Trade Frictions and Micro-Price Behaviors: Historical Applications from the United States

By

James Harrison

Dissertation

Submitted to the Faculty of the

Graduate School of Vanderbilt University

in partial fulfillment of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

in

Economics

August 10, 2018

Nashville, Tennessee

Approved:

Mario Crucini, Ph.D.

Bill Collins, Ph.D.

Joel Rodrigue, Ph.D.

Bob Whaley, Ph.D.

ACKNOWLEDGMENTS

I am grateful to my dissertation committee for their invaluable encouragement, advice, and time. I would not be where I am without Mario Crucini – his contributions to my success would be too long to list. Bill Collins and Peter Rousseau fostered my interest in economic history and have been incredilby supportive throughout my graduate career. Joel Rodrigue provided insighful input and guidance. Bob Whaley was generous with his time. I could not have asked for a better committee.

Other Vanderbilt faculty were also crucial for my success. Jeremy Atack was a wealth of information about data sources, publications, and history – Google should index his brain. Ariel Zimran helped guide me through the job market and provided support when it was sorely needed. Eric Bond fostered my interest in international trade; both he and Matthew Zaragoza-Watkins provided useful feedback for my dissertation. Last but not least, Stephanie So was one of my biggest cheerleaders. She backed me in every possible way, from going the extra mile for my teaching references to being a bedrock of emotional support.

I am also appreciative for the graduate students who have provided me with advice, input, and friendship. I would not have made it through this program without my amazing cohort – Sebastian Tello-Trillo, Jonah Yuen, Jason Campbell, and Matt French. I also am grateful for the companionship of (take a deep breath) Daniel Mangrum, Nina Mangrum, Katie Yewell, Siraj Bawa, Aaron Gamino, Nicolas Maeder, Paul Niekamp, Alyssa Niekamp, Martin Van der Linden, Emily Burchfield, Michael Mathes, Katie Fritzdixon, Andy Fredrickson, Nam Vu, Hakan Tunc, Kate Brady, Karen Shaw, Danielle Drory, Alper Arslan, Dong Cheng, Salama Freed, Chris Cotter, Adam Watkins, Melissa Icenhour, Sarah Wiesen, Joseph Gardella, Gracie Hao, Bernes Karacay, Emily Lawler, Ben Ward, Ayse Sapci, Michael Moody, Craig Benedict, Brantly Callaway, and Nayana Bose. Each of you made my graduate career that much more amazing.

Lastly, I am thankful to my family who has supported me every step of the way. They believed in me even when I didn't.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Surprisingly little is known about the types of frictions that impede trade. Economists typically focus on freight costs and tariffs as comprising the bulk of trade frictions; however, recent reviews of the literature have demonstrated these frictions do not adequately explain observed patterns of trade (Anderson and van Wincoop 2004, Head and Mayer 2013a, Head and Mayer 2013b). This dissertation examines how traditionally under-analyzed trade frictions shape price and export behaviors. In the first chapter, I build an arbitrage model to show freight costs, information lags, and storage costs uniquely impact cross-city price behaviors at the trend, cycle, and seasonal frequencies, respectively. In the second chapter, I empirically estimate the impact of information frictions by exploiting the spread of the telegraph across the United States as an historical experiment that exogenously decreased news lags across markets. In the third chapter, I explore how the deflation of the Great Depression worsened Smoot-Hawley tariffs that were legislated in nominal terms. In all of these chapters, my data consist of price and trade volumes for highly disaggregated goods, and I focus on historical settings because they provide substantial variation in the trade frictions of interest.

In the first chapter, I demonstrate the usefulness of decomposing prices into trend, cycle, and seasonal frequencies by uncovering unique convergent behaviors at each frequency during the US transportation revolution. I then construct an arbitrage model to determine how these behaviors were driven by freight costs, information lags, and storage costs. I find that freight costs accounted for 94% of the decline in price trend differentials, storage costs accounted for 78% of the decline in the seasonal magnitude of prices, and information lags were important for determining cyclical price correlations. These results lead to three conclusions. First, there is an interesting mapping between trade frictions and frequencies of cross-city price behavior. Second, information lags and storage costs – two frictions that are often overlooked because they cannot be subsumed into iceberg transportation costs – are important determinants of cross-city price behavior. Third, the US experienced a massive convergence in commodity prices during the transportation revolution.

I narrow my focus to information frictions in the second chapter to take advantage of high-frequency data on news delays. I use the spread of the telegraph across the United States as an historical experiment that exogenously decreased news lags across markets. I use the resulting variation in daily news lags to empirically test Steinwender's (2018) model of arbitrage in the presence of information frictions. My results for the cotton trade between New Orleans and New York are broadly consistent with her model – I find the telegraph decreased price differentials by 21.2%, decreased the variance of these differentials by 62.4%, increased export volatility by 42.3%, and increased exports by 5.6%. These results suggest the importance of traditionally unobserved trade frictions, such as information lags, in determining economic outcomes.

In the third chapter, I use a broad panel of imports to determine the degree to which Smoot-Hawley distorted tariff burdens and import volumes. The balanced panel is the largest of its kind, consisting of 926 goods between 1926 and 1933. This panel allows me to leverage microeconometric techniques and to analyze a wider array of industries than previous literature. I find Smoot-Hawley can only explain about 30% of the increase in tariffs on dutiable imports and 5% of the decline in aggregate import volumes, while the remainder can be explained by nominal distortions and changes in national income. These results are broadly consistent with the previous literature by Crucini (1994) and Irwin (1998b).

Overall, these findings underscore the importance of traditionally under-analyzed trade frictions in distorting trade behaviors – freight costs are important for determining long-run price differentials, information lags cause substantial short-run variation in export and price behaviors, and storage costs impact the seasonal magnitudes of prices. This suggests economists and policy makers should be more attuned to the myriad ways in which seemingly unimportant or unrelated frictions impact trade behaviors.

CHAPTER 1

HOW DO TRADE FRICTIONS DIFFERENTIALLY IMPACT TRADE OUTCOMES? LESSONS FROM THE US TRANSPORTATION REVOLUTION

1.1 Introduction

Economists have long been puzzled by the size and persistence of price differentials across locations. What is preventing arbitrage of these price differentials? Two branches of literature have approached this question from different angles. The international finance literature has traditionally focused on the importance of volatile nominal exchange rates in creating differences between sticky prices (Mussa 1986, Engel and Rogers 1996). However, recent studies of disaggregated goods find that nominal exchange rates explain only a fraction of price differentials (Crucini and Telmer 2012), and price differentials persist even under fixed exchange rate regimes (Rogoff, Froot and Kim 2001). On the other hand, the international trade literature has traditionally focused on the importance of trade frictions that can be modeled as iceberg transportation costs, such as freight costs and tariffs. However, gravity models suggest that freight costs and tariffs are not onerous enough to explain the observed pattern of international trade (Anderson and van Wincoop 2004).

What explains the persistence of these price differentials if freight rates, tariffs, and nominal exchange rates do not? Recent literature has begun to focus on the importance of transportation frictions that cannot be subsumed by iceberg transportation costs, such as information lags (Allen 2014, Steinwender 2018) and transportation lags (Djankov, Freund and Pham 2010, Hummels and Schaur 2013, Coleman 2009). I expand upon this literature by constructing a model to compare how freight costs, information lags, and storage costs differentially impact price behaviors. I find each friction largely impacts prices at different frequencies (trend, cycle, seasonal), in effect giving each friction a unique frequency "signature." In particular, I find that during the US transportation revolution (1820-1860), freight costs accounted for 94% of the decline in long-run price trend differentials, storage costs accounted for 78% of the decline in seasonal price fluctuations, and information frictions were important for determining cyclical price correlations (provided that freight costs are sufficiently low).

I use the transportation revolution to study the impact of trade frictions for several reasons. First, modern freight data is often proprietary and must control for substitution between competing modes (e.g. land, sea, and air) (Hummels 2007). Second, information lags can be difficult to measure in modern data (Anderson and van Wincoop 2004, Steinwender 2018). Third, modern trade frictions offer comparatively little time-variation, so their effects are difficult to identify (Williamson and O'Rourke 1999). Historical newspapers offer solutions to these issues by providing highly time-varying data on prices, freight costs, insurance rates, storage costs, and information lags[1].

I begin by decomposing a newly digitized panel of monthly wholesale prices by frequency for 15 commodities in five US cities from 1820-1860. This decomposition is helpful because each frequency heuristically embodies a different arbitrage activity -- differences in price trends demonstrate arbitragers' ability to equalize prices across locations, the correlation of cyclical deviations indicate the speed with which arbitragers can identify and exploit shocks, and magnitudes of seasonal price swings represent arbitragers' adeptness at smoothing deterministic seasonal fluctuations. I find that arbitragers improved their ability to equalize long run prices, exploit stochastic shocks, and smooth deterministic seasonality throughout the transportation revolution.

Which trade frictions are responsible for the results at each frequency? At first glance, it may seem straightforward that price trend convergence is caused by declining freight costs (caused by the proliferation of railroads, canals, and steamboats), increasing cyclical price correlation is caused by faster information and transportation speeds (from the telegraph and steam engine), and dampening seasonal magnitudes of price swings are caused by better storage (due to warehouses, silos, and preservation techniques). However, an improved use of storage can be used to exploit seasonal freight costs to reduce price trend differentials, a decreasing frequency of autarky can improve cyclical price correlation, and a dampening of freight cost seasonality may reduce seasonal magnitudes of prices.

I use a structural estimation to disentangle the impacts of trade frictions at each frequency. I construct a two-location partial equilibrium arbitrage model in which every period agents choose to export, store, or sell an exogenously produced seasonal commodity (Coleman 2009). I then subject agents to freight costs, information lags (Steinwender 2018), and storage costs (Williams & Wright 1991) to determine how arbitrage behaviors respond at each frequency.

I calibrate the model to the flour trade between Cincinnati and New Orleans, and the paucity of data requires creative estimation strategies. The paper's most novel calibrations include estimating stochastic supply shocks using weather obtained from historical tree rings, predicting flour demand elasticities from trade flows through Chicago, and extracting unobserved freight costs from bilateral price differentials with a dynamic factor model. Other parameters are also calibrated to historical data, much of which I obtain from original sources such as newspapers and local chamber of commerce reports.

The contributions of the paper are threefold. First, they demonstrate an interesting mapping between trade frictions and different frequencies of arbitrage behavior. Second, they stress the importance of trade frictions that cannot be easily subsumed into iceberg transportation costs such as storage costs and information lags which are still important for rural markets in emerging economies. Third, they contribute to the historical narrative of a comparatively understudied period. I find that arbitragers became more adept at exploiting short-run shocks throughout the period while

[1] Information lags cannot be observed directly, but can be inferred from the rapidity with which news from distant markets that are published in local newspapers (**?**)

previous literature has found the opposite (Jacks 2005). I also find most improvements to arbitrage occurred before 1850, suggesting the importance of steamboats, warehouses, canals, and the telegraph over the railroad for antebellum market convergence.

1.2 Data

I demonstrate the usefulness of decomposing prices into trend, cycle, and seasonal frequencies using a newly digitized dataset of historical commodity prices.[2] The prices are obtained from Cole (1938) and consist of price quotes from historical newspapers that informed farmers of local commodity prices.[3] The Cole data contain the midpoint of prices observed in weekly newspapers on the date closest to the 15th of every month. The Cole (1938) contributors then supplemented and cross-checked these prices with ledgers from local merchants and institutions to ensure the veracity of the data.

I analyze price frequencies for a subset of the Cole data which consist of 15 commodities across five geographically diverse cities.[4] The basket of goods comprises roughly 36.8% of non-housing non-energy expenditures in the late nineteenth century, and the number of observations for each good is listed in Table 1.1.[5][6] The cities include Charleston on the South Atlantic, New Orleans on the Gulf of Mexico, Cincinnati in the Midwest, and New York and Philadelphia on the North Atlantic.[7] Figure 1.1 shows that three cities had immediate access to the Atlantic and could easily arbitrage between each other. On the other hand, New Orleans had larger transportation and information delays as it had to circumnavigate Florida to access the Atlantic. Finally, Cincinnati did not export directly to the East Coast because the Appalachians were difficult to traverse; Cincinnati will loom large in the results because it engaged in a lengthy and expensive trade via the Ohio and Mississippi Rivers with New Orleans which transshipped with the world market.[8]

[2] The dataset is freely available at the Center for International Price Research at `http://.centerforinternationalprices.org/micro-price-data/cole-historical-data/`

[3] The prices in Cole (1938) are compiled from price histories that were funded by the International Scientific Committee on Price History (ISCPH) and include studies of prices in Boston (Crandall 1934), Charleston (Taylor 1932a, Taylor 1932b) Cincinnati (Berry 1943), New Orleans (Taylor 1931), New York (Warren and Peasron 1932, Stoker 1932), and Philadelphia (Bezanson, Gray and Hussey 1935, Bezanson and Gray 1937, Bezanson 1951, Bezanson 1954).

[4] The unbalanced nature of the Cole panel makes it difficult to determine how the impacts of trade frictions evolved. Although the panel spans from 1700-1860 across 46 goods of 549 product types in six cities, only six price series are observed in 1700 while 169 are observed in 1859. I prune the price series to provide a balanced panel from which the impact of trade frictions can be consistently determined.

I prune using three criteria. First, I remove all series that are not observed in at least 85% of periods to avoid excessive interpolation. Second, I exclude all goods that are not observed in at least three cities to ensure that geographical integration can be gleaned from the data. Third, I eliminate any series with substantial quality differences between locations or over time. Small-to-moderate quality differences remain, and this may bias my results for price convergence (Persson 2004). However, the wideness of the panel ameliorates this issue by "averaging out" the bias across many goods. In addition, I avoid bilateral calculations that are sensitive to changes in quality.

[5] The expenditure data are constructed by Hoover (1960). Hoover constructs expenditures by major group (food, clothing, etc.) from an 1875 survey on expenditures by the Massachusetts Bureau of Statistics and Labor. Expenditures by major group are then broken down into minor groups using data from the Aldrich Report (1890-1891). My calculation interprets Hoover's qualities loosely. For example, I treat both "superfine" and "extra family" flour simply as "flour." My calculated expenditure share likely understates the actual share because I omit intermediate goods such as cotton and nails that are made into clothing and housing.

[6] Missing observations are interpolated using the conditional distribution from the state space modeling of price series from equation 1.1

[7] Boston is dropped from the sample due to a lack of observations after 1797.

[8] All cities in the panel have access to some form of water transport; therefore, the panel will underestimate the importance of the railroad. However, landlocked cities tended to be sparsely populated until after the introduction of the railroad, while the observed cities were among the

Trade patterns will prove important when exploring the behaviors of price frequencies. The Midwest grew wheat and corn, but these had weight-to-value ratios that made exporting unprofitable. Instead, Cincinnati turned wheat into flour and corn into whiskey and pig feed which had more favorable weight-to-value ratios. New Orleans transshipped these goods in addition to sugar, molasses, and cotton to the East Coast which often exchanged manufactured goods or specie for these goods.

Two other studies have used the Cole panel to study antebellum price convergence. Slaughter (2001) compares annual rates of price and wage convergence for a total of 1,080 price observations. I use a a monthly frequency to analyze barriers to short-run arbitrage, which when combined with a broader panel of goods gives a total of 31,680 observations. Jacks (2005, 2006) uses the Cole data in threshold autoregression analysis of historical wheat prices from 101 cities around the world. To the degree that my calculations are comparable, I corroborate Jacks' finding of declining freight costs between 1820 and 1860, but I contradict his finding of worsening speeds of price adjustment from 1820-1860. This may be caused by his reliance on wheat as the only good in his panel. This is an understandable feature of a panel that spans an impressive 101 cities around the world, but it may give misleading results if wheat is not representative of commodities traded in the antebellum US.[9]

1.3 Price Frequency Decomposition

I decompose the Cole prices into trend, cycle, and seasonal frequencies to demonstrate a novel mapping between arbitrage activities and frequencies of price behaviors. I use a structural time series model to decompose log prices as

$$p_{ijt} = p^T_{ijt} + p^C_{ijt} + p^S_{ijt} + e_{ijt} \tag{1.1}$$

where i indexes goods, j indexes cities, and t indexes time.[10] The stochastic trend, p^T_{ijt}, captures long-run movements in the data, the stochastic cycle, p^C_{ijt}, embodies short-run percentage deviations from this trend, and the seasonal, p^S_{ijt}, captures seasonally deterministic fluctuations.[11]

The cross-city dispersion of price trends embodies persistent trade costs between locations. Panel 1 of Figure 1.2 shows an example of this using flour prices. The sample begins with substantial price dispersion that declines as exporters found it cheaper to arbitrage between Cincinnati and the rest of the country. Such convergence may have resulted from lower long-run freight costs as arbitragers adopted new technologies, such as steamboats and railroads, or new infrastructure, such as canals and river dredging.

largest in the country.

[9] Indeed, wheat's weight-to-value ratio was too high in the US to be commonly traded before the advent of railroads.

[10] Other authors have used non-parametric frequency decompositions, such as fourier (Granger and Elliot 1967) and wavelet decompositions (Andersson and Ljungberg 2015), to explore the impact of trade frictions on price behaviors. However, it is not clear how to map these non-parametric price frequencies to arbitrage behaviors.

[11] The stochastic trend is extracted using a spline that has a signal-to-noise ratio analogous to the Hodrick-Prescott filter, the stochastic cycle is obtained using an ARMA specification, and the seasonal is composed of stochastic monthly dummies subject to their own time-varying slopes. Technical details regarding the structural time series model are provided in Appendix **??**.

The cross-city co-movement of cyclical prices encapsulates the speed with which arbitragers identify and exploit a city's idiosyncratic shocks. Panel 2 of Figure 1.2 shows that New Orleans experienced substantial idiosyncratic flour price shocks at the beginning of the sample; however, cyclical price co-movement increased as arbitragers exploited price shocks with greater rapidity. This co-movement may have improved as transportation and information lags decreased with the adoption of the steamboat, railroad, and telegraph.

Seasonal price fluctuations reflect the ability of arbitragers to smooth seasonally deterministic price fluctuations. Panel 3 of Figure 1.2 demonstrates that New Orleans was subject to the vicissitudes of seasonal flour production and transportation costs until arbitragers became more adept at smoothing these seasonal processes. These fluctuations may have dampened with the adoption of storage technologies such as grain elevators and warehouses or with declining seasonal swings in freight costs due to shallow draft steam boats and river dredging.

This shows that flour price behaviors converged across all three frequencies and demonstrates the usefulness of the frequency decomposition. Are these findings unique to flour prices or are they consistent across the panel of Cole data? I answer this question by using the entire panel of Cole prices to explore the evolution of each frequency in turn.

1.3.1 Price Trends

In this subsection, I demonstrate the usefulness of mapping arbitrage behaviors to the trend frequency by studying price trend convergence across the panel of Cole prices. I calculate the dispersion of price trends across cities, $\bar{\sigma}_{it}^2 = var_j\left(p_{ijt}^T\right)$, average it across all goods, and plot it in Figure 1.3. Average dispersion declines by 75.7% over the sample and comes in two waves – the larger wave spans 1820-1830, after the introduction of the steamboat, and the smaller wave that spans 1850-1860, after the introduction of railroads. The relative sizes of these waves indicate the importance of declining river over rail transportation costs in the antebellum US and suggest that Cincinnati, the city with the highest river transportation costs, should experience the most price convergence. I decompose price dispersion by city and plot the shares in Figure 1.3.[12] Indeed, I find that Cincinnati explains 71.9% of the convergence while 10.4% of the convergence is attributable to Charleston, 8.4% to New Orleans, 6.2% to New York, and 3.1% to Philadelphia.[13] To what degree is this convergence shared across goods?

I find that barriers to arbitrage declined for all goods in the sample. I calculate the annual rate of sigma-convergence, $\sigma_{it} = \sqrt{var_j\left(p_{ijt}^T\right)}$, by good and present the results for each decade in the middle columns of Table 1.2.[14] All goods experienced sigma-convergence over the entire sample, and only a handful of goods experienced statistically significant sigma-divergence in any sub-period of the sample.[15] The average rate of sigma-convergence is 1.84% per year

[12]For details of the variance accounting technique, see Federico (2010). The basic premise is to calculate the fraction of average geographic price dispersion attributable to each good in a city and then sum over all goods.

[13]The block-boostrapped (by good) standard errors are 11.41, 7.26, 10.15, and 3.16, and 4.93 respectively.

[14]I use the geographic variance to calculate city shares because it is decomposable by city while its square root, sigma-convergence, is not. I use sigma-convergence to calculate the rate of convergence by good because it is a commonly used statistic that allows my results to be compared to other studies that have used sigma-convergence. I provide details on how I calculate the annual rate of sigma-convergence in Appendix **??**.

[15]Sigma divergence can be driven by local commodity cycles if goods are not traded between all cities in the sample.

from 1820-1860. How fast is this rate of convergence? Federico (2010) finds a convergence rate of 1.90% for wheat prices in European markets from 1816-1870 which compares to 2.3% in the antebellum US.[16]

Rates of sigma-convergence varied widely by good – pork exhibited the highest rate at 3.09% per year, while whiskey experienced the lowest rate at 0.64% per year. This variation in sigma-convergence can be largely explained by differing weight-to-value ratios across goods. Figure 1.4 shows that high weight-to-value goods, such as flour and molasses, have high price dispersion, while low weight-to-value goods, such as cotton and coffee, have low price dispersion – a relationship which weakens over time. [17]

Another result from Table 1.2 is that wheat and corn exhibit sigma-convergence during decades in which their weight-to-value ratio was too high to be profitably traded. The long-distance hauling of these crops remains rare until the use of railroads in the 1850s (Berry 1943); however, their prices exhibit sigma-convergence well before the advent of the railroad. What is causing this convergence? A possible explanation is that corn and wheat enter as factors of production into goods that have low enough weight-to-value ratios to be traded (e.g. pork, lard, bacon, flour, and whiskey). As the prices of these low weight-to-value goods converge, so do the prices of their inputs by factor price equalization.

1.3.2 Price Cycles

I now demonstrate the usefulness of mapping arbitrage behaviors to the cyclical frequency by studying price co-movement across the Cole panel. As trade frictions fall, speculators can better identify and exploit a city's idiosyncratic price shocks against those prevailing in the rest of the country, so the co-movement of cyclical prices increases across cities. I measure this degree of co-movement using a dynamic factor model.[18]

I specify the dynamic factor model for each commodity as

$$p^c_{jt} = \lambda_j(L)\,G_t + e_{jt} \tag{1.2}$$

where G_t is a dynamic factor which is common across all locations for a particular good. This dynamic factor embodies shocks that are common across all cities, but it is unobserved and must be extracted from the data using state space methods. The city-specific lag polynomial, $\lambda_j(L)$, allows these common shocks to impact local commodity prices

[16] These results should be interpreted with caution as they are sensitive to the small sample of cities included in each analysis.

[17] The relationship between the weight-to-value of a good and its price dispersion can be explained by freight costs being charged by weight in the mid-19th century (Berry 1943). Under this freight cost structure, a simple two-city model demonstrates that price dispersion is proportional to a good's weight-to-value ratio (Hummels 2010). Let W be a good's weight and F be the cost of shipping per pound from city j to j'. Bilateral prices are then described by $P_{j'} = P_j + FW$, so that $\frac{P_{j'}}{P_j} = \left(1 + F\frac{W}{P_j}\right)$. This shows that price dispersion, $\frac{P_{j'}}{P_j}$, declines as weight-to-value ratios, $\frac{W}{P_j}$, decline. Additionally, higher weight-to-value goods experience faster rates of price convergence for a given decline in freight costs, F. Therefore, weight-to-value ratios can explain much of the cross-good variation in sigma-convergence in Table 1.2.

[18] Dynamic factors are well-suited for panels of micro-price data for three main reasons. First, they allow co-movement to be detected with both lags and leads. This is useful when slow information or transportation speeds induce lag structures in price co-movement. Second, they do not imply positive trade between locations as bilateral calculations might. Third, they report a single statistic, the variance share of a price series that is attributable to the dynamic factor, which is easy to interpret (Uebele 2011).

differentially across both cities and time. The idiosyncratic price shocks, e_{jt}, represent local shocks that are not correlated across cities. The common and idiosyncratic shocks are allowed to have persistence, specified as

$$\begin{aligned} \psi_G(L)\,G_t &= \varepsilon_{G,t}, \quad \varepsilon_{G,t} \sim N\left(0, \sigma_G^2\right) \\ \psi_{jt}(L)\,e_{jt} &= \varepsilon_{jt}, \quad \varepsilon_{jt} \sim N\left(0, \sigma_j^2\right) \end{aligned} \tag{1.3}$$

where $\psi(L)$ are lag polynomials and ε are innovations.[19]

This model can be explained in the context of cyclical flour prices. Short-run flour price fluctuations are determined by common shocks, $G_{flour,t}$, and local shocks, $e_{flour,jt}$. Common shocks may include a bad wheat harvest or aggregate demand shocks, while local shocks may include insufficient local flour storage or local freight costs shocks. As trade frictions decline, exporters become increasingly able to arbitrage local flour price shocks against prices prevailing in the rest of the country, thereby increasing the share of flour price variation that can be explained by common price shocks.

I measure cyclical price co-movement by estimating a dynamic factor model for each good in overlapping ten-year windows every five years from 1820-1860 and calculating the share of cyclical price variation that is attributable to common shocks. I average variance shares by city and plot the results in Figure 1.5 where a variance share of 1 indicates perfect co-movement and a variance share of 0 indicates zero co-movement.

At the start of the sample, cities that had access to speedy arbitrage via the Atlantic were dominated by common shocks, while Cincinnati and New Orleans were dominated by local shocks. As transportation and information speeds increased with the proliferation of improvements such as the steam engine and telegraph, Cincinnati and New Orleans became more adept at arbitraging local shocks. Table 1.3 shows that all cities exhibit increases in price co-movement (all statistically significant except for Charleston), and all cities exhibit similar levels of price co-movement by the end of the sample.

Arbitragers became more efficient at exploiting price shocks in almost all sectors of the economy. Table 1.4 shows the variance shares aggregated by good. No good exhibits a statistically significant decline in cyclical price co-movement, while 12 of the 15 goods show statistically significant increases. Among the largest increases in price co-movement are attributable to pork products (bacon, lard, and pork), manufactured products (nails), and sugar products (molasses, sugar). These results help explain the rapid integration of Cincinnati and New Orleans into the national market – Cincinnati was a major exporter of pork products to New Orleans, and New Orleans was a major exporter of sugar products to the rest of the country.

[19]Technical details regarding the dynamic factor model are available in Appendix 1.8.

1.3.3 Price Seasonality

Here I demonstrate the usefulness of mapping arbitrage behaviors to the seasonal frequency by studying the magnitude of their fluctuations in the Cole panel as measured by their intra-year standard deviations. I plot the seasonal magnitudes averaged by city in Figure 1.6 which demonstrates two results. First, New Orleans and Cincinnati experienced greater seasonality than cities on the Atlantic, so easy access to the world market helped arbitragers smooth seasonal price fluctuations. Second, a consistent pattern emerges that price seasonality decreases from 1820 through the mid-1840s and then increases through 1860.[20] What causes this non-monotonicity in seasonal price smoothing?

Table 1.6 demonstrates that seasonal crops such as coffee, corn, cotton, sugar, and wheat (with rice being the exception) experienced the largest increases in seasonal price fluctuations after 1840. Assuming that storage capacities did not erode, this indicates that seasonal supply shocks outstripped arbitragers' abilities to cheaply ship or store them. There are two likely causes for this increase in seasonal shocks. First, seasonal crop production expanded as the farming population increased.[21] Second, falling trade costs allowed seasonal production to be funneled through trading centers from greater distances.

In juxtaposition, Cincinnati's major exports of flour, bacon, lard, and pork begin the sample with the largest seasonal fluctuations in prices; however, these prices also exhibited among the largest decreases in seasonality over time. This may indicate that storage capabilities improved or that seasonal fluctuations in freight costs declined.

The empirical analyses of the trend, cycle, and seasonal components have suggested that arbitragers became increasingly able to equalize prices across locations, exploit price shocks, and, to some degree, smooth seasonal price fluctuations. Although decomposing prices by frequency has helped to distinguish between different barriers to arbitrage, the relative importance of different theoretical trade frictions has yet to be explored at these frequencies.

1.4 Arbitrage Model

This section presents an arbitrage model to explain the price behaviors observed in the empirical sections. I build upon previous models by combining three time-varying trade frictions – freight costs, storage costs (Williams and Wright 1991), and information lags (Steinwender 2018) – in the presence of seasonality. To my knowledge, this is the first arbitrage model that allows for both trade and storage in the presence of seasonality. Seasonality combines with trade frictions in interesting ways that manifest in price behavior at the trend, cycle, and seasonal frequencies.

Suppose that Y_t flour is produced in Cincinnati every period. Agents then decide how much of the local production to consume, Q_t, or export, X_t, so that market clearing requires $Y_t = Q_t + X_t$. Local flour demand is defined by the iso-elastic demand curve $P_t^{Cin} = (Q_t/A_t)^{\beta}$ where β is the demand elasticity, P_t^{Cin} is the flour price in Cincinnati, and

[20] Standard errors were bootstrapped using the conditional distributions of the Kalman smoothed seasonal prices.

[21] This assumes that farmers produced more than they consumed, which is consistent with the increase in agricultural exports over this period.

$A_t = \gamma pop_t + u_t$ is the extent of the market at time t.

I model arbitragers as exporting flour from Cincinnati in partial equilibrium in return for a world price.[22] Exporters operate under perfect competition to maximize their profit function,

$$\pi_t = \max_{Y_t \geq X_t \geq 0} \{P_t^{NO} X_t - \tau_t X_t - P_t^{Cin} X_t\} \tag{1.4}$$

where $P_t^{NO} > P_t^{Cin}$ is the price in New Orleans and τ_t are freight costs. The profit-maximizing exporter equalizes the marginal benefits of exporting, P_t^{NO}, to the marginal costs, $P_t^{Cin} + \tau_t$, as long as exporting is profitable. That is,

$$\begin{aligned} P_t^{NO} &= P_t^{Cin} + \tau_t \quad \text{if } X_t > 0 \\ P_t^{NO} &\leq P_t^{Cin} + \tau_t \quad \text{if } X_t = 0 \end{aligned} \tag{1.5}$$

When marginal benefits outweigh marginal costs, exporters continue to ship until Cincinnati's prices increase to equal (net of freight costs) inelastic world prices. On the other hand, Cincinnati resorts to autarky when marginal benefits are outweighed by marginal costs.

Freight costs are a major determinant of price dispersion. If exports are positive, bilateral price differentials are determined entirely by freight costs, $P_t^{NO} - P_t^{Cin} = \tau_t$. Therefore, as freight costs decline, price dispersion declines. This relationship becomes more complex as I introduce seasonality, cyclicality, and storage to the model because it allows arbitragers to exploit fluctuations to reduce long-run price dispersion.

