ESSAYS ON INTERNATIONAL TRADE

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TOBIAS SYTSMA

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Student: Tobias Sytsma

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This dissertation has been accepted and approved in partial fulfillment of the requirements for the Doctor of Philosophy degree in the Economics by:

Bruce Blonigen	Co-chair
Wesley W. Wilson	Co-chair
Anca Cristea	Core Member
Michael Russo	Institutional Representative

and

Kate Mondloch	Interim Vice Provost and Dean of the Graduate School

Original approval signatures are on file with the University of Oregon Graduate School.

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DISSERTATION ABSTRACT

Tobias Sytsma

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Through trade policy actions, decades of global trade liberalization have resulted in lower formal trade barriers. However, there remain significant barriers to trade that fall outside the realm of traditional policy tools. This dissertation analyzes two under-studied non-tariff trade barriers: natural disasters and rules of origin. While there are fundamental differences in how these trade barriers arise, both natural disasters and rules of origin have meaningful implications for the functioning of global trade systems, the formation of global value chains, and consumer welfare.

The three essays in this dissertation provide evidence that these under-studied trade barriers have a significant impact on trade flows. In Chapter II, I find that rules of origin liberalization can restore preferential market access and improve firm-level export growth in least-developed countries (LDCs). In Chapter III, I find evidence that hurricanes reduce trade volumes from US ports, and that the effect is highly persistent. Finally, in Chapter IV, using detailed data on international shipments, I show that hurricane activity around US ports-of-exit affects aggregate exports through price indices, and as a result, affects average consumer welfare.

In the case of rules of origin, the results highlight the crucial role that non-tariff barriers play in the formation of trade agreements. In the case of natural disasters, the findings presented in this dissertation highlight the importance of designing policy aimed at addressing unexpected shocks to global trade.

CURRICULUM VITAE

NAME OF AUTHOR: Tobias Sytsma

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENDED:

University of Oregon, Eugene, OR
University of San Francisco, CA
Portland State University, OR

DEGREES AWARDED:

Doctor of Philosophy, Economics, 2020, University of Oregon
Masters of Science, Economics, 2014, University of San Francisco
Bachelors of Science, Economics, 2012, Portland State University

AREAS OF SPECIAL INTEREST:

International Economics, Development Economics, Applied Econometrics

GRANTS, AWARDS AND HONORS:

Outstanding Teaching Award, U of O Department of Economics, 2019

WTO Essay Award for Young Economists Finalist, World Trade Organization, 2019

Gerloff Homand Scholarship in International Economics, U of O Department of Economics, 2017

Graduate Teaching Fellowship, University of Oregon, 2015-2020

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For my wife, Jen.

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CHAPTER I

INTRODUCTION

Over the past several decades, many nations have made an effort to liberalize international trade by reducing formal trade barriers. For example, the average global tariff rate declined from roughly 15 percent in the 1990s to five percent by 2017 (World Bank 2020). Due to global trade liberalization, the average ratio of trade to GDP has increased from roughly 20 percent in 1995 to 30 percent in 2014. A growing fraction of this trade is occurring within value chains.[1] Just-in-time production, which aims to minimize the amount of time between manufacturing and final good consumption, further underscores the need for timely processing of imports and exports. Thus, while formal trade barriers have fallen, an understanding of informal trade barriers remains highly relevant in the context of modern global supply chains. This dissertation contains three essays in which I examine how informal and non-tariff trade barriers influence the flow of global trade. Non-tariff trade barriers have implications for whether the gains from trade exceed the costs, the distributional consequences of trade reform, and international relations.

A large body of evidence suggests that non-tariff trade barriers, such as shipping distances, national borders, and currency unions, have a substantial effect on trade flows (see Anderson and Van Wincoop (2004) for a review of this literature). In this dissertation, I contribute to the literature by analyzing two under-studied trade barriers: natural disasters and rules of origin. The imposition of the former is primarily out of policy-makers' control, while policy-makers directly

[1] "International Trade Statistics, 2015." World Trade Organization.

control the imposition of the latter. There are fundamental differences in how these trade barriers arise; however, an understanding of how they influence trade flows is crucial for designing effective trade policy.

In the first essay, I study how non-tariff barriers influence the flow of global trade. In particular, I analyze the response of firm-level exports to rules of origin. Rules of origin are the criteria used to define the national source of final goods within preferential trade agreements. Generally, rules of origin require the use of domestically produced inputs in final goods. Requiring that final goods contain a specified amount of domestic content prevents trade deflection, which occurs when goods from countries outside of the trade agreement can access preferential tariff rates through intermediate inputs. When intermediate inputs are costly to produce domestically, many producers of final goods find it challenging to satisfy rules of origin. This results in under-utilization of trade preferences and limited market access.

I analyze how exporting firms respond to rules of origin using transaction-level customs data on Bangladeshi apparel firms. In 2011, the EU revised the rules of origin associated with imports of apparel from least developed countries (LDCs), including Bangladesh. Combining the timing of the policy change, the countries it applied to, and technical differences in the production of woven versus knitted textiles, I estimate a triple-difference-in-differences model. I find that liberalizing rules of origin not only induced new firms to export to the EU, but also increased the number of products incumbent firms exported, and increased export revenue. Finally, I provide evidence that the rules of origin revision resulted in a reallocation of market share among incumbent firms from low-productivity to high-productivity firms. The market share reallocation across firms indicates that the overall industry became more productive following the policy change.

The firm-level responses to rules of origin liberalization can be interpreted through the lens of standard heterogeneous firm models (i.e., Melitz 2003). In the appendix of Chapter 2, I extend the multi-product firm model in Bernard, Redding and Schott (2011) by including multiple tariff regimes and rules of origin. Using the methods in Kee, Nicita and Olarreaga (2009), I estimate that the ad-valorem tariff equivalent of the EU's rules of origin is roughly 6.2%. This tariff-equivalent is roughly half of the difference between the preferential tariffs and the non-preferential tariffs that were applied if exporters could not satisfy the rules of origin. Thus, the rules of origin effectively cut the preferential margin in half. The results highlight how non-tariff trade barriers have implications for development-oriented trade policy, and the political economy of trade relationships between high- and low-income nations.

In the second essay, I study the impact of hurricanes on US port-level trade flows. I focus specifically on the temporal and spatial displacement of trade from US ports following storms. Hurricanes are highly destructive to coastal areas where many major customs ports are located. For trade to remain relatively unimpeded by hurricane damage at ports, trade flows must be diverted from hurricane-affected ports to surrounding ports. If surrounding ports are not able to facilitate this displacement of trade, then trade that was meant to be processed by hurricane-affected ports must wait until the hurricane damage is repaired.

I collect monthly data on US port-level export flows and combine it with monthly hurricane wind speeds. The exogenous variation in hurricane wind speeds experienced at ports allows me to analyze the effect of natural disasters as a barrier to trade without relying on potentially endogenous recorded damage data. I find evidence that a marginal increase in hurricane wind speeds reduces trade from affected ports by a small but statistically significant amount. The effect is persistent for roughly ten months, and this results in substantial cumulative losses in export value from affected ports over the two years following the storm. However, I also find evidence that surrounding ports can absorb the displaced trade. Using spatial econometric techniques, I show that most of the displaced trade appears to be accommodated by ports within a 10 to a 20-mile radius from an affected port.

In the third essay, I study the welfare implications of hurricanes using data linking US exporters to global importers. I derive a theoretical model of trade that incorporates port-level hurricane-related trade frictions. I then estimate the parameters of the model using data that tracks US export shipments from the state of production, through the port of exit to an importing country. I couple this dataset with information on the port-of-exit hurricane exposure, which I measure using maximum sustained wind speeds. I use the estimates of the model's parameters to calculate global consumers' willingness to pay to avoid hurricane activity.

I find evidence that importers would have been willing to pay over $6 billion to have avoided the 2005 hurricane season. The 2005 Atlantic hurricane season was estimated to have cost roughly $127 billion (in 2020 USD) in damage (National Centers for Environmental Information 2020). Thus, the $6 billion that importers of US goods would have been willing to pay to avoid the 2005 hurricane season is approximately 2.7% of the total damage costs. The willingness to pay to avoid other hurricane seasons are similar in magnitude.

I also use the estimates of the model's parameters to simulate the welfare losses from an 11% increase in hurricane activity, which is the predicted rise in Atlantic basin hurricane intensity by 2100 (Knutson et al. 2010). I find that importers of US goods would need to be compensated roughly $500 million per year (in 2020 USD) to be indifferent about the rise in hurricane intensity.

CHAPTER II

IMPROVING PREFERENTIAL MARKET ACCESS THROUGH RULES OF ORIGIN: FIRM-LEVEL EVIDENCE FROM BANGLADESH

2.1 Introduction

Every preferential trade agreement requires criteria by which a product's origin is determined, known as the rules of origin, to prevent tariff fraud.[1] Fragmented production processes can make it difficult to establish where a product is made. Even simple products, like t-shirts, can cross international borders multiple times during production.[2] Yet, a product's "origin" is crucial in the context of preferential trade agreements, which provide tariff relief to goods made in some countries but not others. The standard convention is to define a product's origin based on the last country in which it underwent a sufficient transformation. Sufficient transformations can be defined in multiple ways, but one common practice is requiring that products are made from locally-sourced intermediate inputs.[3] By varying how much local content is required, countries use rules of origin to control access to trade preferences. However, when rules of origin are too restrictive, they can exclude countries that were intended to receive preferential treatment under the trade agreement.

[1]For example, to prevent trans-shipment– where a country outside of a trade agreement trans-ships a product through a participating nation to get access to preferential tariff rates in a destination market.

[2]"Planet Money Makes A T-Shirt." NPR. NPR, n.d. https://apps.npr.org/tshirt/#/title.

[3]Other standard rules of origin take the form of value-added thresholds and changes in tariff classifications (Augier, Gasiorek and Tong 2005).

I study how revisions to rules of origin in potential export destinations influence firm- and industry-level export behavior. Specifically, I analyze the changes to the rules of origin in the EU's Generalized System of Preferences (GSP). This non-reciprocal trade agreement grants preferential status to imports from developing countries. An essential component of the EU's GSP offers tariff-free market access to apparel products, an important export sector, from the 48 least-developed countries (LDCs) conditional on satisfying rules of origin that required the use of locally-sourced textiles. However, capacity constraints in the production of textiles in LDCs kept apparel producers from utilizing the preferential tariffs. Failure to satisfy the rules of origin meant the product was imported under non-preferential tariffs, which are roughly 13.5% for apparel products. In 2011, the EU reformed the rules of origin to improve market access for LDCs. The revised rules allowed apparel producers in LDCs to use imported textiles in their exported products. The preferential tariff rates for apparel products in the EU were not adjusted when the rules of origin were revised. Thus, this setting offers a unique opportunity to analyze how exporters respond to rules of origin in the absence of changes to tariff rates.

Manufacturing firms in LDCs cite rules of origin applied by trade partners as a key difficulty in serving export markets due to the limited availability of locally-sourced inputs and burdensome paperwork required to document that the rules have been satisfied (ITC 2015). The hope that requiring locally-sourced inputs would create backward-linkages within essential sectors, like apparel, have fallen flat (Brenton and Imagawa 2005). Instead, local content requirements have resulted in low preference utilization rates among LDCs. Thus, rules of origin impede export-oriented growth policies. The Doha Development Round of global trade negotiations have sparked debates about the role of rules of origin in trade policy (Fergusson 2008), and calls to liberalize rules of origin such that they account for global value chains have grown (Geraets, Carroll and Willems 2015). The United Nations Sustainable Development Goals directly address the restrictive nature of rules of origin, stating that *"ensuring that preferential rules of origin applicable to imports from least developed countries are transparent and simple"* is a critical component of trade-related goals (Rosa 2017).

Even with the increased policy attention, rules of origin have been an understudied component of trade policy (Conconi et al. 2018).[4] For example, a large body of economic literature focuses on the firm-level responses to tariff liberalization policies in developing countries (Pavcnik 2002; Amiti and Konings 2007; Bustos 2011; Bas and Strauss-Kahn 2015), yet the firm-level responses to rules of origin liberalization have not been studied. I use transaction-level customs data on the universe of Bangladeshi apparel exporting firms to analyze how the EU's rules of origin revision influenced firm-level outcomes. Unlike the apparel industries in other LDCs, which effectively function as trans-shipment locations for Chinese apparel firms (Rotunno, Vézina and Wang 2013), the apparel industry in Bangladesh is almost entirely locally-owned (Bakht et al. 2006; Lopez-Acevedo and Robertson. 2016). I exploit variation in the input-cost differentials across apparel products and export destinations, before and after the EU's policy change to control for the potential endogeneity of the 2011 rules of origin revision. This set up allows me to provide new insights into the relationships between trade policy,

[4]Reasons for the lack of empirical attention paid to rules of origin in the economic literature range from their perceived banality (Augier, Gasiorek and Tong 2005), to their legal complexity (Cadot, Estevadeordal and Suwa-Eisenmann 2005). Historically, rules of origin policy have remained static within existing trade agreements, and their lack of variation has made it difficult to isolate their influence on trade flows.

market access, and firm-level export performance. For example, several studies provide evidence that country- and industry-level trade flows respond to changes in rules of origin (e.g., Andersson 2016; Curran and Nadvi 2015; Bombarda and Gamberoni 2013; Conconi et al. 2018), but they are unable to distinguish between within-firm and across-firm responses.[5] Understanding whether the trade response is driven by the intensive-margin of incumbent firms, the expansion of product-scope by incumbent firms, or the entry of new firms is important for designing effective trade policy.

I find evidence that the relaxation of the EU's rules of origin resulted in substantial revenue gains for exporting firms. These revenue gains mainly came from existing product lines, although I do find evidence that incumbent firms expanded their product-scope following the rules of origin liberalization as well. I also find that the rules of origin liberalization resulted in more firms exporting to the EU. The market access gains in the EU did not appear to result in firms shifting export activity away from other markets, indicating firms had the capacity to increase production without raising marginal costs. I also find evidence that the largest firms gained market share at the expense of smaller firms following the rules of origin liberalization, indicating that the rules of origin revision corrected an inefficient allocation of resources within the industry.

These firm-level responses to the rules of origin liberalization can be interpreted through the lens of standard heterogeneous firm models (Melitz 2003;

[5] Several studies use cross-sectional firm-level data to analyze how firms endogenously sort across export markets based on differences in rules of origin across destination markets (Demidova, Kee and Krishna. 2012; Cherkashin et al. 2015). Using variation in the restrictiveness of rules of origin over time within an existing agreement allows me to analyze how this endogenous sorting changes, and whether the changes make the industry more or less productive. Further, the multi-product firm framework allows me to analyze how the endogenous sort of products *within* exporting firms changes when rules of origin change.

Bernard, Redding and Schott 2011). In the appendix, I extend the heterogeneous multi-product firm model in Bernard, Redding, and Schott (2011) by incorporating multiple tariff regimes and rules of origin to show how the model predicts these firm-level responses and explain how restrictive rules of origin result in low preference utilization rates. Using the methods in Kee, Nicita and Olarreaga (2009), I estimate the ad-valorem tariff equivalence of the initial rules of origin is 6.2%.[6] This tariff-equivalence is roughly half of the difference between the LDC-specific preferential tariffs (0 percent), and Most Favored Nation tariff rates that are applied if rules of origin are not satisfied (between 12 and 15 percent). Thus, the rules of origin effectively cut the preferential margin in half.

The remainder of this chapter is organized as follows. In Section 2, I discuss the context in which this study takes place. In Sections 3 and 4, I discuss the empirical framework and present the empirical results. In Sections 5, I examine additional industry-level responses. Finally, Section 6 concludes.

2.2 Institutional Context

This section provides a brief overview of the institutional context of market access to the EU for LDC apparel exporters, the apparel production process, and the economic importance of the apparel export industry in Bangladesh.

[6]The ad-valorem tariff equivalence (AVE) is: AVE $= \frac{exp(\beta_1)-1}{1-\sigma}$, where β_1 is the estimated effect of the rules of origin revision on trade volumes, and σ is the import demand elasticity. The value of $\sigma = 4$ is used. This value is the median value for apparel products taken from Broda and Weinstein 2006. β_1 is estimated in the empirical section of this paper (column (3) of Table 4).

The EU's Everything But Arms Agreement

The EU's Generalized System of Preferences (GSP) is a unilateral agreement that grants preferential tariff treatment for imports of goods from many developing countries. Within the GSP, the "Everything But Arms" (EBA) arrangement allows for duty-free and quota-free trade in all products, except arms and ammunition, between EU countries and the 48 LDCs. Many industrialized and newly-industrialized countries have similar non-reciprocal trade arrangements with LDCs that grant tariff-free, or nearly tariff-free access to apparel produced in LDCs (Tavares 2019). The EBA went into effect in 2001, with the stated goal of helping LDCs integrate further into the global economy. Initially, for an apparel product to qualify for the EBA, the product had to be assembled from domestically produced fabric.[7] Apart from the local content requirements, exporters must declare a "statement of origin" with documentation supporting their claim. The statement of origin is verified by customs authorities in the importing EU country (European Commission 2019).

The local fabric requirement was designed to encourage backward-linkages in developing economies. However, LDCs were critical of the rule for being too difficult for many producers to satisfy due to capacity constraints and lack of investment capital in the production of textiles (Barber et al. 2004). Small concessions were made in the EBA at the time it was ratified to allow garments made from textiles imported from other LDCs to qualify (Sekkel 2009). However, even with these concessions, it remained difficult for apparel producers to satisfy

[7]This style of rule of origin is commonly referred to as a "double-transformation" and refers to a production process where imported inputs are transformed at least two times before being exported as final goods. In the context of apparel, the double-transformation rule allowed for the use of imported thread in clothing, but not imported textiles.

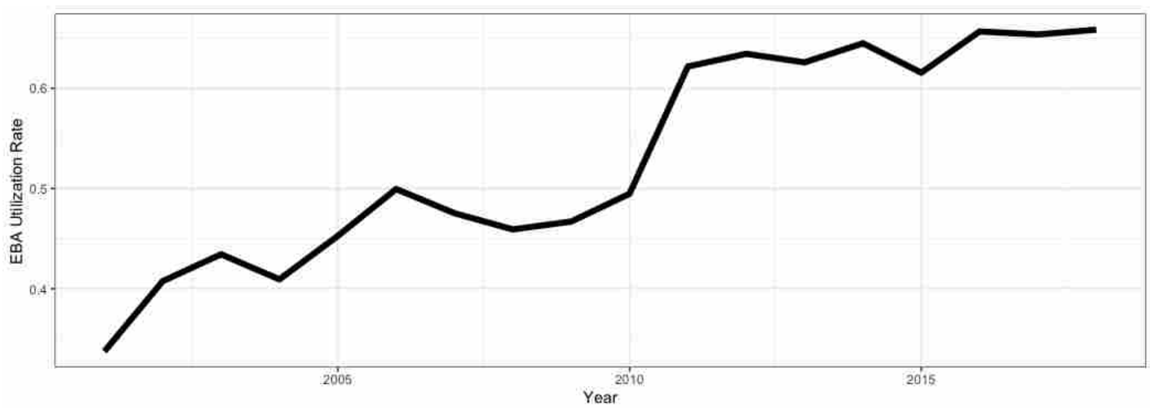
the rules of origin. Apparel products made from textiles imported from major textiles producers like China, Hong Kong, India, and Pakistan would not qualify for the EBA, as these countries were not LDCs as determined by the United Nations. Only 1% of woven textile imports into Bangladesh came from other LDCs, and the vast majority (roughly 70%) of imports came from China and Hong Kong.[8] Most Favored Nation (MFN) tariffs of between 12% and 15% tariff was applied to apparel goods that were not able to satisfy these rules of origin. Between 2001 and 2010, an average of 45% of apparel from LDCs entered the EU under the EBA each year, with the remaining 55% entering under MFN tariffs (EuroStat 2020).

Citing the qualms raised by LDCs at the Doha Development Round of global trade negotiations, the EU announced there would be a revision of the rules of origin associated with the EBA for several products.[9] The announcement came in November 2010, then, on January 1st, 2011, the new rules of origin were put into effect. One of the most significant changes came in the form of a relaxation of the local fabric requirement for apparel. The new rules allowed apparel producers in LDCs to source textiles globally, de-coupling the apparel production sector from the capacity-constrained textile production sectors in these countries. The effect of the policy change on EBA utilization rates was substantial. Figure 1 displays the fraction of apparel imports from LDCs that entered under the EBA over time.

[8] United Nations. (2003). UN Comtrade. https://comtrade.un.org.

[9] In the November 18th, 2010, Commission Regulation, the European Commission states "In the context of the Doha Development Agenda, the need to ensure a better integration of developing countries into the world economy has been recognized, in particular through improved access to the markets of developed countries.". Further, the commission highlights the difficulty LDCs have in gaining access to preferential rates: "The rules of origin should reflect the features of specific sectors but also allow beneficiary countries a real possibility to access the preferential tariff treatment granted". (Publications Office of the European Union 2010).

FIGURE 1. Utilization of the EBA by LDCs



Notes: This figure displays the average annual utilization rate of the EBA for LDC apparel exports. Data for the figure comes from EuroStat (2020).

Between 2010 and 2011, the fraction of apparel products that entered the EU tariff-free under the EBA increased by 13 percentage points (EuroStat 2020).

Apparel production

Apparel production is a labor-intensive process. However, the full production process of turning raw materials into clothing involves several capital-intensive stages. Apparel manufacturing takes place in three broad steps: (1) spinning of yarn from natural or human-made fibers, (2) the production of fabric or textiles, and (3) the production of final apparel goods. While the third stage is a labor-intensive process, the first two are more capital-intensive. In the case of Bangladesh (and many other LDCs), apparel products are mainly produced for export markets, not domestic consumption.

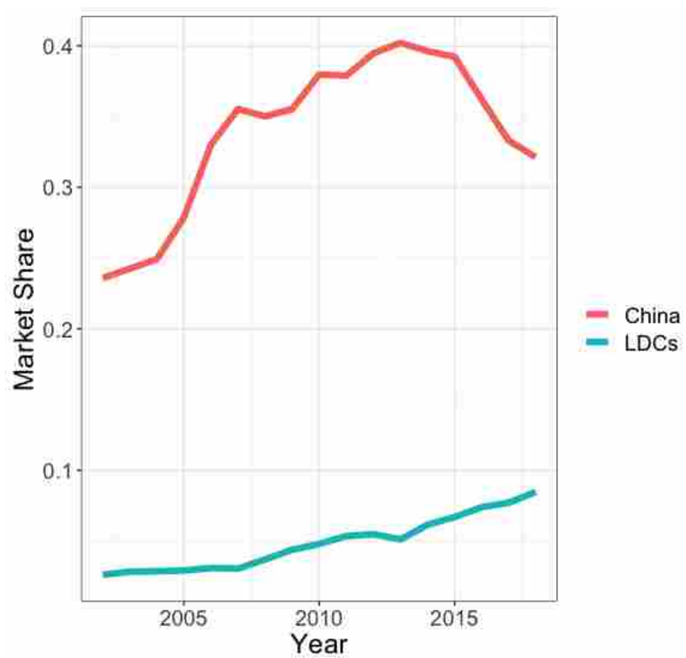
The general process outlined above is similar for all apparel. However, there is heterogeneity in the amount of capital needed to produce different fabrics. This difference can be seen in the production of woven versus knitted fabric. Production of woven fabric requires weaving multiple threads over and under each other in a criss-cross pattern, and is done in large plants. Producing woven fabrics is an energy-intensive process, and while labor-intensive hand-looms can create woven fabric, they are typically too inefficient to use at a large scale (Frederick and Staritz 2012). Dying and treating woven textiles is also capital-intensive. Knit fabric is much less capital-intensive to produce. Knit fabric can be produced at a smaller scale using small circular knit machines (Curran and Nadvi 2015). Many knitted apparel products are made directly from pre-dyed yarn, which cuts down on production costs.

