, construct $\hat{c}_n^j$ from equation 36.
3. Construct a model-implied value for prices $\tilde{\hat{P}}_n^j$ from equation 42.
4. Construct $\hat{\pi}_{in}^k$ from equation 35.
5. Construct $Y_n' = Y_n \hat{Y}_n$ from equation 38.
6. Construct trade imbalances D_n' from equation 39 using the guess for spending.
7. Using population, wage, and rental rate guesses, plus trade imbalance from above, construct per-capita income in the post period I_n' from equation 33.
8. Compute changes in welfare from equation 32, and model-implied changes in population $\tilde{\hat{L}}_n$ from equation 34.
9. Compute a model-implied value of spending $\tilde{X}_n^{k'}$ from 37.
10. Form objective function based on:

$$
\begin{aligned}
0 &= \hat{P}_n^j - \tilde{\hat{P}}_n^j \\
0 &= \hat{L}_n - \tilde{\hat{L}}_n \\
0 &= \tilde{X}_n^{k'} - X_n^{k'} \\
0 &= \hat{r}_n - \frac{\sum_j (1-\omega_n^j) \gamma_n^j Y_n^{j'}}{r_n l_n} \\
0 &= \hat{w}_n - \frac{\sum_j \omega_n^j \gamma_n^j Y_n^{j'}}{w_n L_n \hat{L}_n}
\end{aligned}
$$

where the last two lines come from equations 41 and 40 respectively. The optimization procedure then iterates through steps 1 through 10 until all values of 10 are zero.

C.4.3 Quantifying Trade Costs

To feed bilateral changes in trade costs into the model, I want to measure initial trade costs along each pair of locations. I assume that trade costs between two locations are the product of the railroad distance of the route and a constant X, which coverts distance to revenue: $\tau_{od} = km_{od}^{\kappa} \cdot X$. If I observed revenue per ton earned along every route, then I could use that to measure initial trade costs along each pair of states. However, I do not observe this in the data for every route since there is no trade in agricultural products along some routes. Aggregating over every route where $revenue_{od} > 0$, I can compute total RTM:

$$RTM = \frac{\sum_{od} revenue_{od}}{\sum_{o'd'} tons_{o'd'} \cdot km_{o'd'}}$$

Then, since $revenue_{od} = c_o \tau_{od} Ton_{od}$, I can re-write this as:

$$RTM = \frac{\sum_{od} c_o \tau_{od} Ton_{od}}{\sum_{o'd'} tons_{o'd'} \cdot km_{o'd'}} = \frac{\sum_{od} c_o km_{od}^{\kappa} \cdot X \cdot Ton_{od}}{\sum_{o'd'} tons_{o'd'} \cdot km_{o'd'}} = X \frac{\sum_{od} c_o km_{od}^{\kappa} \cdot Ton_{od}}{\sum_{o'd'} tons_{o'd'} \cdot km_{o'd'}}$$

Setting these two equal to each other and solving for X:

$$\frac{\sum_{od} revenue_{od}}{\sum_{o'd'} tons_{o'd'} \cdot km_{o'd'}} = X \frac{\sum_{od} c_o \cdot km_{od}^{\kappa} \cdot Ton_{od}}{\sum_{o'd'} tons_{o'd'} \cdot km_{o'd'}} \implies X = \frac{\frac{\sum_{od} revenue_{od}}{\sum_{o'd'} tons_{o'd'} \cdot km_{o'd'}}}{\frac{\sum_{od} c_o \cdot km_{od}^{\kappa} \cdot Ton_{od}}{\sum_{o'd'} tons_{o'd'} \cdot km_{o'd'}}}$$

I measure c_o, which is the cost of producing agricultural goods at location o as the dollar value received for a unit of wheat in state o, measured from the USDA in 1950. Given this estimate of X, I solve for initial trade costs across all locations.