The frequency and duration of autarky are also important determinants of cyclical price co-movement. If $P_t^{NO} - \tau_t \leq P_t^{Cin}$, Cincinnati operates in autarky. Autarky implies that Cincinnati's prices do not respond to changes in world prices; therefore, cyclical price co-movement decreases. The frequency and duration of this autarky will be among the major determinants of cyclical price co-movement in the simulations. Therefore, I add richness to the length and duration of autarky by including cyclicality, seasonality, and storage in the model.

Cyclicality

I add cyclicality by assigning AR(1) dynamics to freight costs, world prices, and Cincinnati's flour demand. These shocks augment cyclical price co-movement by augmenting the frequency and duration of autarky and by inducing volatility in freight costs. However, the model unrealistically assumes that arbitragers instantaneously equalize price shocks (net of freight costs) when exports are positive.

I introduce arbitrage lags to prevent arbitragers from instantaneously equalizing price shocks. Following Coleman

[22] The exogeneity of the world price limits the richness of the model, but it is useful for several reasons. First, trading with a world price is consistent with many of the empirical methods used in the descriptive sections, such as sigma-convergence and dynamic factor models. Second, trading centers tended to be small relative to the commodity markets to which they exported. Third, addition of a second elastic price increases the computational requirements exponentially.

(2009), I introduce a transportation lag of one period. Forward contracts did not exist during this period, so exporters formed expectations about prices they would receive upon future delivery. With AR(1) world price dynamics, these expectations during a one month transportation lag are $E_t\left(P_{t+1}^{NO}\right) = \alpha + \rho P_t^{NO}$. Therefore, arbitragers are unable to fully exploit price shocks because they expect world prices to have reverted toward the mean by the time of delivery.

Following Steinwender (2018), I also introduce information lags so that exporters use old price information to forecast prices upon delivery. With a one period information and transportation lag, exporters use a two-step-ahead AR(1) forecast, $E_t\left(P_{t+1}^{NO}|I_{t-1}\right) = (1+\rho)\,\alpha + \rho^2 P_{t-1}^{NO}$, where I_{t-1} is the exporter's information set in time t about world prices in time $t-1$. As information lags become longer, greater weight is placed on the constant in the forecast, α, and less weight is placed on observed price shocks. If the information lag becomes infinite, arbitragers become uninformed of all world price shocks and simply forecast it to be its long run average, $\alpha/(1-\rho)$.

The exporter now weighs his expectations about future marginal benefits against the marginal cost of exporting

$$\begin{aligned} \tfrac{(1-\delta)}{(1+r)} E_t\left[P_{t+1}^{NO}|I_{t-L}\right] &= P_t^{Cin} + \tau_t \quad \text{if } X_t > 0 \\ \tfrac{(1-\delta)}{(1+r)} E_t\left[P_{t+1}^{NO}|I_{t-L}\right] &\leq P_t^{Cin} + \tau_t \quad \text{if } X_t = 0 \end{aligned} \tag{1.6}$$

where L is the information lag, r is the interest rate, and δ is the flour depreciation rate. Two new features result from the arbitrage lags. First, as information lags increase, price expectations become less accurate and cyclical price co-movement decreases. Second, as time costs become more onerous, long-run price wedges increase.

Seasonality

I introduce deterministic seasonality to production by assuming that annual production, Y_t, occurs in the hinterlands, and a deterministic fraction of this production, ϕ_t^m, arrives in Cincinnati in month m.[23] These seasonal supply fluctuations impact the frequency and duration of autarky, and when in autarky, they introduce seasonality to local prices.

I add deterministic seasonality to freight costs by specifying them as AR(1) with a deterministic trend and seasonality,

$$\log(\tau_t) = \psi_t^m + \theta_i time_t + \lambda \log(\tau_{t-1}) + u_t \tag{1.7}$$

where ψ_t^m are monthly freight cost intercepts.

A relatively clear mapping between trade frictions and price frequencies has been maintained until now – long-run freight costs impact price trend differentials, cyclical freight costs and arbitrage lags affect cyclical price co-movement, and seasonal freight costs and supply augment seasonal price fluctuations. This mapping is upset when freight cost

[23] These imports are supplied inelastically because growing a new crop is time-intensive and farmers cannot hold onto crops if they have to repay debts incurred in production.

trends or seasonality induce periods of autarky that impact cyclical price correlations; however, the mapping is muddled further when arbitragers use storage to harness deterministic seasonality.

Storage is similar to spatial arbitrage, but it equalizes expected flour prices across time (net of storage costs) instead of across space. As such, the two actions are modeled similarly. Following William and Wright (1991) I assume without loss of generality that flour storage occurs for a single period.[24] Consequently, storers operate under perfect competition to maximize their profit function

$$\pi_t = \max_{M_t \geq S_t \geq 0} \left\{ \frac{(1-\delta)}{(1+r)} E_t \left[P_{t+1}^{Cin} \right] S_t - k_t S_t - P_t^{Cin} S_t \right\} \tag{1.8}$$

where k_t are storage costs, S_t is flour stored, and $M_t = \phi_t^m Y_t + (1-\delta) S_{t-1}$ is the amount of flour on hand at the beginning of the period. The profit-maximizing storer weighs his expectations about future marginal benefits against the marginal cost of storage

$$\begin{array}{ll} \frac{(1-\delta)}{(1+r)} E_t \left[P_{t+1}^{Cin} \right] = P_t^{Cin} + k_t & \text{if } S_t > 0 \\ \frac{(1-\delta)}{(1+r)} E_t \left[P_{t+1}^{Cin} \right] \leq P_t^{Cin} + k_t & \text{if } S_t = 0 \end{array} \tag{1.9}$$

As long as storage is expected to be profitable, storers purchase the flour at current prices and store it until expected prices equalize across periods (net of storage and time costs)

Storage muddles the mapping between trade frictions and price behaviors in three major ways. First, storage increases cyclical price co-movement as arbitragers use it to smooth stochastic shocks. Second, storage decreases cyclical price co-movement by allowing exporters to store flour until large world price shocks, thereby increasing the frequency and duration of autarky. Third, storage decreases long-run price differentials as arbitragers use it wait for seasonally low freight costs.

The magnitudes of these effects are not calculable in a closed-form solution because storage introduces a kink into the model. This kink is introduced because aggregate storage cannot be negative – negative storage would imply that Cincinnati could borrow future production for use today.[25] This kink is frequently binding in the month prior to harvest because it is unprofitable to store crops before a deterministic supply shock. Therefore, computational methods are used to solve the model (see Williams and Wright 1991 and Coleman 2009). The computational model consists of two decision variables, S_t and X_t, and nine state variables, M_t, P_t^{NO}, H_t, A_t, Y_t, τ_t, k_t, $year_t$ and L_t, where H_t tracks the (harvest) season.

[24] If arbitragers wish to store for more than one period, they sell flour every period and buy it back at the same price.

[25] The export decision also creates a kink in the current formulation of the model, but this could be circumvented by allowing imports from the national market. No such modifications exist for the storage decision.

1.5 Calibration

This section calibrates the parameters of the arbitrage model which span four main categories: freight costs, imports, demand curves, and other. The many types of parameters have necessitated the use of seven datasets, two of which I construct from primary sources. An overview of the most important parameters, their values, and their estimation methods are provided in Table 1.7.

The calibration focuses on a single representative market,the flour trade between Cincinnati and New Orleans, because data requirements for arbitrage models are steep. Flour is chosen as the representative good over wheat, the typical representative good in historical market integration studies, because wheat's weight-to-value ratio was too high to be worth shipping in the antebellum United States (Berry 1943). Cincinnati is chosen because it exhibits the largest changes in trade frictions in the empirical sections, and it exported most of its flour to New Orleans for transshipment. Prices in New Orleans have a point of contact with world markets, so they effectively proxy for the world price which is taken as exogenous.

1.5.1 Freight Costs

Freight costs are unobserved from 1820-1841, so I estimate their deterministic trend from bilateral price differentials and use a dynamic factor model to estimate shocks from this trend. Freight cost shocks, such as low water levels in rivers, should be shared across goods because freight rates in the mid-19th century were charged by weight.[26] Therefore, dynamic factor models can be used to extract common freight shocks from bilateral price differentials

I begin by rearranging the arbitrage decisions in (1.6) such that $\tau_{it} = E_t\left[P^{NO}_{it+1}|I_{t-L}\right] - P^{Cin}_{it}$. I calculate these freight rates for four common Cincinnati exports (flour, lard, pork, and whiskey) and estimate their log-linear deterministic trends by the regression

$$\log(\tau_{it}) = \phi_i + \beta_i time_t + u_{it} \tag{1.10}$$

where ϕ_i embodies good-specific traits such as weight, bulkiness, and perishability, and β_i embodies the technology for shipping these traits over time.

The stochastic component of (1.10) embodies short-run freight cost shocks, but it also embodies measurement error from three main sources. First, I assumed positive exports in using (1.6) which may not always hold. Second, expectations in (1.6) are taken over a monthly frequency which is too coarse to accurately measure transportation and information lags. Third, prices themselves were collected with measurement error.

[26] This weight-based cost structure was sometimes augmented by other characteristics of the good such as perishability and bulkiness, but weight remained the main determinant of freight costs (Berry 1943).

I extract common freight cost shocks from this measurement error using the dynamic factor model

$$\begin{aligned} u_{it} &= \lambda_i G_t + \varepsilon_{it} \\ G_t &= \psi_t^m + \rho G_{t-1} + v_t \end{aligned} \tag{1.11}$$

where G_t is the AR(1) common factor, v_t are idiosyncratic shocks,ψ_t^m are deterministic monthly dummies, and ε_{it} is the measurement error.

Two factors are of primary concern in estimation. First, should freight rates exhibit deterministic seasonality? Second, how many lags should be included in the formation of expectations? To answer these questions, I predict Cincinnati-New-Orleans flour freight rates using various specifications and compare their fit to observed freight costs from 1841-1860.[27] Table 1.8 shows the results. My preferred specification has deterministic seasonals, a transportation lag of one month, and no information lags. [28] I use this factor model to extrapolate freight costs back to 1820. The estimated seasonality of freight rates is large and incentivizes arbitragers to store flour to exploit these swings.

1.5.2 Production and Imports

I estimate seasonal flour supply shocks using wheat production as a proxy. I observe county-level wheat production decennially and interpolate using population, land productivity, and annual weather. In particular, suppose each acre of farmland, F, has identical productive capacity that is augmented by county i's land productivity, Z_i, and weather, W_{it}, such that $Y_{it} = F_{it}^{\gamma_1} Z_i^{\gamma_2} W_{it}{}^{\gamma_3}$. The quantity of farmland is not observed before 1850, so I assume all farmland requires the same amount of tillage, $\overline{T}$, that uses labor, L_{it}, and capital, K_{it}. Therefore, $T_{it} = A_t L_{it}^{\psi_1} K_{it}^{\psi_2}$, where A_t embodies the technology for tillage and $Y_{it} = \left(A_t \bar{L}_{it}^{\psi_1} \bar{K}_{it}^{\psi_2}\right)^{\gamma_1} Z_i^{\gamma_2} W_{it}{}^{\gamma_3}$.

I estimate this using a log-log regression at the county-level by using labor to proxy for unobservable capital.[29] Therefore,

$$y_{it} = \alpha + \beta_1 YEAR_t + \beta_2 l_{it} + \beta_3 z_i + \beta_4 W_{it} \times I_{it}^{wet} + \beta_5 W_{it} \times I_{it}^{dry} + u_{it} \tag{1.12}$$

where lowercase letters denote logs, $YEAR_t$ assumes that tillage technology, a_t, evolves linearly, and I_{it} is an indicator variable that allows wet and dry weather (which are continuous variables) to affect output differentially.

Decadal population and wheat production are available from the 1850-1880 Population Census and Agricultural

[27] These freight rates imperfectly capture the cost of transport between Cincinnati and New Orleans because flour was also cheaply shipped downstream on wooden rafts called "flatboats." Higher quality flour tended to travel on steamboats to reduce the possibility of spoilage, while lower quality flour was shipped on the raft-like flatboats (Berry 1943). Nonetheless, the fact that steamboats were consistently used to transport flour indicates that the trade-off of higher freight cost for lower spoilage was often worth making and that steamboat freight rates should approximate the true cost of transportation fairly well.

[28] This specification also demonstrates the usefulness of dynamic factor models in extracting unobserved freight costs from a panel of price differentials – freight costs account for only 21.8% of the variation in u_{it} while measurement error accounts for the remaining 78.2%.

[29] I use labor as a proxy for capital by taking advantage of the fact that optimal capital choices are proportional to optimal labor choices by the homotheticity of the Cobb Douglas production function assuming labor and capital costs are equal across time and space.

Census respectively, [30] The quantity of labor devoted to wheat production is unobserved, so it is proxied by multiplying the total rural population of a county by the fraction of its 1880 farmland devoted to wheat production.[31] I restrict counties to those that exist in every decade, have more than ten percent of their cropland devoted to wheat, and lie east of 95 degrees longitude.

Geographic variation in production is provided by crop-specific land productivity which is obtained from the Food and Agriculture Organization's (FAO) Global Agro-Ecological Zones (GAEZ) project.[32] GAEZ uses an agronomic model to predict land suitability at a granular level using information on soil types and conditions, elevation, average land gradient, and climatic variables. Figure 1.8 shows the distribution of land suitability for wheat across the US.

Production shocks are provided by annual weather which is obtained from the North American Drought Atlas. This dataset estimates weather from 1928-1970 using 835 North American tree-ring chronologies and extrapolates backwards using these chronologies that extend back hundreds of years. The predicted weather outcome is the Palmer Drought Severity Index (PDSI) which is based on precipitation and temperature. PDSI is normalized such that within each location, 0 indicates normal weather and positive (negative) numbers indicate wet (dry) spells. PDSI values of 1 to 2 indicate mild wetness, 2 to 3 indicate moderate wetness, 3 to 4 indicate severe wetness, and beyond 4.0 indicates extreme wetness. Negative numbers indicate drought conditions of similar magnitudes.

There are two issues with this tree-ring data. First, 602 of the 835 tree-ring chronologies are located in the West which is mostly unpopulated in my sample. Regardless, the remaining 223 tree rings achieve an R-sq of 0.5-0.8 for the Midwest in an out-of-sample application from 1900-1927 (Cook and Krusic 2004). Second, the resolution of the weather grid is coarse and spans 2.5' longitude by 2.5' latitude. I address this coarseness by interpolating between grid points using a cubic spline, the results of which can be seen in Figure 1.9.

There are two reasons to believe that the residuals in the regression might be spatially correlated. First, measurement error will be propagated to all counties associated with a particular grid point. Second, many of the independent variables are spatially correlated, and this may bias results if unobserved variables, such as geographic variation in the utilization in factors of production, are also spatially correlated. I explicitly control for these issues by using a spatial error model.[33]

Results

I estimate wheat output using decadal data from 1840-1880. The lower bound of this time frame is restricted by a lack of Agricultural Census data prior to 1840, and the upper bound is extended to 1880 to provide variability in

[30]This data has been digitized by the National Historical Geographic Information System (NHGIS).

[31]I calculate rural population in each county by subtracting the total population of a county by its urban population as enumerated in the Census.

[32]Nunn and Qian (2011) popularized this dataset in economics and it has since been applied to historical US trade by Costinot and Donaldson (2016 WP).

[33]The spatial error model is of the form $u_{it} = \lambda W u_{it} + v_{it}$ where W is an inverse distance spatial weighting matrix. I also estimate a Spatial Durbin model to control for unobservable variable bias, but its results are nearly identical to the Spatial Error Model.

weather observations.[34]

The regression results are presented in Table 1.9. Column 1 presents OLS results that predict wet weather as being worse for crop production than dry weather. This result is likely driven by spatial correlation in the errors, as evidenced by a rejection of the null hypothesis of spatially uncorrelated errors by the Moran's I statistic. Column 2 uses a spatial error model to account for this spatial correlation. The results predict that "mildly wetter" conditions than normal increase wheat production by 12%, while moderate droughts decrease production by 16%.[35] Column 3 uses a spatial Durbin model to help control for the potential of serially correlated unobserved variable bias, but its estimates are highly similar to those of the spatial error model. Column 4 tests for the possibility that weather effects are non-linear. Although the coefficients are of the expected signs, they fail to achieve significance. Therefore, my preferred specification is the spatial error model with linear weather effects in column 2.

The high R-sq (0.89) of the decadal regressions suggests annual wheat production can be reliably predicted from 1820-1860. To predict production, I use a cubic spline to interpolate labor to an annual frequency. Finally, I assume all wheat becomes flour at the rate of 4.5 bushels of wheat per barrel of flour.[36] Although this allows me to predict flour output per county, I still need to determine what fraction of this flour is imported into Cincinnati from the hinterlands.

Imports

The geographic extent from which this produce is drawn is informed by the *Annual Statement of Trade and Commerce of Cincinnati* (1855) which declares that "a diameter of 200 miles, is quite enough to test the agricultural capacities of the region around each city." I proxy the fraction of flour production imported into Cincinnati from each county within a 200 mile diameter using the fraction of a county's merchants that trade with Cincinnati.[37] Merchants in the cash-strapped West would be "more or less compelled to receive produce as a payment" in exchange for manufactured goods. The merchant would ship this produce to a major local market such as Cincinnati or St. Louis to purchase more manufactured goods (Clark, 1966 p.42). Therefore, the fraction of flour being sent to Cincinnati from each county is correlated with the fraction of a county's merchants buying in Cincinnati. This fraction is displayed in Figure 1.10.

Two features suggest that the fraction of merchants in each county that trade with Cincinnati may be a decent proxy for the annual amount of flour sent from each county. First, the fraction of merchants has a negative relationship with distance. Second, counties near Louisville trade less with Cincinnati – less than 10% of merchants in counties surrounding Louisville trade in Cincinnati. These features suggest that the fraction of merchants in each county that

[34] I match the annual weather data to the year in which the census is enumerated, which is in the ninth year of each decade.

[35] The regression also predicts that output is increasing returns to scale in labor, but given that labor also proxies for capital and is imperfectly estimated, a slight deviation from constant returns to scale is not unexpected.

[36] This rule of thumb is used by the *Annual Reports of the Trade and Commerce of Chicago* and other contemporaneous sources.

[37] This data is provided by the *Annual Statement of Trade and Commerce of Cincinnati* (1856).

trade with Cincinnati may be a decent proxy for the annual amount of flour sent from each county.

I calibrate the deterministic seasonality of flour imports using monthly data on Cincinnati's imports from 1846-1854.[38] I use OLS with seasonal dummies, apply their estimated value to predicted imports from 1820-1860, and scale the predicted imports to match observed imports. The predicted monthly imports are plotted against observed imports in Figure 1.12.

1.5.3 Demand Parameters

This section calibrates Cincinnati's iso-elastic demand curve parameters. These parameters include demand levels, demand elasticity, and demand shocks. Demand levels are important because Cincinnati's population multiplied by 15.7 times over the sample, and demand elasticity is important because it determines the extent to which prices respond to supply shocks.

Cincinnati's local flour consumption is unobserved, so I proxy its antebellum flour demand elasticity using Chicago's from 1870.[39] I reconstruct Chicago's flour consumption using the market clearing condition $Q_t^D = Q_t^S = R_t - X_t + \Delta S_t + Y_t$, where Q_t^i is quantity of flour supplied/demanded, R_t are local inflows (imports) of flour, X_t are local exports of flour, $\Delta S_t = S_t - S_{t-1}$ is the change in flour locally stored, and Y_t is local production of flour from wheat.[40,41] I calculate monthly flour production from observed wheat consumption by assuming that wheat was consumed exclusively for flour production.[42,43] The one major violation of this assumption is the speculative hoarding of wheat, but I control for this in estimation.

I estimate Chicago's elasticity of flour demand using a simultaneous equation model (SEM) of (log) flour supply and demand specified as

$$\begin{aligned} q_t^S &= \alpha_t^S + \gamma^S p_t^S + \mathbf{z}_t^S \psi^S + u_t^S \\ q_t^D &= \alpha_t^D + \beta p_t^D + \mathbf{z}_t^D \psi^D + u_t^D \end{aligned} \tag{1.13}$$

where β is the elasticity of flour demand, q_t^i is quantity of flour, p_t^i is the price of flour, $\mathbf{z}_t^i$ is a vector of observable exogenous controls, and α_t^i are the time-varying supply and demand shocks, $i \varepsilon \{S, D\}$. Flour prices and quantities are

[38] The flour import data comes from *The Cincinnati Price Current, Commercial Intelligencer, and Merchants' Transcript.*

[39] This assumes the elasticity does not change quickly because flour is a staple of the Western diet and that it is constant over cities in the Midwest.

[40] The completeness of this market clearing condition is supported by its use in the Annual Report of the Milwaukee Grain & Stock Exchange (1872).

[41] Data for flour imports, exports, and storage is obtained from the *Annual Reports of the Trade and Commerce of Chicago*.

[42] I use the conversion rate of 4.5 bushels of wheat per barrel of flour which is used as a rule of thumb by the *Annual Reports of the Trade and Commerce of Chicago*. Chicago's wheat consumption is obtained from issues of the Chicago Tribune from January 1871 through December 1878. Only one day of wheat consumption data was typically reported per issue and were infrequently reported before 1871 and after 1878. Observations are aggregated to the monthly frequency. Any missing daily observations are assigned the average value of consumption for that month.

[43] A back of the envelope calculation indicates flour consumption is roughly equivalent to an average of 0.57 loaves of bread per day per inhabitant of Chicago. This number is within the typical range of per capita flour consumption of the era; for example, the 1855 *Statement of Trade and Commerce of Cincinnati* estimated that locals ate flour equivalent to 0.66 loaves of bread per day. These numbers are undoubtedly too high because rural farmers would also purchase flour in the city; however, it is unknown exactly how many did so. It is also worth noting that bread was a much larger portion of the diet in the nineteenth century than it is now – often being served with two to three meals a day.

endogenous in this SEM, so identification for β is achieved through exogenous shifts in flour supply.

Controls

I control for corners in the wheat market because they violate the assumption that wheat is consumed exclusively for flour production. A market corner temporarily increases the price of a commodity through actions on both the supply side (writing contracts so that commodities only enter Chicago under the ownership of speculators) and the demand side (speculators buying all remaining local produce in Chicago). The goal is to force short sellers, who have written contracts promising to buy a commodity at the end of the month, to pay exorbitant prices to those who have cornered the market. Corners could only last for a couple months; otherwise, commodities would be shipped from elsewhere to take advantage of high prices.

I identify corners by searching contemporary newspapers for reports of corners and use dummy variables as controls.[44] Although no attempts were made to corner the flour market, many efforts were made to corner the wheat market. Wheat speculation affects both flour supply, as wheat is the major input into flour production, and calculated flour demand, as this is a violation of the assumption that wheat consumption is used entirely for flour production.

I also control for the Russo-Turkish War of 1877-1878. Two of the largest producers of wheat in the 1870s were Russia and the United States. The world supply was low in 1876 because of an unexpectedly small US harvest. Before a new crop could be grown, Russia declared war on the Ottoman Empire in April 1877. This caused the world supply of wheat to drop further because the Ottomans controlled the Bosphorus Straits which were a bottleneck of the Russian wheat trade. This suggests the introduction of two dummies to control for the war. The first dummy is equal to one from the start of the war in April 1877 until the US harvest in July 1877, and the second dummy is equal to one from August 1877 through the close of the war in March 1878.

Results

I begin by estimating Chicago's demand elasticity for flour by OLS to obtain baseline estimates. Column 1 of Table 1.10 shows the estimated demand elasticity is -1.78. The endogeneity present in OLS estimates of supply and demand systems tend to be biased toward zero; therefore, -1.78 marks a lower-bound for the demand elasticity.

I use crop-year specific dummies to proxy US wheat production. These dummies are highly correlated with Chicago's flour supply as demonstrated by the F-statistic of 101.26 in column 2 of Table 1.10. However, they may violate the exclusion restriction if unobserved demand shocks are sufficiently serially correlated or year-dependent. Regardless, the estimated elasticity of -2.39 is larger than in the OLS estimation.

[44] Attempts to corner the market were identified by using ProQuest to search the Chicago Tribune for "wheat" and "corner" within 10 words of each other. The articles were then read to verify that the corner occurred in Chicago and to determine the duration of the corner. The search was made on 08/08/2017. Local advertisements were excluded from the search. Attempts to corner the wheat market occurred on 08-09/1871, 05-06/1872, 08/1872, 06-07/1873, and 07/1878.

Monthly inflows of flour into Milwaukee can proxy for the national supply of wheat because Milwaukee also served as a major transshipment point of commodities. These transshipments were unlikely to be correlated with Chicago's flour demand because most shipments were destined for the East. The estimated elasticity of -3.33 in column 3 of Table 1.10 suggests that endogeneity bias is smaller than using crop-year specific dummies. However, the F-stat of 5.8 suggests that Milwaukee flour inflows were not highly correlated with Chicago's consumption.

My preferred specification is to use monthly US flour exports as a proxy for national flour production. The US is a major exporter of flour, so flour exports are dominated by shocks to US crop output rather than short-run shocks to foreign supply and demand. Column 4 of Table 1.10 gives the demand elasticity of -3.97 with a strong first stage. Concerns about endogeneity might be assuaged by observing the fit of the estimated demand curve in Figure 1.11. The curve fits a cluster of downward sloping observations that are suggestive of Chicago's flour demand curve. This suggests the estimated demand elasticity is not overly biased by unobserved demand shocks.

Demand shocks

I reconstruct Cincinnati's demand shocks by substituting the market clearing condition into the iso-elastic demand, $\alpha_t = p_t - \beta \log(R_t - X_t + \Delta S_t + Y_t)$. Monthly exports and inflows are observable in Cincinnati from 1846-1854.[45] Change in storage is unobserved, so I predict it from the fit of a regression of Chicago's change in storage on its exports and inflows.

I also account for the fact that the extent of the market increases as Cincinnati's population increases. I impose the restriction that demand increases proportionally with population so that demand is defined as $\alpha_t = c + pop_t + \rho_\alpha \alpha_{t-1} + u_t$. I find the persistence of demand shocks is $\rho_\alpha = 0.66$ and the variance is $\sigma_\alpha^2 = 0.31$, and I assume these demand curve parameters are constant throughout 1820-1860.

1.5.4 Other Parameters

I calibrate national flour prices based on New Orleans' flour prices in the Cole data. I run an AR(1) regression to obtain the national price persistence, $\rho_p = 0.83$, and its innovation variance, $\sigma_p^2 = 0.89$.

I calculate the interest rate from ten year treasury yields that fluctuated within a narrow band around 5% from 1820 to 1860. I calculate the depreciation rate by observing the premium of new wheat versus wheat described as "old" in 1870s Chicago. I assume that old wheat is exactly one year old. The calculated depreciation rate is roughly 1.5% per month and is constant in the model.

Storage costs are calibrated to those in *The Cincinnati Price Current, Commercial Intelligencer, and Merchants' Transcript* observed in 20 of the 84 months between 1846 and 1852. The data are enlightening despite their paucity

[45] Data is from *The Cincinnati Price Current, Commercial Intelligencer, and Merchants' Transcript.* 1848 is excluded from this range because digitized copies of the newspaper are missing for this year.

– storage costs do not exhibit seasonal variation and only change once (from 6.25 cents per month to 5 cents) over the six year period.[46] Due to the stickiness of observed storage costs, I interpolate missing observations after 1846 using the principle of last observation carried forward. I then assume that unobservable storage costs before 1846 decline linearly from the start of the sample until the first storage cost observation in 1846, with the slope of this line determined by the value that minimizes the difference between the model simulated flour prices and the actual. This results in initial storage costs of 26 cents per month in 1820.

1.6 Simulation

In this section, I simulate the arbitrage model to explore how three different trade frictions – freight costs, storage costs, and information lags – affect price behaviors at the trend, cycle, and seasonal frequencies. Each trade friction has a large impact on price behaviors at a unique frequency, although some trade frictions have secondary effects at additional frequencies.

The simulated model closely replicates observed prices, exports, and inflows in Cincinnati as shown in Figure 1.12. The fit is surprising given that state variables such as freight costs, inflows, and flour demand had to be estimated.[47] However, the AR(1) one-step-ahead forecasts cause exporters to believe that prices in New Orleans revert to the mean faster than they actually do. This is apparent in the mid-1850s when agents consume flour under the expectation that unusually high prices in New Orleans will revert to the mean by the time freight costs seasonally decline. The simulation also has difficulty matching observed exports for years in which they are inexplicably low, such as in 1850. These years of low exports might be explained by variations in crop yields that are not captured by weather shocks. Despite these problems, the overall fit of the simulated series suggests the calibrated model can reliably compute counterfactuals for freight costs, information lags, and storage costs.

I calculate the importance of each trade friction by computing counterfactual frictions. I simulate the model from 1820-1860 holding trade frictions at their 1820 levels. Next, I allow various permutations of trade frictions to equal their 1860 values for the duration of a new simulation and record the resultant price behaviors. Price behaviors were measured using panel techniques in the empirical section, but these are not valid in this two-city case. Instead, I calculate long-run price dispersion with bilateral price differentials, cyclical price co-movement with bilateral correlations, and the magnitude of seasonal price fluctuations using within-year standard deviations. The counterfactuals are presented in Table 1.11.

Freight costs account for 94% of the decline in price differentials, storage costs account for 78% of the decline in seasonal price fluctuations, and the interaction between between better information and lower freight costs increases

[46] Storage costs are structured such that they charge a premium for first month of storage, presumably to pay for the fixed cost of haulage. I simplify this rate structure by assuming that most storage is for short-term transshipment purposes and only use the high rates of the first month.

[47] Demand shocks are set to zero in this figure because although their distribution has been estimated, their realizations are unknown.

cyclical price correlation. However, each trade friction has secondary impacts at other price frequencies. Notably, low storage costs can decrease price differentials and cyclical correlations, and low freight costs can decrease seasonal price fluctuations. How do these secondary effects occur?

I explore the mechanism by which trade frictions affect price behaviors by simulating counterfactuals over a grid ranging from 0% to 200% of a trade friction's 1820 value.[48] I record simulated prices, exports, and storage at each grid point and observe their responses to changes in trade frictions in the subsections below.

1.6.1 Freight Costs

I obtain monthly freight costs from 1842-1860 from Berry (1943), and I use a dynamic factor model to recover the remaining costs from 1820-1841. I use dynamic factor models to recover the common shocks between bilateral price differentials of exports. These shocks are induced by freight costs which were primarily determined by weight.

A decline in long-run freight costs causes bilateral price differentials to decrease as arbitragers export a greater share of Cincinnati's flour. As flour exports increase, Cincinnati's flour supply decreases and prices rise. Without slow transportation, prices would equalize across locations when long-run freight costs decline to zero; however, the time-costs of slow transport (depreciation and foregone interest) continue to drive a wedge between bilateral prices even when freight costs are zero.