China is the largest global exporter of apparel products. Figure 2 displays the market share of China and LDCs in global apparel exports over time. China's market share increased from 21% in 2002 to 30% in 2018. Market share for LDCs is substantially smaller, growing from roughly 2% in 2002 to approximately 8% in 2018. However, apparel production comprises a significant fraction of manufacturing employment in LDCs. In a survey of apparel industries in LDCs, Keane and Velde (2008) find that the sector accounts for roughly 60% of total manufacturing employment across these countries. Naturally, the change to a single-transformation policy had the potential to influence LDC exports significantly and given the reliance on the sector, the entire economies of these countries.

The Apparel Export Industry in Bangladesh

In Bangladesh, the garment industry accounts for roughly 13% of GDP (Heath 2018) and employs approximately 40% of the country's manufacturing labor force (Curran and Nadvi 2015). The vast majority of workers associated with the garment industry in Bangladesh produce clothing, rather than textiles.

FIGURE 2. Market Share in Global Apparel Exports



Notes: This figure displays the market share in global apparel exports for China and all LDCs combined. UN Comtrade data was used to produce this figure.

TABLE 1. Textile Sourcing in by Apparel Firms in LDCs

Study	% Knit Textiles Locally Sourced	% Woven Textiles Locally Sourced
Habib 2016	65%	15%
Frederick and Staritz 2012	60-70%	12-15%
Masum 2016	90%	40%

Notes: This table displays the fraction of apparel firms in LDCs that source textiles locally. Statistics presented are from the sources listed in the table.

Apparel accounts for roughly 80% of Bangladesh's average annual export volume. In 2010, the textile and apparel industries in Bangladesh employed approximately 2.5 million people combined, of which 70% worked in the apparel industry (International Labor Organization, 2020). Unlike other garment-producing LDCs, apparel production is mainly locally owned and financed. In 2005, roughly 97% of apparel firms only sourced capital locally (Bakht et al. 2006). By 2016, this number had only fallen to 91% (Lopez-Acevedo and Robertson. 2016).

Like other LDCs, Bangladesh relies heavily on imported textiles from China, Hong Kong, and India for apparel production. However, given the relative capital intensity of woven textiles woven apparel products rely more heavily on imported textiles than knitted apparel products.[10] Several studies provide estimates of the ability of LDC's textile industry to supply the apparel industry. Table 1 displays survey estimates from three studies on the percent of textiles sourced locally in LDCs for woven and knitted apparel products. In all cases, the percent of locally sourced textiles used in woven apparel production is substantially lower than locally sourced knitted textiles.

Given these differences in the production process of woven versus knitted apparel, the change in the rules of origin from a double-transformation to single-

[10]Figure A2, in the Appendix, shows the average annual imported quantities of woven and knitted textiles in Bangladesh between 2008 and 2013. Woven textiles are imported at higher volumes than knitted textiles, especially after 2011 when the rules of origin were revised.

transformation was likely to affect woven apparel exports more than knitted apparel exports.[11] Evidence of this discrepancy can be seen in the change in EBA utilization rates in Figure 3, which displays the utilization rate of the EBA by Bangladeshi apparel exporters. The utilization rate is calculated as the fraction of EU apparel imports from Bangladesh processed under the EBA, relative to the total EU apparel imports from Bangladesh. The data from the figure comes from Eurostat's Imports by Tariff Regime database.[12]

The utilization rate for knit apparel products is near 100% over the sample period, indicating that almost all knit apparel products from Bangladesh used locally-produced knit textiles. The utilization for woven apparel products was initially quite low, roughly 20% when the EBA began. Woven apparel products responded dramatically to the policy change in 2011, while knitted products did not respond to the policy change. Relative to the change in the utilization rate for knitted products, the utilization rate for woven products increased by roughly 50 percentage points. This difference helps inform the empirical framework used in this paper.

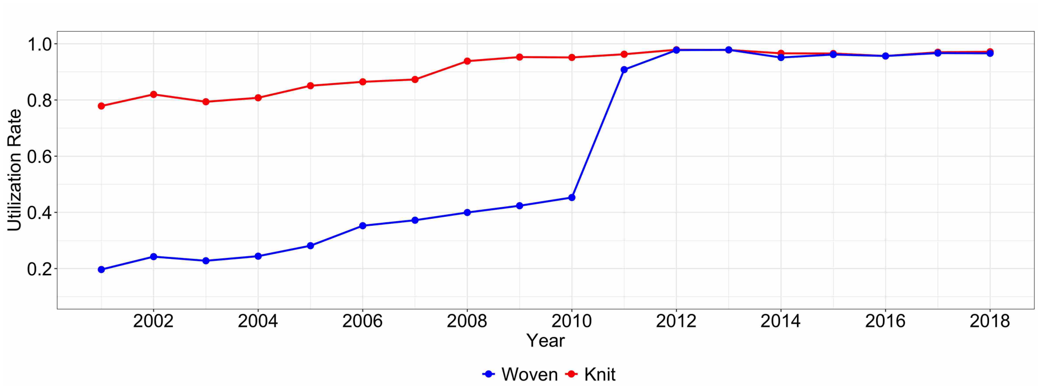
2.3 Empirical framework

In this section, I describe the data and outline the empirical framework used to analyze the firm-level responses to the rule of origin revision.

[11] Recognizing the reliance of the ready-made-garment sector on imported intermediate inputs, Bangladesh has a duty-free policy of their own for imports of textiles used in exported apparel products (Kabir et al. 2019). Thus, for export-oriented firms, a significant cost associated with imported textiles came from the inability of exporters to utilize preferential trade agreements like the EBA.

[12] European Statistical Office. (2020). Adjusted EU-EXTRA Imports by tariff regime, by HS6. Retrieved from http://epp.eurostat.ec.europa.eu/newxtweb/

FIGURE 3. Change in EBA utilization rate for apparel products



Notes: This figure displays utilization rate of the EBA for Bangladeshi apparel products. The data comes from EuroStat. The utilization rate is calculated as the value of imports into the EU that were processed under the EBA, relative to the total value of imports into the EU regardless of how the imports were processed.

Data and Summary Statistics

The primary data source used in this project comes from The Bangladesh National Bureau of Revenue. This panel data set contains information on the universe of export transactions by Bangladeshi firms collected from the bill of entry associated with each export shipment. Firm-level shipment values and quantities by export destination are included in the data set, as is the day of the shipment at the HS8-digit product level. I collapse the data to the annual level, as the change in the rules of origin occurred on January 1st, 2011. The sample used in this study covers transactions between 2008 to 2013, which allows me to focus on the relevant period and include three pre-treatment years (2008-2010), and three post-treatment years (2011-2013).[13] Over the sample period, the EU accounts for roughly 50% of annual export revenue. I aggregate the data at the destination level to EU and non-EU

[13] Ashan and Iqbal (2017) show that this customs data set is reliable by demonstrating that the ratio of annual exports from the customs data to the annual exports from the World Bank data is 0.99 over the sample period.

countries. Finally, I focus specifically on the change from a double-transformation to a single-transformation rule of origin, which only applied to exporters of apparel. Apparel products are defined as exports in HS heading 61 (knitted products), and HS heading 62 (woven products) and account for roughly 75% of the annual export value from Bangladesh. There are 243 unique HS8-digit products in these two categories.

Table 2 presents summary statistics of the data. The table is broken into two panels, one that displays the summary statistics for woven apparel products and one that displays the summary statistics for knitted apparel products. Averages and standard deviations are shown in the table. The statistics in the table are calculated for 2010, the year before the change in the rules of origin. The easiest market for Bangladeshi apparel firms to enter is the market for knitted apparel in the EU. This is due to the reduced tariff rates faced by LDCs in the EU relative to the rest of the world, and due to the relative ease of producing knitted textiles. The table shows that average annual export revenue is highest for knitted products sold in the EU. The competition in knitted products sold in the EU is also highlighted by the number of firms per product, which is highest in this segment of the market. Across all segments of the market, firms export between 4 and 7 products.

Firm-level exports are highly skewed towards its top product, as shown in Table 3. The table shows information for firms that produce between one and ten products and displays the share of total output attributed to each product sold, descending from the firm's largest (in terms of quantity sold) to the tenth largest product. The average output share of the largest product is approximately 3.5

TABLE 2. Summary statistics

	EU Average	ROW Average	Overall Average	Obs
Woven				
Firm-level revenue	922.7	1131.2	1033.2	3887
	(2358.7)	(3204.3)	(2839.7)	
Products per firm	5	5	5	4407
	(7)	(10)	(9)	
Firms per product	84	105	95	240
	(252)	(296)	(274)	
Knit				
Firm-level revenue	1319.8	428.8	836.6	5528
	(3182.2)	(1249.9)	(2382.8)	
Products per firm	7	4	5	6071
	(8)	(7)	(8)	
Firms per product	167	121	144	223
	(605)	(466)	(539)	

Notes: This table displays the summary statistics for the sample. These statistics are calculated in 2010, the year prior to the rules of origin change. Woven products refers to exports from HS heading 62, and knitted products refer to exports from HS heading 61. EU Exports refers to exports to EU member countries. Means are presented in the table, with standard deviations in parentheses below. Firm-level revenue is reported in 100,000 Bangladeshi Taka.

TABLE 3. Within-firm quantity share by product

Rank of Product in Firm's Output	Number of Products Sold by Firm: 1	2	3	4	5	6	7	8	9	10
1	1.000	0.805	0.738	0.692	0.665	0.638	0.616	0.596	0.568	0.554
2		0.193	0.196	0.197	0.193	0.192	0.189	0.188	0.191	0.186
3			0.064	0.079	0.083	0.086	0.089	0.093	0.096	0.095
4				0.031	0.040	0.046	0.050	0.053	0.056	0.059
5					0.018	0.025	0.030	0.032	0.036	0.039
6						0.011	0.017	0.020	0.024	0.026
7							0.008	0.012	0.015	0.018
8								0.006	0.009	0.012
9									0.005	0.007
10										0.004

Notes: The columns of the table report the number of products sold by the firm, while the rows display the share of firm-level output for each product. The rows are in descending order of product rank in output share.

times larger than the second-largest product, although this ratio declines with the number of products sold by the firm.

Endogeneity concerns and the triple-difference approach

A threat to the identification of the effect of the rules of origin revision in the EU stems from the potential endogenous nature of the policy change itself. For example, EU policymakers may have foreseen an increase in demand for apparel products from LDCs for EU consumers and responded by revising the rules of origin for these products. As a result, any change in LDC exports of apparel products to the EU may be driven by underlying changes in economic conditions or demand rather than the revision to the rules of origin. If this demand shock deferentially affected the EU relative to other markets, a difference-in-difference estimator exploiting variation in the export destination before and after the policy change will not recover an unbiased estimate of the effect of the policy change.

To control for potential unobserved destination-specific and product-specific shocks, I exploit additional variation in the cost of producing textiles. As discussed earlier in this paper, the double-transformation policy was particularly constricting for woven apparel products due to the capacity constraints in the woven textile production industry. I use a triple-difference approach, exploiting variation in input-cost differentials across woven and knitted apparel and export destination, before and after the EU policy change.

The triple-difference can be expressed as:

$$\overbrace{[\Delta Y_{EU,WOVEN} - \Delta Y_{ROW,WOVEN}]}^{\text{Woven Difference-in-Differences}} - \underbrace{[\Delta Y_{EU,KNIT} - \Delta Y_{ROW,KNIT}]}_{\text{Knit Difference-in-Differences}}$$

where ΔY refers to a change in outcome Y after the rules of origin liberalization. The first term in brackets is the woven apparel difference-in-difference, and the second term in brackets is the knitted difference-in-difference. This is a sharp design, and the stable groups assumption is satisfied (i.e., there are product-destination groups for which the rules of origin did not change). The common trends assumption requires that the expectation of the difference in the woven and knitted difference-in-differences evolves similarly over time in the absence of treatment. The woven and knit difference-in-differences control for global trends in sales of the two types of apparel products, while their difference controls for destination-specific shocks.

Figure 4 displays the trends in woven and knitted apparel export revenue, to the EU and the rest of the world (ROW), over the sample period. The solid lines represent the (log) average annual firm-level export revenue for woven apparel exports. The dashed lines represent the (log) average annual firm-level export revenue for knitted apparel exports. The gray lines indicate exports to the ROW, while black lines indicate exports to the EU.

The export revenue of both types of products sold to both destinations is increasing over the sample period. Many factors could drive this. For example, the recovery from the great recession occurred within the sample time frame. Thus, the upward trend in the sales of all apparel products, to both destinations could be a response to higher incomes in the latter half of the sample.[14]

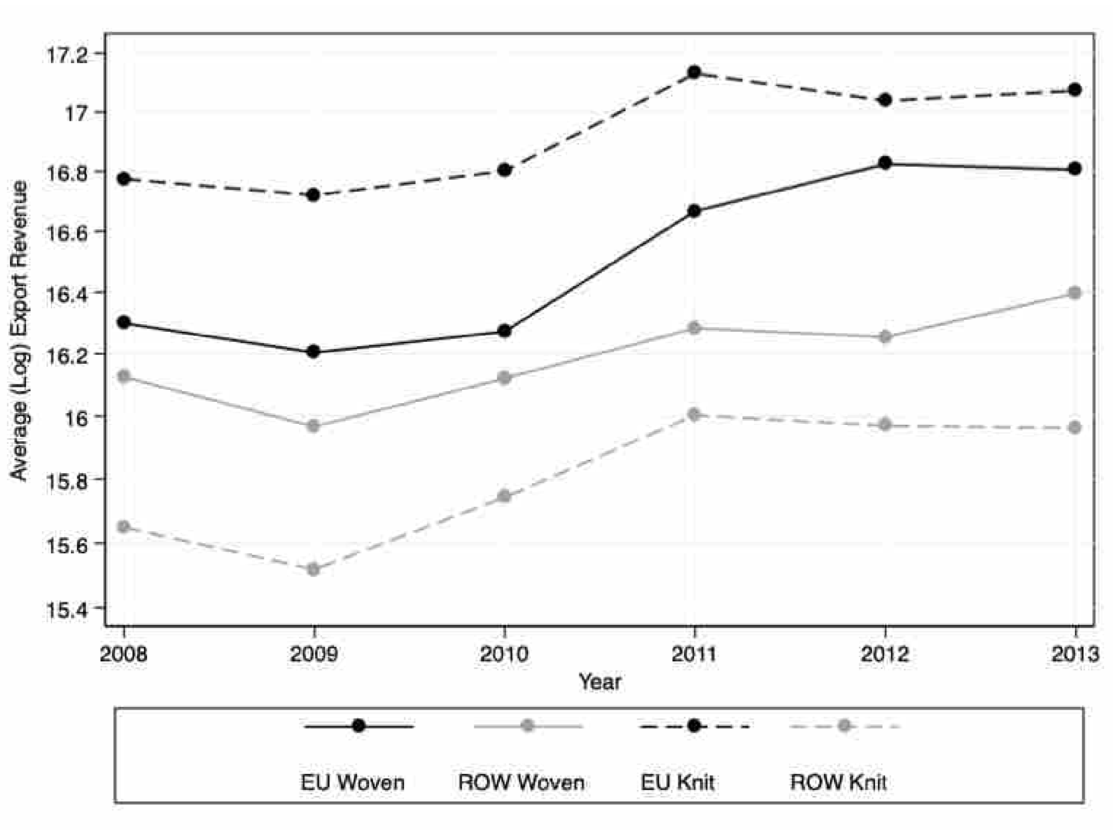
Figure 5 displays the trends in the difference between the solid lines in Figure 4, and the difference between the dashed lines in Figure 4 over time. The jump in the gap in export revenue for woven apparel is apparent in the data, while there does not appear to be any change in the difference in export revenue for knit clothing. The triple-difference is formed by estimating the difference between the two trends in Figure 4.

2.4 Empirical results

In this section, I present evidence of the effects of the EU's 2011 rules of origin revision on Bangladeshi apparel exporter's margins of trade. I first show the impact on firm-product export revenue, followed by evidence of the effect on two extensive margins of trade; the within-firm product level extensive margin, and the between-firm extensive margin. For each margin of trade, I provide evidence of the robustness of the results to increasingly demanding sets of fixed effects that control for potential confounding factors. I examine the robustness of the identifying

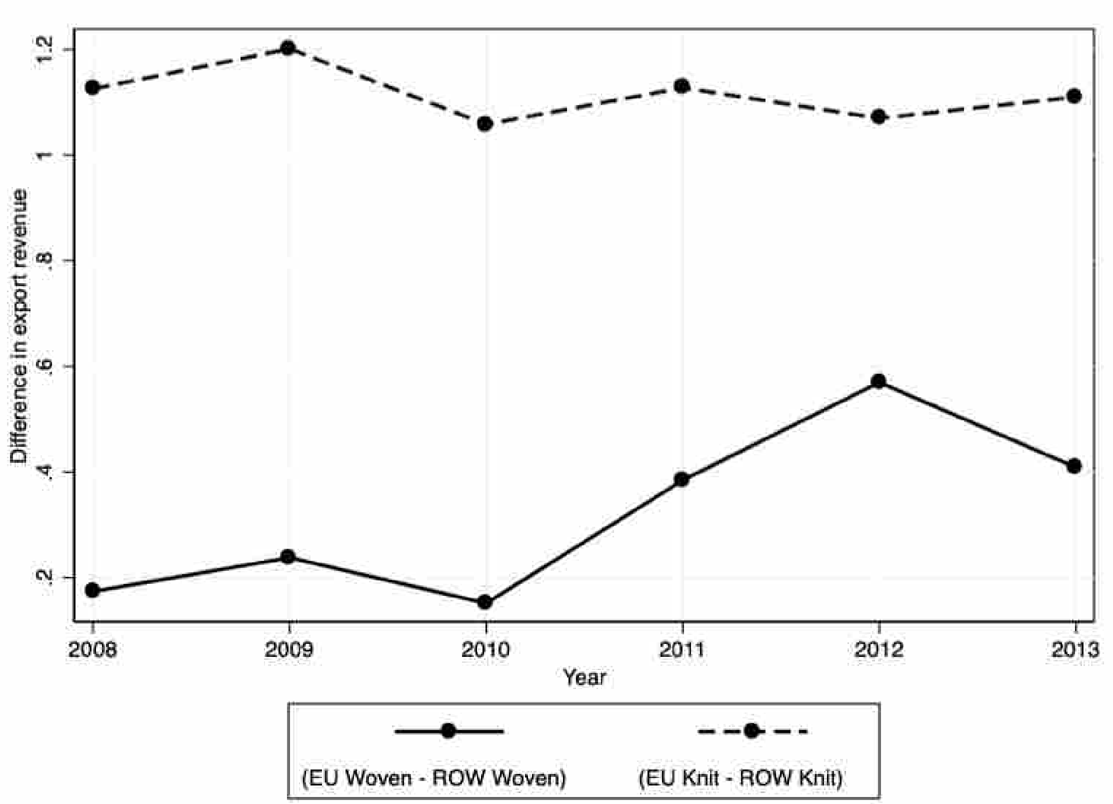
[14]The growth in exports of all products to all destinations over this period indicates that Bangladeshi apparel firms were not capacity constrained. I show that exports of woven apparel to non-EU countries and exports of knit clothing to EU countries did not change by a statistically meaningful amount in Section 4.5.

FIGURE 4. Trends in Total Export Sales



Notes: This figure shows the trends in log average export value of firm-level exports to the EU and ROW in knit and woven apparel over time. The solid lines represent woven apparel exports (HS 62), while the dashed lines represent knitted apparel exports (HS 61). The change in the rules of origin for EU countries occurred on January 1st, 2011.

FIGURE 5. Differenced Trends in Total Export Sales



Notes: This figure shows trends in the difference between the average export value of woven goods to EU countries and to the ROW (solid line) and the difference between average export value of knitted goods to EU countries and the ROW (dashed line). The change in the rules of origin for EU countries occurred on January 1st, 2011.

assumption using an event-study framework, and I explore the robustness of inference to the non-parametric calculation of p-values.

<u>Revenue</u>

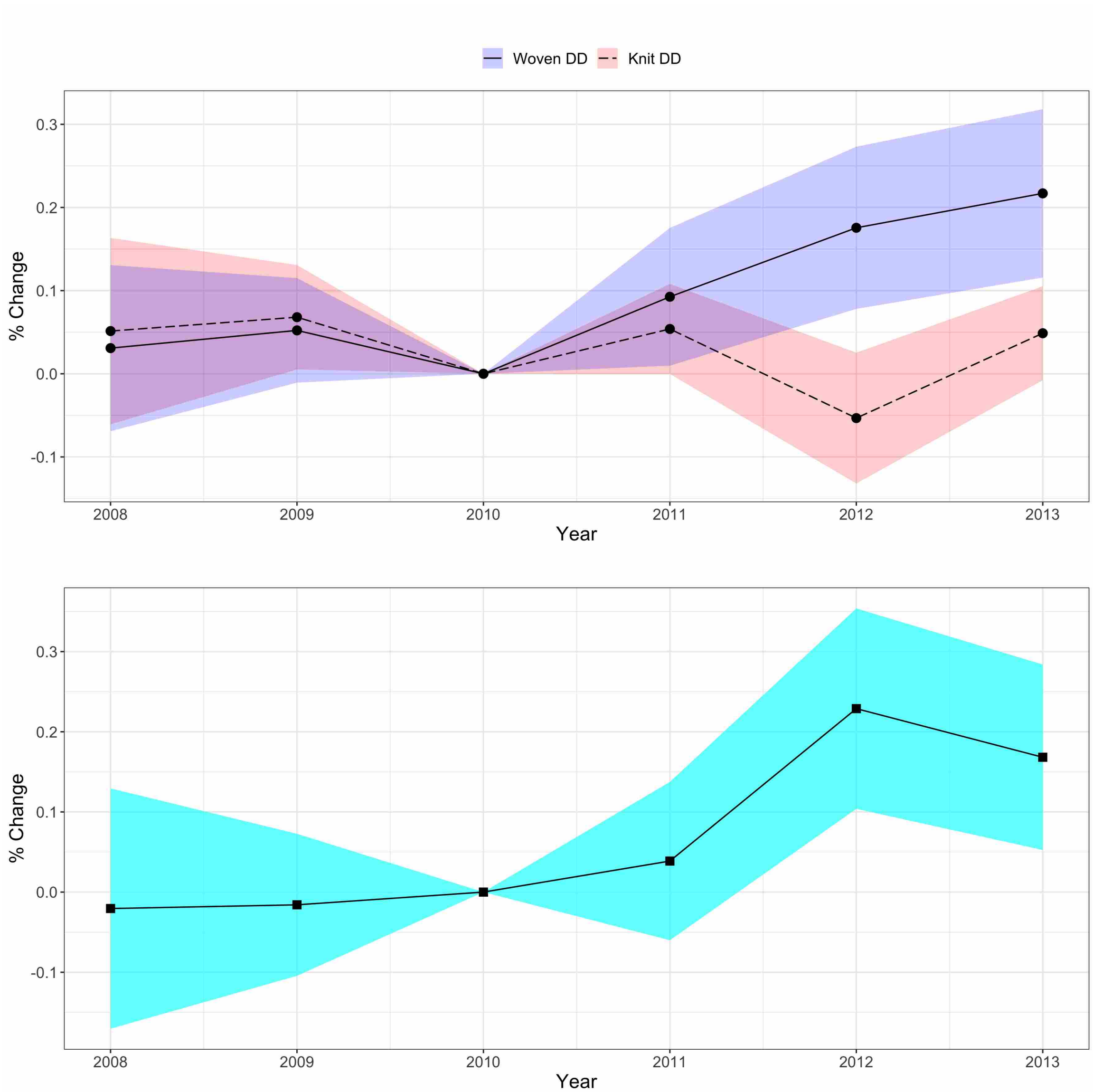
I begin by examining the response of export revenue to the EU's 2011 rules of origin liberalization. I first estimate the woven and knit difference-in-differences (DD) specifications, then estimate the triple-difference. The product-specific DD specifications are given by:

$$\text{Woven DD: } ln(r_{ijkt}) = \phi_{ik} + \lambda_j + \delta_t + \sum_{t=2008}^{t=2013} \beta_t(EU_j * YEAR_t) + u_{ijkt}, \quad \text{if } k \in HS62 \tag{2.1}$$

$$\text{Knit DD: } ln(r_{ijkt}) = \phi_{ik} + \lambda_j + \delta_t + \sum_{t=2008}^{t=2013} \beta_t(EU_j * YEAR) + u_{ijkt}, \quad \text{if } k \in HS61 \tag{2.2}$$

where the outcome is the natural log of export revenue for a firm i selling product k to destination j in year t. I include firm-product, destination, and year fixed effects. Estimates of the β_t terms are presented graphically in the top panel of Figure 6, while the full estimates are shown in the appendix. The difference in sales of woven and knitted apparel between the EU and ROW have a similar trend during the double-transformation period (pre-2011). After the policy change, the difference in export revenue of woven apparel sold in the EU relative to the ROW increase, while the difference in sales of knit products between the EU and ROW does not change.

FIGURE 6. Response of Export Revenue



Notes: The top panel of the figure displays the results of estimating equations 2.1, and 2.2. The bottom row displays the triple-difference results, as specified in equation 2.3. Errors allow for clustering at the product level and 95% confidence intervals are shown. The estimates used to create the figure are shown in the appendix in Table A1.

The triple-difference specification estimates the difference between the woven and knitted DDs. This specification is:

$$\begin{split} ln(r_{ijkt}) = \phi_{ik} + \lambda_j + \delta_t + \beta_0(EU_j * WOVEN_k) + \\ \sum_{t=2008}^{t=2013} \beta_{t,1}(WOVEN_k * YEAR_t) + \sum_{t=2008}^{t=2013} \beta_{t,2}(EU_j * YEAR_t) + \\ \sum_{t=2008}^{t=2013} \beta_{t,3}(EU_j * WOVEN_k * YEAR_t) + u_{ijkt} \end{split} \tag{2.3}$$

where the parameters of interest are the $\beta_{t,3}$'s. The results of estimating equation 2.3 are shown graphically in the bottom left panel of Figure 6. The results indicate that export revenue for woven products sold to the EU increased following the 2011 rules of origin liberalization. The results of the triple-difference are very similar in magnitude to the woven DD estimates.

To further analyze how the EU's rules of origin liberalization influence export revenue, I estimate the following model:

$$ln(r_{ijkt}) = \phi_{ik} + \gamma_{jt} + \lambda_{kt} + \delta_{jk} + \beta_1(EU_j * WOVEN_k * POST_t) + u_{ijkt}. \tag{2.4}$$

In equation 2.4, I control flexibly for firm-product heterogeneity (ϕ_{ik}) using firm-product fixed effects. The inclusion of destination-product fixed effects controls for the $EU_j * WOVEN_k$ interaction term in a highly flexible manner. I control for destination-year and product-year fixed effects to account for the $EU_j * POST_t$, and $WOVEN_k * POST_t$ interactions. Using interacted fixed effects to control for double-interaction terms in a triple-difference-in-differences model is done in Frazer and Van Biesebroeck (2010), where it is referred to as the "unrestrictive" triple-difference model.

The results of estimating equation 2.4 are presented in Table 4. I estimate the rules of origin liberalization resulted in an increase in revenue for sales of woven products sold in the EU by roughly 17%. In column (2), I present the results from a Pseudo-Poisson Maximum Likelihood model, as recommended in Silva and Tenreyro (2006) to account for the potential bias arising from heteroskedasticity. Column (3) of the table presents the results of estimating equation 2.4 for incumbent firms only, where an incumbent is defined as a firm that sold a product to a destination at some point during the double- and single-transformation period. The estimate of the effect of the rules of origin revision is similar in magnitude, roughly a 20% increase for this group of firms. Column (4) of the table repeats this exercise using a different definition of an incumbent firm. Here, an incumbent is defined as a firm that sold a product to an export destination in each year of the sample. The effect of the rules of origin liberalization on these firms is roughly 28%.

Product-level extensive margin

Next, I estimate how the rules of origin revision influenced the product-level extensive margin for exporting firms. Product scope is defined as the number of unique HS8-level products sold by firm i to destination j in year t. Given that this is a low-ordered count variable with zeros, I estimate the response using pseudo-Poisson maximum likelihood. I do not want to capture the entry of new firms when evaluating the product scope response, so, in this section, I only work with a sub-sample of incumbent firms where incumbents are defined as firms that exported to a destination during the double- and single-transformation period. As in the

TABLE 4. Export Revenue

	(1)	(2)	(3)	(4)
		PPML	Incumbents	
Marginal Effect	17%	16%	18.5%	28%
$EU_j * WOVEN_k * POST_t$	0.16***	0.15**	0.17***	0.25***
	(0.052)	(0.069)	(0.051)	(0.081)
Constant	15.67***	18.81***	16.06***	17.42***
	(0.006)	(0.010)	(0.005)	(0.009)
Observations	136,700	136,700	83,159	23,352
R-squared	0.620	0.782	0.617	0.627

Notes: This table presents the results from estimating equation (2.4). The outcome variable is the log export revenue for firm i selling product k to destination j in year t. Column 2 presents the results using PPML estimation, and in this column the dependent variable is in levels. Columns 3 and 4 estimate the response for incumbent firms only. In column 3, incumbents are defined as firms that exported a product to the destination in both the double-transformation and single-transformation period. In column 4, incumbents are defined as firms that exported a product to a destination each year. Errors allow for clustering at the HS8 product-level in all columns. Marginal effects are calculated as 100*$exp(\hat{\beta}_1) - 1$.

previous sub-section, I begin by estimating the woven and knit DD specifications. Then, I estimate the triple-difference. The product-specific DD specifications are given by:

$$\text{Woven DD: } NumProd_{ijt} = exp\{\phi_{ij} + \delta_t + \sum_{t=2008}^{t=2013} \beta_t (EU_j * YEAR_t) + u_{ijt}\}, \quad \text{for } k \in HS62 \tag{2.5}$$

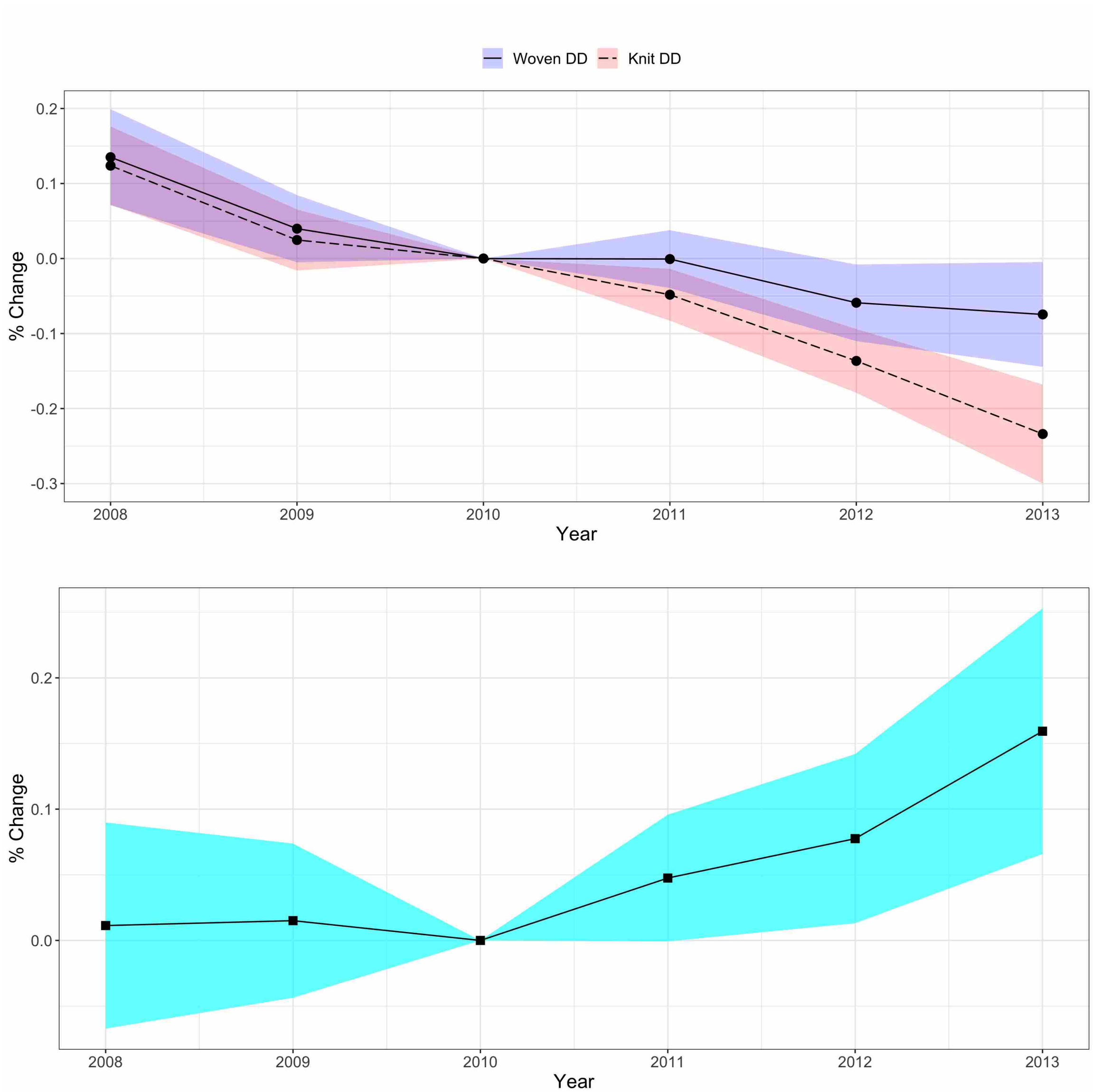
$$\text{Knit DD: } NumProd_{ijt} = exp\{\phi_{ij} + \delta_t + \sum_{t=2008}^{t=2013} \beta_t (EU_j * YEAR_t) + u_{ijt}\}, \quad \text{for } k \in HS61 \tag{2.6}$$

I include firm-destination and year fixed effects. The results are presented graphically in the top panel of Figure 7. Product scope in the EU is declining for both types of products over the entire sample period. After the rules of origin revision, the trends diverge. The number of woven apparel products sold to the EU relative to the ROW, while the number of knit apparel products sold in the EU relative to the ROW continues to decline.

The triple-difference specification estimates the difference between the woven and knitted difference-in-differences. This specification is given by:

$$\begin{gathered} NumProd_{ijkt} = exp\{\phi_{ij} + \delta_t + \beta_0 (EU_j * WOVEN_k) + \\ \sum_{t=2008}^{t=2013} \beta_{t,1} (WOVEN_k * YEAR_t) + \sum_{t=2008}^{t=2013} \beta_{t,2} (EU_j * YEAR_t) + \\ \sum_{t=2008}^{t=2013} \beta_{t,3} (EU_j * WOVEN_k * YEAR_t) + u_{ijkt}\} \end{gathered} \tag{2.7}$$

FIGURE 7. Response of Export Product Scope



Notes: The top panel of the figure displays the results of estimating equations 2.5, and 2.6. The bottom row displays the triple-difference results, as specified in equation 2.7. Errors allow for clustering at the firm level and 95% confidence intervals are shown. The estimates used to create the figure are shown in the appendix in Table A1.

where the k subscripts correspond to HS2 (woven or knitted) product codes. The results of estimating equation (2.7) are shown graphically in the bottom left panel of Figure 7. The difference between the woven DD and knit DD is not statistically different from zero during the double-transformation period (pre-2011), and this is consistent with the identifying assumption. The results also indicate that product scope for woven apparel products increased following the 2011 rules of origin liberalization.

To further analyze how the EU's rules of origin liberalization influenced exported product scope, I estimate the unrestrictive DDD:

$$NumProds_{ijkt} = exp\{\phi_{ij}+\gamma_{jt}+\lambda_{kt}+\delta_{jk}+\beta_1(EU_j{*}WOVEN_k{*}POST_t)+u_{ijkt}\}. \quad (2.8)$$

Here, I include sets of interacted fixed effects to flexibly control for trends in the number of woven or knit products sold and trends in the number of products sold to different destinations, and allow each destination-HS2 product to have a unique intercept. The results of estimating equation 2.8 are presented in column (1) of Table 5. I estimate the rules of origin liberalization increased firm-level product scope of roughly 9%. The 9% increase in product scope translates to roughly 0.5 additional products, based on 2010 averages.

<u>Firm-level extensive margin</u>

Finally, I estimate the effect of the rules of origin liberalization on the firm-level extensive margin. To do this, I begin by defining the outcome variable by counting the number of firms exporting each HS8-level product to the EU and the

TABLE 5. Firm-Product Export Revenue

	(1)	(2)
Outcome:	$NumProds_{ijkt}$	$Firms_{jkt}$
Marginal Effect	9.6%	8.2%
$EU_j * WOVEN_k * POST_t$	0.092***	0.079**
	(0.027)	(0.031)
Constant	2.384***	6.605***
	(0.003)	(0.003)
Marginal Effect Evaluated at 2010 Mean	0.5 Products	7 Firms
Observations	45,684	2,544
Firm-HS2 FE	x	
Dest-Year FE	x	x
HS2-Year FE	x	
HS8-Year FE		x
Dest-HS2 FE	x	
Dest-HS8 FE		x

Notes: This table presents the results of estimating the extensive margin effects of the 2011 rules of origin liberalization. Errors in the first column allow for clustering at the firm-level, while errors in the third column allow for clustering at the product-level. The outcome in first column is the number of woven or knitted products (HS8 products within HS2 headings) sold by incumbent firm i to destination j in year t. The outcome in the second column is the number of firms selling product k (at the HS8 level) to destination j in year t. Marginal effects are calculated as 100*$exp(\hat{\beta}_1) - 1$.

ROW. I estimate the response using a pseudo-Poisson model. I first analyze the woven and knit DD specifications, then estimate the triple-difference. The product-specific DD specifications are given by:

$$\text{Woven DD: } Firms_{jkt} = exp\{\phi_{jk} + \delta_t + \sum_{t=2008}^{t=2013} \beta_t (EU_j * YEAR_t) + u_{jkt}\}, \quad \text{for } k \in HS62 \tag{2.9}$$

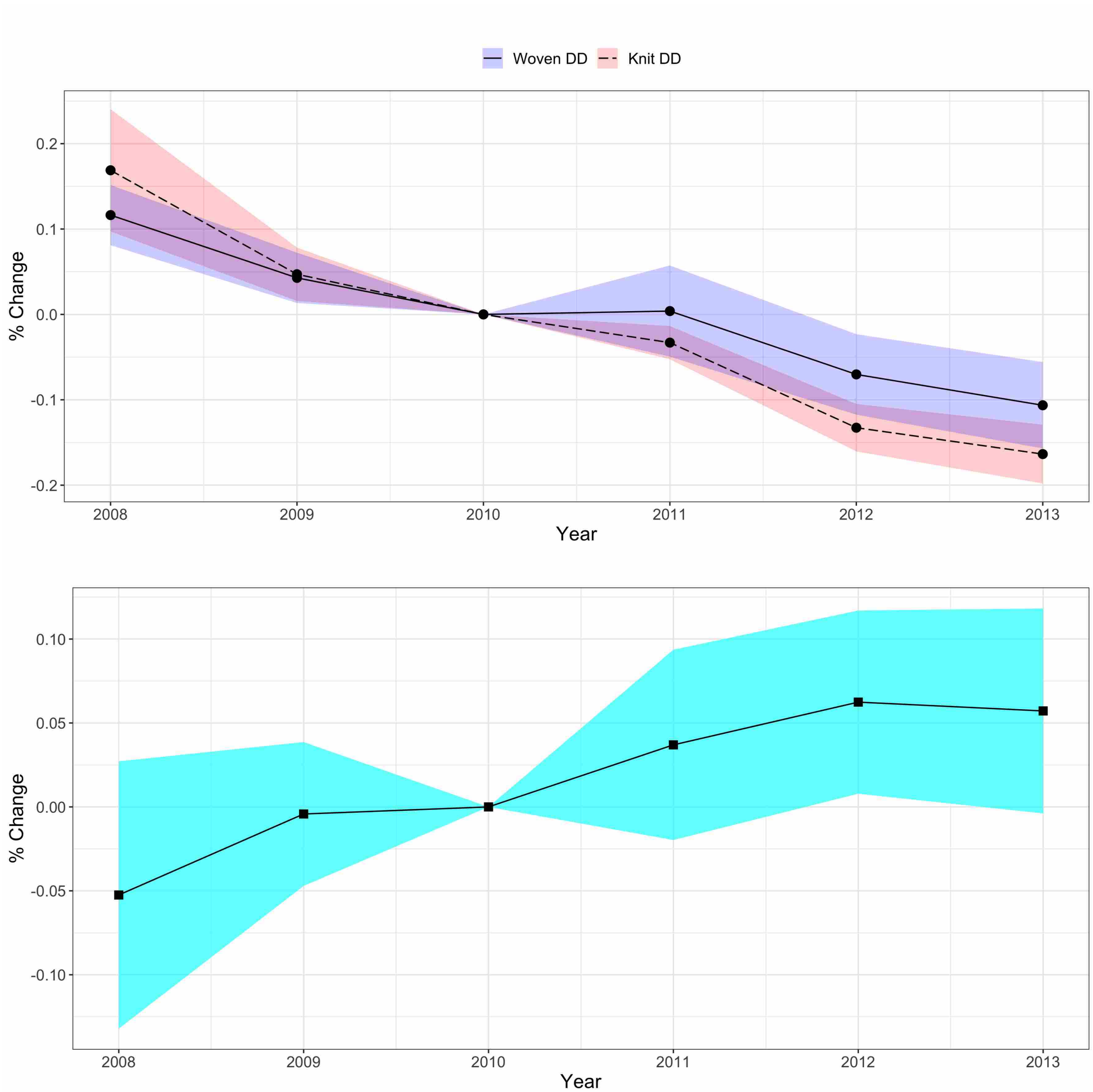
$$\text{Knit DD: } Firms_{jkt} = exp\{\phi_{jk} + \delta_t + \sum_{t=2008}^{t=2013} \beta_t (EU_j * YEAR_t) + u_{jkt}\}, \quad \text{for } k \in HS61 \tag{2.10}$$

Point estimates of the β_t terms are presented graphically in the top panel of Figure 8. Similar to the product-level extensive margin, both DDs are declining over the entire sample period. After the rules of origin revision, the trends diverge, and the number of firms selling woven apparel products to the EU relative to the ROW flattens out. In contrast, the number of firms selling knit apparel products to the EU relative to the ROW continues to decline.

The triple-difference specification estimates the difference between the woven and knitted DDs. This specification is given by:

$$\begin{aligned} Firms_{jkt} = exp\{\phi_{jk} + \delta_t + \beta_0 (EU_j * WOVEN_k) + \\ \sum_{t=2008}^{t=2013} \beta_{t,1} (WOVEN_k * YEAR_t) + \sum_{t=2008}^{t=2013} \beta_{t,2} (EU_j * YEAR_t) + \\ \sum_{t=2008}^{t=2013} \beta_{t,3} (EU_j * WOVEN_k * YEAR_t) + u_{jkt}\}. \end{aligned} \tag{2.11}$$

FIGURE 8. Firm-level Extensive Margin



Notes: The top panel of the figure displays the results of estimating equations 2.9, and 2.10. The bottom row displays the triple-difference results, as specified in equation 2.11. Errors allow for clustering at the product level and 95% confidence intervals are shown. The estimates used to create the figure are shown in the appendix in Table A1.

The results of estimating equation (2.11) are shown graphically in the bottom panel of Figure 8. The results indicate that the number of firms selling woven apparel products increased following the 2011 rules of origin liberalization.

To further analyze how the EU's rules of origin liberalization influenced the firm-level extensive margin, I estimate the following model:

$$Firms_{jkt} = exp\{\gamma_{jt} + \lambda_{kt} + \delta_{jk} + \beta_1(EU_j * WOVEN_k * POST_t) + u_{jkt}\}. \quad (2.12)$$

Here, I include sets of interacted fixed effects. The results of estimating equation (2.12) are presented in column (3) Table 5. I estimate the rules of origin liberalization increased the firm-level extensive margin of roughly 8%. The 8% increase in product scope translates to roughly seven new firms per woven product, based on 2010 averages.

<u>Permutation tests</u>

As an additional test, I use randomization inference to calculate the probability of observing the magnitudes I estimate in the previous section, conditional on fixed effects, under the null of no effect. This application of exact inference in the context of a difference-in-differences framework is similar to exercises in Conley and Taber (2011), and Bertrand, Duflo and Mullainathan (2004). For each margin (export revenue, product-level extensive, and firm-level extensive), I conduct three tests. First, I randomly shuffle which products are classified as woven and which are classified as knit while ensuring that the number of woven and knit products in the randomized sample is the same as the actual sample. I then re-estimate specifications (4), (8), and (12) using this created data set. I repeat this process 10,000 times, each time storing the estimate of β_1, the coefficient on $EU_j * WOVEN_k * POST_t$. Then, I shuffle which years are classified as pre and post the rules of origin revision, and which destinations are EU using a similar process.