If long-run freight costs become so onerous that arbitragers export less frequently, prices decouple and cyclical price correlations decrease. In addition, autarky magnifies Cincinnati's seasonal price fluctuations as it consumes a larger share of its seasonal flour inflows. Arbitragers increase storage to exploit these seasonal price fluctuations, but storage is too costly for arbitragers to completely smooth seasonality.

Cyclical and seasonal price fluctuations are only impacted when long-run costs exceed their estimated 1820 value by 150%. Can the introduction of freight rate cyclicality help to explain price correlations and seasonal fluctuations over a more realistic range of values?

Cyclical Freight Costs

I isolate the impact of cyclical freight costs on price behavior by holding long-run freight costs at their 1820 level and eliminating their seasonal fluctuations. I then adjust the standard deviation of freight cost shocks and observe their impact on price behaviors. Figure 1.14 shows that as freight cost shocks decrease, price trend differentials remain constant, cyclical price correlations increase slightly, and seasonal price fluctuations decline substantially.

Freight cost shocks have a small impact on cyclical price correlation because they have a half-life of only 2.2 months, and therefore spells of autarky are comparatively short. In simulations where freight cost shocks are twice

[48] The initial calibrated trade frictions are the following: long-run trade costs = \$1.68, storage costs = \$0.26/mo, and information lag =1 month

their estimated value, Cincinnati's longest spell with no exports is five months, while it is nine months when long-run freight costs are twice their 1820 value. The short duration of freight cost shocks ensures that Cincinnati's prices respond to world price shocks with regularity, and this prevents price correlations from falling too precipitously even if spells of autarky occur frequently.

The unpredictability of freight cost shocks also induces large seasonal price fluctuations. Arbitragers find it too expensive to store in preparation for stochastic freight cost shocks, so they find themselves in autarky more frequently as the shocks get larger. As a result, agents find themselves consuming a greater share of seasonal production and price seasonality increases. How might the storage response differ when freight cost variation is induced by deterministic fluctuations in freight costs?

Seasonal Freight Costs

I isolate the impact of deterministically seasonal freight fluctuations on price behavior by fixing long-run freight costs and shocks at their 1820 levels. I then adjust the seasonal magnitudes of freight costs and observe their impact on price behaviors. Figure 1.15 shows that as seasonal freight cost fluctuations increase, price trend differentials decrease, cyclical price correlations decrease, and seasonal price fluctuations increase modestly.

Long-run price differentials decrease as seasonal freight cost fluctuations increase because arbitragers exploit these fluctuations by storing flour until freight costs are seasonally low. By always waiting to export until freight cost are low, arbitragers are able to decrease long-run price differentials.

This increased reliance on storage decreases cyclical price correlations as arbitragers export less frequently. The frequency of exporting declines from 85% with no seasonality to 48% with extreme seasonality. However, the longest duration of these spells is only four months because seasonality is not persistent. Therefore, price correlation decreases moderately during months in which freight costs are seasonally high and exports are zero.

Deterministically seasonal freight cost fluctuations have a small impact on seasonal price fluctuations because arbitragers can predict them and use storage to smooth prices accordingly. In fact, seasonal price fluctuations respond less to changes in deterministic seasonal shocks than they do to changes in stochastic cyclical shocks. This is because arbitragers cannot predict stochastic shocks and are therefore less willing to pay for storage to exploit them.

1.6.2 Storage

In this subsection, I explore the impact of storage costs on price behavior. Figure 1.16 shows that as storage costs decrease, price trend differentials decrease, cyclical price correlations increase, and seasonal price fluctuations decline. These effects are largely driven by the interplay between storage and freight cost seasonality.

A decline in storage costs decreases both price trend differentials and seasonal price fluctuations by making it cheaper for arbitragers to exploit deterministic seasonality in freight costs. When storage costs are high, arbitragers are forced to export or consume flour as soon as possible; however, as storage costs decline, arbitragers begin to store flour until freight costs are low. As arbitragers are able to do this more consistently, their actions reduce both price trend differentials and seasonal price fluctuations.

Two factors modulate these price behaviors. First, the ability to use storage to decrease price trend differentials depends on the magnitude of seasonal freight cost fluctuations. As these fluctuations decline, storage becomes less important to arbitragers because there is less to gain by waiting for seasonally low freight costs. Second, the time costs of storage (depreciation and foregone interest) prevent arbitragers from hoarding flour when storage costs are low. Without time costs, arbitragers would store vast quantities of flour when storage costs are low and export it all when price differentials are as large as possible.

Storage costs do not have a large impact on cyclical price correlation because of two opposing forces. Lower storage costs increase price correlation by enabling arbitragers to smooth Cincinnati's supply and demand shocks. However, lower storage costs also incentivize arbitragers to refrain from exporting until an advantageous moment. Therefore, the frequency of exporting decreases and world price shocks are not transmitted to Cincinnati as often. These opposing forces largely cancel each other out in these simulations and cyclical price correlation only increases by a small amount.

1.6.3 Information Lags

In this subsection, I explore the impact of information frictions on price behavior. Figure 1.17 shows that as information frictions decrease, price trend differentials remain constant, cyclical price correlations greatly increase, and seasonal price fluctuations decrease.

Price trend differentials do not change as information lags decline because there is no mechanism by which arbitragers can use information to decrease long-run freight costs. In the case of declining storage costs, arbitragers could augment freight rates by storing flour until seasonal freight costs decline, but information cannot be exploited in a similar fashion. Therefore, price trend differentials remain constant regardless the level of information.

Cyclical price correlations increase and seasonal price fluctuations decrease as a decline in information frictions allows arbitragers to exploit world price shocks more efficiently. Agents use improved information to decide how much to consume or export in a given period without using expensive storage (set at its 1820 value) to exploit future price shocks. As information lags decline, agents base their consumption decisions less on deterministic seasonality and more on stochastic world price shocks. This increases cyclical price correlations dramatically due to the coarseness of the monthly frequency of observation. However, information lags often lasted longer than a month in Cincinnati before the steam engine allowed for quick upstream travel; therefore, these changes in information frictions are not unrealistic.

1.6.4 Inflows

In this subsection, I explore the impact of inflows of flour into Cincinnati on price behavior. Although flour inflows are not a trade friction, they may have played an important role in the increasing seasonal price fluctuations observed after 1840. Figure 1.18 shows that as inflows increase, price trend differentials increase, cyclical price correlations increase, and seasonal price fluctuations increase.

A rise in flour inflows simultaneously increases price trend differentials and cyclical price correlations. As flour inflows increase, flour supply rises and Cincinnati's prices decline. This increases price trend differentials and profits from arbitrage. As arbitrage becomes more profitable, the frequency of exporting increases which causes bilateral price correlations to rise as world price shocks are transmitted to Cincinnati more frequently.

A rise in flour inflows also magnifies seasonal price fluctuations due to the seasonality of inflows. As flour inflows increase, the magnitude of its deterministic seasonality also increases. This induces greater seasonality in flour consumption which manifests as larger seasonal price fluctuations in autarky.

1.6.5 Interpretation and Application

The simulations suggest that long-run price convergence in the antebellum United States was driven primarily by declining storage and long-run freight costs. Section 1.3.1 found that there were two major waves of long-run price convergence in the antebellum US, 1820-1830 and 1850-1860. Some of this convergence was probably due to the proliferation of steamboats and river improvements from 1820-1830 and the spread of railroads in the 1850s. Storage costs likely played a larger role in the first wave than the second because Cincinnati's observed storage costs were fairly low and stable (ranging from \$0.0625/mo to \$0.05/mo) from 1846-1852 and were estimated to be much higher (\$0.26/mo) in 1820. Additionally, the increasing seasonal price fluctuations observed across the US after 1840 suggests that storage costs did not decline rapidly during the second wave of price convergence. This implies that long-run freight costs likely played a large role in both waves of price convergence, while storage likely played a larger role in the first wave than the second.

The simulation also indicates that increases in cyclical price co-movement were driven by declining information lags and increasing flour inflows. Information lags between the coastal cities and Cincinnati declined dramatically over the course of the sample. The upstream trip from New Orleans to Cincinnati took several weeks with good weather in the early 1820s, and upwards of a month in bad weather. The continuing improvement in steamboat travel speeds throughout the entire sample helped to decrease these information lags. In addition, the introduction of the telegraph in the late 1840s virtually eliminated information lags across all cities. Inflows from the hinterlands also increased throughout the sample as the farming population grew and as declining freight costs allowed these inflows to be drawn from greater distances. The increase in inflows drove down local prices which increased the frequency of exporting and the co-movement between cyclical prices.

Finally, the simulation reveals that the U-shape of seasonal price fluctuations in the antebellum United States was likely driven by a combination of declining storage costs and increasing flour inflows. The simulation results suggest that storage costs declined from 1820-1840 which decreased seasonal price fluctuations. However, the decline in storage costs was outweighed by an increase in inflows flooding into commercial centers from 1840-1860.

1.7 Conclusion

This paper has demonstrated how freight costs, information lags, and storage costs map into cross-sectional price behaviors at the trend, cycle, and seasonal frequencies, respectively. In general, this is a useful classification; however, there are several cases in which this strict classification does not hold. Notably, freight costs can decrease cyclical price correlation if export frequency falls, low storage costs can reduce price trend dispersion if arbitragers exploit seasonal freight fluctuations, and faster information can reduce price seasonality if arbitragers exploit shocks during months in which freight costs are high. Fortunately, these spillover effects tend to only be large when trade frictions take extreme values, and thus the simple mapping largely holds true.

These results are important because the trade literature has traditionally focused on freight costs and tariffs to the exclusion of other trade frictions. However, this paper suggests that other trade frictions may play a larger role in modern price dispersion than previously appreciated. Even if modern freight costs, information lags, and storage costs are low, the logistical difficulties of quickly exploiting arbitrage opportunities on a global scale are immense. Companies such as Walmart and Amazon have built commercial empires on their ability to exploit such opportunities. Therefore, impacts of market segmentation and trade frictions should be studied further to better understand modern price dispersion.

These findings can also be applied to the broader historical market integration literature. The paucity of historical data often precludes using anything except prices to determine the evolution of trade frictions. This paper suggests different price frequencies can be used to determine not only when markets converged, but how they converged. At the very least, this paper demonstrates that information is lost by focusing on a subset of price frequencies.

By applying this decomposition to antebellum US commodity prices, I also shed light on a previously understudied period of historical market integration. I use newly digitized data to find that US prices experienced declining dispersion from 1820-1830 and 1850-1860, increasing cyclical correlation from 1830-1850, and non-monotonic decreases in seasonality from 1820-1860. These results are shared across most agricultural sectors, but they are particularly strong in Cincinnati and New Orleans. Although my findings of trend convergence match those of previous studies, my findings of increased cyclical price co-movement differs from Jacks (2005), and my analysis of seasonal price fluctuations explores a new dimension of historical market integration.

Finally, I introduce new methods of estimating historical series through my efforts to calibrate the arbitrage model. I use a dynamic factor model to calculate unobservable freight costs from a panel of price differentials, I calculate the demand elasticity for flour using trade flows of wheat through the United States as an instrument, and I demonstrate the usefulness of using tree ring chronologies to predict annual weather outcomes. These methods may prove useful in other historical studies.

Future work is needed to endogenize world prices, freight costs, and storage costs. The combination of inelastic world prices and freight costs allows arbitragers to flood the market with exports when freight costs are low. Endogenizing these variables would cause freight costs to increase and world prices to decline which would prevent arbitragers from flooding the market. Introducing capacity constraints and time to build into the storage sector could also explain the non-monotonic decline in price seasonality. Such work would help determine how historical trade frictions evolved.

1.8 Appendix

A structural time series model is used to decompose prices into a trend, cycle, seasonal, and error term. As in Durbin and Koopman 2012, the state space model is written as

$$p_{ijt} = Z_t \alpha_t + \varepsilon_t$$

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t$$

where $\varepsilon_t \sim N(0, H_t)$, $\eta_t \sim N(0, Q_t)$, $Z_t = (Z_T, Z_C, Z_S)$, $\alpha_t = (\alpha_T, \alpha_C, \alpha_S)$, $T_t = blockdiag(T_T, T_C, T_S)$, $Q_t = blockdiag(Q_T, Q_C, Q_S)$, $R_t = blockdiag(R_T, R_C, R_S)$ are described below.

The trend component is modeled using a spline with a parameterization analogous to a Hodrick-Prescott filter. I use a spline instead of a local linear trend model because it is important to for price series of the same good to have a similar level of trend smoothness across locations, and a spline provides a convenient way of enforcing this restriction. Without similar levels of trend smoothness, the cyclical components would not be as readily comparable across price series and measures of co-movement may be misleading. The trend component is modeled as

$$\alpha_T = (\mu_t \;\; \mu_{t-1})' \qquad T_T = \begin{bmatrix} 2 & -1 \\ 1 & 0 \end{bmatrix}$$

$$Z_T = (1 \;\; 0) \qquad R_T = (0 \;\; 1)$$

$$Q_T = \begin{bmatrix} 0 & 0 \\ 0 & \frac{\sigma_e^2 + \sigma_\varepsilon^2/\left(1-\rho^2\right)}{\lambda} \end{bmatrix}$$

where σ_e^2 is the variance of the error term of the observation equation, σ_ε^2 is the variance of the cyclical component (described below), ρ is the AR(1) coefficient of the cyclical component (described below), and $\lambda = 129,600$ is the spline value set to correspond to a HP filter on monthly data.

The cyclical component is modeled using an ARMA(1,1) specification. The more common trigonometric approach to cyclical modeling often collapses to an AR(1) with these historical price series because the estimated cyclical frequency approaches zero. Therefore, for expositional simplicity and stability I enforce an AR(1) specification across all series with an added MA(1) component. The cyclical component is modeled as

$$\alpha_C = (y_t \;\; \varepsilon_t)' \quad T_C = \begin{bmatrix} \rho & \theta \\ 0 & 0 \end{bmatrix}$$

$$Z_C = (1 \;\; 0) \qquad R_C = (1 \;\; 1)$$

$$Q_C = \sigma_\varepsilon^2$$

The seasonal component is modeled by a generalized form of the stochastic seasonal dummy model (Harvey 1989). The traditional stochastic seasonal dummy model places the restriction that twelve consecutive seasonal dummies, γ_t, sum to a stochastic error term, $\omega_t \sim N\left(0, \sigma_\omega^2\right)$; that is, $\sum_{j=0}^{s-1} \gamma_{t-j} = \omega_t$. This model allows seasonal magnitudes to react to stochastic conditions in a given year, but it is not particularly well suited to model permanently changing seasonal amplitudes across years. Changing seasonality can be modeled by adding a slope term to each of the seasonal dummies such that

$$\sum_{j=0}^{s-1} \gamma_{t-j} = \beta_{t-1}^{(s)} + \omega_t$$

$$\sum_{j=0}^{s-1} \beta_{t-j}^{(s)} = \zeta_t^{(s)}$$

where $\beta_t^{(s)}$ is a slope term for month s, and $\zeta_t^{(s)} \sim N\left(0, \sigma_\zeta^2\right)$. The slope terms are restricted to sum to an error term so that the seasonal component will roughly sum to zero over a 12 month period. The state space representation is

$$\alpha_S = \left(\gamma_t, \gamma_{t-1}, \cdots \gamma_{t-10}, \beta_t^{(s)}, \beta_{t-1}^{(s)}, ..., \beta_{t-10}^{(s)}\right) \qquad T_C = \begin{bmatrix} \tau_C & I_{11} \\ 0 & \tau_C \end{bmatrix}_{[22x22]}$$

$$Z_S = (1,0,0,...,0) \qquad R_S = (1,0,0,0,0,0,0,0,0,0,0,1,0,...,0)$$

$$Q_S = blockdiag\left(q_\gamma, q_\beta\right)_{[22x22]} \qquad \tau_C = \begin{bmatrix} -1 & -1 & \cdots & -1 & -1 \\ 1 & 0 & & 0 & 0 \\ 0 & 1 & & 0 & 0 \\ & & \ddots & & \\ 0 & 0 & & 1 & 0 \end{bmatrix}_{[11\times 11]}$$

$$q_\gamma = \begin{bmatrix} \sigma_\gamma^2 & 0 & & 0 \\ 0 & 0 & & 0 \\ & & \ddots & \\ 0 & 0 & & 0 \end{bmatrix}_{[11x11]} \qquad q_\beta = \begin{bmatrix} \sigma_\beta^2 & 0 & & 0 \\ 0 & 0 & & 0 \\ & & \ddots & \\ 0 & 0 & & 0 \end{bmatrix}_{[11x11]}$$

Any estimated seasonal with less than one statistically significant observation per year on average is deemed to not be seasonal. In this case, the seasonal component is dropped and the state space model is run again.

In Section 1.3.1, I calculate good-specific rates of sigma-convergence by decade to determine if declines in long-run geographic price dispersion were shared across all sectors in the economy. Sigma-convergence is calculated as $\sigma_{it} = \sqrt{var_j\left(p_{ijt}^T\right)}$ and is ideally suited for the Cole data for three reasons. First, sigma-convergence is used across a wide variety of price convergence studies and therefore results can be compared across studies. Second, sigma-convergence is comparatively robust to unobserved quality differentials across locations because they are "averaged out" across many locations (Federico 2010) . Third, sigma-convergence does not suggest that the cities of interest are trading with each other as might be implied by bilateral measures of convergence. Although bilateral measures of convergence are more meaningful, it is often difficult or impossible to obtain the data that prove that two locations trade with each other and therefore any such bilateral results might be misleading.

Good-specific trends in sigma-convergence are extracted by a structural time series model similar to (1.1),

$$log\left(\sigma_{it}\right) = \sigma_{it}^T + \sigma_{it}^C + \sigma_{it}^S + e_{it} \tag{1.14}$$

where σ_{it}^T is a piecewise linear trend, σ_{it}^C is an ARMA cyclical component, and σ_{it}^S are stochastic seasonal dummies with their own varying slopes. The trend component is specified as a piecewise linear trend so that rates of sigma-convergence can be calculated for each decade, and it is equivalent to the specification

$$\sigma_{it}^{T} = \alpha + \sum_k \beta_k \times time \times I_k \tag{1.15}$$

where β_k is the time coefficient for decade k, I_k is a dummy equal to one during decade k, and $k \varepsilon \{1820s, 1830s, 1840s, 1850s\}$. The log-linear specification of (1.15) means that the β_k can be interpreted as the rates of long-run sigma convergence during decade k.

Dynamic Factor Model

The dynamic factor model is estimated using a combination of Bayesian and state space methods. The methodology is presented in Kim and Nelson (1999), and consists of an MCMC approach which uses Kalman filtering techniques to extract the factors and Bayesian estimation to extract the remaining parameters.[49] Let $\Psi = (\psi_G, \psi_p)$, and $\Sigma = (\sigma_G^2, \sigma_p^2)$. Then, the main steps are:

1. Provide initial values for G_{it}, λ_{ij}, Ψ, and Σ
2. Conditional on p_{ijt}^{c}, λ_{ij}, Ψ, and Σ draw G_{it} by Kalman filtering techniques
3. Conditional on G_{it}, and p_{ijt}^{c} draw λ_{ij}, Ψ, and Σ by Bayesian methods
4. Return to step 2.

At the end of each iteration, a model-implied variance decomposition is performed to determine the share of price variation that is attributable to each of the components. The good-specific and common factors are modeled as having 3 lags, and all lag polynomials are of order 3. The initial values of the factors are randomly drawn from a $N(0,1)$ distribution. The prior distribution of λ_{ij} and Ψ are assumed to be Gaussian with mean 0 and variance 1. The prior distribution of Σ is assumed to be that of an inverse chi square distribution with 4 degrees of freedom and a scale of .01. An issue with dynamic factor models is that the sign and magnitude of the factors cannot be identified without specifying additional restrictions. I achieve identification by normalizing the first lag coefficient for each good-specific factor, $\lambda_{i1}(1)$ to equal unity. For each good, I order Philadelphia as the numeraire series because Philadelphia is highly integrated into the national market and has no missing observations. After a burn-in of 10,000 draws, another 30,000 draws are taken with estimates stored every 50 draws. The results are based on the posterior distribution of these 400 stored draws.

[49] Specifically, Carter and Kohn's (1994) multi-move technique is used to extract the factors while Chib and Greenberg's (1994) methods are used to estimate the remaining parameters. My code is modified from that used in Moench et al. (2013).

The model implied variance decomposition is obtained from (1.2) which is reproduced below

$$p^c_{ijt} = \lambda_{ij}(L)\,G_{it} + e_{p,ijt}$$

The components on the right hand side are assumed to be orthogonal. This allows the variance of equation (1.2) to be simply calculated as

$$var\left(p^c_{ijt}\right) = \lambda^2_{ij}(L)\,var(G_t) + var(e_{p,ijt})\,. \tag{1.16}$$

The appropriate Yule-Walker equations are then applied to equation (1.3) to obtain the sample variances of each of the components on the right hand side of equation (1.16) as a function of Ψ and Σ.[50] The right hand side is then a function of the estimated parameters Λ, Ψ, and Σ. These estimated parameters are treated as the true model parameters, and the variance share of each component is calculated as

$$1 = \frac{\lambda^2_{ij}(L)\,\lambda^2_i(L)\,var(F_t)}{var\left(p^c_{ijt}\right)} + \frac{var(e_{p,ijt})}{var\left(p^c_{ijt}\right)}. \tag{1.17}$$

Model implied variance decompositions have a few shortcomings. First, while the components on the right hand side of equation(1.2) are assumed to be orthogonal, this is not imposed in the estimation procedures and could bias a model that has some correlation in finite samples. This issue is especially pronounced in the Cole data when the lag structure of the model is small. Second, the procedure relies upon the accuracy of the estimates of the full set of true parameters; small variations in parameters can yield especially large differences in implied variance when the estimated factors are near a unit root. This is addressed by discarding outliers of the implied variance. An alternative to model implied variance is to explicitly orthogonalize the factors draw-by-draw and compute the variance decomposition as a regression of the observed data on the orthogonalized factors (Crucini, Kose and Otrok 2011, Kose, Otrok and Whiteman 2003). Orthogonalization is not applied in this paper because the lag structure of this model is more complex than in Kose et al (2003), and choosing an orthogonalization order for these lags would be a dubious prospect.

[50] See __ for an application of the Yule-Walker equations

Table 1.1: Number of Observations

	Charleston	Cincinnati	New Orleans	New York	Philadelphia
Bacon	477	480	480	0	480
Butter	477	480	480	480	480
Coffee	471	480	480	475	480
Corn	480	480	0	474	480
Cotton	480	480	480	480	480
Flour	480	480	480	472	480
Lard	480	480	480	480	480
Linseed Oil	0	480	0	460	480
Molasses	480	457	480	478	480
Nails	0	480	480	480	480
Pork	0	480	468	480	480
Rice	480	450	0	476	480
Sugar	480	480	476	467	480
Wheat	0	480	0	411	480
Whiskey	469	480	480	480	480

Notes: The maximum number of observations is 480.

Table 1.2: Sigma Convergence

	Avg. σ_{it}	Annualized Rates of Sigma Convergence (in %)					Avg. σ_{it}
	1820-1825	1820-1830	1830-1840	1840-1850	1850-1860	1820-1860	1855-1860
Bacon	0.41	-1.53	-5.42^{***}	4.96^{***}	-7.27^{***}	-1.69^{***}	0.18
		(2.44)	(1.54)	(1.66)	(1.67)	(0.34)	
Butter	0.39	1.87^{*}	-1.34^{*}	-1.63^{**}	-0.95	-0.87^{***}	0.32
		(0.98)	(0.73)	(0.71)	(0.87)	(0.14)	
Coffee	0.18	-7.16^{***}	2.82^{***}	-3.18^{***}	-2.54^{***}	-1.72^{***}	0.08
		(1.08)	(1.05)	(0.87)	(0.96)	(0.22)	
Corn	0.50	-2.60	-1.73	0.27	-7.56^{***}	-2.15^{***}	0.22
		(2.27)	(1.76)	(1.67)	(1.40)	(0.31)	
Cotton	0.15	-7.82^{***}	1.79	-0.42	-2.70^{*}	-1.25^{***}	0.07
		(1.57)	(1.43)	(1.28)	(1.41)	(0.35)	
Flour	0.31	-6.30^{***}	-0.31	-1.74	-1.99	-2.03^{***}	0.13
		(1.66)	(1.48)	(1.28)	(1.52)	(0.45)	
Lard	0.26	-0.46	-6.50^{***}	0.37	-5.26^{***}	-3.03^{***}	0.09
		(1.14)	(0.78)	(0.79)	(0.99)	(0.24)	
Linseed Oil	0.10	1.79	0.11	-8.10^{***}	2.52	-2.15^{***}	0.07
		(2.51)	(1.94)	(1.63)	(2.21)	(0.46)	
Molasses	0.41	-5.11^{***}	-1.21	-2.91^{**}	3.52^{***}	-1.68^{***}	0.22
		(1.98)	(1.46)	(1.18)	(1.32)	(0.22)	
Nails	0.16	-8.58^{***}	0.92	1.48	-2.43	-1.03^{**}	0.08
		(1.96)	(1.84)	(1.78)	(2.35)	(0.43)	
Pork	0.21	-0.14	-5.44^{***}	1.44^{*}	-10.20^{***}	-3.09^{***}	0.06
		(0.97)	(0.72)	(0.75)	(0.66)	(0.27)	
Rice	0.37	-5.20^{***}	-0.90	-4.38^{***}	-0.39	-2.73^{***}	0.16
		(1.88)	(1.46)	(1.37)	(1.68)	(0.35)	
Sugar	0.24	-5.66^{***}	1.75	-2.66^{*}	-0.20	-1.29^{***}	0.14
		(1.95)	(1.67)	(1.40)	(1.42)	(0.34)	
Wheat	0.51	-2.07	-4.12^{***}	0.00	-3.53^{***}	-2.30^{***}	0.21
		(1.69)	(1.23)	(1.14)	(1.02)	(0.26)	
Whiskey	0.21	-7.31^{***}	1.62	1.30	-2.76^{**}	-0.64^{**}	0.14
		(1.38)	(1.09)	(1.13)	(1.18)	(0.30)	
Average	0.29	-3.75^{***}	-1.20^{***}	-1.01^{***}	-2.78^{***}	-1.84^{***}	0.14
		(0.46)	(0.36)	(0.33)	(0.37)	(0.08)	

Notes: Standard errors in parentheses.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

Table 1.3: Factor Variance Shares of Cyclical Prices (by City)

	1820-1830	1825-1835	1830-1840	1835-1845	1840-1850	1845-1855	1850-1860	Difference
Charleston	0.57***	0.53***	0.50***	0.60***	0.61***	0.68***	0.62***	0.04
	(0.04)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.05)
Cincinnati	0.15***	0.17***	0.25***	0.39***	0.50***	0.61***	0.66***	0.51***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
New Orleans	0.26***	0.31***	0.50***	0.58***	0.62***	0.73***	0.70***	0.43***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
New York	0.50***	0.61***	0.70***	0.69***	0.67***	0.75***	0.73***	0.23***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Philadelphia	0.71***	0.75***	0.76***	0.77***	0.76***	0.75***	0.77***	0.06**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)

Notes: This table provides the means of the posterior distributions for the variance shares of factors aggregated to the city level. Standard deviations of the posterior are in parentheses. Column "Difference" tests the difference in means between the 1850s and 1820s with a two sample t-test.

*** Significant at the 1 percent level

** Significant at the 5 percent level

* Significant at the 10 percent level

Table 1.4: Factor Variance Shares of Cyclical Prices (by Good)

	1820-1830	1825-1835	1830-1840	1835-1845	1840-1850	1845-1855	1850-1860	Difference
Bacon	0.22***	0.14***	0.34***	0.46***	0.62***	0.73***	0.70***	0.49***
	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.08)
Butter	0.29***	0.24***	0.35***	0.39***	0.40***	0.42***	0.33***	0.05
	(0.06)	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)	(0.04)	(0.07)
Coffee	0.47***	0.41***	0.46***	0.63***	0.82***	0.86***	0.67***	0.20***
	(0.04)	(0.05)	(0.05)	(0.06)	(0.04)	(0.02)	(0.04)	(0.06)
Corn	0.70***	0.63***	0.49***	0.58***	0.67***	0.68***	0.60***	−0.09*
	(0.04)	(0.05)	(0.04)	(0.05)	(0.03)	(0.03)	(0.04)	(0.06)
Cotton	0.68***	0.71***	0.74***	0.76***	0.79***	0.88***	0.83***	0.15***
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.02)	(0.03)	(0.05)
Flour	0.65***	0.62***	0.69***	0.76***	0.70***	0.82***	0.81***	0.16***
	(0.04)	(0.05)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.06)
Lard	0.36***	0.52***	0.71***	0.78***	0.76***	0.79***	0.73***	0.37***
	(0.10)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.10)
Lin. Oil	0.57***	0.55***	0.54***	0.58***	0.57***	0.58***	0.69***	0.12*
	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.07)
Molass.	0.38***	0.38***	0.37***	0.41***	0.50***	0.50***	0.69***	0.30***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.07)	(0.07)	(0.09)
Nails	0.27***	0.31***	0.55***	0.56***	0.39***	0.77***	0.75***	0.49***
	(0.02)	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)
Pork	0.37***	0.55***	0.67***	0.78***	0.74***	0.75***	0.87***	0.50***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.02)	(0.05)
Rice	0.34***	0.44***	0.49***	0.54***	0.62***	0.67***	0.57***	0.23***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)
Sugar	0.23***	0.42***	0.59***	0.61***	0.60***	0.66***	0.72***	0.49***
	(0.04)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.04)	(0.06)
Wheat	0.59***	0.55***	0.57***	0.64***	0.60***	0.76***	0.82***	0.23***
	(0.04)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.06)
Whiskey	0.54***	0.67***	0.59***	0.60***	0.65***	0.67***	0.72***	0.18***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.04)	(0.07)

Notes: This table provides the means of the posterior distributions for the variance shares of factors aggregated to the good level. Standard deviations of the posterior are in parentheses. Column "Difference" tests the difference in means between the 1850s and 1820s with a two sample t-test.

*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

Table 1.5: Seasonal Magnitudes Averaged by City

	1820-1830	1825-1835	1830-1840	1835-1845	1840-1850	1845-1855	1850-1860	Difference
Charleston	0.049***	0.044***	0.040***	0.037***	0.037***	0.038***	0.041***	−0.008***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Cincinnati	0.064***	0.056***	0.052***	0.052***	0.053***	0.056***	0.061***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
New Orleans	0.081***	0.074***	0.066***	0.061***	0.058***	0.059***	0.064***	−0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
New York	0.051***	0.046***	0.042***	0.041***	0.040***	0.043***	0.047***	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Philadelphia	0.039***	0.035***	0.032***	0.031***	0.032***	0.035***	0.040***	0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)

Notes: Seasonal magnitudes are measured as the annual standard deviation of the (log) price seasonal. Standard errors are bootstrapped using the conditional distributions of the (Kalman smoothed) seasonal frequencies. Column "Difference" tests the difference in means between the 1850s and 1820s with a two sample t-test.