P-values are calculated under the sharp null of no effect ($\beta_1 = 0$) non-parametrically from the empirical null distribution as the ratio of the number of times the estimate under randomization was at least as large as the actual estimate relative to the total number of randomized evaluations of the triple-difference. Column (1) of Table 6 presents the results. For each outcome I show the results when products are randomized, when destinations are randomized, and when years are randomized. In all cases, these p-values are less than 1%.

MacKinnon and Webb (2019) note that when treated groups have a different number of observations as control groups randomization inference based on beta coefficients can over-reject. This may be relevant in the context of this study. For example, 53% of HS8 level products are woven products and there are more non-EU countries than EU countries in the sample. As a secondary test, it is recommended to use t-statistics rather than coefficients. Randomization inference based on t-statistics tend to under-reject, making this a more conservative test (MacKinnon and Webb 2019). I examine the probability of observing a t-statistic of at least 2 using the same permutation procedure described above. Column (2) of Table 6 presents the results of the permutation test based on t-statistics. Across all outcomes and sources of randomization, the p-values are larger than the β_1 based p-values. In nearly all cases, even these conservative p-values are less than 0.05.

TABLE 6. Permutation Tests

Outcome	p-value based on β_1	p-value based on t-statistic
Revenue		
Product randomization	< 0.001	0.020
Destination randomization	< 0.001	0.024
Year randomization	< 0.001	0.023
Number of products		
Product randomization	< 0.001	0.024
Destination randomization	< 0.001	0.010
Year randomization	< 0.001	0.024
Number of firms		
Product randomization	0.004	0.061
Destination randomization	0.006	0.048
Year randomization	0.005	0.063

Notes: This table presents the results from permutation tests. For each outcome, non-parametric p-values are calculated based on random permutations of which products are classified as woven, or which destinations are classified as EU, or which years are classified as post-2011. The first column show the p-values based on estimates of the triple-difference effect (β_1 in equation 2.4, 2.8, and 2.12). The second column presents p-values based on t-statistics. There were 10,000 replications used to produce results in both columns.

Effects in other markets

Next, I analyze how the EU's rules of origin revision may have influenced exports to other markets. For example, if Bangladeshi firms face capacity constraints, an increase in sales of apparel to EU countries may have come at the expense of exports to other countries. Similarly, an increase in the sales of woven clothing in the EU may have come at the expense of exports of knit apparel in the EU. As resources are reallocated within the firm, an increase in quantity sold in one market could increase the marginal cost of production for other markets.

To examine the response of the quantity of knit apparel to EU countries after the rules of origin liberalization, I estimate the following specification.

$$ln(q_{ijkt}) = \alpha_{ik} + \delta_{kt} + \gamma_{jk} + \beta_1(EU_j * POST_t) + u_{ijkt} \quad \text{if } k \in HS61 \qquad (2.13)$$

Where q_{ijkt} is the quantity (number of units in a shipment) of exports of product k. The sample is limited to incumbent firms and limited to firms that also exported woven apparel products in year t. Thus, this specification examines how the quantity of knit products exported to the EU responded within firms that also exported woven products.

To examine how the response of woven products in non-EU countries, I estimate the following specification

$$ln(q_{ijkt}) = \alpha_{ik} + \delta_{jt} + \gamma_{jk} + \beta_1(WOVEN_k * POST_t) + u_{ijkt} \quad \text{if } j \neq EU \qquad (2.14)$$

Here, I estimate equation (14) on a sample of incumbent firms that also exported products to the EU in year t. Therefore, this specification allows me to examine the change in the quantity of woven apparel exported to non-EU countries within firms that also exported to the EU. If firms face capacity constraints, or if firms substitute one market or product for another following a change in trade policy for any other reason, estimates of β_1 is equation (13) or (14) would negative.

Results of estimating equations (13) and (14) are presented in Table 7. In the first column, I find that firms exporting woven apparel in year t did not change their sales of knit apparel to the EU after 2010 by a statistically meaningful amount. In the second column, I estimate that firms exporting to the EU in year t reduced their sales of woven apparel in non-EU countries by roughly 1%, although the estimate is very noisy. Taken together, these results indicate that Bangladeshi apparel firms could increase sales of woven apparel products to the EU without sacrificing sales of knit apparel products to the EU or sales of woven apparel to non-EU countries.

TABLE 7. Effects in other markets

	(1)	(2)
$EU_j * POST_t$	0.03	
	(0.043)	
$WOVEN_k * POST_t$		-0.01
		(0.039)
Constant	9.07***	9.06***
	(0.013)	(0.149)
Observations	21,745	27,369
R-squared	0.632	0.252

Notes: This table presents the results of estimating equations (13) and (14). Standard errors allow for clustering at the product level in both specifications. Both specifications are estimated using only incumbent firms.

2.5 Industry Responses

In this section, I examine how the rules of origin revision influenced the composition of the apparel export industry in Bangladesh. I first consider how market shares adjusted across entrants, incumbents, and exiting firms. Then, focusing on incumbent firms, I analyze the response of market shares across incumbent firms of different productivity.

Market share reallocation

Following Khandelwal, Schott and Wei (2013), I decompose export growth into one intensive margin and two extensive margins. The intensive margin is composed of incumbent firms, which are defined as firms that exported the same HS8-level product to the same destination before and after the 2011 policy change. The extensive margins are composed of entering and exiting firms, which consist of firms that began exporting an HS8-level product to a destination after the policy change and stopped exporting an HS8-level product to a destination after the policy change, respectively.

I then break the two extensive margins down further. Within entrants, I define "destination adders" as firms that exported an HS8-level product during the pre- and post-policy change period, but began exporting the HS8-level product to a new destination after the policy change. Next, I define "product adders" as firms that exported a product to a destination during the pre- and post-policy change period, but began exporting a new HS8-level product to the destination after the policy change. Finally, I define a group of firms called "brand new" firms. These firms began exporting a new HS8-level product to a new destination after the policy change. Exiters are decomposed similarly, expect rather than adding products of destinations, "destination droppers" drop destinations, "product droppers" drop products, and "complete exiters" drop a product-destination pair after the policy change.

For each of these margins (m), I calculate the quantity and value market share across destination-products (jk) in each year. These market shares are defined by:

$$\Phi_{mjkt} = (\sum_{i \in m} Y_{ijkt} / \sum_{m} \sum_{i} Y_{ijkt}) \tag{2.15}$$

where Y refers to either value or quantity of export shipments. I then estimate the following triple-difference regression model for each margin separately:

$$\Phi_{jkt} = \alpha_0 + \beta_1(EU_j * WOVEN_k * POST_t) + \\ \beta_2(EU_j * WOVEN_k) + \beta_3(WOVEN_k * POST_t) + \beta_4(EU_j * POST_t) + \\ \beta_5(EU_j * WOVEN_k) + \beta_6 EU_j + \beta_7 WOVEN_k + \beta_8 POST_t + \epsilon_{jkt} \tag{2.16}$$

The estimates of β_1 from estimating equation (2.16) for all nine margins are presented in Table 8, and more detailed results are presented in Table A2 in the Appendix.

TABLE 8. Total Market Share Change

	Quantity Share	Value Share
Incumbent	-0.032	-0.027
Total Entrants	0.13***	0.12***
Product Adders	0.10***	0.11***
Destination Adders	0.002	0.001
Brand New	0.03	0.01
Total Exit	-0.096***	-0.094**
Product Dropper	-0.058	-0.060
Destination Dropper	0.001	0.0003
Complete Exit	-0.04*	-0.034*
Net Entry	0.032	0.027

Notes: This table displays the results from estimating equation (16) for each margin, shown in equation (15), separately. The full table can be found in the Appendix (Table A2). *p-value≤ 0.1, **p-value≤ 0.05, ***p-value≤ 0.01.

The market share of incumbents exporting woven products to EU countries did not change by a statistically significant amount following the policy change. However, the market share of entrants who begin selling a woven product to the EU after the policy change increases by 13 percentage points. Within entrants, product adders contribute 77% to this increase. This indicates that the primary margin of adjustment among entrants comes from firms that were already exporting to the EU and added a woven product after the policy change.

I find evidence that the market share for exiting firms declines by roughly 9.6 percentage points more in the woven-EU market relative to other product-destination markets. Among exiters, the market share of compete exiters is the only marginally significant contributor. This indicates that the firms that stopped selling woven products to the EU after the policy change didn't continue to export knit products to the EU, and didn't continue to export woven products to the ROW. The last row of Table 8 shows the change in net entry, which is not statistically significant.

Incumbent market share reallocation

The evidence provided in Table 8 indicates that incumbent firms did not lose market share to entrants after the 2011 rules of origin liberalization in the EU. However, market share may have been reallocated within incumbents. To examine this, I use the number of products a firm exports as a proxy measurement for firm productivity. This measure of productivity is consistent with a model of multi-product firms in which firms must pay product-specific fixed costs to export. High productivity firms have lower marginal costs of production and can cover a broader range of product-specific fixed export costs. The theoretical model in the appendix of this paper shows this mechanism more formally. Measuring firm productivity using the number of products within a firm is also done in Bernard, Redding, and Schott (2011).

For each incumbent firm, I determine the average number of products exported per year during the double-transformation period (pre-2011). I then break this measure into quartiles.[15] Next, I follow a similar procedure outlined above, calculating the product-destination level market share for each quartile. I then estimate the triple-difference model in equation (2.16) using the market share of each quartile as a dependent variable. The estimates of β_1 are shown in Table 9.

TABLE 9. Incumbent Share Change

	Quantity Share	Value Share
Quartile 1	0.02	0.01
Quartile 2	-0.04	-0.03
Quartile 3	-0.07*	-0.07*
Quartile 4	0.09**	0.09**

Notes: This table displays the results of estimating equation (2.16) for each quartile of productivity, measured by the number of products exported in the double-transformation period. The full table is in the appendix (Table A3). *p-value$\leq$ 0.1, **p-value$\leq$ 0.05.

I find evidence that the market share of firms in the highest quartile of productivity increased by nine percentage points after the rules of origin liberalization. The market share gains for the highest productivity firms mainly come from firms in the third quartile of productivity, not the lower end of the productivity distribution. The lack of reallocation effects at the low end of the productivity distribution is surprising. However, firms at the low end of the productivity distribution may offer products of a lower quality than firms at the high end. Thus, there may be less competition between low (potentially informal)

[15]Firms in the first quartile exported roughly two products per year, firms in the second quartile exported roughly three products per year, firms in the third quartile exported roughly six products per year, and firms in the fourth quartile exported roughly 12 products per year.

firms and high productivity firms and more competition between firms at the upper end of the productivity distribution.

2.6 Conclusion

In this paper, I study how rules of origin in potential export markets influence the export behavior of firms in LDCs. Access to preferential tariffs is conditional on satisfying rules of origin. When rules of origin require capital-intensive transformations of imported intermediate inputs, they can be costly for exporting LDC firms to comply with. In this sense, rules of origin undermine market access for exporters in LDCs. Exploiting technical differences in the production of different types of textiles, and a revision to the rules of origin governing preferential access to the EU market for apparel producers in LDCs, I find rules of origin not only restrict firm entry into the export market, but also reduce the range of products they sell, and the average export revenue they earn per product.

The results highlight that in the context of a labor-abundant country (like many LDCs), firms that must rely on capital-intensive inputs are put at a disadvantage under strict rules of origin. Given the small amount of textile production in Bangladesh (and other LDCs), the potential losses from this policy change for Bangladeshi woven textiles producers are likely second-order in terms of magnitude, although data limitations restrict me from directly analyzing this. From a policy perspective, the results shed light on an under-studied trade barrier that is typically embedded within preferential trade agreements. Policymakers attempting to improve conditions in developing countries through trade policy may be able to affect outcomes without lowering traditional barriers like tariffs or quotas by adjusting the rules of origin.

Additionally, the results in this paper underscore the implicit trade-off between trade preferences and rules of origin. Deep trade preferences with restrictive rules of origin can provide similar market access as shallow trade preferences and more permissive rules of origin. This trade-off is especially critical because preference depth cannot increase indefinitely. The difference between preferential tariffs and MFN tariffs is bounded below at zero. Even the upper bound of the difference has been falling as MFN tariffs have declined over time.[16] In the face of preference erosion, rules of origin offer a potential policy tool that may be used to continue to improve or restore market access for LDCs.

Lastly, in this paper, I offer additional context to debates regarding the trade relationships between high- and low-income countries. Flentø and Ponte (2017) note that while there is a consensus in trade and development policy circles that trade negotiations between developed and LDCs should aim to reduce trade barriers for exporters in LDCs, there is less consensus on how this should be achieved. The results of this study show that revising rules of origin is a viable option within this debate.

[16] World Bank. "Tariff rate, most favored nation, simple mean, all products (%)". *Integrated Data Base*. https://data.worldbank.org/indicator/TM.TAX.MRCH.SM.FN.ZS. Accessed on 06/10/2019.

CHAPTER III

THE EFFECT OF HURRICANES ON US EXPORTS: A PORT-LEVEL ANALYSIS

3.1 Introduction

Natural disasters are extreme events that completely suspend economic activity in affected regions for a period of time. Studies from several disciplines have highlighted the economic and social impact of natural disasters.[1] Global trade's reliance on coastal infrastructure makes it particularly vulnerable to hurricanes, one of the most frequent natural disasters in the USA. The damages caused by storms to ports are well documented. For example, Hurricane Katrina caused $1.7 billion in damages to Southern Louisiana ports (Santella, Steinberg and Sengul 2010), Hurricane Ike caused $2.4 billion in damages to Texan ports (FEMA 2008). Hurricane Sandy resulted in $2.2 billion damages to the Port of New York and New Jersey (Strunsky 2013). The effect of hurricane-related disruptions on port-level trade flows is less understood. The importance of the relationship between trade and hurricanes is underscored by the expansion of global supply chains, and the risks that disruption will grow over time as climatic disasters intensify due to climate change (Knutson and Tuleya 2004; Bender et al. 2010; Camargo and Hsiang 2016). A growing body of literature suggests that understanding the intricacies in the relationship between climate change-related hazards and economic systems is necessary for developing effective resiliency planning and policy (Becker et al. 2015).

[1] For example, Cameron and Shah (2015) examine risk-taking behavior following natural disasters, and Li et al., (2010) study migration following Hurricane Katrina.

The existing published literature on the response of trade to natural disasters tends to measure the effect using aggregate national-level trade statistics (Gassebner, Keck and Teh 2010; Oh and Reuveny 2010; Felbermayr and Gröschl 2013; Pelli and Tschopp 2017). Unsurprisingly, these studies find a small effect, or in some cases a null result.[2] The few studies that examine the response of trade to disasters using more disaggregate trade data only focuses on the response to a single natural disaster in a case-study style analysis (Martincus and Blyde 2013).[3] In this paper, I offer a comprehensive analysis of the effects of hurricanes on port-level exports. To this end, I examine the direct effect and spillover effects across ports of 68 hurricanes, over 12 years, on exports from major East and Gulf Coast ports in the USA.[4]

The analysis in this paper proceeds in several stages. First, I derive an empirical specification from a theoretical model of port-choice that aggregates up to a structure resembling the gravity model of trade. The model ties together typical modeling methods used in the port-choice literature (i.e., discrete choice models) and the gravity model of trade, the typical modeling method used in empirical studies of international trade. I estimate the effects of hurricanes on port-level

[2]Pelli and Tschopp (2017) find that hurricane intensity does not affect average industry-level exports. However, the authors do find heterogeneity in effects across industries based on revealed comparative advantage.

[3]Several working papers examine the effects of natural disasters on port-level trade using case-studies. Friedt (2017) analyzes port-level trade responses to Hurricane Katrina, and Hamano and Vermeulen (2016) study the port-level response to the 2011 Japanese tsunami.

[4]The hurricanes included in this panel are all storms that came within 155 miles (250 km) to the US coast. The storms included are Bill, Claudette, Erika, Grace, Henri, Isabel, Alex, Bonnie, Charley, Frances, Gaston, Hermine, Ivan, Jeanne, Matthew, Arlene, Cindy, Dennis, Emily, Katrina, Ophelia, Rita, Tammy, Wilma, Alberto, Beryl, Chris, Ernesto, Andrea, Barry, Erin, Gabrielle, Humberto, Noel, Cristobal, Dolly, Edouard, Fay, Gustav, Hanna, Ike, Kyle, Paloma, Claudette, Ida, Alex, Bonnie, Earl, Hermine, Nicole, Paula, Bret, Don, Emily, Irene, Lee, Alberto, Beryl, Debby, Isaac, Sandy, Andrea, Dorian, Karen, Arthur, Ana, Bill, and Claudette. Note, some storm names are repeated over the years. The storms listed are in alphabetical order by year.

trade using variation in hurricane wind speeds experienced at Eastern US ports and monthly port-level export data. I find evidence that hurricane intensity reduces the value of exports from an affected port. The effect is present for several months and results in large cumulative losses in port-level export value.[5] For example, experiencing wind speeds of 40 meters per second (a Category I storm) leads to a cumulative loss in total port export value of roughly $264 million over the two years following the storm. The effect is equivalent to four months worth of export value. The lost export value is not recovered over two years after a storm.

Next, I examine the heterogeneity in the effect of hurricane intensity across several margins. Heterogeneity across geographic regions indicates that ports located in areas with less historical exposure to hurricanes lose more export value per meter per second of wind speed than ports in areas with more experience. For example, five months after a Category I hurricane, ports in the fourth percentile (out of five) of historical hurricane-exposure have lost roughly twice as much export value than ports in the fifth percentile of hurricane-exposure. I also find evidence of heterogeneity in the effect of hurricane wind speed across products exported by ports. For example, exports of plastic goods respond very strongly to hurricane wind speeds, while exports of transport equipment do not. Not only does there exist heterogeneity across products, but there is also heterogeneity across products *within* ports. I find exports of top-ranked products (in terms of port-level export share) experience the most significant and persistent decline in export value following a hurricane. In this sense, ports respond to hurricanes in a different way than multi-product firms respond to trade shocks, which are typically found to

[5]Using other measures of hurricane intensity, like maximum wind gusts and rainfall levels, produce similar results. These results are available upon request. The use of maximum sustained wind speeds is a frequently used measure of hurricane intensity in the literature (Strobl 2011; Hsiang and Jina 2014; Pelli and Tschopp 2017).

focus on core-competencies (Bernard, Redding and Schott 2011). I do not find evidence that ports focus on their "core-competencies" in the presence of a trade shock.

Finally, I examine the effect of hurricane wind speeds on neighboring ports (i.e., the port substitution of exports following hurricanes). Using spatial econometric techniques, I find evidence that an increase in wind speed experienced at neighboring ports *increases* port-level exports, and that this increase is also persistent. The persistence in the spillover effect offsets the persistent losses suffered at affected ports. The diversion appears to be permanent, at least over two years following the hurricane. This result is consistent with sunk cost hysteresis and highlights the path-dependence in port use over time. The diversion of port-level trade flows from affected to less-affected ports can help explain the small aggregated effects of hurricanes on trade found in previous studies.

This paper is organized as follows. In the next section, I discuss the theoretical framework and the empirical specifications, as well as the source of identifying variation. In Section 3, I discuss the data used in this study. In Section 4, I present the main results of this study, while in Section 5, I discuss the robustness of the results. I Section 6, I examine the heterogeneity in the result. In Section 7, I analyze the spillover effects of hurricanes across ports. Finally, Section 8 provides a discussion of the main findings and concludes the paper.

3.2 Theoretical Framework and Empirical Specification

Choice models are the predominant way of modeling the use of ports in the transport literature (Nir, Lin and Liang 2003; Tiwari, Itoh and Doi 2003; Tavasszy et al. 2011; Veldman, Garcia-Alonso and Vallejo-Pinto 2011), while gravity models have been the workhorse model in the empirical trade literate (see: Chaney, 2018 for an overview). I model port-choice using a choice model set up and discuss how this can be aggregated into a gravity model framework. I then discuss how the gravity model framework is taken to the data.

Suppose there is a population of consumers in country j who demand goods and services from port k which is located in country i. Going forward, country i subscripts will be suppressed because the empirical analysis only consists of ports in the USA (i.e. i=USA). Each consumer must decide which of a discrete number of ports $k = 1, \ldots N$ to use, and receives the following utility from consuming goods from k:

$$V_{jk} = lnY_j - \alpha lnp_{jk} + \epsilon_{jk}, \quad \alpha > 0 \tag{3.1}$$

where Y_j is income, p_{jk} is the price associated with consuming goods from port k for consumer j, and ϵ_{jk} is an iid drawn from a general extreme value distribution $F(\epsilon)$. Given this set up, aggregate expected utility for all consumers in j can be expressed as function of prices and incomes.[6] Thus, the indirect utility function of the representative consumer is given by:

$$G_j(p_1, p_2, \ldots, p_n, Y) = Y_j \sum_{k=1}^{N} p_{jk}^{-\alpha} \tag{3.2}$$

Using Roy's Identity, the expected value of aggregate demand for goods and services from port k is given by:

$$X_{jk} = Y_j \frac{\alpha p_{jk}^{-\alpha}}{\sum_{n=1}^{N} p_{jn}^{-\alpha}} \tag{3.3}$$

[6]Feenstra (2015) offers an excellent discussion on the aggregation of choice models.

Redefining $\sigma = 1 + \alpha$, equation (3) bares a resemblance to the Gravity Equation, where σ represents the trade elasticity. The resemblance becomes stronger when prices are expressed as a function of trade costs, where $\tau_{jk} > 1$ represents iceberg trade costs and A_k represents the efficiency associated with port k, which has been shown to differ across ports (Blonigen and Wilson 2008):

$$p_{jk} = \frac{\tau_{jk}}{A_k} \tag{3.4}$$

Breaking trade costs down into components influenced by hurricanes and other exogenous factors (e.g. external and internal distances), τ_{jk} can be expressed as follows:

$$\tau_{jk} = d_{jk}^{\theta_1} \xi_{jk} e^{\theta_2 wind_k} \tag{3.5}$$

Here, $wind_k$ represents the hurricane wind speed experienced at port k, d_{jk} captures exogenous trade costs, and ξ_{jk} is a random component capturing measurement error. Wind speeds enter the pricing equation exponentially. This functional form is chosen for several reasons. First, in order to estimate the persistence of the effect of hurricane wind speeds on trade flows a distributed lag model will be used. This requires log-linearizing equation (3). As a result, wind speed will enter the estimation equation in levels, rather than in logs. This is important because the existing literature strongly recommends against estimating log-log relationships between economic outcomes and natural disaster intensity measures. Empirical evidence from Camargo and Hsiang (2016) indicates that using log-log models to estimate the effect of natural disasters on economic outcomes tends to produce elasticity measures that are unreasonably large. The authors note that when using physical properties of natural disasters as a measure of disaster intensity it is typically best to leave these variables in their level form, rather than transform them. Second, log-transforming wind speeds results in a very large decline in observations. Given that the vast majority of months there are no hurricane wind speeds, a log transformation of the explanatory variable does not allow me to estimate a distributed lag model or capture the persistence of the effect. Parameters θ_1, and θ_2 govern the responsiveness of trade costs to changes in the specified components.