*** Significant at the 1 percent level

** Significant at the 5 percent level

* Significant at the 10 percent level

Table 1.6: Seasonal Magnitudes Averaged by Good

	1820-1830	1825-1835	1830-1840	1835-1845	1840-1850	1845-1855	1850-1860	Difference
Bacon	0.067***	0.062***	0.056***	0.053***	0.053***	0.056***	0.062***	−0.005**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Butter	0.064***	0.057***	0.051***	0.049***	0.045***	0.050***	0.056***	−0.008**
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Coffee	0.024***	0.022***	0.020***	0.019***	0.019***	0.022***	0.025***	0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Corn	0.058***	0.055***	0.053***	0.051***	0.052***	0.055***	0.059***	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Cotton	0.030***	0.027***	0.025***	0.025***	0.027***	0.030***	0.035***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Flour	0.077***	0.064***	0.054***	0.045***	0.041***	0.042***	0.049***	−0.028***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Lard	0.083***	0.073***	0.066***	0.061***	0.057***	0.055***	0.056***	−0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Molass.	0.049***	0.047***	0.040***	0.036***	0.034***	0.036***	0.041***	−0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Pork	0.067***	0.051***	0.042***	0.040***	0.039***	0.040***	0.043***	−0.023***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Rice	0.053***	0.044***	0.044***	0.045***	0.045***	0.045***	0.047***	−0.005
	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)
Sugar	0.050***	0.046***	0.045***	0.046***	0.050***	0.056***	0.063***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Wheat	0.037***	0.035***	0.034***	0.036***	0.040***	0.046***	0.054***	0.017***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Whiskey	0.056***	0.054***	0.052***	0.052***	0.053***	0.054***	0.058***	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)

Notes: Nails and linseed oil are omitted because fewer than 3 series of each exhibited statistically significant seasonality. Seasonal magnitudes are measured as the annual standard deviation of the (log) price seasonal. Standard errors are bootstrapped using the conditional distributions of the (Kalman smoothed) seasonal frequencies. Column "Difference" tests the difference in means between the 1850s and 1820s with a two sample t-test.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

Table 1.7: Selected Calibrated Parameters

Parameter	Value	Method / Name
Freight Costs:		***Factor Model w/ Seasonal Dummies***
θ	-0.03	Freight cost time trend
λ	0.73	Freight cost persistence
σ_τ^2	0.19	Transportation cost innovation variance
Production:		***Panel regression by county-time***
ψ_w^+	0.06	Wet weather coefficient
ψ_w^-	-0.08	Dry weather coefficient
Demand:		***Simultaneous Equation Model***
β	-3.97	Demand Elasticity
ρ_α	0.86	Demand shock persistence
σ_α^2	0.15	Demand innovation variance
Other:		
δ	0.015	Monthly Depreciation Rate
r	0.004	Monthly Interest Rate
ρ_p	0.83	National price persistence
σ_p^2	0.86	National price innovation variance

Table 1.8: Estimated Trade Cost Statistics

Method of Estimating $\hat{\tau}_t$:	Transportation Lags	Information Lags	$\sigma_{\hat{\tau}}$	ρ	$\text{corr}(\tau, \hat{\tau})$	$\frac{1}{T}\sum \lvert\log(\hat{\tau}_t/\tau)\rvert$
Observed	N/A	N/A	0.0013	0.6237	N/A	N/A
Factor (seasonal dum)	N	N	0.0030	0.8287	0.3234	0.3214
Factor (seasonal dum)	Y	N	0.0014	0.8308	0.4476	0.3377
Factor (seasonal dum)	Y	Y	0.0035	0.8169	0.2945	0.3778
Factor	N	N	0.0030	0.7580	0.1088	0.3732
Factor	Y	N	0.0035	0.7226	0.1672	0.3846
Factor	Y	Y	0.0009	0.6838	0.0800	0.4073

Note: ρ is obtained from regression $\log(\hat{\tau}_t) = \phi + \beta t + \rho \log(\hat{\tau}_{t-1}) + u_t$

Table 1.9: Production Regression

Dependent Variable: log(Wheat Production)	OLS (1)	Spatial Error (2)	Spatial Durbin (3)	Spatial Error (4)
Cons.	-54.41^{***}	-124.26^{***}	0.27^{***}	-128.64^{***}
	(2.45)	(8.00)	(0.03)	(8.46)
Year	0.03^{***}	0.07^{***}	0.18	0.07^{***}
	(0.00)	(0.00)	(0.13)	(0.00)
log(Labor)	1.15^{***}	1.11^{***}	1.13^{***}	1.11^{***}
	(0.02)	(0.01)	(0.05)	(0.01)
log(Land Prod.)	0.70^{***}	0.43^{***}	0.44^{***}	0.43^{***}
	(0.03)	(0.04)	(0.03)	(0.04)
Wet PDSI	-0.20^{***}	0.06^{**}	0.09^{**}	0.04
	(0.01)	(0.03)	(0.04)	(0.06)
Dry PDSI	-0.17^{***}	-0.08^{***}	-0.07^{**}	-0.05
	(0.02)	(0.03)	(0.03)	(0.07)
Wet PDSI-sq				0.01
				(0.02)
Dry PDSI-sq				-0.02
				(0.02)
λ		0.93^{***}	0.90^{***}	0.94^{***}
		(0.00)	(0.05)	(0.00)
Nobs	3492	3492	3492	3492
R-sq	0.76	0.89	0.89	0.89
Moran‘s I (p-val)	0.00			

Notes: Standard errors are in parentheses. The spatial weighting matrix is an inverse distance weighting matrix. Labor is defined as the rural population of a county multiplied by its fraction of cropland devoted to wheat in 1880.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

Table 1.10: Demand Curve Estimation

Dependent Variable: log(Flour Consumption)	OLS (1)	LIML (2)	2SLS (3)	2SLS (4)	LIML (5)	LIML (6)
log(Price)	-1.78^{***}	-2.39^{***}	-3.33^{*}	-3.97^{***}	-3.95^{***}	-2.77^{***}
	(0.38)	(0.65)	(1.73)	(1.29)	(1.29)	(0.81)
Constant	4.20^{***}	5.19^{***}	6.71^{**}	7.75^{***}	7.72^{***}	5.80^{***}
	(0.57)	(1.04)	(2.83)	(2.12)	(2.12)	(1.31)
First Stage						
log(Mil. Imports)			-0.08^{**}		-0.01	-0.01
			(0.03)		(0.05)	(0.03)
log(US Exports)				-0.23^{***}	-0.21^{***}	-0.13^{*}
				(0.05)	(0.08)	(0.07)
Constant		1.54^{***}	1.81^{***}	2.40^{***}	2.38^{***}	2.00^{***}
		(0.01)	(0.09)	(0.15)	(0.18)	(0.22)
War FE	X	X	X	X	X	X
Corner FE	X	X	X	X	X	X
Crop-Year FE		X				X
Obs.	104	104	104	104	104	104
R-sq.	0.30	0.28	0.20	0.10	0.10	0.26
F-Stat		101.26	5.80	22.04	12.38	97.92
Overid. Test (p-val.)					0.52	0.01

Notes: Dependent variable is quantity of flour consumed in Chicago. Newey-West HAC standard errors in parentheses. Overidentification tests are performed using Anderson-Rubin's likelihood-ratio test, and the null-hypothesis is exogenous instruments.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

Table 1.11: Cincinnati-New-Orleans Counterfactual Flour Price Behaviors

Counterfactual:	Log Trend Diff	Cyclical Corr	Seasonal Std. Dev.
None	-1.70	0.83	0.42
Freight Only	-1.03	0.76	0.26
Storage Only	-1.53	0.77	0.23
Info Only	-1.66	0.80	0.38
Freight & Storage	-1.04	0.77	0.19
Freight & Info	-1.05	0.88	0.24
Storage & Info	-1.50	0.76	0.21
Freight & Storage & Info	-0.98	0.84	0.18

Notes: All frictions are held at their 1820 level except those listed in the first column which are held at their 1860 values. The simulation is run from 1820-1860 with these values.

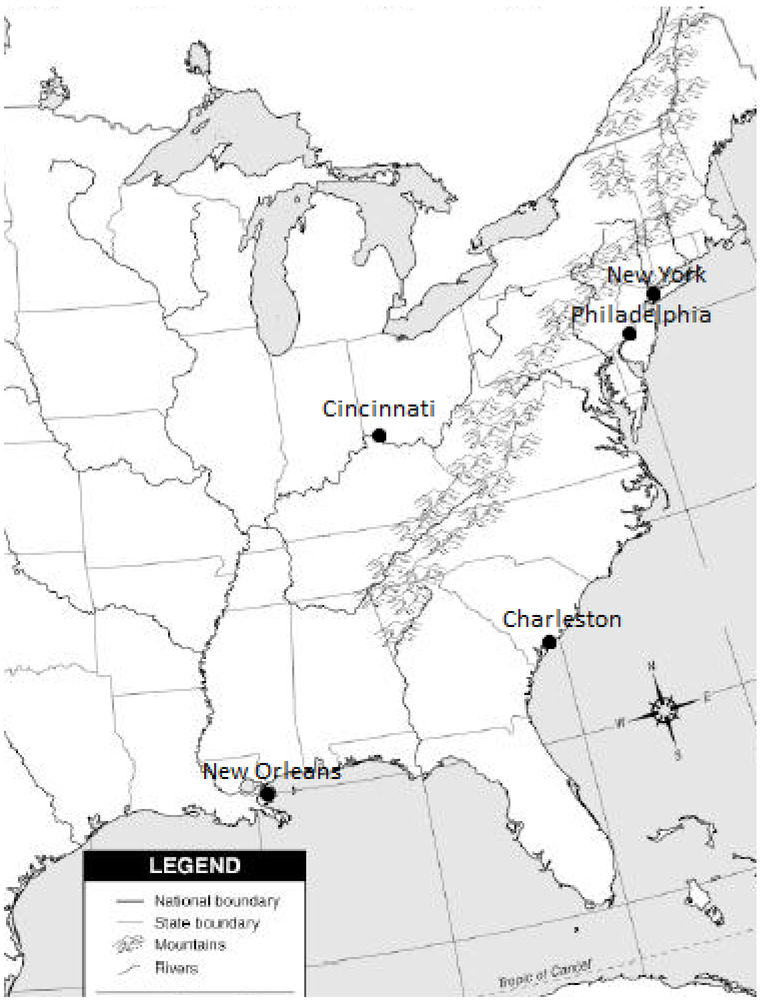

Figure 1.1: Cities in Sample

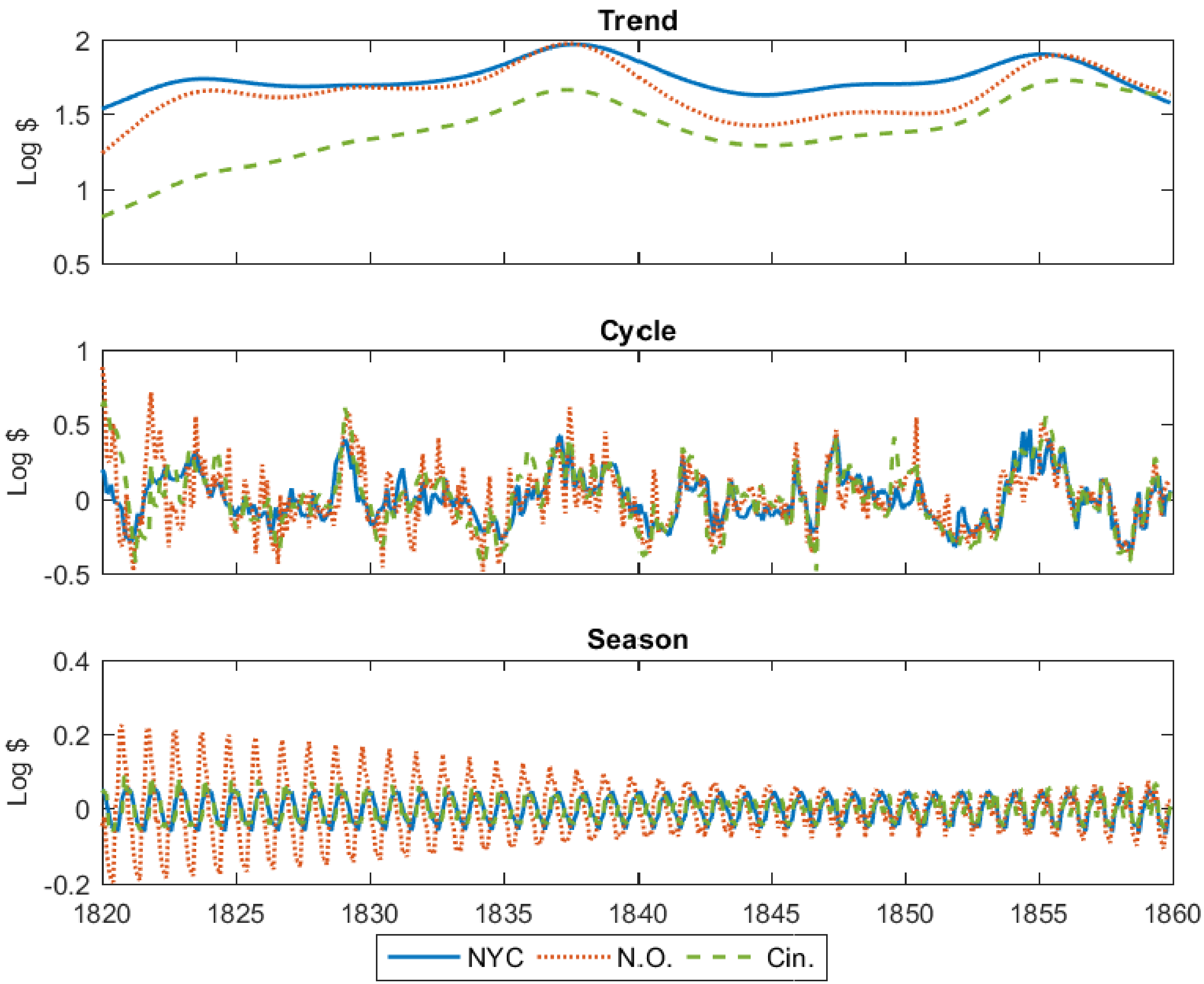

Figure 1.2: Frequency Decomposition of Flour Prices

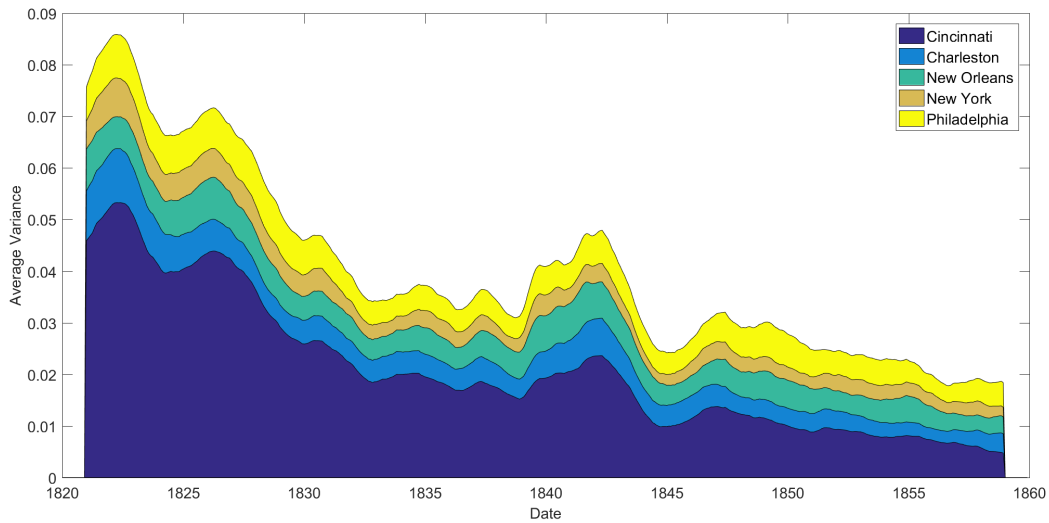

Figure 1.3: Variance Decomposition by City

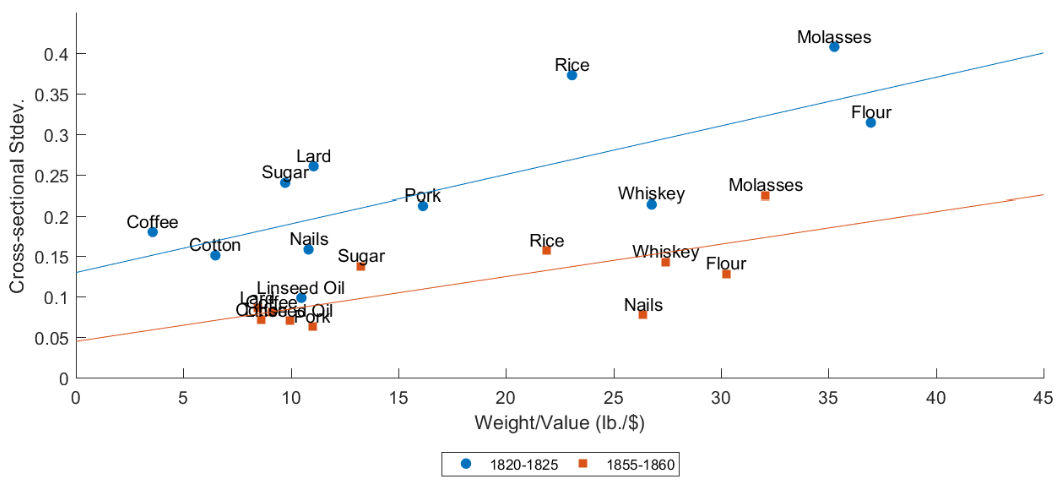

Figure 1.4: Sigma Convergence vs. Weight-to-Value

Notes: Bacon and butter are omitted due to perishability. Corn and wheat are omitted because they are inputs to other traded goods.

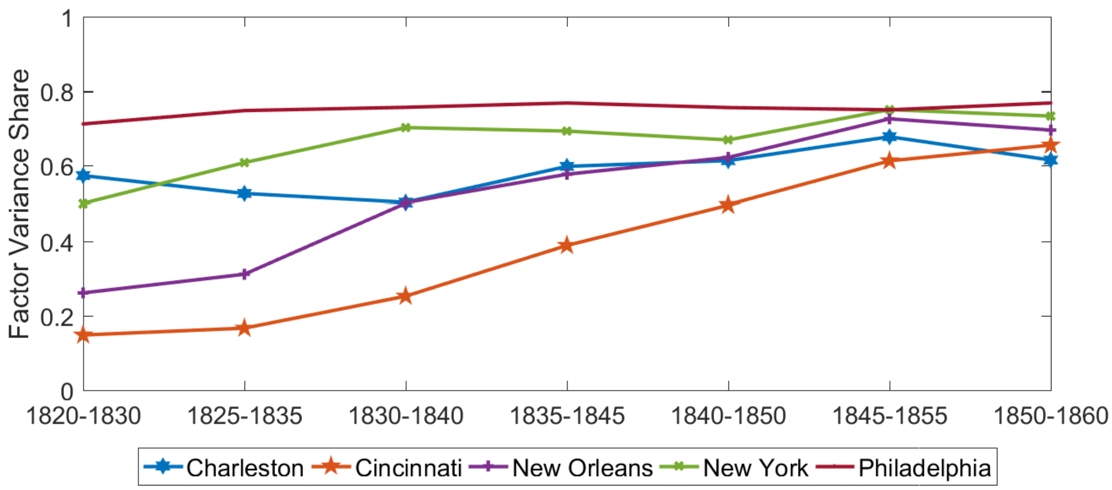

Figure 1.5: Factor Variance Shares Averaged by City

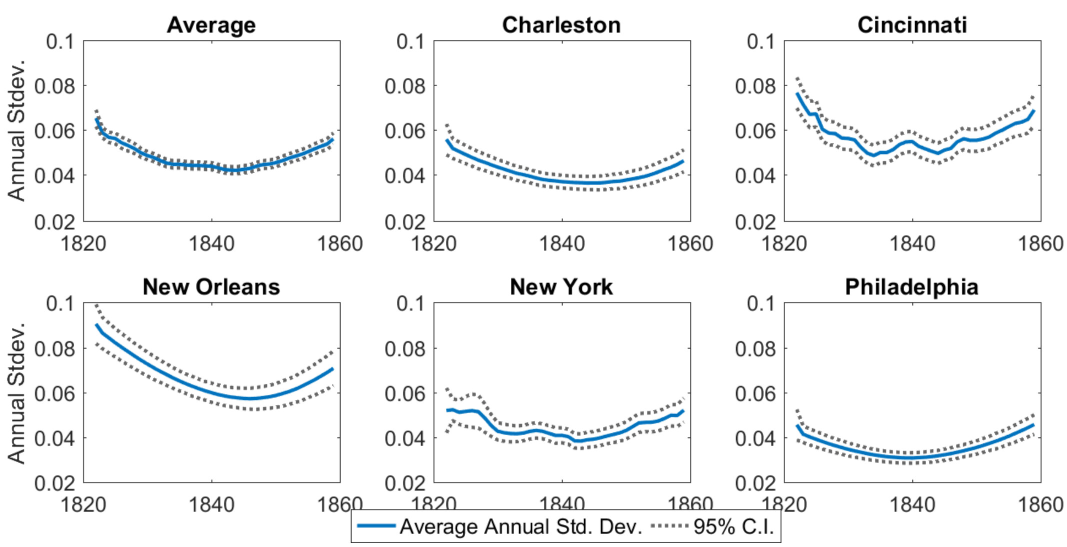

Figure 1.6: Average Seasonal Amplitudes (by City)

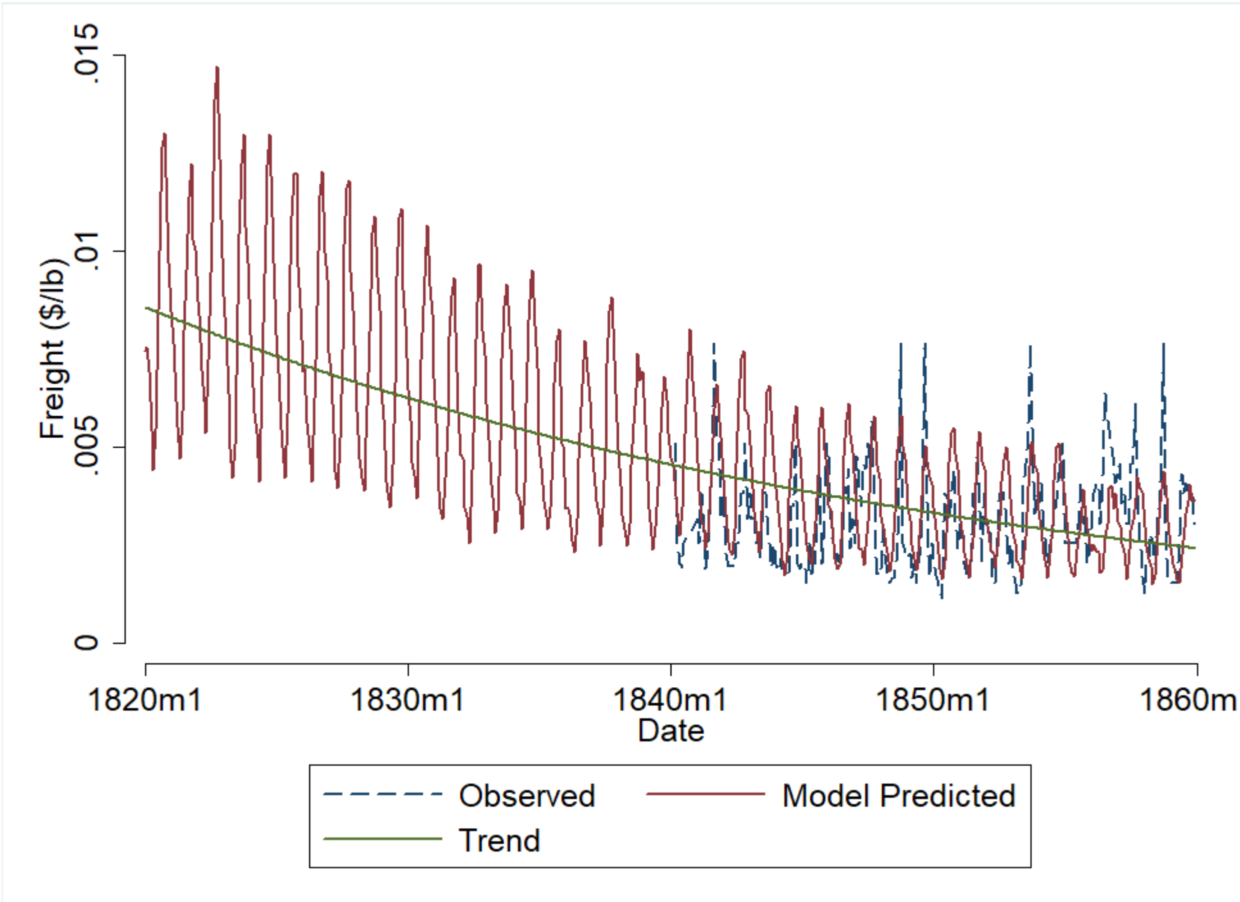

Figure 1.7: Estimated Freight Costs vs. Actual

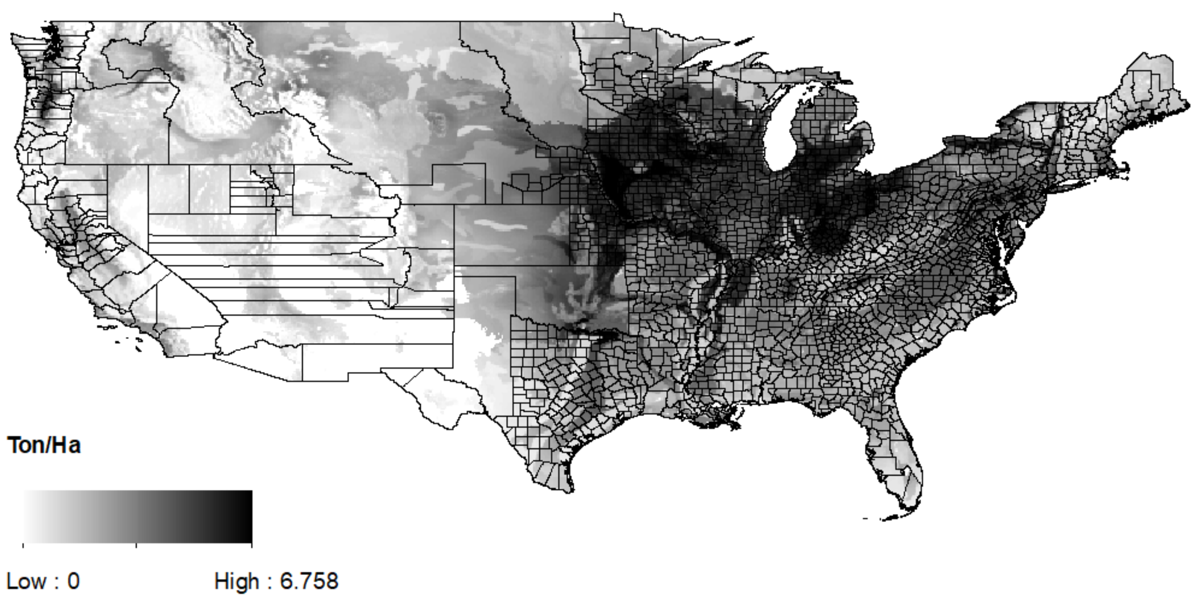

Figure 1.8: Land Suitability for Wheat

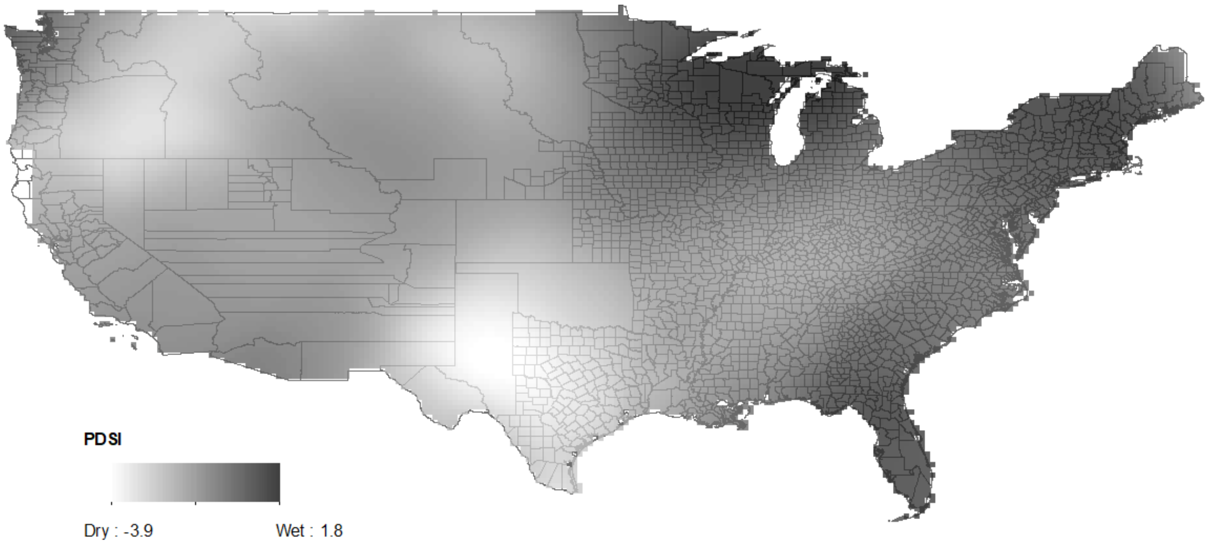

Figure 1.9: Weather Map 1859

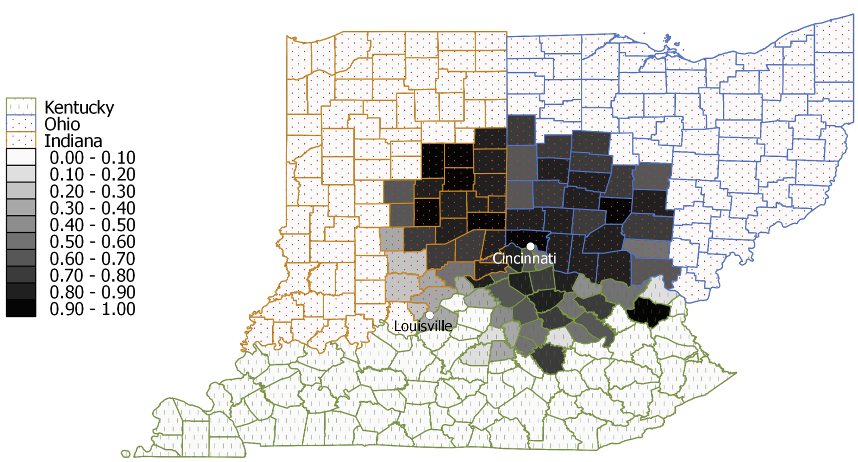

Figure 1.10: Fraction of Merchants who Trade in Cincinnati (within 100 mile radius)

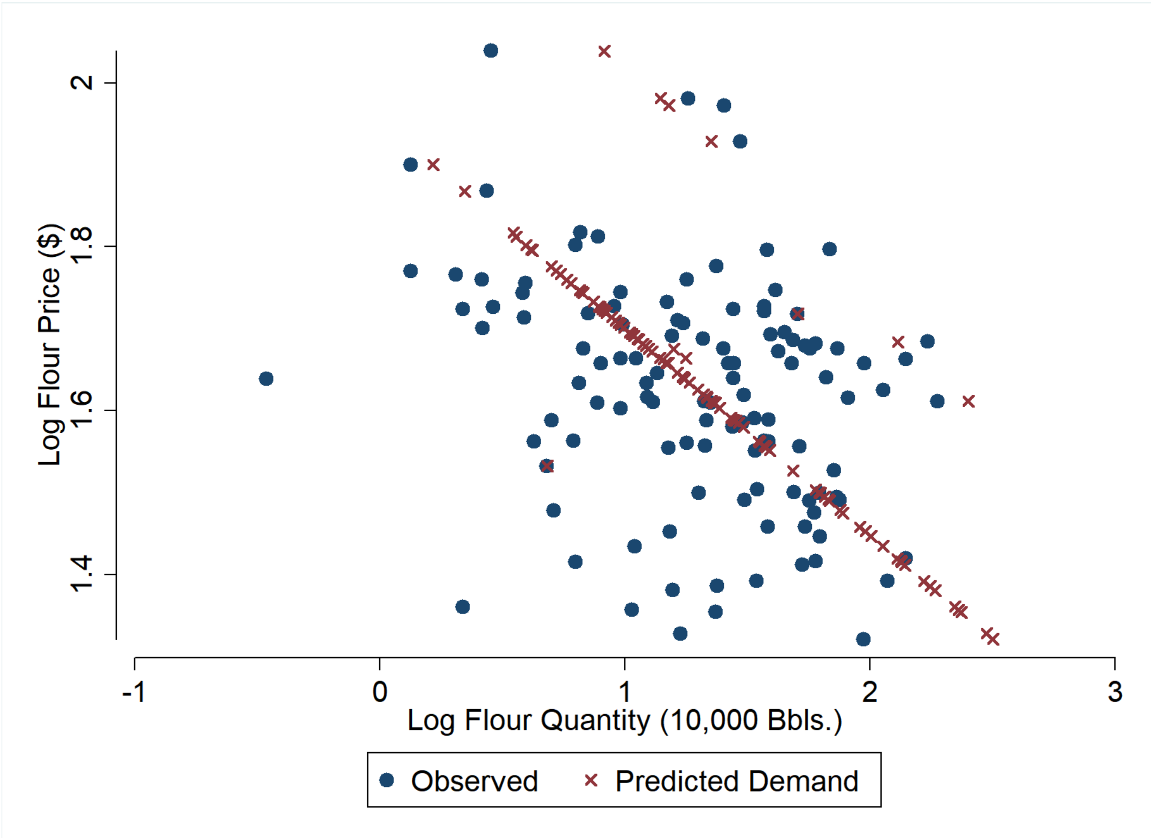

Figure 1.11: Price and Quantity of Flour in Chicago (Monthly 1871-1878)
Notes: The predicted demand is obtained using monthly US exports of flour as an instrument.

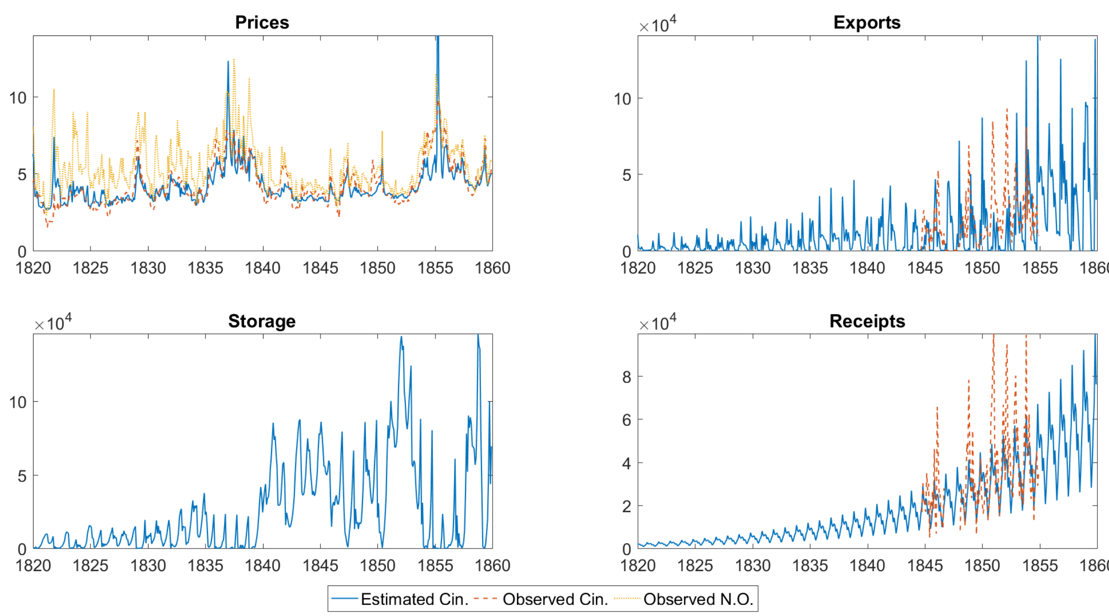

Figure 1.12: Simulated vs. Observed Series
Notes: Cincinnati demand shocks are set to zero in these simulations because although I can estimate their distribution, I do not know their actualizations.

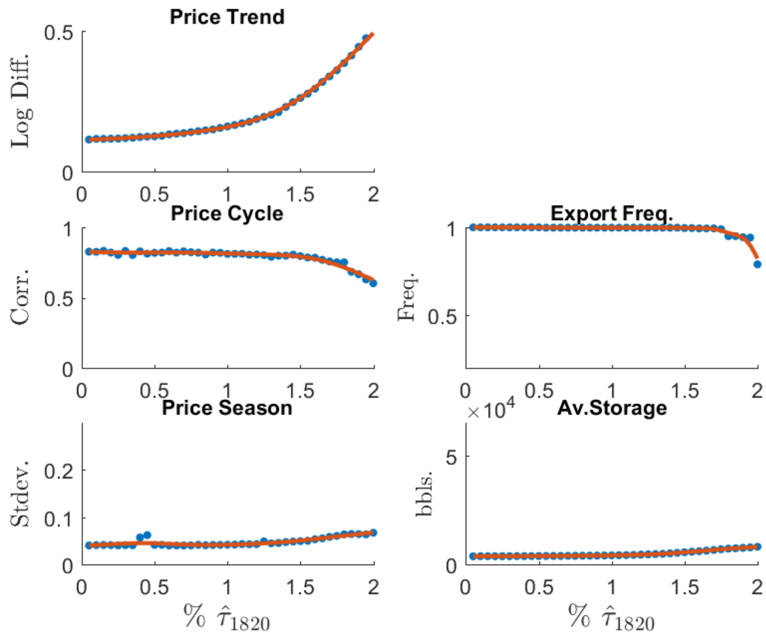

Figure 1.13: Simulated Reposes to Long-run Freight Costs

Notes: This specification excludes cyclical and seasonal freight cost fluctuations and adjusts the value of long-run freight costs compared to their estimated 1820 value.

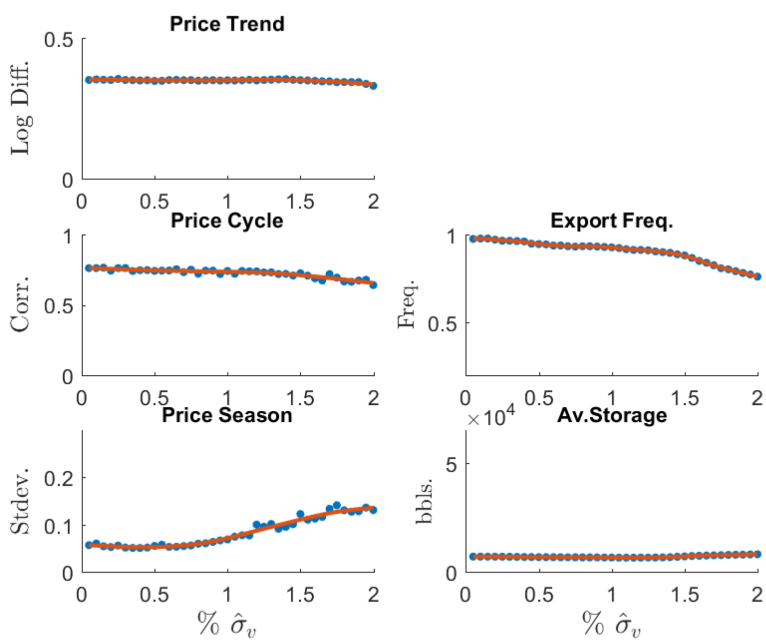

Figure 1.14: Simulated Reposes to Freight Cost Shocks

Notes: This specification excludes seasonal freight cost fluctuations and adjusts the value of cyclical freight cost shocks compared to their estimated 1820 value.

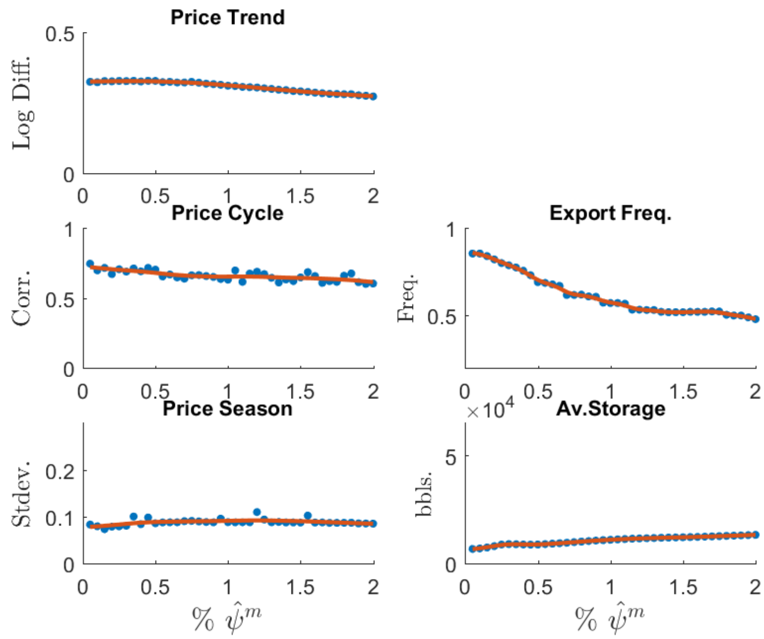

Figure 1.15: Simulated Reposes to Freight Cost Seasonality
Notes: This specification adjusts the magnitude of seasonal freight cost fluctuations compared to their 1820 value

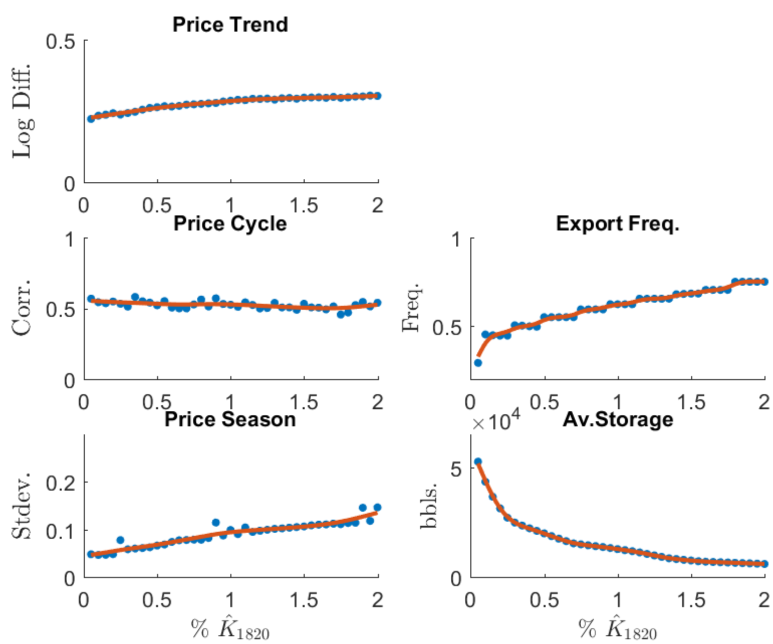

Figure 1.16: Simulated Responses to Storage Costs
Notes: Storage is allowed to vary from 0-200% of its 1820 value.

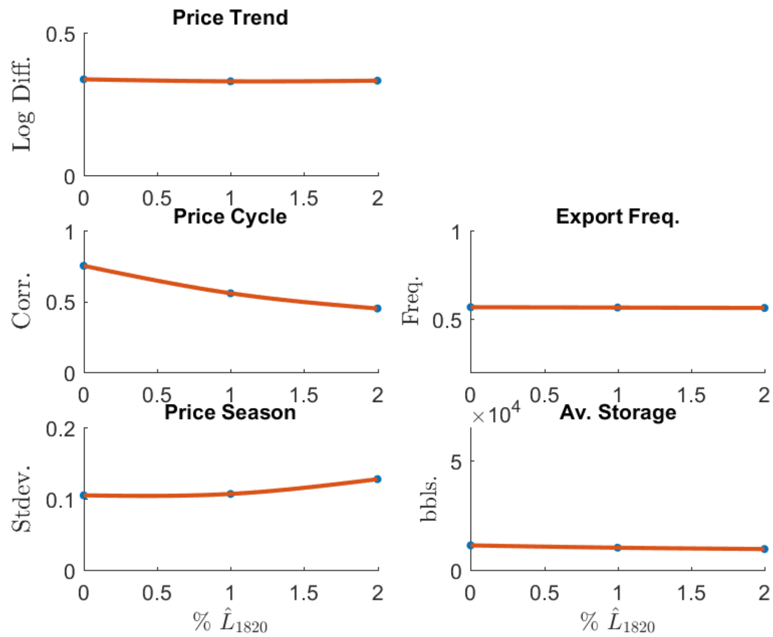

Figure 1.17: Simulated Responses to Information Frictions

Notes: Information lags must be discrete, so only 3 simulations are run spanning from 0-2 months.

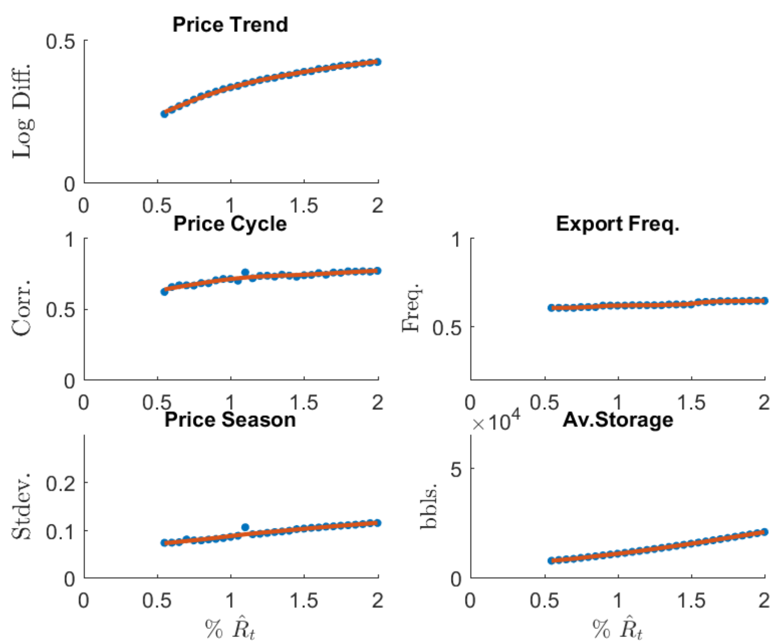

Figure 1.18: Simulated Responses to Seasonal Supply

Notes: Population is allowed to vary from 50-200% of its 1820 value.

CHAPTER 2

HOW DO INFORMATION FRICTIONS IMPACT TRADE? EVIDENCE FROM THE TELEGRAPH

2.1 Introduction

Surprisingly little is known about the types of frictions that impede trade. Economists typically focus on freight costs and tariffs as comprising the bulk of trade frictions; however, recent reviews of the literature have demonstrated these frictions do not adequately explain observed patterns of trade (Anderson and van Wincoop 2004, Head and Mayer 2013a, Head and Mayer 2013b). This dissertation examines how traditionally under-analyzed trade frictions shape price and export behaviors. In the first chapter, I build an arbitrage model to show freight costs, information lags, and storage costs uniquely impact cross-city price behaviors at the trend, cycle, and seasonal frequencies, respectively. In the second chapter, I empirically estimate the impact of information frictions by exploiting the spread of the telegraph across the United States as an historical experiment that exoegenously decreased news lags across markets. In the third chapter, I explore how the deflation of the Great Depression worsened Smoot-Hawley tariffs that were legislated in nominal terms. In all of these chapters, my data consist of price and export volumes for highly disaggregated goods, and I focus on historical settings because they provide substantial variation in the trade frictions of interest.

In the first chapter, I demonstrate the usefulness of decomposing prices into trend, cycle, and seasonal frequencies by uncovering unique convergent behaviors at each frequency during the US transportation revolution. I then construct an arbitrage model to determine how these behaviors were driven by freight costs, information lags, and storage costs. I find that freight costs accounted for 94% of the decline in price trend differentials, storage costs accounted for 78% of the decline in the seasonal magnitude of prices, and information lags were important for determining cyclical price correlations. These results lead to three conclusions. First, there is an interesting mapping between trade frictions and frequencies of cross-city price behavior. Second, information lags and storage costs – two frictions that are often overlooked because they cannot be subsumed into iceberg transportation costs – are important determinants of cross-city price behavior. Third, the US experienced a massive convergence in commodity prices during the transportation revolution.

I narrow my focus to information frictions in the second chapter to take advantage of high-frequency data on news delays. I use the spread of the telegraph across the United States as an historical experiment that exogenously decreased news lags across markets. I use the resulting variation in daily news lags to empirically test Steinwender's (2018) model of arbitrage in the presence of information frictions. My results for the cotton trade between New Orleans and New York are broadly consistent with her model – I find the telegraph decreased price differentials by

21.2%, decreased the variance of these differentials by 62.4%, increased export volatility by 42.3%, and increased exports by 5.6%. These results suggest the importance of traditionally unobserved trade frictions, such as information lags, in determining economic outcomes.

In the third chapter, I use a broad panel of imports to determine the degree to which Smoot-Hawley distorted tariff burdens and import volumes. The balanced panel is the largest of its kind, consisting of 926 goods between 1926 and 1933. This panel allows me to leverage microeconometric techniques and to analyze a wider array of industries than previous literature. I find Smoot-Hawley can only explain about 30% of the increase in tariffs on dutiable imports and 5% of the decline in aggregate import volumes, while the remainder can be explained by nominal distortions and changes in national income. These results are broadly consistent with the previous literature by Crucini (1994) and Irwin (1998b).

Overall, these findings underscore the importance of traditionally under-analyzed trade frictions in distorting trade behaviors – freight costs are important for determining long-run price differentials, information lags cause substantial short-run variation in export and price behaviors, and storage costs impact the seasonal magnitudes of prices. This suggests economists and policy makers should be more attuned to the myriad ways in which seemingly unimportant or unrelated frictions impact trade behaviors.

The field of trade has evolved rapidly over the past decade, yet economists still puzzle over large and persistent price differentials of identical goods across locations (Rogoff et al. 2001, Williamson and O'Rourke 1999, Shiue and Keller 2007). Anderson and van Wincoop (2004) note that such dispersion cannot be explained by observable trade frictions, such as freight costs or tariffs, and suggest it is explained by unobservable trade frictions such as information, time, or red tape barriers. In this spirit, Steinwender (2018) introduces information frictions to an arbitrage model to show how the trans-Atlantic telegraph impacted trade outcomes. She motivates her model by estimating the impact of the one-shot introduction of the telegraph; however, she focuses on simulating the model instead of empirically testing its predictions.

I am the first to empirically test the predictions of Steinwender's model using daily news lags. I use the proliferation of the telegraph across the United States as an historical experiment that provides variation in information speeds. This period provides more variation than the laying of the trans-Atlantic cable because it was marred by recurring telegraphic failures as the technology was still new. This daily variation allows me to test the model's predictions that information lags increase the level and volatility of price differentials while decreasing the those of exports. My empirical results are broadly consistent with these predictions; however, I do not find a statistically significant increase in the level of exports, possibly because my sample is too short to adequately control for the seasonality of exports. These results demonstrate information frictions, despite being often overlooked in the literature, can explain a large share of unresolved price deviations and export behaviors between locations.

I adopt two empirical strategies to measure the economic impacts of this historical experiment. My first strategy estimates the impact of the one-shot implementation of the telegraph. This strategy is powerful because it provides a large exogenous increase in information speed, but its estimates may be confounded by unobserved factors. An added benefit of this approach is that the results can be compared to similar estimations made in Steinwender (2018), so they provide a robustness check against unobserved confounding factors in her sample. My second strategy uses an arbitrage model to inform my estimation. This strategy is more robust because it estimates the impact of multiple short-run information delays in addition to one-shot effect, and the model allows me to identify possible confounding factors.

I inform my estimation strategy using Steinwender's (2018) partial equilibrium model of arbitrage in the presence of information delays. This model is based off of Williams and Wright (1991) in which New Orleans exports cotton to New York, but cotton can be stored in either location indefinitely. As in Coleman (2009), shipping cotton to New York takes time, so agents have to forecast the price they expect receive upon delivery.[1] Information lags increase forecast errors which cause cotton prices to decouple and exporters to be more cautious.

I collect roughly two years of data from historical newspapers to estimate the impact of news lags on the cotton market. I study cotton for two reasons. First, it is such a valuable crop during this period that its data are more complete than other crops and recorded across many qualities. Second, it helps make my results comparable to Steinwender (2018) who also studies cotton markets. My dataset includes daily prices in New York and New Orleans in addition to cotton exports, inflows, and storage. This dataset allows me to test the impact of information access on prices, which is standard in the literature (see e.g. Ejrnaes and Persson 2010), but it also allows me to measure the real impacts of information on cotton quantities. I use Steinwender's method of obtaining daily news lags by calculating the difference between a newspaper's publish date in New Orleans and the date of its latest market report from New York. The frequent telegraphic failures of the period provide large variation in news lags over time, and this proves useful for testing predictions derived from the arbitrage model.

I use my dataset to test four predictions the model makes about the impact of news lags on arbitrage behaviors. First, I estimate that each day of delayed information causes prices to decouple by 5.3%, and the cumulative impact of the telegraph decreased price differentials by 21.2%. Second, I find each day of delayed information diminishes the volatility of price differentials by 22.8%, and the overall impact of the telegraph decreased this volatility by 62.4%. Third, I do not find statistically significant evidence that short-run fluctuations in information speeds affected export volatility, but the long-run impact of the telegraph increased export volatility by 42.3%. Fourth, I do not find statistically significant evidence that news lags increased exports, although the results are of the correct sign and sometimes border on significance. These results demonstrate information frictions have a large impact on arbitrage behaviors and suggest the need for further research on traditionally unobserved trade frictions.

[1] Forward contracts did not exist during this period.

2.2 Data

I collect data on wholesale cotton markets from daily newspapers to test the impact of news lags on market outcomes.[2] This dataset includes information on prices, exports, arrivals, storage, and freight costs for 603 business days spanning from Aug 3, 1847 to July 5, 1849. The first successful telegraphic transmission between New York and New Orleans occurred on July 19, 1848. Therefore, the sample includes 301 business days both before and after the telegraph.

Newspapers provided a wealth of wholesale market information during the nineteenth century that can be used to test the impact of news lags on market outcomes. A newspaper's customer base consisted largely of farmers and others who specialized in the trading or processing of farm produce. Therefore, readers were interested in detailed market information regarding staple crops. Newspapers met this need by summarizing wholesale trades and reprinting the latest market reports from popular export destinations.

I collect daily prices for cotton of identical quality across locations. Seven qualities of cotton are quoted in newspapers ranging from "inferior" to "fine." I use "middling" cotton because it is the most common type of cotton and is observed in the greatest number of periods. New York newspapers also distinguish cotton by its origin, so I use prices for "New Orleans middling" cotton in both locations. This specificity of quality lessens the likelihood that the results are driven by unobserved differences or changes in quality, and is one of the main reasons I focus on cotton (Pippenger and Phillips 2008).

I also collect daily data on the flows of cotton through New Orleans including cotton inflows (from the US interior), exports, and storage. Unfortunately, these data are not distinguished by quality, but middling cotton is the most common quality, and price differences between qualities are unlikely to change substantially over the two year sample. Additionally, exports are not distinguished by destination. This is unlikely to augment my estimated impact of news lags on export behavior because most foreign news reached New Orleans through New York, so a reduction in news lags between the two locations produces an identical decline to all destination markets.[3]

Following Steinwender (2018), I reconstruct news lags in New Orleans from market reports in local newspapers. Newspapers reprinted the latest market reports from major export destinations along with their original publication date. I calculate news lags as the difference in business days between the publication of market reports in New York and their reprinting in New Orleans. Could private information have traveled faster than information available to newspapers? If so, I would underestimate the impact of news lags by missing an initial response. Rumors of private information sometimes swept the markets and were noted in newspaper reports, but these occasions were rare. In fact,

[2] Detailed information on newspaper sources and data collection is available in the Appendix.

[3] News of foreign markets typically traveled by steamships specializing in the rapid transportation of news and passengers between Liverpool and major East Coast ports. This news would be repeated throughout the US by the mail system, trading vessels, or horse riders hired to deliver timelier news. New Orleans was primarily frequented by slower vessels that specialized in carrying cargo. As a result, the East Coast was typically apprised of European news before other cities.

competition among local newspapers encouraged them to hire fast horse riders to obtain news from export markets as quickly as possible for publication. Therefore, the occurrence of private information is likely rare and mitigated by newspapers' efforts to obtain information as swiftly as possible.[4]

Lastly, I collect information on transportation costs. Freight rates between New Orleans and New York are reported at a bi-weekly frequency. My task is simplified because I do not need to consider both sail and steam shipping rates as almost all cotton was shipped by sail during this period. Since freight rates often went unchanged for weeks at a time, little information is lost when I linearly interpolate freight rates for the remaining days of the week. I add data on cartage, wharfage, storage, packaging, and fire insurance fees in New Orleans to transportation costs, but I do not observe similar fees for the unloading process in New York. These missing fees do not bias my point estimates unless changes in unobserved fees are correlated with news lags, but they will cause me to understate the percentage of price differentials explained by information lags. Finally, I collect data on shipping times between New Orleans and New York which were listed in local newspapers. Additional details of the data and their sources are available in the Appendix.

2.3 Model

In this section, I motivate and inform my empirical analysis of news lags by introducing Steinwender's (2018) arbitrage model. Her model is based on Williams & Wright's (1991) two-location arbitrage model with storage. The two locations are New Orleans, which exports cotton, and New York, which uses the cotton in production. Two types of agents populate the model – exporters, which ship cotton from New Orleans to New York, and storers, which allow for inter-temporal smoothing in both locations. Following Coleman (2009), she adds transportation lags to prevent prices from instantaneously equalizing across locations. She then adds information lags to determine how they impact arbitrage behaviors.

Cotton prices in New Orleans are determined by the linear inverse supply function

$$p_t^{NO} = a_{s,t}\left(s_t^{NO}, y_t\right) + b_s x_t \tag{2.1}$$

where x_t are exports and the supply intercept, $a_{s,t}$, is a function of the cotton stock in New Orleans, s_t^{NO}, and inflows of cotton into New Orleans from the US interior, y_t. Cotton prices increase when more is exported, less is received from the interior, or less is released from storage.

Cotton prices in New York City are determined by the linear inverse demand function

$$p_t^{NYC} = a_{D,t} - b_D\left(x_{t-k} - \Delta s_t^{NY}\right) \tag{2.2}$$

[4] See Appendix for further discussion and calculations.

where $a_{D,t}$ is a demand intercept subject to AR(1) shocks, s_t^{NYC} is the cotton stock in New York City, and k is the number of periods cotton takes to be exported from New Orleans to New York City. Cotton prices decline when more is received or released from storage.

Storage and exports are determined endogenously below, but cotton inflows are assumed exogenous for two reasons. First, cotton is price inelastic in the short run because its production is determined in advance during planting and cannot be adjusted until next planting season. Second, cotton's delivery to New Orleans is largely dependent upon seasonal harvest cycles and transportation costs; the need to pay off short-term debt prohibited farmers from storing cotton on their farm for long.

I endogenize exports by assuming agents operate under perfect competition to maximize their expected profit function,

$$\max_{x_t \geq 0} \left(E\left[p_{t+k}^{NY}|I_t\right] - p_t^{NO} - \tau_t\right) x_t \tag{2.3}$$

where I_t is the exporter's current information set about market conditions in New York and τ_t are freight costs. The exporter buys cotton in New Orleans today for p_t^{NO} and pays τ_t to ship it in expectation of receiving p_{t+k}^{NYC} upon delivery in k periods. If expected profits are positive, the exporter continues to export until the expected marginal benefits, $E\left[p_{t+k}^{NYC}|I_t\right]$, equal the marginal costs, $p_t + \tau_t$. That is,

$$\begin{aligned} E\left[p_{t+k}^{NY}|I_t\right] &= p_t^{NO} + \tau_t \quad \text{if } x_t > 0 \\ E\left[p_{t+k}^{NY}|I_t\right] &\leq p_t^{NO} + \tau_t \quad \text{if } x_t = 0 \end{aligned} \tag{2.4}$$

Optimal exports are obtained by substituting the price equations (2.1) and (2.2) into these optimality conditions,

$$x_t = \max\left\{\frac{E\left[a_{D,t+k} + b_D \Delta s_{t+k}^{NY}|I_t\right] - a_{S,t}\left(s_t^{NO}, y_t\right) - \tau_t}{b_S + b_D}, 0\right\} \tag{2.5}$$

where s_t does not permit a closed form solution.[5] Exports increase as agents expect higher future demand or increased cotton storage, but they decline as local supply decreases or freight costs increase.