Log-linearizing equation (3) and including time subscripts (t) results in the following equation:

$$lnX_{jkt} = lnY_{jt} - \alpha(1-\sigma)lnd_{jkt}^{\theta_1} + \alpha(1-\sigma)lnA_{kt} - \theta_2\alpha(1-\sigma)wind_{kt} - ln\sum_{n=1}^{N} p_{jnt}^{-\alpha} + ln\xi_{jkt} \tag{3.6}$$

This equation is taken to the data using the following specification:

$$lnX_{jkmy} = \gamma_{jkm} + \delta_{jky} + \beta wind_{kmy} + u_{jkmy} \tag{3.7}$$

where, the time dimension corresponds to month (m) and year (y). Port-importer-month and port-importer-year fixed effects control flexibly for exogenous trade costs, fixed port-level productivity, and $ln\sum_{n=1}^{N} p_{jnt}^{-\alpha}$ which functions as a bilateral-resistance term (as in Anderson and Van Wincoop 2003). In some specifications of the model, I control for prices at ports surrounding port k using spatial econometric techniques rather than capturing them with a fixed effect.

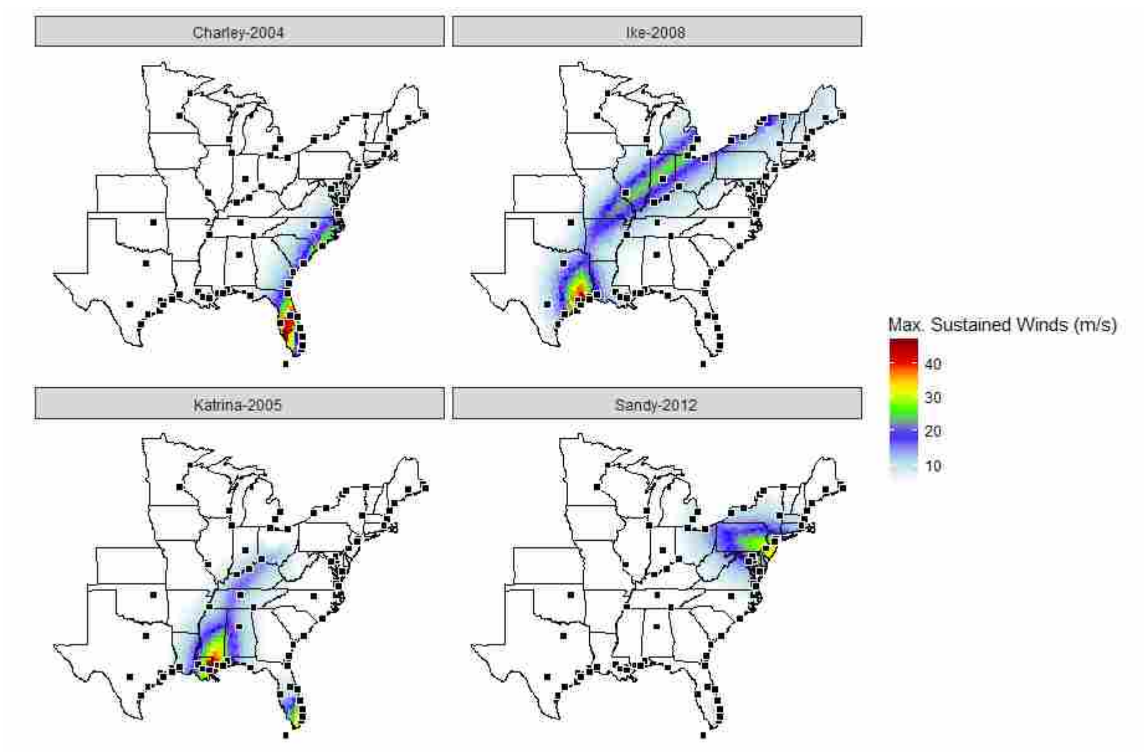
Equation (7) is derived from the theory. However, an examination of aggregate port-level trade flows is also important to the analysis. Some bilateral trade flows may fall in response to hurricanes, while others may remain unaffected or even increase in the wake of a hurricane. Therefore, the net effect on total port-level trade may differ from the effect on bilateral trade depending on the importance of the affected trade flows. I also estimate the effect of hurricane intensity on exports at the port level, aggregating over all destination markets. Here, the dependent variable is the sum of exports from a port, across all trading partners, products, and modes of transport. In this specification, port-month and port-year fixed effects are used. This specification is shown below:

$$lnX_{kmy} = \gamma_{km} + \delta_{ky} + \beta wind_{kmy} + u_{kmy} \tag{3.8}$$

Before discussing the distributed lag versions of equations (7) and (8) a discussion of the identifying variation is necessary. The source of variation used to identify the key parameters of interest (β_{kmy}) comes from two exogenous forces: the temporal variation in hurricane intensity (i.e. the month within a year that the hurricane winds are experienced) and the spatial variation in hurricane occurrence (i.e., which ports are hit by the hurricane at any given point in time). Figure 9 displays the wind speeds generated by four large storms in the data set and highlights these sources of variation.

Controlling for the average monthly wind speed at each port with port-month fixed effects, and average annual hurricane wind speed experienced at each port using port-year fixed effects results in identifying variation coming from deviations from the average monthly wind speed at each port over time. Importantly, this variation is orthogonal to other trade costs. The distance between importers and ports, or the characteristics of a port have no effect on the hurricane wind speed experienced at the port. The flexible time fixed effects also control for

FIGURE 9. Hurricane paths of four large storms



Note: This figure displays the spatial coverage of four large storms in the data set, and the location of ports used in this study. The hurricane tracking data come from HURDAT. Using the methods in Anderson et al. (2020), the Willoughby, Darling and Rahn (2006) model of hurricane vortex profiles recreates each storm's surface wind field.

macroeconomic fluctuations, and seasonality associated with trade from specific ports.

In order to estimate the persistence of the effect of hurricanes on port-level trade flows, I augment equations (7) and (8) using a distributed lag model. The fixed effects in both specifications remain the same, but rather than only estimating the contemporaneous effect of wind speed on trade, I estimate the lagged effect as well.

$$lnX_{kmy} = \gamma_{km} + \delta_{ky} + \sum_{t=0}^{T} \beta_t wind_{kmy-t} + u_{kmy} \tag{3.9}$$

$$lnX_{jkmy} = \gamma_{jkm} + \delta_{jky} + \sum_{t=0}^{T} \beta_t wind_{kmy-t} + u_{jkmy} \tag{3.10}$$

Equations (9) and (10) are the main estimating equations used in this paper. These equations estimate the effect of an increase in wind speed at port k in month and year my, as well as the effect of that increase in wind speed on trade from the port in proceeding time periods t. This allows me to trace out the effect of hurricanes on port-level trade flows over time. The cumulative effect of wind speed experienced in a given month and year on trade over T months can be calculated as $\Omega_T = \sum_{t=0}^{T} \beta_t$. For example, the four month cumulative effect of hurricane wind speed experienced in August would be the sum of the effect on trade in August, September, October, and November. In the main specifications of this study, I allow for errors clustering at the port-level, although I also test the robustness of the results to spatially correlated errors.

3.3 Data

Region of study

Data on port-level trade value comes from the US Census USA Trade Online Database.[7] This database contains monthly data on trade between US ports to partner-countries for the years between 2003 and 2015. I collect a sample of data containing information on exports from the major ports in the Eastern half of the USA, which are the ports exposed to hurricanes. The ports in the sample account for over 99% of monthly total trade from the region of study. Figure 9 displays the location of the ports used in this study along with the hurricane track and wind profiles of four large storms in the data set. The full list of ports used in the study are displayed in Table B1. The average value of monthly exports from a port to an importing country and total monthly exports from a port are presented in Table 10.[8]

TABLE 10. Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Log of Bilateral Export Value	12.97	2.75	7.82	22.71	625,189
Wind Speed (m/s)	1.31	3.97	0	51.53	10,873
Number of Trading Partners	57.50	54.32	1	199	10,873
Total Export Value	18.39	2.60	7.92	22.92	10,873
Pct of coastal ports	0.68	0.47	0	1	72

Note: This table displays the summary statistics for the estimation sample. The data covers monthly U.S. trade from 72 ports over the period 2003-2015.

[7] https://usatrade.census.gov/

[8] All ports are matched by name with data from the US Army Corp of Engineers, which contains information on port latitude and longitude as well as the county in which the port is located.

Data on hurricane tracks and wind speeds come from the National Hurricane center's HURDAT re-analysis data set.[9] This data set contains information on all storms (ranging from tropical depressions to hurricanes) in the Atlantic basin. Every six hours, the hurricane eye's latitude and longitude are measured along with the maximum 1-minute sustained winds. I use the Willoughby, Darling and Rahn (2006) model of hurricane wind profiles to construct the wind speed experienced at individual ports in the Eastern half of the United States, referencing methods outlined in Anderson et al. (2020).[10] Following Anttila-Hughes and Hsiang (2013), if multiple storms occur at a port in a given month, the monthly maximum wind speed is used. In months where no sustained winds generated by a hurricane occurred, the sustained wind speed is zero. This process results in a panel consisting of the maximum sustained hurricane wind speed experienced at each port in each month of the sample period. The average monthly hurricane wind speed in the sample is 1.3 meters per second with a standard deviation of 4 meters per second. The highest wind speed experienced in the sample is 51.5 meters per second (115 mph).

3.4 Results

First, I estimate the relationship between total exports from a port and the sustained wind speed experienced at the port, as shown in equation (9). Columns (1) through (6) of Table 11 presents the results. In each column additional lagged wind speed variables are included. Coefficients can be interpreted as percent changes in port-level export value per meter per second of hurricane wind speed.

[9] $http://www.aoml.noaa.gov/hrd/hurdat/Data_storm.html$

[10] Details of the methods used in this study can be found here: https://cran.r-project.org/web/packages/stormwindmodel/index.html

TABLE 11. Response of port-level trade to hurricane intensity

	Total Exports						Bilateral Exports	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8) PPML
$wind_{kmy}$	-0.1	-0.1	-0.1	-0.2	-0.2*	-0.2*	-0.2***	-0.001*
	(0.13)	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)	(0.06)	(0.0004)
$wind_{kmy-1}$		-0.3**	-0.3**	-0.4**	-0.4***	-0.4***	-0.1	-0.001*
		(0.14)	(0.13)	(0.14)	(0.14)	(0.14)	(0.08)	(0.0007)
$wind_{kmy-2}$			-0.3***	-0.3***	-0.3***	-0.4***	-0.1	-0.002***
			(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.0008)
$wind_{kmy-3}$				-0.4***	-0.4**	-0.4**	-0.2**	-0.002***
				(0.14)	(0.14)	(0.14)	(0.09)	(0.06)
$wind_{kmy-4}$					-0.002*	-0.002*	-0.002**	-0.002***
					(0.13)	(0.13)	(0.07)	(0.06)
$wind_{kmy-5}$						-0.3**	-0.2***	-0.002***
						(0.12)	(0.07)	(0.06)
Constant	18.852***	18.889***	18.912***	18.928***	18.938***	18.948***	13.990***	19.109***
	(0.0016)	(0.0022)	(0.0025)	(0.0040)	(0.0050)	(0.0058)	(0.0053)	(0.0030)
Observations	9,496	9,403	9,324	9,255	9,190	9,126	395,720	395,720
r2_within	6.10e-05	0.000824	0.00152	0.00242	0.00270	0.00326	0.000235	.
Port-month FE	x	x	x	x	x	x		
Port-year FE	x	x	x	x	x	x		
Port-partner-month FE							x	x
Port-partner-year FE							x	x

Note: The table presents the appended results of estimating equations (9) and (10), in text using five lags. The variable "wind" controls for the maximum sustained wind speed from a hurricane experienced at a port in a given month. The dependent variable in columns (1) through (6) is the log of total port level exports. The dependent variable in column (7) through (8) is the log of bilateral exports from a port to an importing country. Coefficients can be interpreted directly as partial elasticities, except for in column (8). PPML estimation is used in column (8) and the results should be interpreted as changes in expected log counts. Errors allow for clustering at the port level in all columns.

I find evidence that an increase in hurricane wind speed experienced at a port reduces the value of exports from the port over the following five months. This roughly accounts for the length of a hurricane season in the USA. I find less evidence of a contemporaneous effect of hurricane wind speed on exports at the aggregate port-level. This is due to the fact that many of the largest storms over the sample time period occurred at the end of a month. Thus, much of the trade from a port had already exited prior to the hurricane event.

Columns (7) through (8) of Table 11 display the results of estimating the effect of hurricane wind speed on bilateral port-level trade as in equation (10). In Column (7), I present the results when equation (10) is estimated using OLS. Here, I find more evidence of a contemporaneous effect of hurricane wind speed.

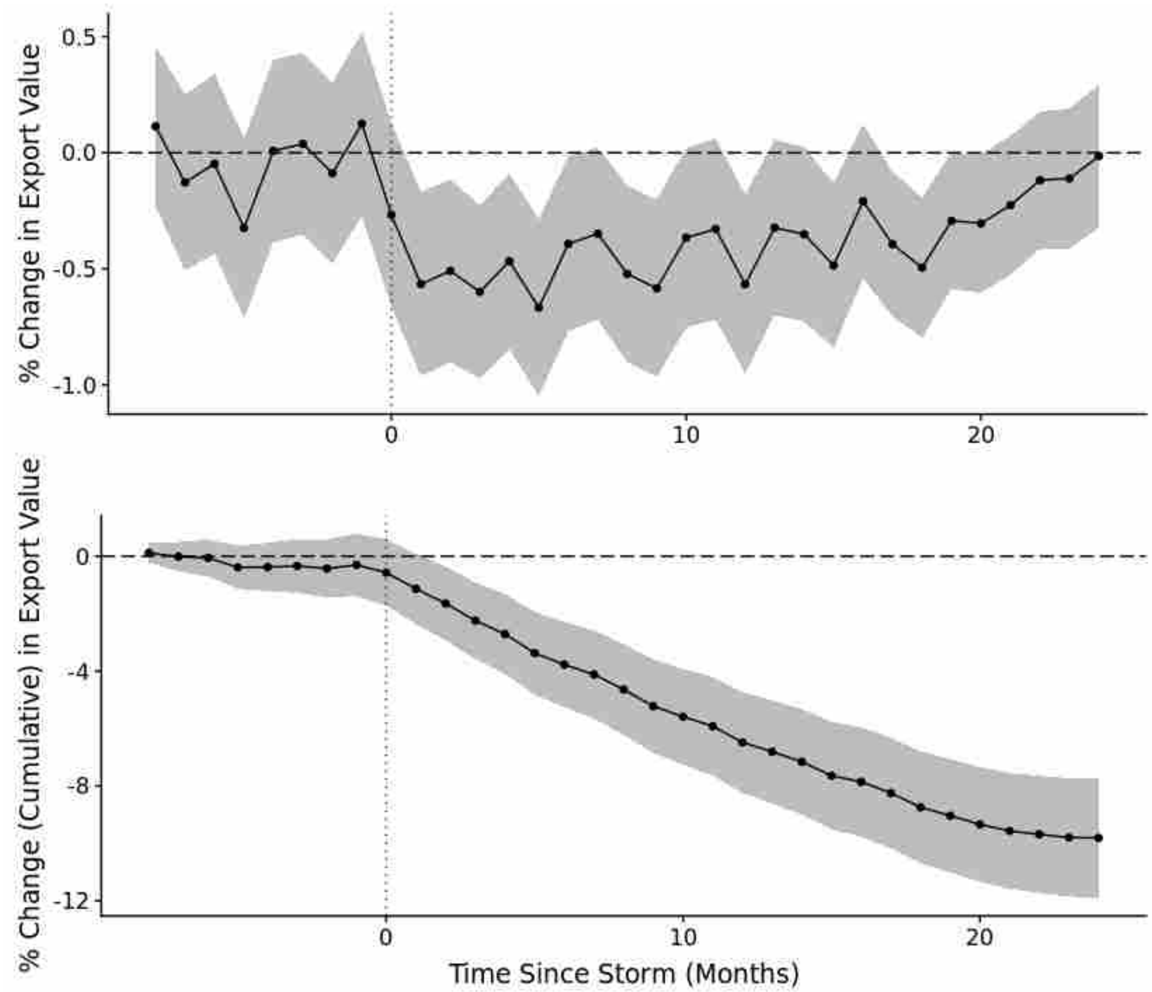
However, the effect is not robust to PPML estimation, which is shown in column (8). Again, given that many storms occur at the end of the month the lack of contemporaneous effect is not surprising. Estimates from OLS and PPML display persistence, as the effect of a meter per second of hurricane wind speed is still present after five months. Overall, the results are consistent with the total port-level results. Hurricanes depress bilateral export values from affected ports over the months following the storm.

Next, I estimate a the full distributed lag model. I include eight lead terms as a simple check of the parallel trend assumptions. These eight months account for the length of the average hurricane off-season. Either individually or taken jointly, they are not statistically significant. The distributed lag model includes 24 months after the winds are experienced, which accounts for roughly two distinct hurricane seasons. In later sections, I show the results are robust when more lagged terms are added. Column 1 of Table B2 presents the results from estimating equation (9) with the full set of leads and lags. I find a one meter per second increase in sustained wind speed results in a decline in total port export value by roughly 0.6% in the subsequent month, and that this effect is relatively persistent. The top panel of Figure 10 displays the results presented in column 1 of Table B2. The bottom panel of Figure 10 displays the cumulative lost export value over the 24 month period. Because I find no evidence that any lost export value is recovered in the months following the storm, the cumulative losses are substantial: a one meter per second increase in sustained wind speed generates a cumulative loss of export value of roughly 10% over the following two year period. The sum of the lagged terms (i.e. $\sum_{t=0}^{t=-24} \hat{\beta}_t$) are jointly statistically different from zero at 1% significance level, while the sum of the lead terms (i.e. $\sum_{t=+8}^{t=+1} \hat{\beta}_t$) are not jointly statistically significant at traditional level.

Figure 11 presents results from estimating the effect of hurricane wind speed on bilateral port-level exports using equation (10). Column 1 of Table B3 presents the estimates with an extended set of leads and lags. I find exports from an affected port to the average importing country fall by approximately 0.2% per month for roughly a year after the sustained winds were experienced. The cumulative results are presented in the bottom panel of Figure 11, where the horizontal line represents the counterfactual situation where no sustained winds occurred. Again, because I find no evidence that lost trade value is recovered over this period, the cumulative losses generated by sustained wind speeds over a two year period are substantial. I find a one meter per second increase in sustained winds generated by a hurricane leads to a decline in bilateral export value of roughly 6% over the following two years.

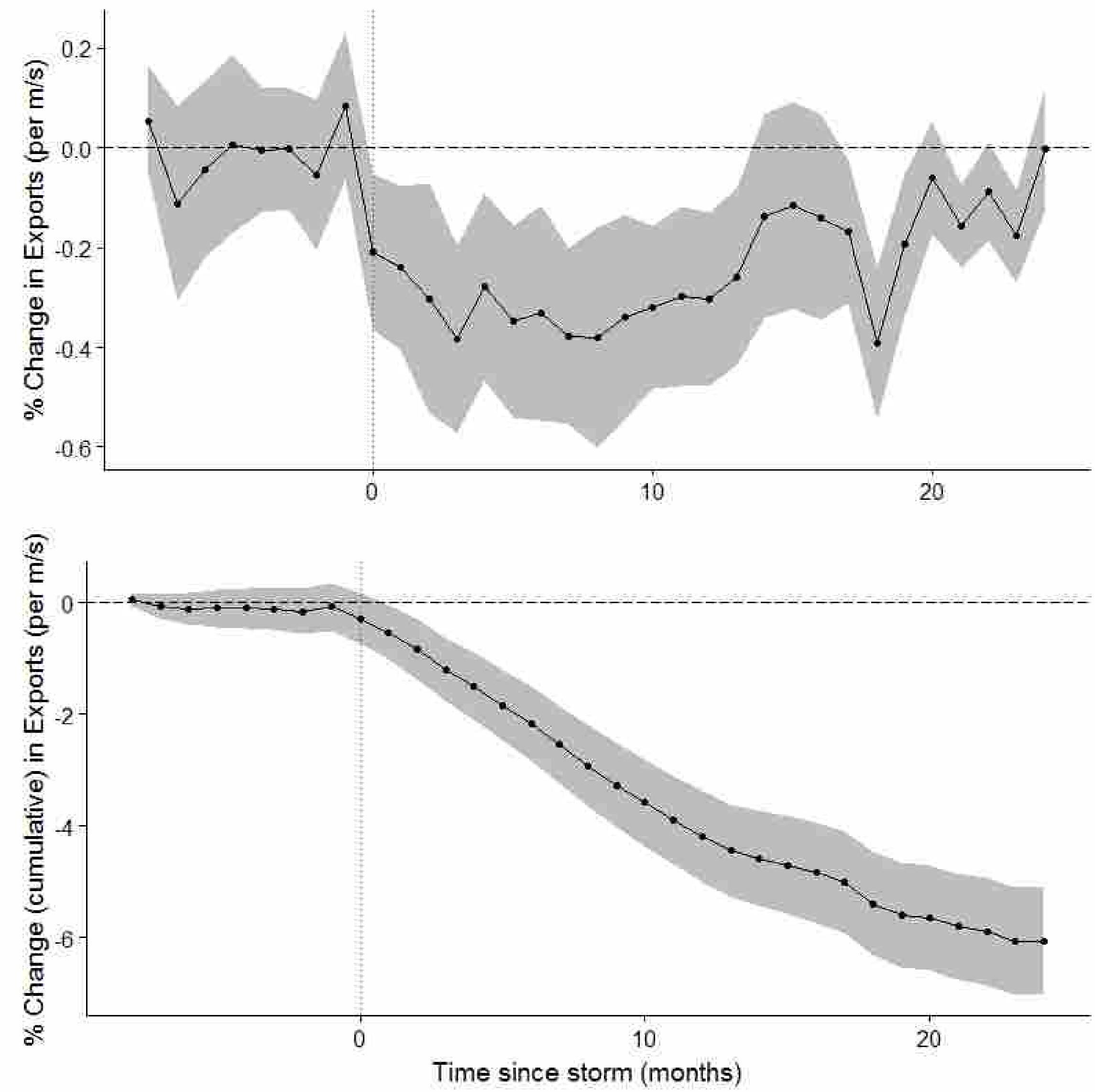
Given the large number of zero trade flows at the bilateral-level, which may result in biased estimates according to Silva and Tenreyro (2006), I also estimate equation (10) using PPML estimation. The results are very similar to the results of the log-linear model, and are displayed graphically in Figure B1, and in column 2 of Table B3. Similarly, I present the results when exports to Atlantic Basin countries are removed from the sample. These countries may experience the same hurricanes as US ports, and as a result some of the effect attributed to hurricane exposure of US ports may actually come from destruction in the importing country. When excluding these countries from the sample produces results that are very similar to those shown in Figure 11. Figure B2 displays the results of estimating equation (10) excluding these countries.