The volatility and average quantity of exports increases as information lags decline. When news of shocks from New York reaches exporters in New Orleans quickly, arbitragers know the shocks will be more likely to persist over the duration of the voyage to New York. As a result, export volatility increases because arbitragers export more to exploit positive shocks and less to avoid negative shocks. However, faster information speeds do not allow arbitragers to export less than zero during negative shocks. This creates an asymmetry in which timelier information allows arbitragers to fully exploit all positive shocks, but they cannot export negative amounts during negative shocks. This

[5] Storage this period depends on expected storage next period which, in turn, depends on expected storage in future periods. Since storage has a non-negativity constraint, this cannot be solved as a dynamic programming problem (Williams and Wright 1991). For a numerical approach to solving for storage, see Coleman (2009) and Williams and Wright (1991).

asymmetry causes average exports to increase as news lags decline.[6]

The export function can be used to show that shipping-lagged price differentials are dependent on forecast errors when exports are positive; otherwise, they are a function of local supply and demand. That is,

$$p_t^{NY} - p_{t-k}^{NO} - \tau_{t-k} = \begin{cases} a_{D,t} + b_D \Delta s_t^{NY} - a_s\left(s_t^{NO}, y_t\right) - \tau_{t-k} & \text{if } x_{t-k} = 0 \\ \left(a_{D,t} - E\left[a_{D,t}|I_{t-k}\right]\right) + b_D\left(\Delta s_t - E\left[\Delta s_t^{NY}|I_{t-k}\right]\right) & \text{if } x_{t-k} > 0 \end{cases} \tag{2.6}$$

Information speeds only impact shipping-lagged price differentials when arbitragers are exporting and make errors in forecasting demand or storage. Faster information decreases these forecast errors which diminishes the magnitude of shipping-lagged price differentials.[7] Since forecast errors are only made when exports are positive, news lags disproportionately impact shipping-lagged price differentials when there is a positive price shock in New York because this is when arbitragers are more likely to export. This means faster information speeds are more likely to decrease shipping-lagged price differentials during positive than negative shocks, so faster information diminishes the these differentials on average. Timlier information also diminishes the variation in these differentials because the variance of forecast errors decreases as information sets improve. This is instructive, but most studies of information lags focus on contemporaneous, not shipping-lagged, price differentials because shipping lags are difficult to observe in other settings. Do news lags impact contemporaneous price differentials in a similar manner?

While contemporaneous price differentials depend on the same forecast errors as shipping-lagged price differentials, they also depend on changes in supply, freight costs, expected demand, and expected storage. That is, when $x_t > 0$ and $x_{t-k} > 0$

$$p_t^{NY} - p_t^{NO} - \tau_t = \theta_t - \gamma \Delta_k\left[a_{s,t}\left(s_t^{NO}, y_t\right) + \tau_t\right] - (1-\gamma)\Delta_k E\left[a_{D,t+k} + b_D \Delta s_{t+k}^{NY}|I_t\right] \tag{2.7}$$

where $\gamma \equiv \frac{b_D}{b_S + b_D}$ and $\theta_t \equiv \left(a_{D,t} - E\left[a_{D,t}|I_{t-k}\right]\right) + b_D\left(\Delta s_t^{NY} - E\left[\Delta s_t|I_{t-k}\right]\right)$ is the same forecasting error made in (2.6). The final term in (2.7) measures the change in exporter's expectations of demand and storage conditions over time and is zero in expectation given sufficiently non-persistent shocks. Therefore, a decline in news lags diminishes these price differentials by decreasing forecast errors that were made k periods prior – the same mechanism as before. However, the impact of news lags on the variance of these price differentials is amiguous. The forecast errors made while exporting, θ_t, decline when news lags from k periods ago diminish, but the variance of the last term in (2.6) increases when news lags from this period or k periods ago decline.[8]

[6] For formal proofs, see Steinwender (2018).

[7] Forecasting errors in demand and stock should partially offset each other because an unexpected positive shock to demand should result in a release of cotton from storage to exploit the price shock. However, the demand shock will be larger than the storage shock because storage only perfectly offsets shocks if the amount in storage is infinite (Williams and Wright 1991). In addition, Steinwender (2018) estimates b_D to be 0.031, largely discounting the impact of incorrectly forecasting changes in storage.

[8] Expectations of AR(1) functions asymptotically approach the

This model has generated four testable predictions about how news lags impact arbitrage behavior. First, price differentials decline as exporters disproportionately reduce their forecast errors during positive price shocks. Second, the volatility of these differentials decreases as the variation in forecast errors declines. Third, variation in exports increases as arbitragers become better positioned to respond to demand shocks. Fourth, exports increase because arbitragers fully exploit positive price shocks, but they cannot export less than zero during negative shocks.

2.4 Empirics

In this section, I test Steinwender's (2018) four theoretical predictions regarding the impact of news lags on arbitrage behavior. My empirical strategies exploit variation in news lags induced by the introduction of the telegraph and its frequent failures. I find broad support for three of the theoretical predictions, but I lack statistical significance to conclude that exports increased during the period due to changes in information lags. This suggests trade frictions that are traditionally unobserved, such as information frictions, are important determinants of economic outcomes.

The sample period exhibits substantial variation in news lags that can be exploited to determine the impact of information on arbitrage behaviors. Figure 2.1 demonstrates three sources of variation in news lags which are consistent with the historical narrative. First, news lags declined slightly as the telegraph extended incrementally toward New Orleans. Second, the implementation of the telegraph (demarked by the vertical line) decreased news lags from 7.49 days to 4.6 days on average. News lags do not immediately decline to 1 day because operating protocols and technical shortcomings prevented the speedy dissemination of news.[9] Third, the telegraph increased the variation in news lags by roughly 30%. This increase in variation is caused by frequent failures and repairs of telegraph lines.

The impact of the telegraph on arbitrage behaviors is suggested by the summary statistics in Table 2.1. The decline in news lags is concurrent with a fall in price differentials, a decrease in the volatility of price differentials, an increase in exports, and a rise in export variation. These results are consistent with the theoretical predictions; however, they may be driven by a contemporaneous decline in freight costs, an increase in cotton inflows from the interior, or other confounding variables.

I use two empirical strategies to control for these confounding variables when estimating the impact of news lags on arbitrage behaviors. First, I inform my regression specifications using the model use short-run variation in news lags to provide unexpected shocks to market information. This strategy is comparatively robust to confounding factors, but it can be difficult to achieve statistical power. Therefore, I also estimate the one-shot impact of the telegraph which acts as a natural experiment that exogenously reduces news lags. This strategy is statistically powerful because it measures the combined impact of news reductions induced by the telegraph; however, it is possibly sensitive to confounding factors not addressed in the model. These empirical strategies rely on the assumption that arbitragers do not hold

[9] Newspapers in New Orleans often complained about the slowness telegraphs as messages would get "lost" in transmission at stations between New York and New Orleans. In addition, complaints surfaced that the local telegraph office was slow in delivering messages.

back exports in anticipation of an impending decline in news lags. As in Steinwender (2018), I argue that declines in news lags could not have been predicted due to recurring telegraphic delays and failures that varied in duration and frequency. I use these empirical strategies to test the model's four theoretical predictions in the next four subsections.

2.4.1 Price Differentials

In this subsection, I find news lags are responsible for a large portion of price differentials in my sample. This result is apparent in Figure 2.2 which displays the evolution of price differentials and tansportation costs throughout the sample. Freight costs appear to explain a greater share of price differentials after the telegraph is complete. The results are largely driven by better information leading to a decline in arbitragers' forecast errors which, as explained in Section 2.3, disproportionately narrows price gaps during positive price shocks. Since (2.6) demonstrates shipping-lagged price differentials are comprised entirely of forecast errors when exports are positive, the magnitude of these differentials serves as a convenient test of the impact of news lags on forecast errors.

I find news lags substantially increase the magnitude of shipping-lagged price differentials, $\left|q_t^k\right| \equiv \left|p_t^{NY} - p_{t-k}^{NO} - \tau_{t-k}\right|$. I do not observe forecast errors, but they should increase as information becomes more outdated. I test this relationship by regressing the magnitude of shipping-lagged price differentials on news delays when lagged exports are positive.[10] I find each day of delayed news increases price differentials by 4.3% of their pre-telegraph mean and present the results in column 1 of Table 2.2.

I check if the estimated impact of news lags is robust to different functional forms and potential confounding variables in columns 2 and 3, respectively. I check for non-linear impacts of information delays on forecast errors because AR(1) forecasts decline asymptotically toward the average price as news lags worsen. I add a quadratic news lag to the regression in column 2 and find a small and statistically insignificant result.[11] The impact of news lags also persists after controlling for supply shocks in column 3. Although the model does not predict that shipping-lagged price differentials are affected by supply shocks, I control for lagged exports, storage, and inflows of cotton into New Orleans.[12] The results are largely unchanged, which supports the validity of the model.

News lags impact contemporaneous price differentials, $q_t^0 \equiv p_t^{NY} - p_t^{NO} - \tau_t$, to a similar degree. A seemingly reasonable regression would be to test the impact of current news lags on this differential; however, (2.7) demonstrates only news lags that happened during shipping k periods ago impact price differentials in expectation. Nonetheless, I include current news lags as a falsification test to check for spurious results. Column 4 shows that each additional

[10] Section 2.3 demonstrates forecast errors are only made when exports are positive.

[11] I also tried a log-linear specification, but there are several shipping-lagged price differentials at, or very close to, zero. When these observations are dropped, I find nearly identical results to the linear specification.

[12] The coefficients of these controls are omitted because they suffer from committed variable bias. Exports and storage are functions of demand in New York which is unobserved.

day of shipping-lagged news delays decreases price differentials by 2.7%, but contemporaneous news delays have no statistically significant impact as predicted.

The cumulative effect of the telegraph on current price differentials is large. Column 5 replaces news lags with a telegraph dummy and shows the telegraph reduced these differentials by a substantial 21.2% of their pre-telegraph mean.[13] Dividing this estimate by the average decline in news lags after the telegraph (3.36 days) gives a daily impact of 6.31% and is substantially higher than the estimate in column 4.[14] Alternatively, the trans-Atlantic cable decreased news lags by approximately 9 days and decreased price differentials by about 36% which suggests a daily impact of about 4.1% (Steinwender 2018). This suggests there may be non-linear returns to reducing information delays. In addition, this regression demonstrates that even after controlling for the *level* freight costs, it is also important to control for *changes* in freight costs as suggested by (2.7). The estimated impact of the telegraph could be biased if there is a change in transportation costs that is coincident with the adoption of the telegraph – even if the level of transportation costs is already a covariate. For example, omitting changes in transportation costs from this regression reduces the impact of the telegraph to 18.3%.[15]

Lastly, I find the results are not entirely driven by the implementation of the telegraph but by variation in news lags *within* pre- and post-telegraph due to telegraphic failures and other news delays. I include both news lags and a telegraph dummy in the regression and present the results in column 6. The impact of news lags within each era remains unchanged, which demonstrates the importance of short-run fluctuations in information speed.

These regressions demonstrate the estimated impact of information delays on price differentials is substantial and consistent throughout all specifications. Each day of delayed information is consistently estimated to increase price differentials from $0.027-$0.030, even when the dependent variable changes from shipping-lagged to contemporaneous price differentials. This consistency across dependent variables is explained by (2.6) and (2.7) in that they both depend on the same forecast errors made k periods prior.

2.4.2 Volatility of Price Differentials

In this subsection, I show speedier information decreases the volatility of price differentials both in the long-run, as the telegraph is permanently implemented, and in the short-run, as temporary failures and delays are overcome. This result is apparent in Figure 2.2, in which price volatility decreases substantially after the implementation of the telegraph. The volatility of price differentials declines because timelier information allows arbitragers to better exploit price shocks in New York before they dissipate. As a result, more price shocks are shared across locations, so the volatility of price differentials decreases.

[13] This regression excludes an arbitrary "adoption" period of 80 business days during which news lags remained large even after the adoption of the telegraph.

[14] The average news lag is calculated for the post-adoption period to match the sample in column 5.

[15] Regression results are omitted from Table 2.2.

I estimate the impact of news lags using log-linear regressions of price volatility on news lags. As in Steinwender (2018), I calculate price volatility as

$$\widehat{\text{var}}\left(q_t\right) = \begin{cases} \frac{N_{pre}}{N_{pre}-1}\left(q_t - \overline{q}_{pre}\right)^2 & \text{if } t < tel \\ \frac{N_{post}}{N_{post}-1}\left(q_t - \overline{q}_{post}\right)^2 & \text{if } t \geq tel \end{cases}$$

where q_t is the price differential of study. Although this estimator is based on the squared-deviation on a single day, it is an unbiased estimator of the variance. I then use a log-linear specification to capture the non-linear impact of news lags on price volatility.

I find news lags increase the volatility of shipping-lagged price differentials, $\widehat{\text{var}}\left(p_t^{NY} - p_{t-k}^{NO} - \tau_{t-k}\right)$. I focus on periods in which lagged exports are positive, so price variation is driven entirely by forecast errors made in (2.6), k days previously. Column 1 of Table 2.3 shows each day of information delay increases price volatility by 20.1% as forecast errors increase. I also include contemporaneous news lags as a falsification test, and they are not statistically significant as expected.

The cumulative effect of the telegraph on shipping-lagged price variation is substantial, yet short-run fluctuations in information delays are also important within pre- and post-telegraph eras. A telegraph dummy accounts for a substantial 81.4% of pre-telegraph price variation in column 2. I add news lags in column 3 and find these short-run fluctuations in information speed impact price variation even after accounting for the telegraph. This demonstrates news delays substantially impact the forecasting errors that comprise shipping-lagged price differentials in both the short- and long-run.

News lags increase the volatility of contemporaneous price differentials, $\widehat{\text{var}}\left(p_t^{NY} - p_t^{NO} - \tau_t\right)$, through two opposing channels by (2.7). First, news lags from k days ago introduce forecast errors for exports arriving in New York today, and this increases volatility of price differentials by an estimated 22.8% in column 4. Second, contemporaneous news lags cause forecasts of demand shocks in New York to revert toward the mean, so price shocks are not transmitted as strongly across locations. Contemporaneous news lags are not statistically significant in column 4, and the estimates are of the incorrect sign.

The overall impact of the telegraph on the variation in prices differentials is large, while news lags within pre- and post-telegraph eras do not have a statistically significant impact. I use a telegraph dummy in column 5 to find the telegraph causes a 62.4% decline in the volatility of contemporary price differentials, and I add news lags in column 6 to find short-run news lags in the pre- and post-telegraph eras do not have a statistically significant impact on volatility. Dividing the point estimate in column 5 by the average decline in information lags suggests each day of delayed news causes an 18.6% increase in the volatility of contemporaneous price differentials. For comparison, the 9 day decline in news lags induced by the trans-Atlantic cable decreased price differentials by about 90%, and each day of delayed news increased price volatility by 15% (without controlling for news lags from k periods ago) (Steinwender 2018).

2.4.3 Export Volatility

In this subsection, I show export volatility increases with the introduction of the telegraph, but I do not find a statistical impact for short-run fluctuations in news delays. This can be seen in Figure 2.3 where export volatility appears to increase throughout the season after the introduction of the telegraph. Export volatility increases when news is more recent because arbitragers know price shocks are more likely to persist until their cotton is delivered, so they export more during positive shocks and less during negative shocks.

To control for seasonality, I calculate the volatility of exports by computing their squared deviation from a trend component. I extract the trend component using a Baxter King filter to remove fluctuations lasting longer than the sample's most protracted news delay of 12 days. I compute volatility as the squared deviation of exports from their trend, $\widehat{\text{var}}(x_t) = (x_t - \bar{x}_t)^2$, where $\bar{x}_t$ is the trend component. As in the previous subsection, I use a log-linear specification to calculate the impact of news lags on export variance.

I do not find a statistically significant impact of news lags on export volatility. Column 1 of Table 2.4 estimates each day of delayed information as decreasing export volatility by 4.8%. Although this result is not statistically significant, it is of the correct sign and a plausible magnitude. These results are biased if shipping is not supplied elastically because exports and transportation costs would be simultaneously determined. I estimate the regression without transportation costs in column 2 and find news lags decreased export volatility by 5.9%. Again, this regression does not achieve statistical significance, but it comes close. Perhaps the impact of news lag fluctuations is too fleeting to be measured in this limited sample and measuring the permanent impact of the telegraph would provide more statistical power.

I find the telegraph had a large cumulative impact on export volatility. Using a dummy variable, I estimate the telegraph increased volatility by anywhere from 36.2-42.3% with and without controlling for transportation costs in columns 3 and 4, respectively. Unlike daily news lags, the cumulative effects of the telegraph are statistically significant, suggesting a larger sample size may provide the statistical power to achieve statistical significance of news lags in columns 1 and 2.

2.4.4 Export Magnitudes

In this subsection, I do not find statistically significant evidence that information delays impact the level of exports. As the previous section demonstrated, the volatility of exports increases as news lags decline because agents can better exploit short-run price shocks. This increased volatility should increase average exports because better information incentivizes arbitragers to export more during positive price shocks, but they are not able to export less than zero during a bad price shock.[16] This asymmetry should cause average exports to increase.

Daily export behaviors are difficult to test econometrically for two reasons. First, exports are highly non-stationary as shown in Figure 2.3. Cotton inflows, exports, and storage are clearly dominated by seasonal cycles, and this violates the stationarity assumption that exports have a constant mean. Second, exports are truncated at zero, and this must be dealt with using censored regression techniques. Both of these issues might be solved by taking first-differences of exports, but this would eliminate most of the variation in news lags. What is the best way to handle these econometric issues?

I begin by taking the log-differences of the data year-over-year, but I do not find statistically significant impact of news lags on export levels. Taking differences year-over-year eliminates both the seasonal cycle and the censored nature of exports; however, it comes at the cost of roughly halving my number of observations which reduces statistical significance. This reduction in statistical significance is apparent when I regress the differences in exports against the differences in news lags in column 1 of Table 2.5. Although the estimated impact of news lags is reasonably large, each day of delayed information diminishes exports by 4.5%, the standard errors are large due to the small number of observations. In addition, the impact of the telegraph is embodied by the constant term which is insignificant and of the opposite sign than anticipated. In column 2, I run the same regression without transportation costs to check for the possibility of simultaneity bias. Although news lags approach significance in this regression, the standard errors are once again too large. Is it possible to test this regression without losing so many observations?

Taking advantage of co-integrating relationships, I still do not find news lags impact exports to a statistically significant degree. Figure 2.3 and market clearing conditions suggest that exports should be co-integrated with cotton inflows and stock. I test the impact of news lags using a tobit model with and without transportation costs in columns 3 and 4, respectively. I find the estimated impact of news lags is small and not statistically significant. In columns 5 and 6, I test the cumulative impact of the telegraph on exports with a dummy and estimate an impact of around 5.5%, but these results are also statistically insignificant.

2.5 Conclusion

This paper uses the rollout of the telegraph across the United States to demonstrate that a decline in information frictions decreases the level and variance of cotton price differentials while increasing those of exports. The cumulative impacts of the telegraph are substantial – price differentials fall by 21.2%, price variation falls by 62.4%, exports increase by 42.3%, and export volatility increases by 5.6%.

My results validate Steinwender's (2018) reduced-form findings and model of information frictions. The large impact I find for the rollout of the telegraph across the US bolsters her findings for the trans-Atlantic cable and

[16] Figure 2.3 shows this constraint is frequently binding, especially at the end of the crop cycle.

ameliorates concerns that her results may be driven by confounding factors such as supply disruptions after the Civil War, the introduction of futures contracts, or other unobservables. I also use the period's tremendous variation in daily news lags to be the first to empirically test the model. I find the model is robust to falsification tests, and I achieve statistically significant results for most of the model's predictions.

The results also demonstrate the importance of traditionally unobserved frictions on economic outcomes. Reviews of the literature have stressed that determinants of trade costs have remained poorly understood, with freight costs and tariffs explaining only a fraction of barriers to trade (Anderson and van Wincoop 2004, Head and Mayer 2013a, Head and Mayer 2013b). This paper validates these studies by showing the importance of information lags, a traditionally unobserved friction, and suggests other unobserved frictions may have large impacts as well.

The results speak to the importance of information frictions in the modern world as well. Advances in machine learning allow firms to reduce their forecast errors by using big data. The model suggests that this, combined with improved supply chain management, reduces trade frictions and allows firms to exploit fluctuations in prices around the world in less time than ever before.

It may prove fruitful for a future study to explore the impact of information lags on the direction of trade. Before the telegraph, New York was a popular cotton transshipment point because it allowed exporters to hedge by comparing local prices against the latest European reports which were available about eight days earlier than in New Orleans. After the telegraph, European market reports were available in both locations simultaneously, and the prospect of paying higher freight costs to transship from New York became less appealing. Southern cotton exports to New York fell by 70% between 1850 and 1859 while exports to foreign ports increased by 90% over the same period.[17] The historical narrative for this shift is that the telegraph allowed for a primitive form of forward contracts, called "selling in transit," that eliminated the need to transship to New York. A study of this period could parse the benefits of faster information from the financial instruments that were made feasible by information being able to travel appreciably faster than goods for the first time in history.

Another area of future study is calculating the welfare gains caused by a reduction in news lags. Steinwender (2018) calculates welfare gains by simulating the model using supply and demand elasticities estimated through an instrumental variable strategy. The strategy, although clever, requires many assumptions, and it would be useful to have alternative methods of calculating elasticities. Several alternative instrumental variable methods suggest themselves. For example, in 1846, 5/6 of the Louisiana cotton crop was eaten by insects; in 1850, New Orleans suffered a market corner on cotton; and bread prices throughout the nineteenth century are inversely related to cotton demand (Boyle 1934, Watkins 1908). The elasticities can also be partially recovered by using the coefficient on the change in transportation costs estimated in Table 2.2 (assuming that freight costs are uncorrelated with cotton supply and demand

[17] Statistics were obtained from *The Annual Report of the Chamber of Commerce of the State of New York for the Year 1858.*

shocks) because it represents the ratio of demand to supply elasticities by (2.7).

2.6 Appendix

This Appendix details my data collection process. I obtain all data in this study from historical newspapers. Occasionally, these newspapers have missing, illegible, or qualitative data that prove unusable for the purposes of this paper.[18]

I collect data from multiple newspapers in each location to reduce the number of unusable data points. I use the newspaper judged to be the most dependable in its frequency of data reporting, but I use secondary sources if the primary paper did not have usable data. The prices in differing newspapers are similar; for example, the average price differential between two New Orleans newspapers for a bale of cotton is 0.054 cents – less than one percent of the average price of 7.48 cents and less than half the smallest possible discrete price differential of 0.125 cents.

I collect New York City data from three newspapers: *The New York Herald*, *The New York Daily Tribune*, and *The New York Shipping and Commercial List*. Daily prices are primarily collected from *The New York Daily Tribune*, the secondary source is *The New York Herald*, and the tertiary source is *The New York Shipping and Commercial List.*[19] Weekly quantities of storage, exports, and inflows are obtained from *The New York Shipping and Commercial List.*

I use two sources to collect data for New Orleans: *The Daily Picayune* and *The New Orleans Commercial Bulletin*. Daily prices are collected from *The Daily Picayune* with the secondary source being *The New Orleans Commercial Bulletin*. News delays are primarily obtained from the *The Daily Picayune* because they paid for express riders to bring news faster than news available to *The New Orleans Commercial Bulletin*. It is assumed that no news arrived if no mention is made of New York market information. Daily quantities of storage, exports, and inflows are obtained from *The New Orleans Commercial Bulletin.* Freight costs are available bi-weekly from *The New Orleans Commercial Bulletin* and are linearly interpolated to the daily frequency. I obtain other transportation costs from a variety of sources and provide their values in Table 2.6.

My estimations are biased if agents frequently acted on private news obtained before it was published in newspapers. Some market reports suggest the existence of such private information; for example, "At the date of our last review, the market closed dull and drooping, its depression being attributed to a report that [news items] had been received by private express, and that they were unfavorable. This proved to be the fact, and the telegraphic slip, which contained the only intelligence received, was published [the next morning]."[20] Market reports mentioning private information were rare, but reporters may not have been aware of the prevalence of privately obtained information.

[18]The vast majority of qualitative data was used to describe prices. For example, the qualitative data contained phrases such as “prices are firm,” “prices are drooping,” and “prices are at outside quotations.” All qualitative data points were dropped except for variants on the phrase “no change in prices.”

[19]*The New York Shipping and Commercial List* reports cotton prices based on the American classification scheme instead of the Liverpool classification scheme used by all other newspapers in this study. I use a regression to predict the prices under the American scheme by using the observed prices in the Liverpool scheme. The regression includes a linear time trend to capture drifts in quality over time and is represented by $p_t^{Liverpool} = a + \beta p_t^{American} + \lambda time + e_t$.

[20]Published 1/15/1848 in *The New Orleans Commercial Bulletin*

I determine if private information was obtained substantially faster than newspaper market reports by examining impulse response functions. I perform a vector autoregression for New York and New Orleans prices before and after the implementation of the telegraph and present the results in Table 2.7.[21] The corresponding impulse response functions in Figure 2.4 show prices in New Orleans responding with a lag of approximately six to nine days before the telegraph and about one to four days after the telegraph. The average news lag reported in newspapers was about eight days before the telegraph and about four days afterward. The magnitudes of the impulse response function at each given news lag are not large enough to suggest that agents consistently obtained substantially faster information than the newspapers.

[21] 12 and 9 lags were used in the pre- and post-telegraph periods because those were the longest news lags in each period, respectively.

Table 2.1: Summary Statistics

	(1) Pre	(2) Post	(3) Diff
News Lags	7.53	4.63	-2.89^{***}
	(1.15)	(2.05)	(0.13)
Price Differences	1.05	0.98	-0.07^{**}
	(0.41)	(0.23)	(0.03)
Freight	0.46	0.39	-0.08^{***}
	(0.12)	(0.17)	(0.01)
Exports	3.97	4.01	0.04
	(3.19)	(3.63)	(0.28)
Inflows	3.67	3.76	0.10
	(3.65)	(3.25)	(0.28)

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard deviations are in parentheses.

Table 2.2: The Impact of News Lags on Price Differentials

	(1) $\lvert q_t^k \rvert$	(2) $\lvert q_t^k \rvert$	(3) $\lvert q_t^k \rvert$	(4) q_t^0	(5) q_t^0	(6) q_t^0
NewsLag_{t-k}	0.029^{***}	0.030	0.027^{***}	0.027^{***}		0.030^{***}
	(0.010)	(0.043)	(0.010)	(0.007)		(0.009)
NewsLag_{t-k}^2		-0.000				
		(0.004)				
NewsLag_t				0.007		
				(0.009)		
Telegraph					-0.109^{***}	-0.004
					(0.036)	(0.051)
$\Delta_k \tau_t$				-0.208	-0.255^{*}	-0.271^{*}
				(0.134)	(0.151)	(0.149)
Constant	0.420^{***}	0.417^{***}	0.562^{***}	0.443^{***}	0.643^{***}	0.424^{***}
	(0.057)	(0.106)	(0.075)	(0.053)	(0.065)	(0.088)
% of $\overline{pdiff}$	0.043		0.040	0.053	-0.212	
Controls			X	X	X	X

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Newey West standard errors (2 lags) are in parentheses. The controls include lagged values of cotton storage, exports, and inflows in New Orleans. All specifications omit observations with autarky $k = 20$ days prior. The specification with contemporaneous price differentials also omits observations with autarky in the current period. The telegraph dummy specifications omit an arbitrary 80 observations after the first telegraph connection as news lags decline slowly.

Table 2.3: The Impact of News Lags on Price Differential Volatility

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln\left(\widehat{\text{var}}\left(q_t^k\right)\right)$	$\ln\left(\widehat{\text{var}}\left(q_t^k\right)\right)$	$\ln\left(\widehat{\text{var}}\left(q_t^k\right)\right)$	$\ln\left(\widehat{\text{var}}\left(q_t^0\right)\right)$	$\log\left(\widehat{\text{var}}\left(q_t^0\right)\right)$	$\ln\left(\widehat{\text{var}}\left(q_t^0\right)\right)$
NewsLag_{t-k}	0.201^{***}		0.125^{*}	0.228^{**}		0.036
	(0.054)		(0.066)	(0.113)		(0.139)
NewsLag_t	0.072			0.149		0.051
	(0.063)			(0.098)		(0.129)
Telegraph		-1.268^{***}	-0.832^{**}		-1.629^{***}	-1.340^{**}
		(0.220)	(0.337)		(0.351)	(0.642)
$\Delta_k \tau_t$				0.173^{**}	0.144	0.142
				(0.083)	(0.088)	(0.090)
Constant	-3.509^{***}	0.248	-0.714	-3.947^{**}	-1.300	-2.004
	(0.896)	(0.893)	(1.033)	(1.542)	(1.488)	(2.151)
% of $\widehat{\text{var}}\left(pdiff_t\right)$	0.201	-0.814			-0.624	
Controls	X	X	X	X	X	X

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Newey West standard errors (2 lags) are in parentheses. The controls include lagged values of log cotton storage, exports, and inflows in New Orleans. All specifications omit observations with autarky $k = 20$ days prior. The specification with contemporaneous price differentials also omits observations with autarky in the current period. The telegraph dummy specifications omit an arbitrary 80 observations after the first telegraph connection as news lags decline slowly. Due to the asymptotic nature of the log specification, I drop all observations for which the price variance is less than 0.001.

Table 2.4: The Impact of News Lags on the Variation of Exports

	(1)	(2)	(3)	(4)
	$\ln\left(\widehat{\text{var}}\left(x_t\right)\right)$	$\ln\left(\widehat{\text{var}}\left(x_t\right)\right)$	$\ln\left(\widehat{\text{var}}\left(x_t\right)\right)$	$\ln\left(\widehat{\text{var}}\left(x_t\right)\right)$
NewsLag_t	-0.048	-0.059		
	(0.037)	(0.038)		
Telegraph			0.362^{*}	0.423^{**}
			(0.186)	(0.188)
$\log(\tau_{t-1})$	-0.901^{***}		-0.900^{***}	
	(0.284)		(0.326)	
Constant	-5.305^{***}	-3.693^{***}	-5.686^{***}	-4.623^{***}
	(0.825)	(0.617)	(0.812)	(0.715)
Controls	X	X	X	X

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Newey West standard errors (1 lag) are in parentheses. The telegraph dummy specifications omit an arbitrary number of observations after the first telegraph connection as news lags decline slowly.

Table 2.5: The Impact of News Lags on Exports

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta_y \ln(x_t)$	$\Delta_y \ln(x_t)$	$\ln(x_t)$	$\ln(x_t)$	$\ln(x_t)$	$\ln(x_t)$
Δ_yNewsLag$_t$	-0.045	-0.059				
	(0.046)	(0.045)				
NewsLag$_t$			-0.015	-0.016		
			(0.014)	(0.014)		
Telegraph					0.051	0.056
					(0.065)	(0.065)
$\Delta_y \log(\tau_t)$	-0.485^{**}					
	(0.228)					
$\log(\tau_{t-1})$			-0.179		-0.188	
			(0.119)		(0.129)	
Constant	-0.103	-0.201	-2.918^{***}	-2.558^{***}	-2.908^{***}	-2.612^{***}
	(0.185)	(0.168)	(0.406)	(0.295)	(0.426)	(0.351)
Controls	X	X	X	X	X	X

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Newey West standard errors (2 lags) are in parentheses. The telegraph dummy specifications omit an arbitrary number of observations after the first telegraph connection as news lags decline slowly.

Table 2.6: Shipping Costs

Name	cents/lb	Source
Freight Costs		*The New Orleans Commercial Bulletin*
Storage	0.04	*The New Orleans Chamber of Commerce* (1846,1852)
Bagging, Twine, Mending, Marking	0.04	Boyle (1934)
Cartage	0.02	Boyle (1934)
Wharfage	0.01	Boyle (1934)
Fire Insurance	0.1%	Boyle (1934)

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard deviations are in parentheses.

Table 2.7: Vector Autoregression of Cotton Prices

	Before Telegraph		After Telegraph	
	Δp_t^{NO}	Δp_t^{NYC}	Δp_t^{NO}	Δp_t^{NYC}
Δp_{t-1}^{NO}	-0.121^{**}	-0.048	0.003	0.111^{**}
	(0.057)	(0.052)	(0.067)	(0.047)
Δp_{t-2}^{NO}	-0.195^{***}	0.043	-0.104	0.038
	(0.057)	(0.052)	(0.067)	(0.048)
Δp_{t-3}^{NO}	-0.186^{***}	-0.042	0.062	0.031
	(0.058)	(0.053)	(0.067)	(0.049)
Δp_{t-4}^{NO}	-0.163^{***}	0.147^{***}	-0.003	0.142^{***}
	(0.057)	(0.052)	(0.067)	(0.049)
Δp_{t-5}^{NO}	-0.182^{***}	0.033	-0.027	0.076
	(0.057)	(0.052)	(0.067)	(0.050)
Δp_{t-6}^{NO}	-0.165^{***}	0.155^{***}	-0.013	0.048
	(0.056)	(0.051)	(0.066)	(0.049)
Δp_{t-7}^{NO}	-0.124^{**}	0.091^{*}	-0.010	0.037
	(0.056)	(0.051)	(0.066)	(0.049)
Δp_{t-8}^{NO}	-0.108^{**}	0.042	0.046	0.028
	(0.055)	(0.050)	(0.066)	(0.049)
Δp_{t-9}^{NO}	0.053	0.141^{***}	0.062	-0.032
	(0.055)	(0.050)	(0.065)	(0.051)
Δp_{t-10}^{NO}	0.013	0.069		
	(0.055)	(0.050)		
Δp_{t-11}^{NO}	-0.010	0.094^{*}		
	(0.054)	(0.050)		
Δp_{t-12}^{NO}	-0.081	-0.008		
	(0.054)	(0.049)		
Δp_{t-1}^{NYC}	0.121^{*}	0.024	0.074	0.093
	(0.063)	(0.057)	(0.095)	(0.068)
Δp_{t-2}^{NYC}	0.116^{*}	0.013	0.074	-0.103
	(0.063)	(0.057)	(0.095)	(0.069)
Δp_{t-3}^{NYC}	0.094	-0.038	0.098	-0.100
	(0.062)	(0.057)	(0.096)	(0.071)
Δp_{t-4}^{NYC}	0.031	0.013	-0.084	-0.108
	(0.062)	(0.057)	(0.096)	(0.069)
Δp_{t-5}^{NYC}	0.168^{***}	-0.005	0.162^{*}	-0.020
	(0.062)	(0.057)	(0.096)	(0.071)
Δp_{t-6}^{NYC}	0.239^{***}	-0.023	0.037	-0.148^{**}
	(0.063)	(0.057)	(0.095)	(0.070)
Δp_{t-7}^{NYC}	0.187^{***}	0.002	-0.044	0.096
	(0.064)	(0.058)	(0.094)	(0.071)
Δp_{t-8}^{NYC}	0.192^{***}	0.090	-0.053	-0.057
	(0.064)	(0.059)	(0.094)	(0.070)
Δp_{t-9}^{NYC}	0.257^{***}	-0.061	-0.035	0.044
	(0.065)	(0.059)	(0.093)	(0.072)
Δp_{t-10}^{NYC}	0.092	-0.087		
	(0.065)	(0.060)		
Δp_{t-11}^{NYC}	0.152^{**}	-0.019		
	(0.066)	(0.060)		
Δp_{t-12}^{NYC}	0.140^{**}	-0.117^{*}		
	(0.066)	(0.060)		
_cons	-0.007	-0.009	0.005	0.009
	(0.010)	(0.009)	(0.004)	(0.006)

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are in parentheses. 12 and 9 lags were used in the pre- and post-telegraph periods because those were the longest news lags in each period, respectively.

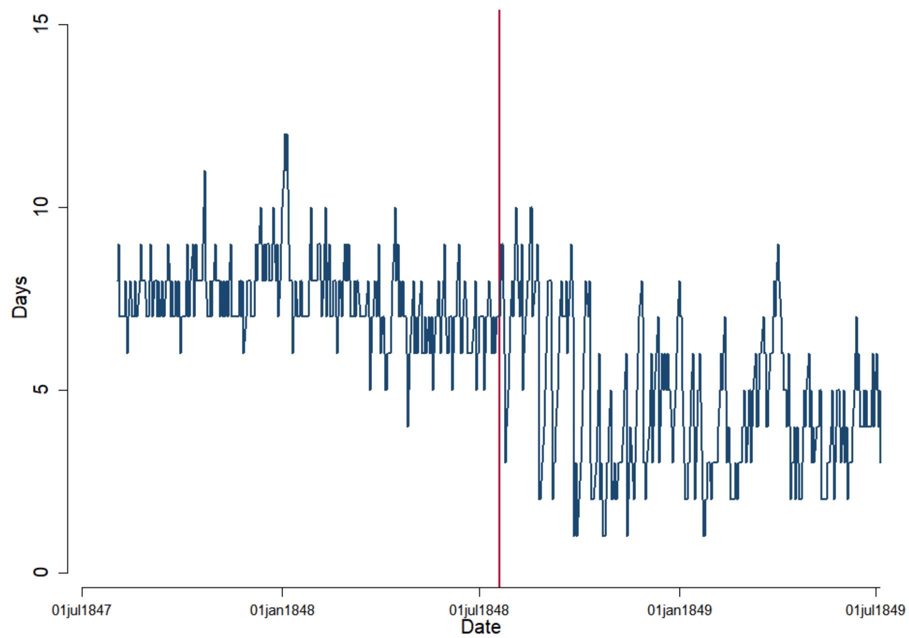

Figure 2.1: News Lags

Notes: The vertical line demarcates the first telegraph received in New Orleans.

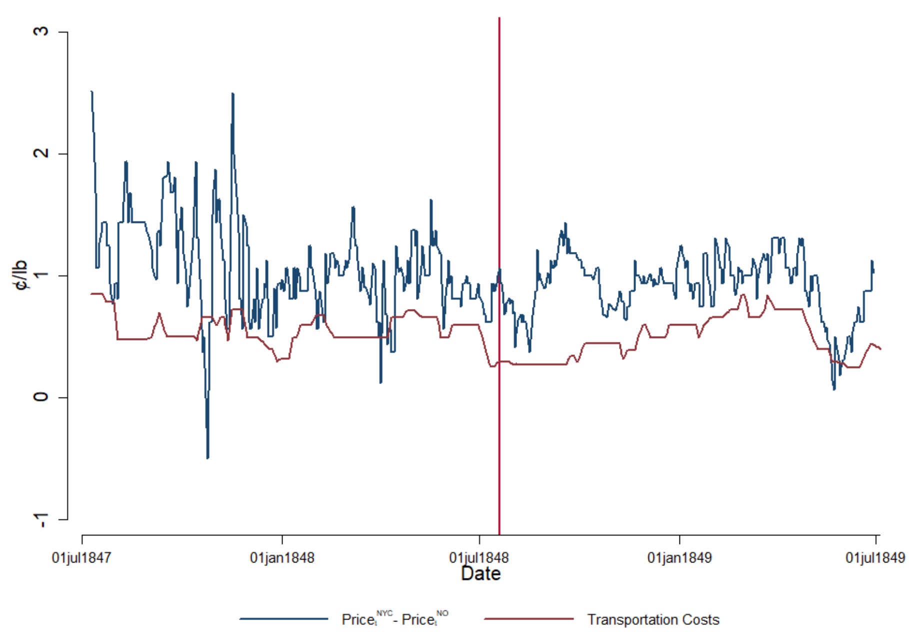

Figure 2.2: Cotton Price Differentials

Notes: The vertical line demarcates the first telegraph received in New Orleans.

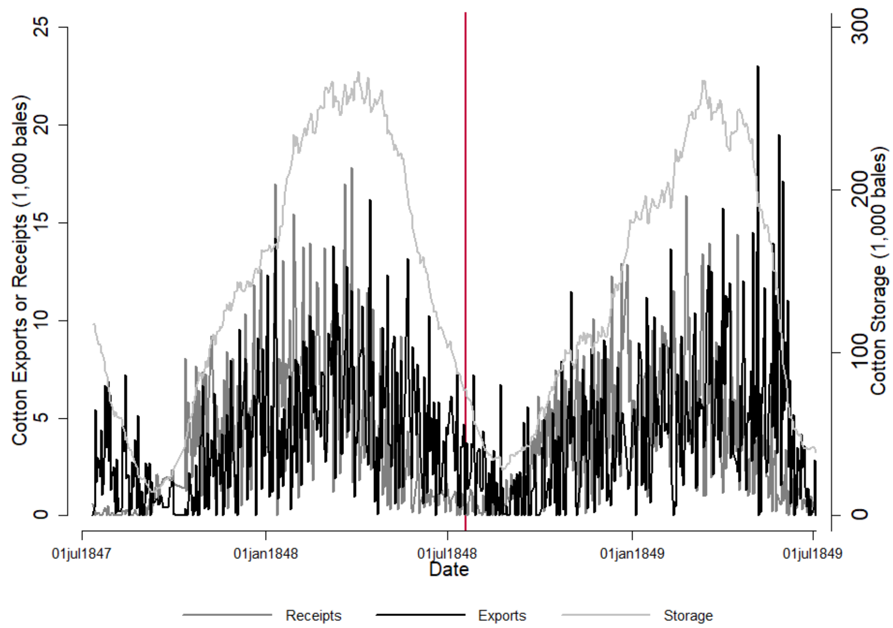

Figure 2.3: Cotton Quantities in New Orleans

Notes: The vertical line demarcates the first telegraph received in New Orleans.

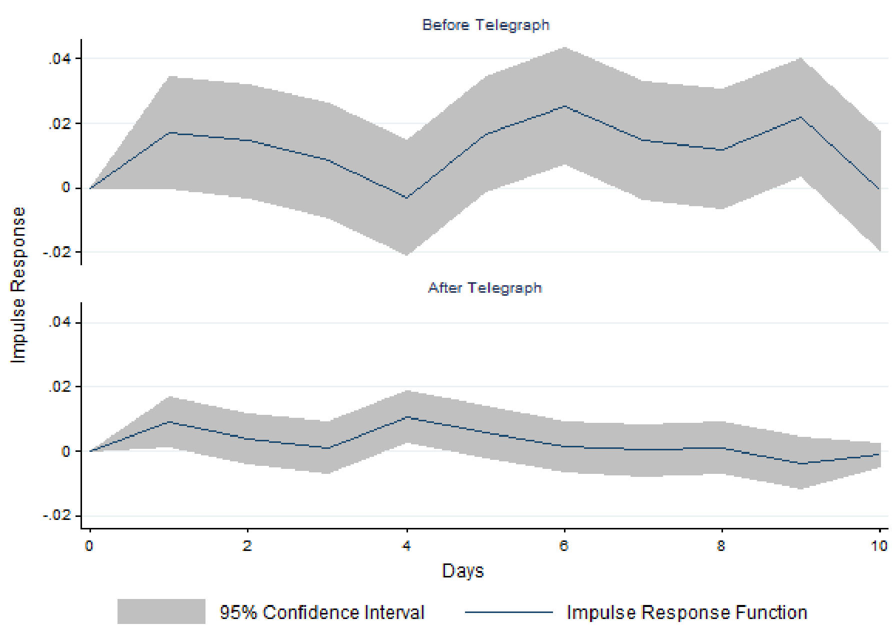

Figure 2.4: Impulse Response Function of New Orleans Prices to New York Shocks

Notes: The impulse response function is derived from a VAR of prices (first differences) presented in Table 2.7. Shocks to New York prices have a statistically significant impact on New Orleans prices 6 and 9 days later before the telegraph, and 1 and 4 days after the telegraph.

CHAPTER 3

IMPACTS OF THE SMOOT-HAWLEY TARIFF: EVIDENCE FROM MICRO-DATA

3.1 Introduction

A popular view of the Smoot-Hawley tariff has been that its enactment was largely responsible for the collapse of interwar trade and the onset of the Great Depression. However, recent work has shown that Smoot-Hawley did not substantially increase tariff burdens – it was only responsible for about a 4-8% decrease in aggregate imports and a 0.2% decrease in TFP (Crucini 1994, Irwin 1998b, Bond, Crucini, Potter and Rodrigue 2013). This paper uses a new panel of tariffs to explore these distortionary impacts of Smoot-Hawley across a wider swath of industries than previous studies.

Determining the impact of Smoot-Hawley is complicated by the existence of two types of tariffs levied during the era – ad valorem and specific.[1] Ad valorem tariffs charge a percentage of an import's value, so their burden is robust to changes in the price level. Alternatively, specific tariffs charge a nominal rate per physical unit imported (e.g. $0.05/lb); consequently, their burden becomes more onerous during deflation as the nominal prices of imports tends to fall while the duty is nominally rigid. To determine the true impact of Smoot-Hawley, I must parse the legislative intent of Smoot-Hawley from the nominal distortions caused by deflation during the Great Depression.

I begin by finding Smoot-Hawley had comparatively modest impacts on tariff levels among dutiable goods during the Great Depression. I use Crucini's (1994) tariff decomposition to determine the degree to which tariff burdens were distorted by legislative intent versus declines in the price level. I find Smoot-Hawley can only explain about 30% of the increase in tariffs while the remainder is explained by the decline in price levels during the Depression. I then perform a variance decomposition to determine the impact of the legislated and nominal components across industries throughout the sample and find the largest tariffs were levied on agricultural industries.

I also find Smoot-Hawley had limited impacts on import volumes. I use cross-sectional regressions to determine Smoot-Hawley only decreased import volumes by 5%. These aggregate findings are similar to those in previous literature, but the broader panel allows me to study individual industries more closely and to provide more robust results.

[1]Combinations of ad-valorem and specific tariffs were also sometimes levied on a single good. In addition, ad valorem ceilings or floors were sometimes placed on goods with specific duties.

3.2 Data

I use a newly digitized dataset of The Foreign Trade and Navigation of the United States (*U.S. Department of Commerce, 1926-1933*). This dataset includes import quantities, values, and tariffs for an average of 5,158 goods per period.[2,3] The frequency of observation is annual from 1926 to 1933, except 1930 is parsed into two periods by the passage of Smoot-Hawley, for a total of nine periods.

Several issues cause the dataset to be unbalanced. These issues include the re-categorization of existing goods, listing of new goods, and missing data; for example, cheese is disaggregated from one variety into six, and vacuum cleaners only became listed after Smoot-Hawley. Further, the line-item structure of tariff legislation varied considerably from one piece of legislation to the next. I overcome this using a combination of manual and algorithmic matching to track goods across years.[4]

I use a balanced panel consisting of 926 goods that accounts for 52.4% of the value of total dutiable imports as shown in Table 3.1. I tend to observe a higher share of value for commodities, such as vegetables and chemicals, than for manufactures, such as machinery and vehicles, because commodity classifications are less likely to change over time. Table 3.1 also shows this panel approximates the full dataset well with an ad-valorem equivalent tariff that is only 0.3 percentage points (0.9 percent) lower than the aggregate tariff.

The balanced panel is substantially more complete than those used in previous studies. Irwin (1998a, 1998b, 2011) uses "average" tariffs (total duties collected divided by total import value) for aggregate categories and cannot parse results by individual goods. Crucini (1994) constructs a panel of 32 imports that account for 28% of the value of total imports, but only seven of these imports have ad-valorem tariffs. Since ad-valorem tariffs are robust to price-level fluctuations, their under-representation may result in an overestimation of the impact of deflation on tariffs during the Great Depression. Further, major categories (wood, paper, wool, silk, and beverages) are entirely unrepresented in his sample. Finally, Bond et al. (2013) use a similar panel to this paper, but with fewer periods.

3.3 Descriptive Statistics

The Smoot-Hawley tariff was originally intended to help farmers after the close of WWI precipitated a collapse in commodity prices. American farmers had drastically expanded agricultural production to meet foreign demand during the war, but commodity prices collapsed after soldiers returned home. Smoot-Hawley's stated focus was to place protectionist tariffs on agricultural imports, but it also left open the possibility of increasing tariffs on non-agricultural goods so as to garner additional political support and protect domestic manufactures. This non-specificity opened the

[2]The value of imports is measured as the f.o.b. foreign value or export value, whichever is higher, converted to US dollars at the prevailing exchange rate.

[3]In comparison, the HS-6 (2017) classification lists 6276 goods.

[4]Details of the matching process are provided in the Appendix.

gates for politicians to engage in vote trading to increase tariffs on the produce of their respective localities.

Logrolling resulted in large tariff changes on a wide array of goods. The intensive and extensive margins of these tariff changes are displayed in Figure 3.1. The top panel shows tariffs increased for many agricultural industries, notably dairy, vegetables, sugar, and oilseed, so Smoot-Hawley's stated objective of placing protective tariffs on agricultural goods appears to have been met.[5] However, many non-agricultural goods also benefited from the legislation, such as caffeinated beverages, leather shoes, iron, and paints. Interestingly, the objective of aiding farmers was also met by decreasing the tariff on some intermediate goods including non-ferrous metals, gums and resins, lumber, and fertilizer. The bottom panel shows the fraction of goods in each industry that were impacted by Smoot-Hawley. Most tariff changes were concentrated in agricultural industries while other industries had fewer tariff changes that tended to be of larger magnitude. Lastly, a large swath of intermediate and manufactured goods received no tariff change at all. These results are largely consistent with those of the complete panel – out of 3,293 dutiable items in the complete panel, the final bill made 887 increases, 235 decreases, and left 2,171 duties unchanged (Irwin 2011).

Specific tariffs were the dominant tariff type and were disproportionately levied on intermediate and agricultural goods. The top panel of Figure 3.2 shows specific tariffs comprised most of the duties collected; in fact, three industries with mostly specific tariffs -- sugar, tobacco, and oilseed -- account for nearly 65% of all duties collected. This concentration of import duties suggests aggregate results will be driven by a handful of industries, but there is substantial variation in tariff rates and types across industries. The bottom panel of Figure 3.2 shows the fraction of duties levied by tariff type across different industries. Specific tariffs were highly represented in agricultural industries (such as the oilseed, egg, spices, dairy, sugar, grains, fruit and nuts, tobacco, and vegetable oil industries) and the intermediate good industries (such as the petroleum and coal, fertilizer, lumber, explosives, non-metallic minerals, gums and resins, iron and steel intermediates, and nonferrous metal industries), while ad-valorem tariffs tended to be levied on finished goods (such as textile manufactures, recreational goods, leather shoes, electrical apparatuses, diamonds, toiletries, paper manufactures, industrial machinery, wood manufactures, and iron and steel manufactures).

What accounts for this variation in tariff types across industries? Irwin (1998a) uses congressional testimony to find ad valorem tariffs tended to be favored by Democrats because of their transparency and equity; that is, the burdens of ad valorem rates can be readily assessed by voters and do not fall disproportionately on lower quality imports. Alternatively, Republicans preferred specific tariffs because taxing quantities prevented importers from fraudulently claiming a low taxable value for their goods. As a result, the composition of tariff types largely depended upon the governmental party in power when the tariffs were last changed. Since the Smoot-Hawley tariff was a Republican bill intended to benefit farmers, most agricultural tariffs in the sample are specific; therefore, they are disproportionately dependent on the price level.[6]

[5] The change in ad valorem equivalent tariffs are calculated as the difference between the first and second halves of 1930 (holding quantities and prices constant at their starting level).

[6] The Fordney-McCumber bill that preceded Smoot-Hawley was also Republican, so tariffs at the beginning of the sample are also dispropor-

These specific tariffs were plagued by a massive deflation during the Great Depression. It is commonly understood that consumer prices fell dramatically during the period, but it is seldom appreciated that import price levels fell roughly twice as far. Figure 3.3 shows the CPI-U, PPI, and three calculations of the import price index (IPI).[7] Consumer and producer prices fell by nearly 30% and 35%, respectively, between 1926 and 1933, but import prices fell by approximately 60% over the same period. This possibly occurs as tariff increases cause imported goods to reduce their prices to remain competitive with local production. Curiously, import prices begin declining even before the crash of 1929. This premature decline may be caused by weighting issues if importers substituted away from expensive imports or if relative prices fell for imports with large weights, such as sugar or tobacco.

I circumvent weighting issues in calculating the import price index by using a factor model to extract common inflationary signals from the balanced panel. Instead of weighting prices by quantities, factor models weight prices based on the strength of their inflationary signal relative to their noise (Bryan and Cecchetti 1993). I extract a single factor using the methodology of Bai and Ng (2002) and plot the results in Figure 3.3.[8] The factor model maintains the same long-run import price decline, but it also satisfies *a priori* expectations by demonstrating comparative price stability before 1929.

This 60% decline in import prices has been found to have had major distortionary impacts on tariff levels and the quantity of imports (Crucini 1994, Crucini and Kahn 1996, Irwin 1998b, Irwin 1998a, Irwin 2011, Bond et al. 2013); however, these distortions have never been examined with such a detailed dataset. The next two section examine tariff and quantity distortions in turn.

3.4 Tariffs

Specific and ad valorem tariffs can be aggregated into ad valorem equivalent tariffs, τ_{it}, that are defined as tariff duties divided by the value of imports. That is,

$$\tau_{it} = \frac{\tau_{is}^{av} P_{it} Q_{it} + \tau_{is}^{spec} Q_{it}}{P_{it} Q_{it}} = \tau_{is}^{av} + \frac{\tau_{is}^{spec}}{P_{it}} \tag{3.1}$$

where τ_{is}^{av} are the legislated ad valorem tariffs, τ_{is}^{spec} are the legislated specific tariffs, P_{it} are prices, and Q_{it} are quantities for import i in period t with tariffs legislated in period s. The aggregate ad valorem equivalent tariff is plotted using constant and variable weights in the top panels of Figure 3.4. Under both weighting schemes, the tariff remains comparatively stagnant until the passage of the Smoot-Hawley tariff, whereupon its burden roughly doubles over the next three years from 33.2% to 69.2%. How much of this increase can be attributed to legislative intent as

tionately denominated as specific.

[7] The Fisher index of the full price panel is obtained from *Indexes of U.S. Exports and Imports by Economic Class (1919–1971), U.S. Bureau of the Census, 1972.*

[8] The factor model is specified as $p_{it} = \lambda_i \pi_t + u_{it}$, where π_t is a static factor.

opposed to distortions of specific tariffs by the massive declines in price levels?

Following Crucini (1994), ad valorem equivalent tariffs can be decomposed into legislative (τ_{is}^{L}), inflationary (τ_{it}^{π}), and relative price (τ_{it}^{RP}) components as,

$$\tau_{it} = \underbrace{\left[\tau_{is}^{av} + \frac{\tau_{is}^{spec}}{P_{is-1}}\right]}_{\text{Legislative}} + \underbrace{\left[\frac{\tau_{is}^{spec}}{P_{is-1}}\left(\frac{P_s}{P_t} - 1\right)\right]}_{\text{Inflationary}} + \underbrace{\left[\frac{\tau_{is}^{spec}}{P_{is-1}}\left(\frac{P_{is-1}}{P_{it}} - \frac{P_s}{P_t}\right)\right]}_{\text{Relative Price}} \equiv \tau_{it}^{L} + \tau_{it}^{\pi} + \tau_{it}^{RP} \tag{3.2}$$

where P_t are aggregate price-levels, and lagged prices are used because tariff revisions were often based on prices that were a year or more old by the time of passage.[9] The legislative component embodies legislators' intended tariff burden based on prices at the time of passage, the inflationary component captures how fluctuations in aggregate price-levels distort the tariff burden from its intended legislated levels, and the relative price component represents how variation in an import's price relative to inflation increases or decreases the tariff burden.[10] Note that for a duty without a specific component, prices do not distort tariffs and the legislative component is the only non-zero term.

The decomposition demonstrates price fluctuations caused much larger changes in tariff burdens than the legislative intent of the Smoot-Hawley bill. The top panels of Figure 3.4 show the evolution of the legislative component and the bottom panels depict the nominal distortions. The ad valorem equivalent tariff increases from 40.2 in 1930 to 69.2 percentage points during its peak in 1932, where the legislative component accounts for 30.8% of this change, the inflationary component induces 153.6% of this change, and the relative price term produces -84.4% of this change.[11]

These results are broadly consistent with the previous literature. Irwin (1998a, 2011) calculates that Smoot-Hawley can explain about 35% of the tariff fluctuations, whereas I estimate a 30.8% impact. Crucini's (1994) smaller panel exhibits larger changes in ad valorem equivalent tariffs (increasing to about 100 percent at their peak in 1932), but the better representation of ad valorem tariffs in this panel make my results less sensitive to price fluctuations. The broader panel also allows me to better capture relative price fluctuations as importers substitute to less expensive goods and to explore tariff changes by industry.

The legislated tariff changes and their nominal distortions exhibited substantial variation across industries between 1930 and 1933. The top panel of Figure 3.5 shows the change in ad valorem equivalent tariffs and their legislative components during this period. Legislated tariff changes ranged from -18% to 48%, with a pattern of the largest changes being placed on agricultural industries and the smallest on manufactures and luxuries. In addition, goods that had the highest proportion of specific tariffs, such as agricultural and intermediate goods, tended to experience the largest nominal tariff distortions, with up to 76 percentage points for eggs and 53 percentage points for sugar.

[9] P_t is the factor model import price index from Figure 3.3. $P_s \equiv P_{1926}$ before Smoot-Hawley, and $P_s \equiv P_{1930b}$ afterwards.

[10] Irwin (1998a) finds that legislators were aware that price fluctuations distorted the burden of specific tariffs, but he concludes that this was of secondary consideration in legislation.

[11] These results are for the variable-weight calculation. For comparison, the ad-valorem equivalent tariff in the full dataset in 1932 is 59.1 percentage points. The fixed-weight calculation has the ad-valorem equivalent tariff increasing from 36 to 73 percentage points, where the legislative component accounts for 43.2% of the change, the inflationary component induces 106.1% of the change, and the relative price term produces -49.3% as the goods that are consumed most experience the largest price declines.

Interestingly, relative price increases outweighed the massive decline in Depression-era price-levels in six industries, suggesting the importance of price fluctuations even when aggregate price-levels are stable. This, combined with the fact that 22.6% of legislated tariff changes in the panel occur in periods not concurrent with Smoot-Hawley's implementation, suggests the importance of determining the role of legislative and nominal tariff distortions across all periods in the panel.

I use a variance decomposition to determine the relative importance of legislative compared to nominal fluctuations throughout the entire panel. I use the fact that $\text{cov}(\tau_{it}, \tau_{it}) = \text{var}(\tau_{it})$ to calculate the tariff variance shares attributable to legislative and nominal fluctuations as

$$1 = \frac{\text{cov}\left(\tau_{it}^{L}, \tau_{it}\right)}{\text{var}(\tau_{it})} + \frac{\text{cov}\left(\tau_{it}^{\pi} + \tau_{it}^{RP}, \tau_{it}\right)}{\text{var}(\tau_{it})}$$

The results are presented in the lower panel of Figure 3.5 and are broadly consistent with the two-period comparison in the top panel. Again, there is much variation in the importance of nominal and legislative fluctuations across industries, with the largest nominal variation disproportionately falling on industries with high proportions of specific tariffs. This indicates nominal price fluctuations non-trivially distort tariffs even when the price-level is reasonably stable.

3.5 Import Volume Distortions

In this section, I find the passage of Smoot-Hawley had a minimal impact on import volume, while macroeconomic events such as deflation and a decline in national income explain most of the decline in imports. I leverage my wide panel of imports to determine the degree to which Smoot-Hawley induced changes in import volume between 1929 and 1932 by running the cross-sectional regression,

$$\Delta\log(Q_{it}) = \alpha + \beta_1\mu_I + \beta_2 SH_i + \beta_3\Delta\tau_{it}^{L} + e_i \tag{3.3}$$

where μ_I are industry-specific fixed effects and SH_i is an indicator variable for imports subjected to Smoot-Hawley tariffs.[12]

I begin by determining the extent to which imports declined due to the combined impacts of the Smoot-Hawley tariffs and Depression. To do this, I run (3.3) with only a constant and report the results in column 1 of Table 3.2. I find goods experienced an average decline in import volume of about 59.8% between 1929 and 1932; however, this masks the wide variation across industries apparent in Figure 3.6. Declines in national income obscure the relationship between import volume and tariff changes, but a few points are worth noting. First, 81% of industries experienced a decline in import volume, ranging from modest to severe. Second, most agricultural commodities experienced compar-

[12] The long difference ends at 1932 because marks the trough of the price level, and the first half of 1930 is not used to difference because of anticipation effects (Irwin 2011).

atively moderate declines in import volume, with the exception of dairy, slaughtering, and animal feed. This suggests agricultural tariffs were largely placed on goods for which American farmers had such a comparative disadvantage that it was unprofitable to produce them even with protective tariffs. Third, sectors that produced capital, such as agricultural tools and industrial machinery, collapsed as the business cycle worsened.

What would have happened to import volumes if Smoot-Hawley had never been passed? To answer this question, I run (3.3) again with the Smoot-Hawley indicator and present the results in column 2. I find the passage of Smoot-Hawley itself had comparatively little impact on aggregate imports – they would still have declined by roughly 55.1% had the legislation not been passed. That Smoot-Hawley can only account for a 4.7% decline in aggregate imports is consistent with partial and general equilibrium models that estimate a modest 4-8% decline in imports (Irwin 1998b). The results also demonstrate goods subject to the Smoot-Hawley tariffs had 32.9% lower import volume; however, this estimate does not control for the fact that Smoot-Hawley disproportionately impacted goods that already had specific tariffs and would have experienced nominal distortions regardless. I control for changes in the legislative component in column 3 to parse the legislative from the nominal impacts of Smoot-Hawley, and the results demonstrate the nominal components account for about 25 percentage points of the estimated impact, while the legislative component accounts for the remaining 7.9 percentage points. This shows Smoot-Hawley legislation played only a minor role in causing the decline in import volume during the Great Depression. Further, it is important to note the estimates of Smoot-Hawley's impact are likely biased upward because they do not control for endogenous consumption switching toward goods with lower tariff increases; however, they still serve as a useful upper-bound for the average impact of the Smoot-Hawley tariffs.