FIGURE 10. Response of port-level exports to hurricane intensity



Note: The top figure presents the results of estimating equation (9) with the full set of 8 leads and 24 lags (point estimates presented in Column 1 of table B2). The bottom figure presents the marginal cumulative effect, calculated from Column 3 of table B2. The dashed horizontal line represents the counterfactual where no sustained winds were experienced. Errors are clustered at the port-level, and port-importer-month and port-importer-year fixed effects are included in the estimation. The shaded area represents the 95% confidence interval.

FIGURE 11. Response of bilateral port-level trade to hurricane intensity



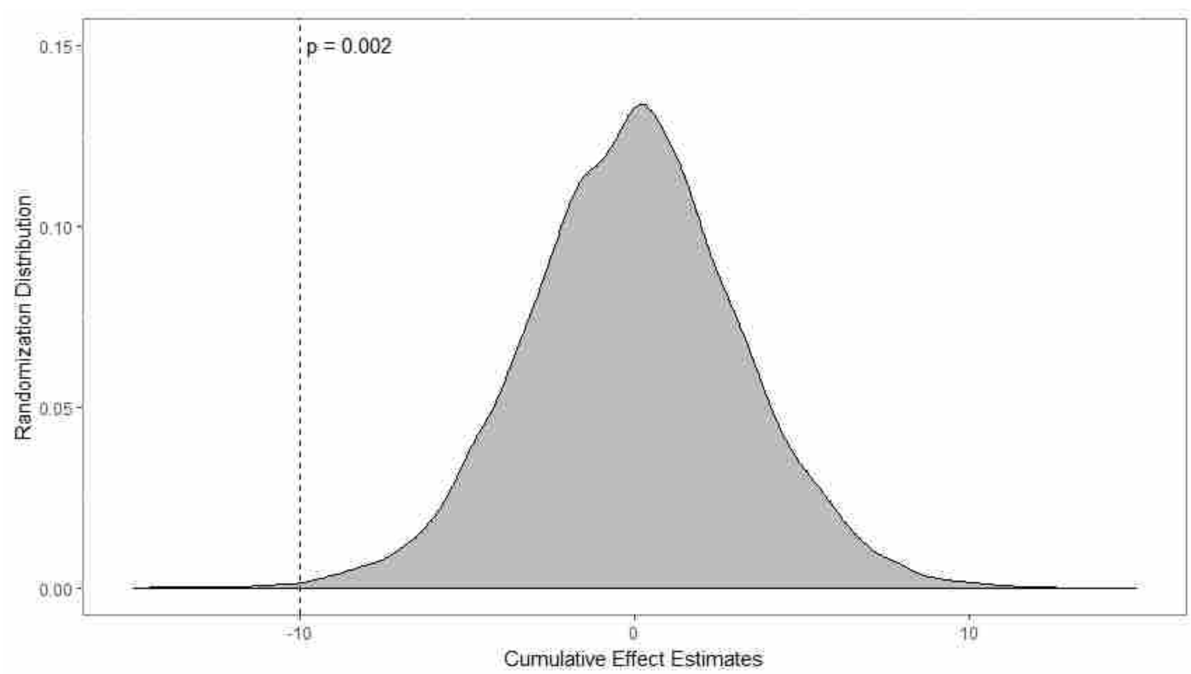
Note: The top figure presents the results of estimating equation (10) with the full set of 8 leads and 24 lags (point estimates presented in Column 1 of Table B3. The bottom figure presents the marginal cumulative effect, calculated from Column 1 of Table B3. The dashed horizontal line represents the counterfactual where no sustained winds were experienced. Errors are clustered at the port level, and port-importer-month and port-importer-year fixed effects are included in the estimation. The shaded area represents the 95% confidence interval.

3.5 Robustness

In this section, I discuss the robustness of the results. First, I examine the robustness of the results in the previous section to alternative specifications of the error structure. Allowing for port-level clustering of errors may lead to an underestimate of the errors if spatial or temporal autocorrelation and heteroskedasticity are present. It is likely that the disturbance term associated with exports from port A is correlated with disturbances associated with a nearby port B, and thus modeling the error term as correlated over space may be necessary. I follow the methods laid out in Conley, and methods adapted by Thiemo Fetzer (2020), to allow for spatial correlation across ports up to 300 miles apart as well as autocorrelation within these spatial clusters over three years. The distance cutoff of 300 miles is chosen based on the circumference of the average hurricane, however, the results are robust to larger spatial cutoffs. The results are presented in column 2 of Table B2. While the standard errors increase in magnitude, the results remain statistically significant when allowing for errors to be spatially or temporally autocorrelated and heteroskedastic in this way.

Next, I examine the possibility that the large effects found in the previous section are a result of misspecification or a spurious relationship. While unlikely, it is possible that some underlying trend in the data is producing the large cumulative losses. To test this, I conduct a randomization test where hurricane wind speeds are randomized across the time periods in the study. These “placebo” hurricanes should have no effect on the port-level trade flows. I then estimate equation (10) using the placebo hurricanes in place of the actual data. I replicate this randomization process 10,000 times, each time calculating the cumulative effect (Ω). Figure 12 displays the distribution of results generated from this exercise. The

FIGURE 12. Results from Randomization of hurricanes



Note: The figure displays the distribution of estimates of the cumulative effect of an increase in hurricane wind speed over the 24 months following when the winds were experienced (Ω_L) using randomly generated hurricane data. The randomization process is over months across ports. The randomization and estimation was done 10,000 times. The estimate obtained using the actual hurricane data is shown with a dashed line. The p-value of this estimate, given the distribution of outcomes using the placebo data is 0.002.

estimate obtained with the actual hurricane data ($\Omega \approx 10$) is shown by the dashed line. Based on the distribution of outcomes from estimating equation (10) with the placebo data, there is a 0.2 percent probability I would have obtained an estimate as extreme as $\Omega = 10$ purely by random chance. Hence, the empirical model recovers an effect only for the particular configuration of storms that actually occurred.

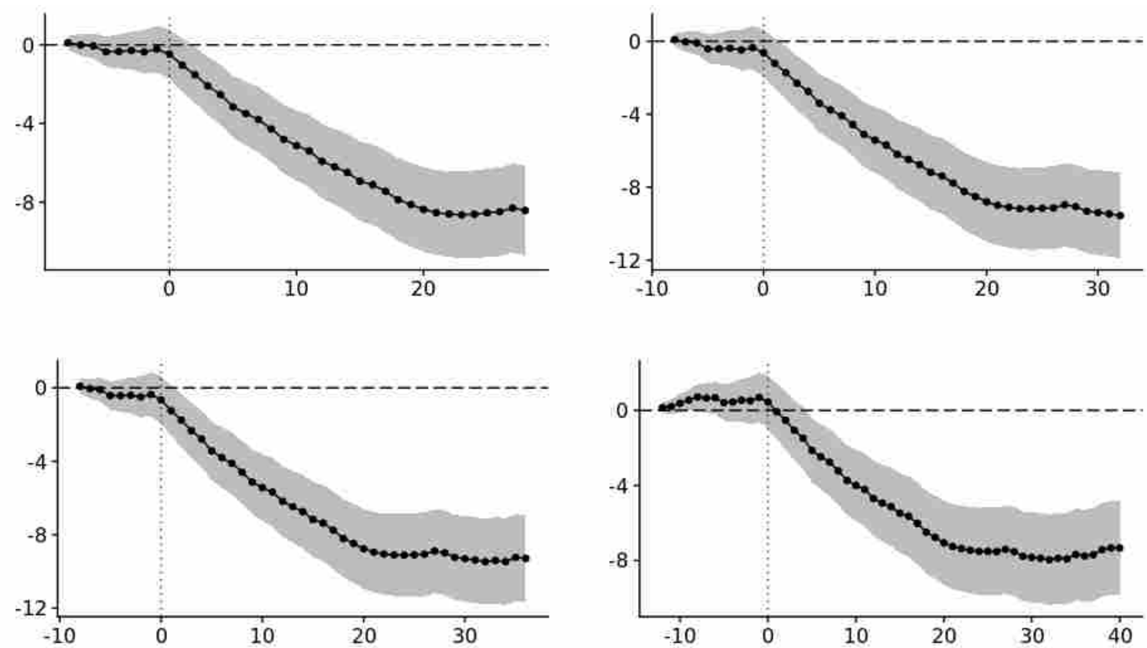
Finally, I examine the robustness of the results to terms in the distributed-lag model. The results presented in Figure 10 seem to indicate that the cumulative loss of port-level export value level off around 10 percent after 24 months. To further examine if this, I estimate equation (10) with additional lagged terms. Not only does this allow me to analyze a longer-term effect of hurricanes on port-level trade flows, but also helps mitigate concerns about the choice of lag structure. Figure 13 displays the results of this exercise. The number of lags included in each figure increase from 28 months, to 40 months. The figure in the bottom right panel, which includes 40 lagged terms, also includes additional 12 lead terms. Due to data limitations, including an excessive number of lead and lag terms is difficult. The US Trade Online data only contains port-level trade flows beginning in 2003, so while hurricane tracking data is available since the 1970s, it is not possible to merge this data with historical port-level flows. That being said, the inclusion of 36 month lags is likely sufficient to pick up any longer-term adjustments that may occur after a hurricane. The results indicate that the cumulative losses appear to level-off at roughly 8-10 percent in all specifications.

3.6 Heterogeneity

Adaptation to hurricane climate

Not all ports in coastal regions have the same historical experience with hurricanes. For example, ports in Florida have a long history of experiencing intense storms, while ports in Maine do not. Ports located in areas that have historically experienced frequent or intense hurricanes may have engaged in adaptive behavior that differs from ports that are not frequently hit. Because adaptation is costly - presumably, adaptation would consist of better port and local infrastructure, or resiliency planning - only areas that have a history of strong and frequent storms would find it beneficial to make such investments.

FIGURE 13. Cumulative effect with additional lagged terms

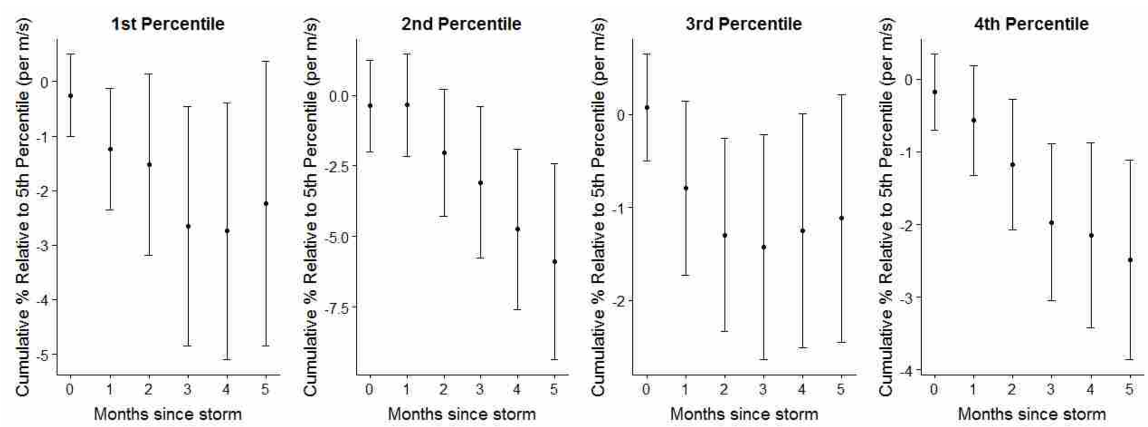


Note: The figure displays the cumulative effects of an increase in hurricane wind speed experienced at a port on port-level exports for specifications with an increasing number of lagged terms.The x-axis for each figure displays the months since the winds were experienced, and the y-axis displays the percent change in export value per m/s of wind speed experienced. The number of lags in each figure are, moving in a clockwise: 28 lags, 32 lags, 36 lags, 40 lags and 12 leads. The gray bands represent the 95% confidence interval, calculated based on Conley errors that allow for clustering up to 300 miles and over one year.

In order to examine how areas have adapted to hurricanes, a measure of the hurricane climate is needed. As recommended by Hsiang and Narita (2012), I use the average monthly wind speed experienced at the port over time as an estimate of hurricane climate. I calculate this variable using hurricane activity that occurred prior to the sample time frame. Specifically, I use data on hurricane wind speeds over the period 1985-2002. With this data I calculate the average monthly wind speed experienced at each port, and then I divide this measure into five percentiles. To illustrate the point at the beginning of this paragraph, Portland, ME is in the second percentile of exposure, while Port Everglades, FL is in the fifth.

I then estimate equation (10) with sustained wind speed interacted with hurricane climate percentile. The omitted percentile is the fifth, meaning the results presented in Table B4 display the effect of sustained wind speeds on exports from ports in different percentiles of hurricane climate, relative to the effect of sustained wind speeds on exports from ports in the highest percentile. I find exports from ports in lower percentiles of hurricane climate see larger declines in export value per meter per second of wind speed than ports in the fifth, and that this difference is relatively persistent over a five month period. Further, the cumulative loss of exports from ports in lower percentile are larger than the losses in the 5th percentile. Figure 14 displays the cumulative losses, relative to ports in the fifth percentile, over the five month period after the hurricane is experienced. The cumulative losses relative to the fifth percentile are large. For example, ports in the fourth percentile of hurricane climate lose roughly 2.5 percent more export value than ports in the fifth percentile five months after the storm. These results indicate the ports located in areas with a history of experiencing intense storms may have adapted to these storms in some way that mitigates their impact.

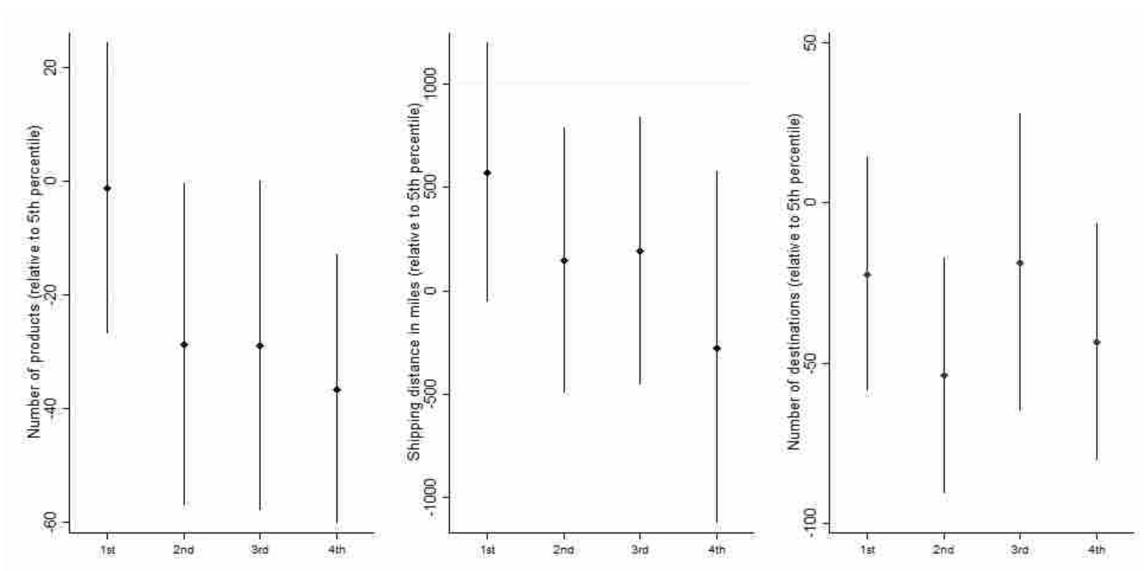
FIGURE 14. Effects of hurricane intensity by hurricane climate



Note: This figure presents the cumulative effect of experiencing a meter per second of hurricane wind speed at ports in different hurricane climate percentiles. The results are relative the losses in the fifth (highest) percentile. The figure is calculated from the results in B4

While identifying the precise mechanisms over with ports in hurricane prone regions have adapted is outside of the scope of this study, I do examine the differences across ports by hurricane climate percentile. To do this, I estimate the difference in the number of products exported, the average distance products are shipped, and the number of countries to which products are shipped by hurricane exposure percentile. The results are presented graphically in Figure 15. Ports in the second, third, and fourth percentile export roughly 30 fewer products per month than ports in the fifth percentile. This difference is statistically different from zero at the 5% level for the second and fourth percentiles. While there is no discernible difference in the average distance that ports ship their goods (shown in the second panel), ports in the second an fourth percentile export to significantly fewer destinations than ports in the fifth percentile.

FIGURE 15. Differences across hurricane climates



Note: This figure displays the differences in the number of products exporter per month, distance in miles that products are shipped, and number of destinations to which products are shipped for ports in different hurricane climate percentiles. These differences are estimated with a simple linear regression of the outcome on dummy variables for each hurricane climate percentile. The omitted category is the fifth percentile, so all results are relative to this category. Standard errors allow for clustering at the port level.

Effect of wind speeds on export product mix

Next, I examine the heterogeneity in the response of port-level exports to hurricane intensity across products. Using data on port-product level data at the HS2 level, I divide products into broad classes as defined by the United Nations.[11] For example, products under the "Live Animals" category contains HS 01-HS 05. I then estimate the effect of hurricane wind speeds on each product category separately using the equation:

$$X_{kzmy} = exp\{\delta_{kzm} + \gamma_{kzy} + \sum_{t=0}^{5} \beta_t wind_{kmy-t}\}\nu_{kmyz} \tag{3.11}$$

which is estimated using PPML to account for zeros. This specification includes port-product-month and port-product-year fixed effects. The results are presented in Table 12. The first column of the table presents the results when all products are pooled together, and each subsequent column presents the estimates from separate regressions. The export of some goods respond to hurricane wind speeds more than other. Exports of vegetables, minerals, plastics, and chemical goods all decline following hurricanes. The effect is particularly persistent for plastic goods. The minerals category contains information about several types of goods. Importantly, mineral fuel and oil falls in this category. When I estimate equation (11) separately for each product type within the minerals category, the effect appears to be driven strongly by exports of oil. This is shown in Table B5.

Next, I examine the heterogeneity in the effect of hurricanes across products, *within* ports. To do this, I rank products within ports based on their share in total port-level monthly exports, then I estimate the effect of hurricane wind speeds on

[11] https://unstats.un.org/unsd/tradekb/Knowledgebase/50043/HS-2002-Classification-by-Section

TABLE 12. Response of different product types

	(1) pooled	(2) live animals	(3) veg	(4) prep food	(5) minerals	(6) chems.	(7) plastics	(8) leather goods	(9) wood goods	(10) clothing	(11) shoes	(12) stone and pearls	(13) metals	(14) machines	(15) transport	(16) photo
$wind_{kt}$	-0.0012***	0.0016	-0.0006	0.0015	-0.0040***	-0.0018	-0.0023**	0.0031	0.0005	-0.0002	-0.0014	-0.0035	0.0009	-0.0012	-0.0001	-0.0027
	(0.0005)	(0.0013)	(0.0013)	(0.0015)	(0.0012)	(0.0014)	(0.0010)	(0.0025)	(0.0010)	(0.0009)	(0.0016)	(0.0026)	(0.0006)	(0.0010)	(0.0011)	(0.0027)
$wind_{kt-1}$	-0.0016**	0.0010	-0.0052***	0.0030***	-0.0054***	-0.0028***	-0.0018***	0.0003	-0.0024**	0.0005	0.0017	-0.0049*	0.0007	-0.0012	0.0004	0.0045
	(0.0007)	(0.0013)	(0.0017)	(0.0010)	(0.0012)	(0.0009)	(0.0007)	(0.0027)	(0.0012)	(0.0012)	(0.0014)	(0.0029)	(0.0013)	(0.0010)	(0.0019)	(0.0063)
$wind_{kt-2}$	-0.0021***	-0.0007	-0.0052***	0.0035***	-0.0038**	-0.0030**	-0.0039***	-0.0010	-0.0018	-0.0010	-0.0003	-0.0063***	0.0001	-0.0021*	-0.0004	0.0001
	(0.0008)	(0.0012)	(0.0011)	(0.0011)	(0.0017)	(0.0012)	(0.0009)	(0.0015)	(0.0011)	(0.0017)	(0.0014)	(0.0014)	(0.0015)	(0.0011)	(0.0020)	(0.0047)
$wind_{kt-3}$	-0.0024***	-0.0004	-0.0046***	0.0026***	-0.0025	-0.0051***	-0.0057***	-0.0009	-0.0030**	-0.0025*	-0.0013	-0.0059***	-0.0001	-0.0022	-0.0011	-0.0003
	(0.0007)	(0.0010)	(0.0007)	(0.0008)	(0.0016)	(0.0015)	(0.0016)	(0.0029)	(0.0015)	(0.0013)	(0.0022)	(0.0012)	(0.0017)	(0.0018)	(0.0014)	(0.0039)
$wind_{kt-4}$	-0.0022***	-0.0015	-0.0065***	0.0018*	-0.0032	-0.0046***	-0.0049***	-0.0021	-0.0005	-0.0014**	0.0003	-0.0050***	0.0002	0.0014	-0.0024	0.0047
	(0.0007)	(0.0015)	(0.0016)	(0.0010)	(0.0031)	(0.0007)	(0.0009)	(0.0025)	(0.0012)	(0.0007)	(0.0024)	(0.0019)	(0.0008)	(0.0021)	(0.0016)	(0.0052)
$wind_{kt-5}$	-0.0013*	-0.0014	-0.0022	0.0010	-0.0043**	-0.0019	-0.0041***	-0.0009	-0.0003	-0.0019	0.0015	-0.0039*	0.0007	-0.0002	-0.0011	0.0030
	(0.0007)	(0.0016)	(0.0015)	(0.0019)	(0.0020)	(0.0013)	(0.0011)	(0.0020)	(0.0012)	(0.0020)	(0.0036)	(0.0020)	(0.0008)	(0.0010)	(0.0015)	(0.0047)
Constant	17.3165***	15.9822***	18.0512***	16.3247***	19.3606***	17.4840***	18.4700***	14.9555***	16.0132***	15.5066***	13.9438***	16.6275***	17.7871***	18.8176***	18.9717***	16.6851***
	(0.0030)	(0.0080)	(0.0086)	(0.0039)	(0.0086)	(0.0054)	(0.0057)	(0.0081)	(0.0057)	(0.0079)	(0.0073)	(0.0094)	(0.0065)	(0.0055)	(0.0075)	(0.0248)
Observations	334,360	14,242	22,470	28,858	11,757	45,802	10,537	7,443	7,081	42,345	8,946	15,223	45,200	9,606	19,662	4,147

Note: This table displays the results of estimating equation (11). The first column displays the result pooled across products, while each column presents the results separately for product types. All columns contain port-product-month and port-product-year fixed effects. All columns allow for errors clustering at the port level.

equation (11) separately for products of different ranks. This allows me to estimate the response of a ports top products to hurricanes, as compared to a ports lower ranked products. The results are presented in Table 13.

The columns of Table 13 correspond to products that were ranked in the top ten, between 10 and 20, 20 and 30, and 30 and 40. Product rankings are based on the month prior to when the hurricane wind speeds are experienced to mitigate issues of simultaneity bias. The results indicate that ports top ranked products respond the most to hurricane wind speeds while lower ranked products do not. The results do not appear to be driven by the choice of using product rankings in time $t-1$, and are robust to using product rankings in time $t-2$, $t-3$, and so on. This is shown in Table 14.

3.7 Spillover effects

The lost export value from ports experiencing sustained hurricane wind speeds may be offset by gains in export value from nearby ports. The persistent losses in port-level exports may have been initially driven by hurricane-related disruptions at the port, but are subsequently driven by persistent diversion of trade to neighboring ports.

TABLE 13. Within-Port Product Ranking

	(1)	(2)	(3)	(4)
Product rank in time $t-1$:	[1-10]	(10-20]	(20-30]	(30-40]
$wind_{kt}$	-0.0017***	0.0004	-0.0013	-0.0007
	(0.0005)	(0.0005)	(0.0009)	(0.0008)
$wind_{kt-1}$	-0.0016**	-0.0024**	-0.0010	-0.0015
	(0.0008)	(0.0012)	(0.0013)	(0.0010)
$wind_{kt-2}$	-0.0020**	-0.0022	-0.0028**	-0.0004
	(0.0009)	(0.0016)	(0.0011)	(0.0011)
$wind_{kt-3}$	-0.0026***	-0.0036***	-0.0019**	-0.0009
	(0.0007)	(0.0012)	(0.0009)	(0.0014)
$wind_{kt-4}$	-0.0029***	-0.0023***	-0.0011	-0.0012
	(0.0007)	(0.0003)	(0.0009)	(0.0013)
$wind_{kt-5}$	-0.0018***	-0.0013**	-0.0016**	-0.0003
	(0.0006)	(0.0005)	(0.0007)	(0.0007)
Constant	19.5386***	17.3555***	16.7307***	16.1667***
	(0.0034)	(0.0042)	(0.0041)	(0.0034)
Observations	59,249	41,889	36,527	32,291

Note: This table displays the results of estimating equation (11), using PPML estimation. The first column restricts the sample to each ports top ten products in the prior month. The second column restricts the sample to each ports top 10-20 products in the prior month. The third column restricts the sample to each ports top 20-30 products in the prior month. The fourth column restricts the sample to each ports top 30-40 products in the prior month. All columns contain port-product-month and port-product-year fixed effects. Errors allow for clustering at the port level in all columns of the table.

TABLE 14. Response of products ranked 1-10

Product ranked 1-10 in:	(1) t-2	(2) t-5	(3) t-12	(4) t-24
$wind_{kmy}$	-0.0016***	-0.0015***	-0.0013**	-0.0015***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$wind_{kmy-1}$	-0.0017**	-0.0018**	-0.0018**	-0.0019**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
$wind_{kmy-2}$	-0.0019**	-0.0019**	-0.0022**	-0.0022**
	(0.0008)	(0.0009)	(0.0009)	(0.0009)
$wind_{kmy-3}$	-0.0027***	-0.0026***	-0.0026***	-0.0028***
	(0.0007)	(0.0006)	(0.0007)	(0.0007)
$wind_{kmy-4}$	-0.0025***	-0.0027***	-0.0027***	-0.0030***
	(0.0007)	(0.0007)	(0.0008)	(0.0007)
$wind_{kmy-5}$	-0.0019***	-0.0016**	-0.0024***	-0.0022***
	(0.0006)	(0.0006)	(0.0006)	(0.0005)
Constant	19.5387***	19.5394***	19.5593***	19.5876***
	(0.0034)	(0.0034)	(0.0034)	(0.0032)
Observations	59,286	59,287	55,317	49,905

Note: This table displays the results of estimating equation (11), using PPML estimation for a ports top 10 products in time period $t - n$, where n varies by column.

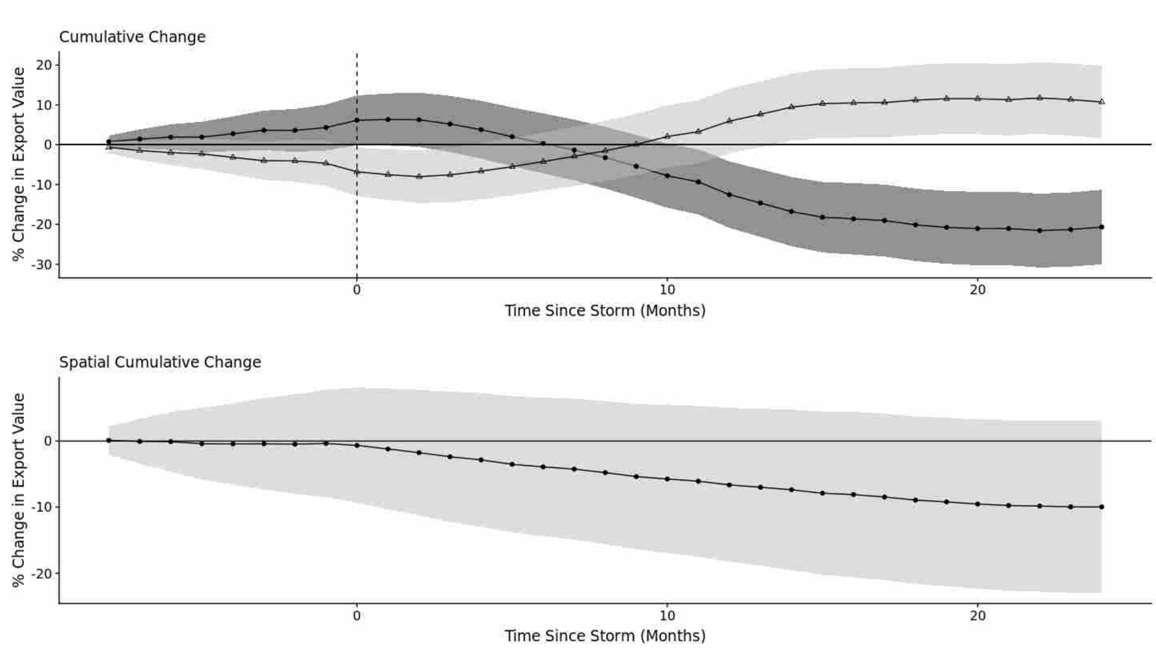
To examine this potential mechanism, I estimate equation (10) while also controlling for the hurricane wind speed experienced at port p's nearest neighbor. The new specification is as follows:

$$ln(X_{kmy}) = \delta_{km} + \gamma_{ky} + \sum_{t=0}^{T} \beta_{1,t} wind_{kmy-t} + \sum_{t=0}^{T} \beta_{2,t} wind_{nmy-t} + \epsilon_{pmy} \qquad (3.12)$$

where $wind_{nmy-t}$ is the distributed lag of wind speed at port k's nearest neighboring port n. To account for spatial correlation in the error term I allow for clustering up to 300 miles. I then calculate the cumulative effect for the wind speeds experienced at port k and port n using $\Omega_{k,T} = \sum_{t=0}^{T} \beta_{1,t}$, and $\Omega_{n,T} = \sum_{t=0}^{T} \beta_{2,t}$. I plot these cumulative effects in Figure 16, and present the full estimates in Table B6.

An increase in wind speed at port k (shown as dots, with dark grey 95% confidence intervals) results in a cumulative loss in export value of 20 percent over the following two years. This indicates that the exclusion of a spatial control for wind speed around port k results in an under-estimate of the own-port effect of hurricanes. However, an increase in wind speed at port k's neighboring port n (shown as triangles, with light grey 95% confidence intervals) results in a cumulative gain in export value of roughly 10 percent. The off-setting effects of hurricane wind speed provides further evidence of the substitution across ports. The bottom panel of Figure 16 displays the cumulative spatial change in export value. This is calculated as the sum of the effects shown in the top panel at each time period. This figure indicates that while neighboring ports are able to "pick up the slack" in trade from affected ports, the net effect is still negative over this small distance, but not statistically significant.

FIGURE 16. Spillover effects to neighboring port



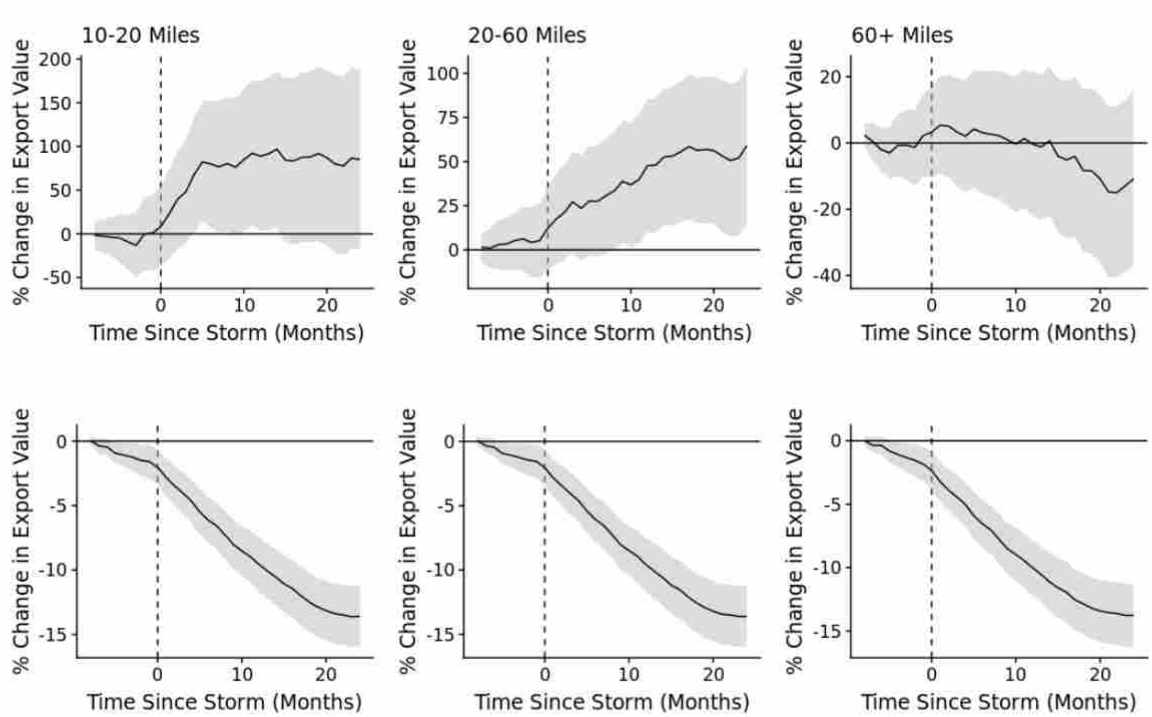
Note: This figure displays the results of the cumulative effects from estimating equation (12). Table B6 presents the results. The time-plot with triangles and dark grey 95% confidence intervals corresponds to the effect of wind speed experienced at port k's neighboring port on port k's exports, while the time-plot with circles and light grey 95% confidence intervals corresponds to the effect of wind speed experienced at port k on port k's exports. The bottom panel displays the difference between the two time plots in the upper panel. Errors allow for spatial clustering up to 300 miles and autocorrelation over 12 months.

Finally, rather than using contiguity measures to define neighboring ports, I use a spatially lagged wind speed variables. I use methods discussed in Hsiang and Jina (2014) and Cressie and Wikle (2015) to estimate a spatial and temporal lag model. To do this, I calculate the average wind speed experienced at all ports around port k, using inverse distance weights to calculate this average. This flexible approach allows me to examine the response of port k's exports to the wind speed at all ports surrounding port k. The inverse distance weights for ports k and $n \neq k$ are constructed as follows:

$$\begin{aligned} w_{k,n} = \frac{1}{dist_{k,n}} \qquad &\text{if } \; dist_{k,n} \in (\Delta_L, \Delta_H); \\ w_{k,n} = 0 \quad &\text{otherwise} \end{aligned} \tag{3.13}$$

Where Δ_L and Δ_H are distance cutoffs. These distance cutoffs allow me to estimate the response of port-level exports to wind speeds experienced at other ports at different distances. The weights defined above are all elements in a weighting matrix, which I use to create a spatially-weighted wind speed measure and estimate equation (12) using this new measure as an additional control rather than the wind speed at k's nearest neighbor. This highly flexible estimation procedure includes eight leads and 24 lag terms for wind speeds at port k, *and* wind speeds around port k. The top panel of Figure 17 presents the cumulative effects of wind speed experienced at ports at difference distance cutoffs from port k, while the bottom panel displays the effect of wind speed experienced at port k on exports from port k. I find that the wind speed experienced at ports between 10 and 20 miles results in cumulative gains in export value over the following two years, and a similar pattern for wind speed experienced at ports between 20 and

FIGURE 17. Spatial spillover effects across ports



Note: This figure displays the cumulative effect from estimating equation (12) using a spatially averaged wind speed measure for winds at surrounding ports n. The spatially weighted wind speed measure is is based on an inverse weighting matrix, with weights given by equation (13). The top panel displays the response in cumulative export value to wind speeds around port k, with cutoffs defined as noted in the figure. The bottom panel displays the response in cumulative export value to wind speeds experienced at port k. Both the top and bottom portion of each subfigure are estimated together, but shown separately for viewing ease.

60 miles. After 60 miles, the effect of wind speed experienced at neighboring ports becomes statistically insignificant. The radius of maximum winds of a hurricane is typically around 30 miles. Thus, the results indicate that lost trade value is recover within two radii. Overall, these results indicate that hurricane wind speeds experienced at ports surrounding port k result in long-run gains in export value for port k. The relatively short distances that export shipments appear to travel following a hurricane points to a high degree of substitutability across ports.

3.8 Summary and Conclusions

Combining port-level export data with hurricane tracking data, this study provides empirical evidence of a negative relationship between hurricane wind speeds and trade from US ports. Overall, the analysis indicates that hurricane wind speeds reduce the value of exports from US ports, and the effect is persistent over time. Each month exports fall by a similar magnitude for about ten months after the storm. After two years, this lost export value is not recovered. I estimate the cumulative effect of a one meter per second increase in sustained wind speed experienced at a port in time t=0 reduces exports from that port by 10%. Experiencing a Category I storm results in the loss of roughly four months worth of export value.

While hurricanes in large cumulative losses in export value, hurricanes at neighboring ports increases results in large cumulative gains in export value. I find evidence that the lost export value from an affected port is diverted to neighboring ports, and the diversion appears to be permanent. This result helps reconcile the small effects found in aggregate trade statistics from previous studies. Further, it highlights the path-dependence in port usage.

Heterogeneity in the results indicate that the effect of hurricane intensity is not constant across different regions of the USA, or across exported products. Ports located in regions of the USA that are less accustom to dealing with hurricanes lose more export value per meter per second of hurricane wind than ports in areas with more historical experience with these storms. I discuss the differences between ports in these regions, finding that ports in the fifth (top) percentile tend to export more products, and export to more destinations that ports in lower percentiles of hurricane climate. The results are suggestive of adaptive behavior by ports in areas that have historic experience with hurricanes, however more work should be done to determine the exact method of adaptation.

Lastly, there appears to be heterogeneity in the effect of hurricanes across products. Some more fragile products (i.e. vegetable products) experience strong declines in export value following a hurricane. Some more durable products (i.e. plastics) also experience a strong and persistent decline in exports. Within ports, exports of top ranked products (in terms of total port-level export share) decline the most following a hurricane. Lower ranked products do not appear to respond to hurricane wind speeds.

CHAPTER IV

THE IMPACT OF HURRICANES ON TRADE AND WELFARE: EVIDENCE FROM US PORT-LEVEL EXPORTS

4.1 Introduction

Over the past three decades, global trade has grown tremendously. The value of international trade as a fraction of GDP rose from 40 percent in 1990 to 60 percent in 2019.[1] The acceleration of global supply chains and "just-in-time" consumption underscore the importance of reliable and timely transportation of products across international borders. As a result, trade and transportation influence incomes and welfare around the world. However, reliance on coastal ports makes global trade flows particularly vulnerable to hurricanes, which are predicted to increase in severity over the next century (Field et al. 2012). In the United States, these storms strike the Gulf and East Coast on an annual basis (between May and October), often shutting down seaports and even disrupting operations at inland ports.[2] There is a growing awareness that the localized economic effects of natural disasters can propagate globally through trade linkages, yet the role of transportation disruptions is not clear. In this paper, I analyze the effect of hurricanes on global trade through the disruptions these storms cause at customs ports.

[1] World Bank. "Trade as a Percent of GDP". *World Bank Development Indicators.* https://data.worldbank.org/indicator/NE.TRD.GNFS.ZS. Accessed on 03/05/2020.

[2] For For example, Hurricane Sandy, in 2012, resulted in the slowing or shutting down of port activity around NY/NJ for nearly a week. The Port Authority of New York and New Jersey did not open maritime traffic until a week after the storm had passed (Smythe 2013). During Hurricane Ike, which struck Houston in 2008, the Texas Port Authority shut down the port of Houston for several days as well, according to news reports (David Koenig 2008).

The relationship between natural disasters and global trade is a growing policy concern (World Trade Organization 2019). Osberghaus (2019) provides a detailed review of the empirical literature on natural disasters and trade flows. The general finding is that export flows decline when they are exposed to natural disasters. However, the magnitude of the effect differs across studies. Of the studies that analyze the effect of natural disasters bilateral trade (Gassebner, Keck and Teh 2010; Oh and Reuveny 2010; Andrade da Silva, Cernat et al. 2012; Felbermayr and Gröschl 2013; Oh 2017; Dallmann 2019; Tembata and Takeuchi 2019), none of them analyze how bilateral trade flows are influenced by natural disasters at ports.[3] I contribute to this literature by providing new evidence of the effect of natural disasters on bilateral trade between US states and global importers. I focus specifically on the effect of hurricanes have on bilateral trade flows through their impact at US customs ports. I use the empirical results to estimate how port-level hurricane activity influences global consumer welfare. To my knowledge, this is the first study to analyze how natural disasters influence welfare through transport-related trade frictions.[4]

My analysis takes place in three stages. First, I derive a nested-CES model of trade in which hurricane activity around ports influences trade flows between trade partners. The structure of the model to informs the empirical exercises in the paper. In the second stage of the analysis, I estimate the parameters of the model empirically using detailed export data on US trade flows and data on hurricane

[3] Hamano and Vermeulen (2016) and Friedt (2017) analyze how natural disaster influence aggregate port-level trade but not focus on bilateral trade.

[4] Other studies have examined how changes in climatic parameters may affect welfare through other channels. For example, Costinot, Donaldson and Smith (2016) estimate the welfare effect of warmer global temperatures on welfare through changes in trade patterns. Hsiang and Jina (2014) analyze the welfare effect of tropical cyclones, but do not do so in the context of global trade.

tracks for all of the storms between 1998 and 2006. The trade data tracks export shipments from US states to importing countries through US customs ports, which allows me to isolate the effect that hurricanes have on transport-related trade frictions rather than potential changes to production. I use a wind field model from the meteorology literature to calculate local hurricane wind speeds at US customs ports for all hurricanes that pass within 250km of the United States over the sample period. My empirical strategy uses variation in deviations from a port's average annual hurricane wind speeds to identify the effects of hurricane intensity at US ports on trade between US states and importing countries.

I find that hurricanes reduce the share of trade through a port by roughly 0.7% per meter per second of wind speed. I find evidence of non-linearity in the response as well: hurricane wind speeds experienced at ports reduce port-level trade volume at an increasing rate. The results highlight how disruptive these storms are on the flow of port-level trade. I estimate that a Category 1 hurricane, with wind speeds of 33 meters per second, has an equivalent effect on trade volume as 6% tariff. These port-level disruptions aggregate up to broader trade frictions between US states and importing countries through price indices. I estimate that a 10% increase in a bilateral trade flows port-level hurricane exposure index reduces aggregate trade volumes by roughly 30%.

In the third stage of the analysis, I use the results of the empirical exercises to calculate consumer welfare effects under counterfactual hurricane scenarios. Specifically, I calculate consumers' willingness to pay to have avoided hurricane activity over the sample period. I find that consumers would have been willing to pay over $6 billion (in 2020 USD) to avoid all hurricane activity during the 2005 hurricane season. The 2005 Atlantic hurricane season is estimated to have had cost of roughly $127 billion (in 2020 USD) in damage (National Centers for Environmental Information 2020). Thus, the $6 billion that importers of US goods would have been willing to pay to avoid the 2005 hurricane season is approximately 4.7% of the total damage costs.

I also use the results to analyze the welfare effects from an increase in hurricane intensity. I estimate that if all storms over the sample period were 11% stronger (the maximum estimate of the increase in Atlantic Basin hurricane intensity from Knutson et al. 2010) consumer welfare – measured by compensating variation as a fraction of current GDP – would decline by 0.005% per year, on average. When this compensating variation is aggregated across all importers, the total comes to roughly $500 million per year.

The remainder of this paper is organized as follows. In Section 2, I derive a model of trade that incorporates hurricane activity at ports as a trade barrier between exporting and importing regions. Section 3 describes the data used in the analysis. Section 4 presents the estimation results for the model parameters. In Section 5, I use the estimates of the models parameters to conduct counterfactual simulation of trade under stronger hurricanes. Finally, Section 6 concludes.

4.2 Theoretical Framework

In this Section, I derive a model of trade in which hurricane activity around ports influences the variable cost of exporting through specific ports. The model is used to ground the empirical exercises later in the paper and to form a framework from which welfare effects can be estimated.

Set-Up

Consider a world consisting of multiple regions $i \in I \equiv \{1, 2, ..., I\}$. In each region there is one factor of production, labor, which is freely mobile within regions but immobile across regions. Labor is used to produce a differentiated, trade-able good and an outside good that is not traded. For simplicity, the outside good can be thought of as services. As in Armington (1969), each region produces a unique variety of the differentiated good. Thus, traded goods are indexed by i as well. The traded good can be sent through ports located within a region, indexed by $k \in K \equiv \{1, 2, ..., K\}$. Following the trade literature, I assume trade costs are of "iceberg" form, meaning in order to deliver one unit of a good from a region i, through a port k to another region j $\tau_{ij}^k > 1$ units must be shipped.[5] Going forward, I will refer to exporters as i, importers as j, and ports as k.

Preferences

In each region j there is a representative consumer with a quasi-linear utility function who derives utility from consuming the outside good and a composite of all traded goods:

$$U_j = C_j^0 + \beta_j lnC_j \tag{4.1}$$

Total demand for goods depend on a region-specific demand shifter, β_j. Aggregate consumption of the traded good is the weighted sum of consumption

[5]Iceberg trade costs refer to the analogy of a floating iceberg. Trade is cost-less except for the part of the iceberg that melts during shipment. Iceberg trade costs are accredited to Samuelson (1954), and are commonly used in the trade literature (e.g. Krugman 1991)

from all trade partners. Further, consumption of goods from a trading partner is the sum of consumption of goods from a trading partner across all ports.

$$C_j = [\sum_i (\beta_{ij})^{\frac{1}{\phi}} (C_{ij})^{\frac{\phi-1}{\phi}}]^{\frac{\phi}{\phi-1}} \tag{4.2}$$

$$C_{ij} = [\sum_k (C_{ij}^k)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{4.3}$$

In equation (2), ϕ governs the elasticity of substitution across trading partners, and because each region produces a unique variety of the traded good, also across varieties. The parameter β_{ij} is an origin (i) and destination (j) specific demand shock. In equation (3), σ governs the elasticity of substitution across ports. Ports become closer to perfect substitutes as σ approaches infinity. Similarly, the variety of goods produced by each region i become closer to perfect substitutes as ϕ approaches infinity.