3.6 Conclusion

In this paper, I demonstrate the small impact Smoot-Hawley had on tariff burdens and import volumes across a broad swath of industries. These variables were instead distorted by a decline in national income and price levels during the Great Depression. The aggregate results are largely consistent with previous studies, but my wide panel allows me to examine impacts by industry. I find increased tariff burdens mostly hit agricultural industries, but declines in import volumes were less concentrated by industry.

In future research, the panel could also be used to determine if lawmakers acted strategically when levying specific as opposed to ad valorem tariffs. Since the burden of specific tariffs increases as the price of a good decreases, specific tariffs endogenously protect domestic production as international competition or business cycles drive prices downward. If lawmakers were aware of this property, they may have intentionally placed specific tariffs on domestically produced goods that experienced large price fluctuations, such as agricultural commodities. In addition, domestic industries with strong lobbying capabilities may have been more successful in securing protective tariffs for themselves

(Magee, Brock and Young 1989). Discrete choice models could be used to determine if these factors increased the likelihood of a good receiving a specific tariff; such models have already shown that lawmakers responded to local economic interests, so it is possible that they can also detect reasons for voting for specific over ad valorem tariffs (Irwin and Krozner 1999).

3.7 Appendix

The raw tariff schedule has 29,212 unique good descriptions with an average number of 1.66 observations each. Given that the sample spans nine periods and the average period only has 5,158 unique goods, this indicates a severe lack of description matches across periods.I track goods across periods using a combination of manual and algorithmic matching.

I begin by manually matching the first three levels of disaggregation (approximately 500 unique categories) across periods. This manual matching reduces the panel to 23,707 unique matches across periods and provides a consistent base from which a fuzzy matching algorithm can applied.

I use a trigram fuzzy matching algorithm to track imports at the seven most disaggregated levels. The trigram methodology breaks import descriptions into as many unique combinations of three consecutive letters as possible. For example, "tariff" consists of four trigrams -- "tar," "ari," "rif," and “iff.”[13] I then sequentially match imports based on their fraction of shared trigrams. Imports cannot be matched if they are observed in the same year, if the intersection of their trigrams is less than 75% of their union, or if they are not within the same second level of disaggregation.[14] This methodology is well-suited for descriptions that have their word order shuffled between years, as is common in this data.[15] Certain matches are also contingent on words that indicate the source or tariff structure of the import. For example, descriptions that include the words “Cuba,” “Virgin Islands,” or “Philippines” indicate the source of the import and are only allowed to match with imports of the same origin. Additionally, descriptions that have numerical values (e.g. 3/4 of an inch) can only be matched with tariffs containing identical numerical values. Finally, I manually check matches that exhibit tariff changes before or after Smoot-Hawley was enacted, as this may indicate a bad match.

This matching algorithm reduces the panel to 13,510 unique goods with an average number of 3.44 observations each. Since the panel is still highly unbalanced, this paper focuses on the 926 of these unique goods that are observed across all nine periods of the sample.

[13] Import descriptions are lengthy, so the average number of trigrams per description is 125.

[14] The second level of disaggregation consists of 99 unique categories.

[15] Distance and soundex algorithms proved to perform poorly because import descriptions were long, and a shuffling of words could impact their calculations substantially.

Table 3.1: Comparison of Aggregate Data vs Balanced Panel from 1926-1933

	Value share of dutiable imports			Ad valorem equivalent tariff		
Tariff Schedule	Aggregate data	Balanced data set	Percentage covered	Aggregate data	Balanced data set	Percentage difference
Animal Products, Edible	5.8	1.4	23.9	21.0	19.7	6.3
Animal Products, Inedible	3.4	1.3	38.2	26.2	14.4	45.0
Chemicals	2.9	1.6	53.5	32.1	24.8	22.8
Machinery and Vehicles	1.4	0.2	14.2	32.1	32.5	−1.3
Metals and Manufactures	7.8	3.0	37.9	32.3	26.2	18.7
Miscellaneous	4.4	0.4	9.2	41.2	21.7	47.4
Nonmetallic Minerals	9.3	4.6	49.5	30.9	19.0	38.5
Textiles	28.1	10.8	38.5	38.7	21.3	45.1
Vegetables, Edible	23.0	18.6	80.7	54.9	61.4	−11.9
Vegetables, Inedible	11.2	9.9	88.6	34.7	36.1	−4.0
Wood and Paper	2.7	0.7	26.6	27.6	35.9	−30.0
All Schedules:	100.0	52.4	52.4	38.8	38.5	0.9

Notes: Calculations are aggregated across 1926-1933.

Table 3.2: Distortions to Import Volumes

	(1)	(2)	(3)
Constant	-0.914^{***}	-0.806^{***}	-0.796^{***}
	(0.055)	(0.069)	(0.069)
SH Dummy		-0.401^{**}	-0.289^{*}
		(0.156)	(0.159)
$\Delta(\tau_{it}^{L})$			-1.396^{***}
			(0.447)
$\%\Delta Q_{it}$	59.7	55.1	54.7
$\%\Delta Q_{it}^{SH}$		32.9	25.0
Fixed Effects	X	X	X

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

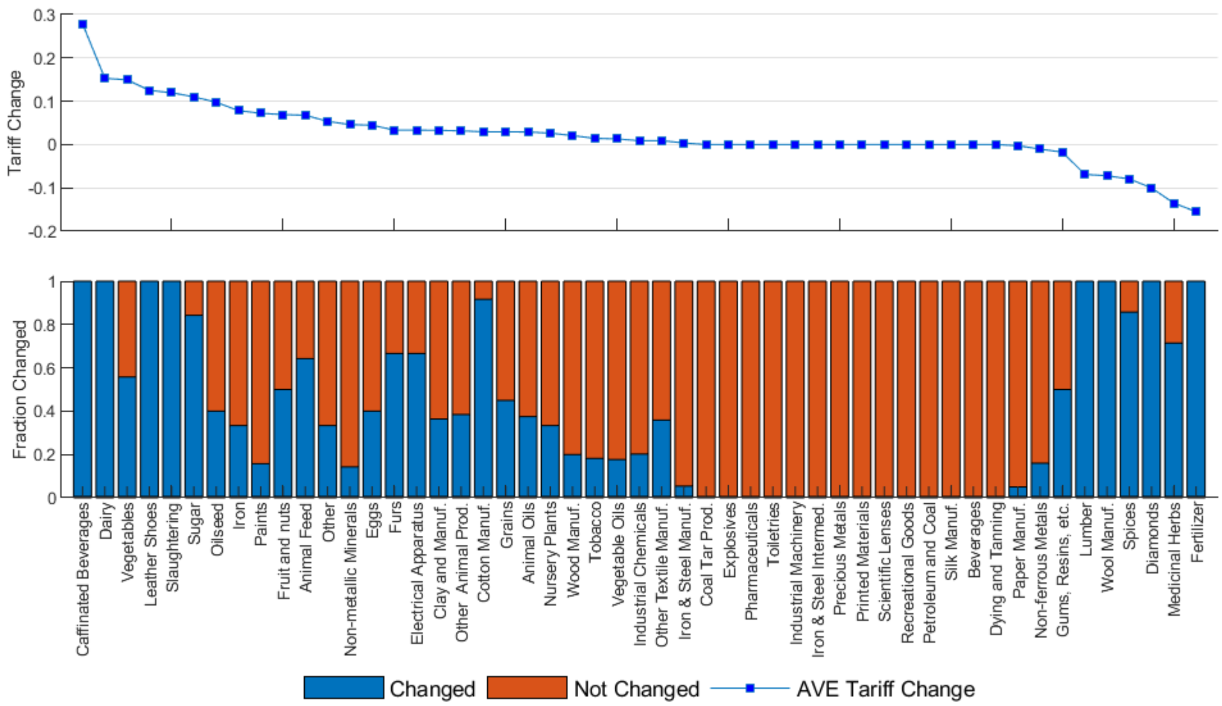

Figure 3.1: Impact of Smoot-Hawley

Notes: Industries are sorted by the change in their ad valorem equivalent tariff between the first and second halves of 1930 (holding quantities and prices constant at their starting level).

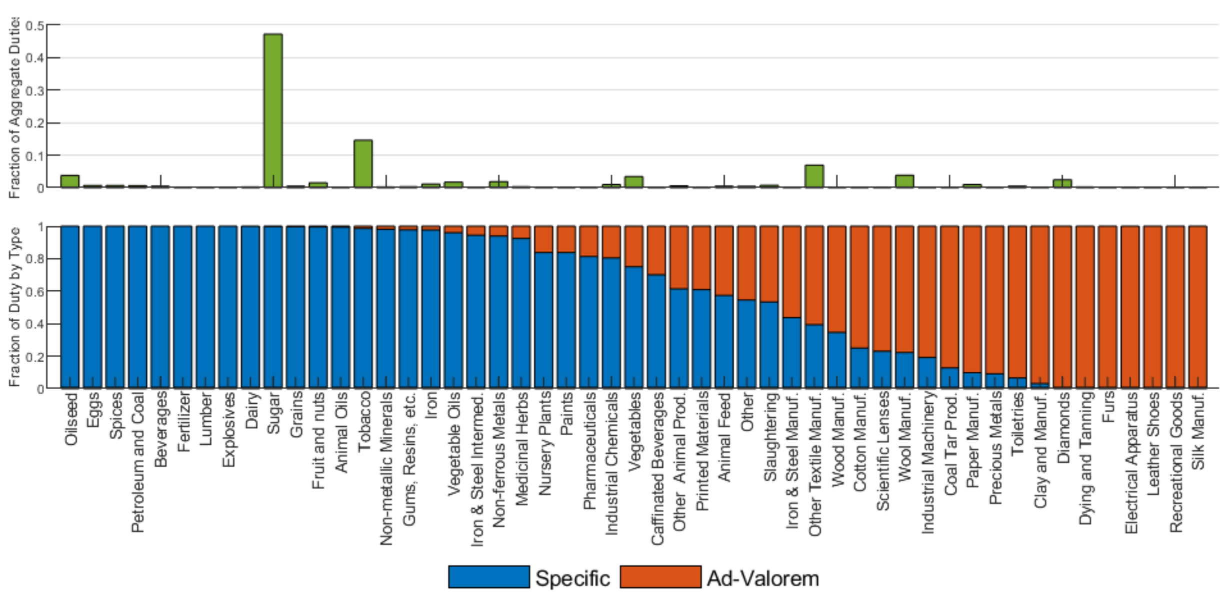

Figure 3.2: Composition of Tariff Type

Notes: Industries are sorted by their fraction of duties by each tariff type. Combination tariffs have been decomposed into their specific and ad-valorem components in this figure. The calculations are averaged across all periods from 1926-1933.

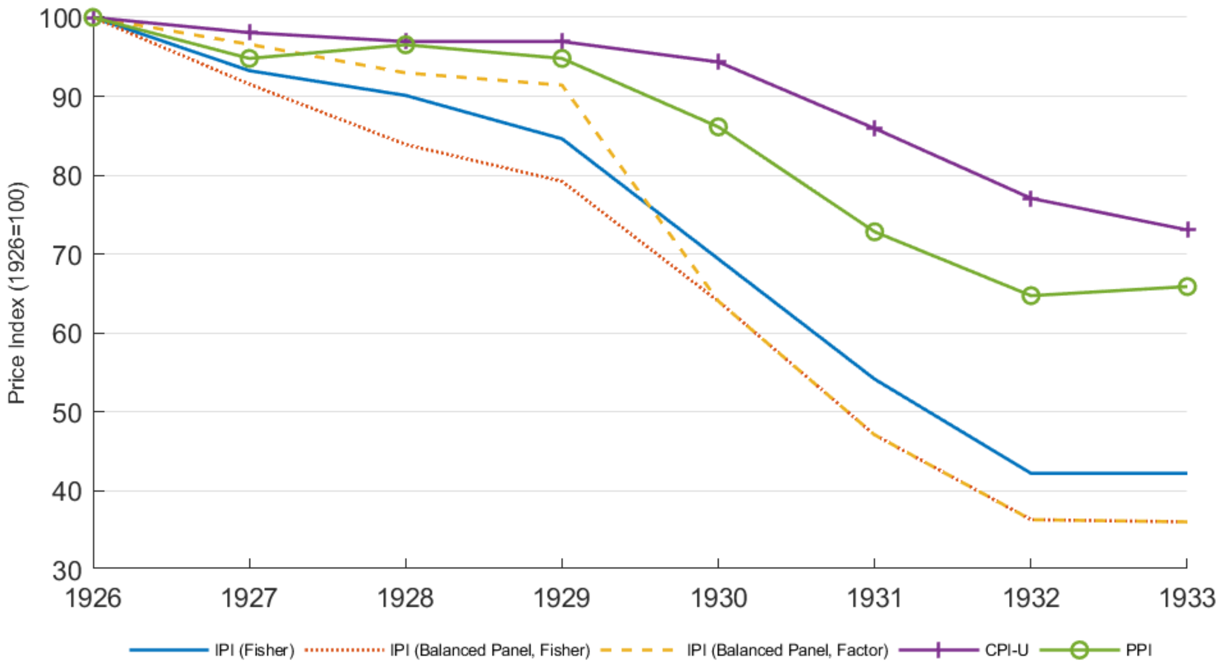

Figure 3.3: Price Levels

Notes: The IPI (Fisher) and IPI (Factor) series are calculated using the balanced panel. The CPI-U and PPI series are obtained from the U.S. Bureau of Labor Statistics (series PPIACO and CPIAUCNS) and the IPI (Fisher, Full Panel) series is obtained from *Indexes of U.S. Exports and Imports by Economic Class (1919–1971), U.S. Bureau of the Census, 1972.*

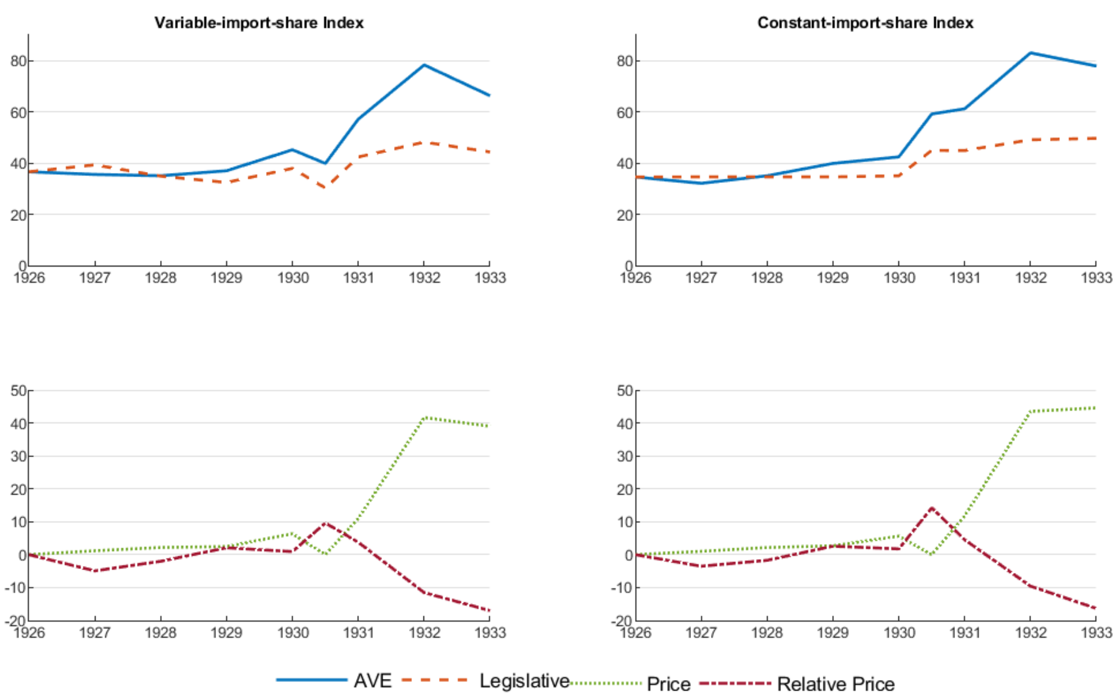

Figure 3.4: Variance Decomposition

Notes:

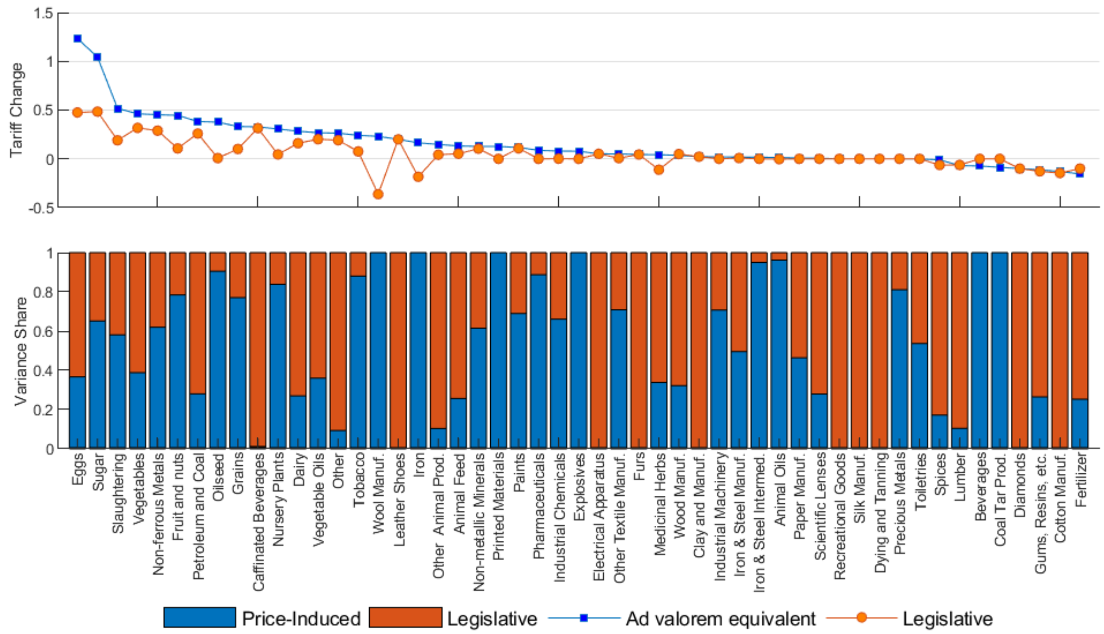

Figure 3.5: Industry-Specific Tariff Variation

Notes: The upper panel depicts the ad valorem equivalent tariff (squares) and legislative (circles) changes by industry between 1930a and 1933. The lower panel depicts the fraction of tariff variation induced by legislation $\left(\tau^L_{is}\right)$ versus price fluctuations $\left(\tau^{\pi}_{it} + \tau^{RP}_{it}\right)$.

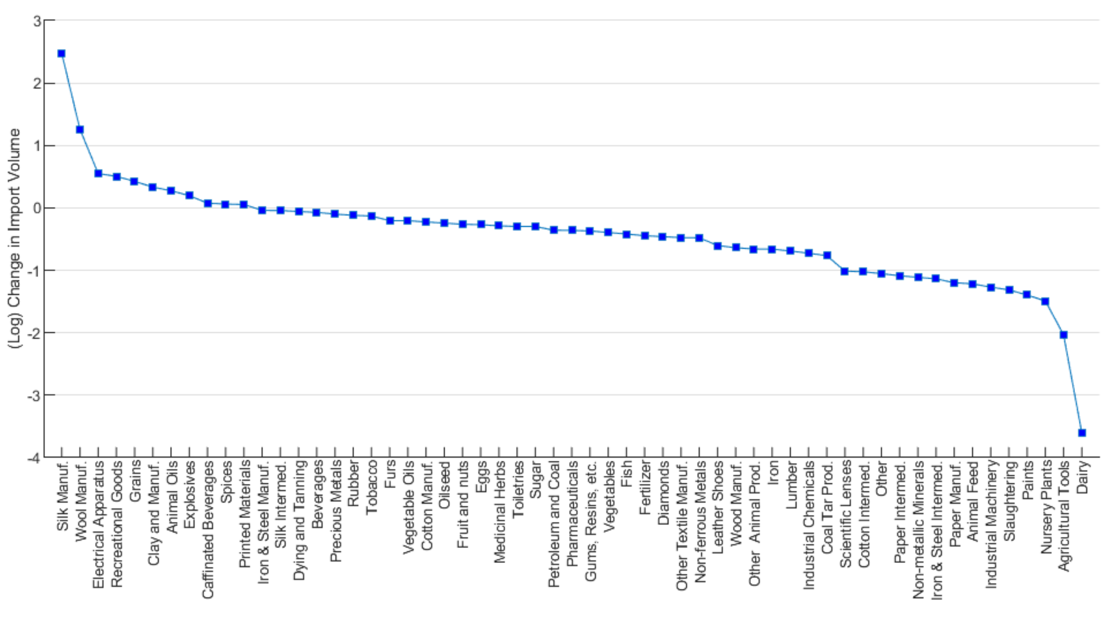

Figure 3.6: Industry-Specific Change in Import Volume

Notes: Changes are calculated between 1929 and 1932.

BIBLIOGRAPHY

Allen, Treb, “Information Frictions in Trade,” *Econometrica*, 2014, *82* (6), 2041–2083.

Anderson, James E. and Eric van Wincoop, “Trade Costs,” *Journal of Economic Literature,*, September 2004, *42* (3), 691–751.

Andersson, Fredrik N.G. and Jonas Ljungberg, “Grain Market Integration in the Baltic Sea Region in the Nineteenth Century,” *Journal of Economic History*, 2015, *75* (3), 749–790.

Bai, Jushan and Serena Ng, “Determining the Number of Factors in Approximate Factor Models,” *Econometrica*, 2002, *70* (1), 191–221.

Berry, Thomas S., *Western Prices before 1861*, Harvard University Press, 1943.

Bezanson, Anne, *Prices and Inflation during the American Revolution, Philadelphia, 1770-1790*, University of Pennsylvania Press, 1951.

____ , *Wholesale Prices in Philadelphia, 1852-1896*, University of Pennsylvania Press, 1954.

____ **and Robert D. Gray**, *Wholesale Prices in Philadelphia 1784 - 1861*, University of Pennsylvania Press, 1937.

____ **,** ____ **, and Miriam Hussey**, *Prices in Colonial Pennsylvania*, University of Pennsylvania Press, 1935.

Bond, Eric W., Mario J. Crucini, Tristan Potter, and Joel Rodrigue, “Misallocation and productivity effects of the Smoot-Hawley tariff,” *Review of Economic Dynamics*, 2013, *16* (1), 120–134.

Boyle, James E., *The New Orleans Cotton Exchange*, Garden City, New York: The Country Life Press, 1934.

Bryan, Michael F. and Stephen G. Cecchetti, “The consumer price index as a measure of inflation,” *Economic Review, Federal Reserve Bank of Cleveland*, 1993, *29* (4), 15–24.

Coleman, A., “Storage, Slow Transport, and the Law of One Price: Theory with Evidence from Ninetheenth-Century U.S. Corn Markets,” *The Review of Economic Statistics*, 2009.

Cook, E.R. and P.J. Krusic, “The North American Drought Atlas,” 2004.

Costinot, Arnaud and Dave Donaldson, “How Large are the Gains from Economic Integration? Theory and Evidence from U.S. Agriculture 1880-1997,” *Econometrica (R&R)*, 2016.

Crandall, Ruth, “Wholesale Commodity Prices in Boston during the Eighteenth Century,” *Review of Economic Statistics*, 1934, *16*, 117–128, 178–183.

Crucini, M. and C. Telmer, “Microeconomic Sources of Real Exchange Rate Variability,” *NBER Working Paper No. 17978*, 2012.

Crucini, Mario J., “Sources of Variation in Real Tariffs Rates: The United States, 1900-1940,” *American Economic Review*, 1994, *84* (3), 732–743.

____ **and James Kahn**, “Tariffs and aggregate economic activity: Lessons from the Great Depression,” *Journal of Monetary Economics*, 1996, *38* (3), 427–467.

____ **, M. Ayhan Kose, and Christopher Otrok**, “What are the driving forces of international business cycles?,” *Review of Economic Dynamics*, 2011, *14*, 156–175.

Djankov, Simeon, Caroline Freund, and Cong Pham, “Trading on Time,” *The Review of Economics and Statistics*, 2010, *92* (1), 166–173.

Durbin, J. and S.J. Koopman, *Time Series Analysis by State Space Methods*, 2 ed., Oxford: Oxford University Press, 2012.

Ejrnaes, Mette and Karl Gunnar Persson, "The gains from improved market efficiency: trade before and after the transatlantic telegraph," *European Review of Economic History*, 2010, *14*, 361–381.

Engel, Charles and John H. Rogers, "How Wide is the Border?," *American Economic Review*, 1996, *86* (5), 1112–1125.

Federico, G., "When did European markets integrate?," *European Review of Economic History*, 2010.

Granger, C.W.J. and C.M. Elliot, "A Fresh Look at Wheat Prices and Markets in the Eighteenth Century," *The Economic HIstory Review*, 1967, *20* (2).

Harvey, Andrew, *Forecasting, Structural Time Series Models, and the Kalman Filter*, Cambridge, Massachusetts: Cambridge University Press, 1989.

Head, Kieth and Thierry Mayer, "Gravity Equations: Toolkit, Cookbook, Workhorse," in "Handbook of International Economics," Vol. 4, Elsevier, 2013.

____ **and** ____ , "What separates us? Sources of resistance to globalization," *Canadian Journal of Economics*, 2013, *46* (4), 1196–1231.

Hoover, Ethel D., "Retail Prices after 1850," in "Trends in the American Economy in the Nineteenth Century, The Conference on Research in Income and Wealth," Princeton University Press, 1960, pp. 141–190.

Hummels, David, "Transportation Costs and International Trade in the Second Era of Globalization," *Journal of Economic Perspectives*, 2007, *21* (3), 131–154.

____ , "Transportation Costs and Adjustments to Trade," in Guido Porto and Bernard M Hoekman, eds., *Trade Adjustment Costs in Develping Countries: Impacts, Determinants and Policy Responses*, World Bank and Centre for Economic Policy Research, 2010.

____ **and George Schaur**, "Time as a Trade Barrier," *American Economic Review*, 2013, *103*, 2935–59.

Irwin, Douglas A., "Changes in U.S. Tariffs: The Role of Import Prices and Commercial Policies," *American Economic Review*, 1998, *88* (4), 1015–1026.

____ , "The Smoot-Hawley Tariff: A Quantitative Assessment," *The Review of Economics and Statistics*, 1998, *80* (2), 326–334.

____ , *Peddling Protectionism: Smoot-Hawley and the Great Depression*, Princeton, N.J.: Princeton University Press, 2011.

____ **and Randall Krozner S**, "Interests, Institutions, and Ideology in Securing Policy Change: The Republican Conversion to Trade Liberalization After Smoot-Hawley," *The Journal of Law and Economics*, 1999, *42* (2), 643–674.

Jacks, D., "Intra- and international commodity market integration in the Atlantic economy, 1800 - 1913," *Explorations in Economic History*, 2005.

____ , "What drove 19th century commodity market integration?," *Explorations in Economic History*, 2006.

Kim, Chang-Jin and Charles R. Nelson, *State-Space Models with Regime Switching*, Cambridge, Massachusetts: The MIT Press, 1999.

Kose, M. Ayhan, Christopher Otrok, and Charles H. Whiteman, "International Business Cycles: World, Region, and Country-Specific Factors," *The American Economic Review*, 2003.

Magee, Stephen P., William A. Brock, and Leslie Young, *Black Hole Tariffs and Endogenous Policy Theory*, Cambridge: Cambridge University Press, 1989.

Minnesota Population Center, "National Historical Geographic Information System: Version 2.0," Technical Report, Minneapolis, MN: University of Minnesota 2011.

Mussa, Michael, "Nominal exchange rate regimes and the behavior of real exchange rates: Evidence and implications," *Carnegie-Rochester Conference Series on Public Policy*, 1986, (1), 117–214.

Nunn, Nathan and Nancy Qian, "The Potato's Contribution to Population and Urbanization: Evidence from a Historical Experiment," *The Quarterly Journal of Economics*, 2011, *126*, 593–650.

Persson, Karl Gunnar, "Mind the gap! Transport costs and price convergence in the nineteenth century Atlantic economy," *European Review of Economic History*, 2004, *8* (2), 125–147.

Pippenger, J. and L. Phillips, "Some pitfalls in testing the law of one price in commodity markets," *Journal of International Money and Finance*, 2008.

Rogoff, Kenneth, Kenneth A. Froot, and Michael Kim, "The Law of One Price over 700 Years," *NBER Working Paper No. 5132*, 2001.

Shiue, Carol H. and Wolfgang Keller, "Markets in China and Europe on the Eve of the Industrial Revolution," *The American Economic Review*, September 2007, *97* (4), 1189–1216.

Slaughter, M., "Does trade liberalization converge factor prices? Evidence from the antebellum transportation revolution," *The Journal of International Trade & Economic Development*, 2001.

Steinwender, Claudia, "Real Effects of Information Frictions: When the States and the Kingdom Became United," *American Economic Review*, 2018, *108* (3), 657–696.

Stoker, Herman M, "Wholesale Prices at New York City, 1720 to 1800," Technical Report 142, New York Agricultural Experiment Station 1932.

Taylor, George R., "Agrarian Discontent in the Mississippi Valley preceding the War of 1812," *Journal of Political Economy*, 1931, *39*, 471–505.

——, "Wholesale Commodity Prices at Charleston, South Carolina, 1732-91," *Journal of Economic and Business History*, 1932, *4*, 356–377.

——, "Wholesale Commodity Prices at Charleston, South Carolina, 1796-1861," *Journal of Economic and Business History*, 1932, *4*, 356–377.

Uebele, M., "National and international market integration in the 19th century: Evidence from comovement," *Explorations in Economic History*, 2011.

Warren, G.F. and F.A. Peasron, "Wholesale Prices for 213 Years, 1720 to 1932," Technical Report 142, New York Agricultural Experiment Station 1932.

Watkins, James L., *King Cotton: A Historical and Statistical Review 1790 to 1908*, New York: Negro Universities Press, 1908.

Williams, Jeffrey C. and Brian D. Wright, *Storage and Commodity Markets*, Cambridge University Press, 1991.

Williamson, J.G. and K.H. O'Rourke, *Globalization and History*, MIT Press, 1999.