Consumers take the price of a good from i sent through port k as given and maximize utility given equations (1), (2), and (3), resulting in the optimal demand for i's variety, from port k:

$$C_{ij}^{k*} = \beta_j \frac{\beta_{ij}[\sum_k (p_{ij}^k)^{(1-\sigma)}]^{\frac{1-\phi}{1-\sigma}}}{\sum_i \beta_{ij}[\sum_k (p_{ij}^k)^{(1-\sigma)}]^{\frac{1-\phi}{1-\sigma}}} \frac{(p_{ij}^k)^{-\sigma}}{\sum_k (p_{ij}^k)^{(1-\sigma)}} \tag{4.4}$$

Equation (4) shows that if ports are perfect substitutes (i.e. if $\sigma \approx \infty$), an increase in p_{ij}^k would not lead to a change in optimal consumption of goods from i ($C_{ij}^* = \sum_k C_{ij}^*$). However, if ports are not perfect substitutes – due, for example, to infrastructure difference across ports – an increase in a port-specific price will lead to a change in the optimal consumption of goods from i.

Production

Each region produces its differentiated variety of the traded good at a constant marginal cost, c_i, and maximizes its profits taking consumer demand as given. Given consumers' CES preferences and the monopolistic competition in product markets, profit-maximizing prices are given by:

$$p_{ij}^k = (\frac{\sigma}{\sigma - 1})c_i \tau_{ij}^k \tag{4.5}$$

Equation (5) shows the optimal price of sending goods through port k to j. This optimal price depends on a constant mark-up over marginal costs and the exporter-port-importer specific trade costs ($\tau_{ij}^k > 1$).

Following the trade literature, I assume trade costs have an exponential form (e.g. Waugh (2010) and Heerman (2020)). Specifically, the functional form for the τ_{ij}^k term is:

$$\tau_{ij}^k = exp(\rho_1 wind^k)(\delta_{ij}^k)^{\rho_2} \tag{4.6}$$

where, $wind^k$ is the hurricane intensity at port k, and δ_{ij}^k are all the other exogenous trade frictions between an ijk group.[6] The ρ_1 parameter governs how trade costs respond to these frictions. Hurricane activity around port k increases the trade frictions associated with exports from i through k to j and raises the price of this trade flow.[7]

[6] If the term δ_{ij}^k is thought of as an exponential function of internal and external distances, whether i and j share a common language, whether i and j are part of a formal trade agreement, and other common trade barriers in the gravity model of trade, the specification in (6) looks even more similar to the exponential trade cost functions use in the literature.

[7] This functional form allows wind speeds of zero to be used in the estimation procedure. If log wind speeds are used, the results of the empirical exercises are very similar, however, many

Structural Gravity Equations

Next, I derive an expression for the value of trade between i and j through port k that resembles the structural "gravity" model which is frequently used in the trade literature to describe trade flows (e.g. Anderson and Van Wincoop 2004). From equation (4), the value of trade from i to j through port k is given by:

$$X_{ij}^k = p_{ij}^k * C_{ij}^{k*} = \beta_j \frac{\beta_{ij}[\sum_k (p_{ij}^k)^{(1-\sigma)}]^{\frac{1-\phi}{1-\sigma}}}{\sum_i \beta_{ij}[\sum_k (p_{ij}^k)^{(1-\sigma)}]^{\frac{1-\phi}{1-\sigma}}} \frac{(p_{ij}^k)^{1-\sigma}}{\sum_k (p_{ij}^k)^{(1-\sigma)}} \tag{4.7}$$

Summing over all ports k produces an expression for the value of trade between i and j:

$$X_{ij} = \beta_{ij} \frac{\beta_j[\sum_k (p_{ij}^k)^{(1-\sigma)}]^{\frac{1-\phi}{1-\sigma}}}{\sum_i \beta_{ij}[\sum_k (p_{ij}^k)^{(1-\sigma)}]^{\frac{1-\phi}{1-\sigma}}} \tag{4.8}$$

Equation (7) corresponds to the lower level of the nested demand structure, while equation (8) corresponds to the upper level. When equation (7) and equation (8) are rewritten in terms of shares, prices are plugged-in using equation (5), and the term θ_{ij} is defined as $\theta_{ij} = [\sum_k (\tau_{ij}^k)^{(1-\sigma)}]^{(1/(1-\sigma))}$ the following expressions result:

$$\frac{X_{ij}^k}{X_{ij}} = \frac{(p_{ij}^k)^{1-\sigma}}{\sum_k (p_{ij}^k)^{(1-\sigma)}} = \frac{(\tau_{ij}^k)^{1-\sigma}}{\theta_{ij}}, \tag{4.9}$$

and

$$\frac{X_{ij}}{X_j} = \frac{\beta_{ij} c_i^{\gamma} \theta_{ij}^{(1-\phi)}}{\sum_i \beta_{ij} c_i^{\gamma} \theta_{ij}^{(1-\phi)}} \tag{4.10}$$

degrees of freedom are lost. Further, as noted in Hsiang (2016), transforming climatic variables often results in unreasonably large estimates of model parameters.

where, $\gamma = (1-\phi)(1-\sigma)$. In equation (9), the constant price mark-up and i's specific unit marginal costs have canceled out. The term θ_{ij} is the sum of the trade frictions between i and j when using port k, which is declining in σ. If ports are highly substitutable (σ is large), then port-level trade frictions (τ_{ij}^k) have a smaller effect on θ_{ij}. This measure is similar to the consumer market access measure in Donaldson and Hornbeck (2016), but is based on trade frictions rather than production costs.

Equations (9) and (10) are taken to the data and used to estimate the models key parameters, namely σ, which governs the price sensitivity of port-level trade flows, ρ_1, which is the tariff-equivalence of a meter per second of hurricane wind speed, and ϕ, which governs the price sensitivity of bilateral trade flows. With estimates of these parameters, the structure of the model can be used to simulate changes in welfare under different hurricane scenarios. In the next section, I discuss the data used to estimate these parameters.

4.3 Data

I work with data containing information on the value of aggregate annual exports from US states to importing countries over the period 1998-2006, along with the customs port of exit through which the goods left the US. I limit the data to the lower 48 states, plus Washington DC. The data set contains 310 ports of exit located across the US, and it covers 168 importing countries. I supplement this data with hurricane tracking data from the National Oceanic and Atmospheric Administration's (NOAA) National Hurricane Center. In this Section I describe these data sets in detail.

US State-Level Export Data

The US Census Foreign Trade Database (FTD) provides data on annual bilateral export flows from all US states to all importing countries through all customs ports of exit from 1998 to 2006.[8] The FTD links information on the origin of movement of shipments, customs port of exit, and importer for all shipments of over $2,500.[9] In the estimation that follows I limit this data set to the lower 48 states and Washington DC, omitting Alaska and Hawaii due to their geographic isolation. Figure 18 displays the location and average annual total port-level export value (in $100,000) for all of the customs ports in the sample. The spatial coverage in the data set is large, and it includes sea, land, and air ports.

The FTD tracks the movement of shipments within the USA. This is useful because it allows me to focus on the effect that hurricanes have on trade frictions, rather than the effect they have on production. The effect of hurricane activity around a port likely affects producers around the port, while leaving other producers in the state unaffected. However, the level of granularity needed to analyze this within-state heterogeneity is not available in the FTD data. To reduce the effect of hurricanes activity on the cost of production, I exclude exports from states in years in which the state experienced a Category 1 storm or greater from the estimating sample.[10] This restriction of the sample helps shut down the

[8] The US Census stopped providing data at this level of detail after 2006, and currently only provides data on port-level trade flows or state-country level trade but no longer contains information on the port-of-exit used.

[9] Origin of movement data has been shown to be a relatively good measure for origin of production (Cassey 2009).

[10] This cutoff removes exports that originate in states directly exposed to hurricane wind speeds. This includes exports from the following states (in the years specified): Alabama (2004), Delaware (1998, 1999), Florida (1999, 2004, 2005), Louisiana (2005), Mississippi (1998, 1999), North Carolina (1998, 1999), and Texas (2003, 2005).

FIGURE 18. Port Locations and Average Export Volume

Note: This figure shows the location of US customs ports in the sample. The size of each point represents the average yearly export value of the port. All port types are included in this image; sea ports, air ports, and land ports.

potential production mechanism and allows me to focus on the effect hurricanes have on trade through the impact they have on trade frictions. This cutoff is chosen based on the literature on natural hazards in which it has been shown that damages from hurricanes start to accumulate around 33 m/s of wind speed (which is the weakest category 1 storm) (Huang, Rosowsky and Sparks 2001).[11] Other studies have this method to define the area of direct impact of hurricanes (see: Murphy and Strobl 2009; Strobl 2011; Czajkowski and Done 2014; Pesko 2018). The resulting sample consists of exports from states that did not directly experience a hurricane but may be indirectly affected by hurricanes through port-level disruptions.

[11] I explore different cutoff values as well, for example excluding exports from states that experienced winds of 30 m/s and 36 m/s. The results presented in this paper do not change in a meaningful way when other cutoffs are used.

Table 15 presents some basic statistical information on the data in this data set. The average export flow (origin-port-destination level) is roughly $7.4 million, although there is a great deal of variation in this value. Total shipment weight is also displayed in the table, as is the average number of ports used by an exporter-importer pair. The average trade flow uses 24 ports per year to exchange goods. However, there is a considerable amount of heterogeneity in this statistic. Some trade flows use only one port, while others use over 100 ports to exchange goods. Table C3, in the appendix, displays the average annual export value, number of ports used, and number of trade partners for all exporting states.

TABLE 15. Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Total trade value (in USD)	763,366	7,413,239	$111,794,760	2,501	17,704,431,616
Total weight (in kg)	649,757	771,686	10,600,000	1	1,510,000,000
Avg # of ports used	763,366	24.1	20.6	1	177
Port-level hurricane winds (in meters per second)	763,366	8.6	8.6	0	51.5

This table displays the summary statistics of the sample. Export value is measured in US Dollars, weight is measured in kilograms. Num. of ports is the number of ports that an origin-destination pair use per year. Port-level hurricane wind is the maximum yearly hurricane wind speed experienced at a port of exit. Some observations report positive value but no weight, which is why there are fewer observations of total weight than total value.

Hurricane Data

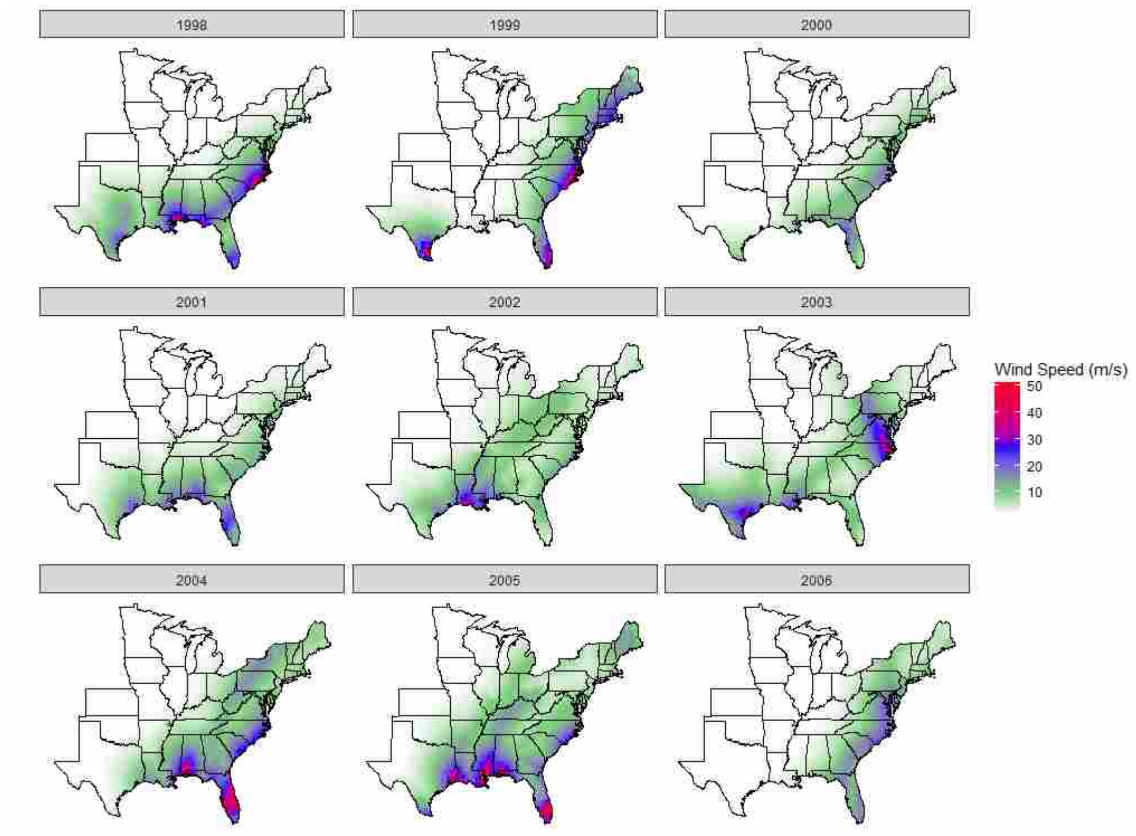
The hurricane tracking data used in this project comes from the USA National Hurricane Center (NHC), and is processed through the procedures outlined in Anderson et al. (2020). Hurricane tracking data comes in six hour intervals, where the latitude and longitude of the storm's eye, the maximum sustained 1-minute wind speeds, and the minimum sea-level pressure are recorded. From this data, full hurricane tracks are created by interpolating the track over 15 minute intervals. Then, the full wind-radii are calculated using the Willoughby, Darling and Rahn (2006) model of hurricane wind profiles.

Figure 19 shows the spatial and temporal variation in hurricane intensity over the years in this study. Intensity is measured by maximum sustained one-minute wind speeds. The figure plots the average annual hurricane wind speed at the county level. Years 2000, 2001, 2002, and 2006 were relatively weaker hurricane years, while years 1998, 1999, 2003, 2004, and 2005 were relatively strong years. The hurricane seasons of 2004 and 2005 were particularly devastating, both causing billions of dollars in damage (Beven et al. 2008). Within these years there is considerable variation among the regions that were most affected by hurricanes. Figure 20 displays the average annual hurricane wind speeds experienced at each port in the sample. Naturally, ports in the Western half of the USA do not experience any hurricane wind speeds.[12]

In order to merge this data with the trade data described above, I calculate the maximum sustained hurricane wind speed experienced at each port in the sample. If multiple storms are experienced at a port in a single year, I use the annual maximum wind speed as a measure of exposure, a practice used in Anttila-Hughes and Hsiang (2012). This results in a panel of hurricane wind speeds at each US port over time, which can then be merged with the annual US trade data. In the fifth row of Table 15, I show the average annual maximum hurricane wind speed at ports is roughly nine meters per second (roughly 20 miles per hour). The highest hurricane wind speed recorded over the sample period is 51 meters per second (about 112 mph), which is from Hurricane Charley.

[12]Pacific hurricanes are excluded from this study due to data limitations and the fact that they do not typically make landfall.

FIGURE 19. Average Annual Hurricane Wind Speeds by US County

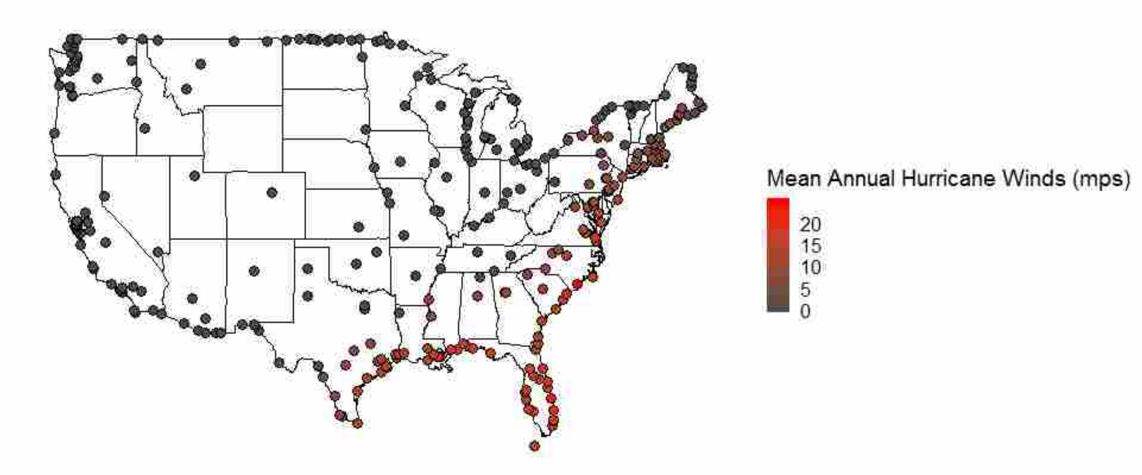


This figure shows the hurricane wind speeds in each year in the sample, measured in meters per second.

4.4 Estimation and Results

The estimation of the model parameters takes place in two phases. In the first phase, I estimate the effect of port-level hurricane wind speed on port-level trade shares, backing out estimates of σ and ρ_1. In the second phase, I examine how these port-level effects are aggregated up to the state-level, obtaining estimates of ϕ.

FIGURE 20. Avg. Annual Port-Level Hurricane Intensity



This figure shows the average annual hurricane wind speeds, measured in meters per second, at each port in the sample.

Port-level Analysis

Taking the log of equation (9) and adding time subscripts results in the following equation:

$$\ln(X^k_{ijt}/X_{ijt}) = \alpha_{ijt} + \nu^k + \eta_1 wind^k_t + \epsilon^k_{ijt} \tag{4.11}$$

where:

$$\alpha_{ijt} = -ln[\sum_k (\tau^k_{ijt})^{(1-\sigma)}] \tag{4.12}$$

$$\epsilon^k_{ijt} \equiv ln[(\delta^k_{ijt})^{\rho_2(1-\sigma)}] \tag{4.13}$$

$$\eta_1 = (1-\sigma)\rho_1 \tag{4.14}$$

Equation (11) highlights why using an exogenous measure of hurricane intensity at a port is extremely important in the following analysis. The identifying assumption in equation (11) is that the conditional expectation of $E[wind_t^k \epsilon_{ijt}^k | \alpha_{ijt}, \nu^k] = E[wind_t^k ln(\delta_{ijt}^k)^{\rho_2(1-\sigma)} | \alpha_{ijt}, \nu^k] = 0$. This assumption requires that the measure of hurricane intensity at port k is uncorrelated with all other trade frictions associated with the exports from state i through port k to country j in year t. This strong assumption is satisfied if the measure of hurricane intensity is based on a purely physical measure, such as the hurricane wind speeds. Factors like internal and external distances, which are captured in the δ_{ijt}^k term, are uncorrelated with the physical wind speed experienced at the port. This does not rule out the potential for port-level hurricane wind speeds to affect the export share through its effect on other trade frictions. The port-level fixed effect (ν^k) means that the identifying variation in equation (11) comes from deviations from average annual port-level hurricane wind speeds, while the exporter-importer-year fixed effect (α_{ijt}) insures that the resulting changes in export share are driven by variation at the port of exit.

The results from estimating equation (11) are presented in Table 16. Each column contains importer-exporter-year fixed effects, port fixed effects, and allows errors to cluster at the state-of-exit level. The state-of-exit is the state in which the port lies. Even though hurricanes are temporary events, their effects are present in annual trade data. The main result of the port-level analysis is presented in column (1) of the table. I estimate that the share of exports from US states to importing countries through a port decline by -0.7% per meter per second of hurricane wind speed experienced at the port.[13] To put the magnitude of this result in perspective,

[13]Because the estimating equation is in log-level form, and the coefficient is less than 0.1, it can be interpreted as $\hat{\eta}_1 * 100$ is the percent change in the export share.

a port experiencing wind speeds of 33 meters per second (a Category 1 storm) results in the share of exports through that port declining by roughly 23%.

In column (2), I include a one year lag and one year lead of the wind speed variable. I find that the effect of hurricanes is only present in the year that the wind speeds were experienced, indicating that the effect is temporary. Notably, the effect of port-level hurricane wind speeds at time $t-1$ have no statistically significant effect on the export share, lending credence to the parallel trends assumption. In column (3) of Table 16, I investigate the non-linear effects of hurricane intensity. In this specification, I include both $wind_t^k$ and $(wind_t^k)^2$. The wind speed variable is normalized at the port-level, which is the recommended method to account for interactions in Balli and Sørensen (2013). I find that there does appear to be non-linear effects of wind speeds, with stronger storms reducing exports by a larger amount. In the appendix, I use spatial econometric methods to control for wind speeds at surrounding ports. I find that the results are robust to the inclusion of this spatially lagged wind speed variable that controls for spatial spillovers.[14] I also show, in the appendix, that the results from estimating the port-level response to hurricane wind speeds are robust to using Pseudo-Poisson Maximum Likelihood (PPML) estimation, as recommended in Silva and Tenreyro (2006) to deal the potential biased estimates in log-linear models.

The coefficient on the hurricane wind speed variable is a function of the price elasticity of substitution across ports, σ. This is clear from equation (14). To back out an estimate of the tariff equivalence of hurricane wind speeds, given in the

[14]Equation 11, above, indicates that the port-importer-year fixed effect can control for all other trade frictions between i and j across all ports. In the case of hurricanes, this may be problematic as the wind speed at port $k' \neq k$ may influence the exports sent through port k. However, the results are robust to the inclusion of a variable that controls flexibly for the wind speeds at ports $k' \neq k$.

TABLE 16. Port-level Results

	Dependent: $ln(\frac{X^k_{ijt}}{X_{ijt}})$		
	(1)	(2)	(3)
$wind^k_{t-1}$		0.003	
		(0.004)	
$wind^k_t$	-0.007***	-0.008***	-0.007***
	(0.002)	(0.003)	(0.002)
$wind^k_{t+1}$		0.001	
		(0.002)	
$(wind^k_t)^2$			-0.0006**
			(0.0002)
N	732,427	337,429	732,427
Adjusted R^2	0.460	0.383	0.460
exporter-importer-year FE	Y	Y	Y
port FE	Y	Y	Y

This table displays the results of estimating equation (12). The dependent variable is the log of the share of exports from an origin to a destination through a given port. Each column contains origin-destination-year fixed effects, and port fixed effects. Errors allow for clustered at the state of exit (i.e. the state in which the port of exit is located).

model by the parameter ρ_1, an estimate of the price elasticity of substitution across ports is needed.

I estimate σ using data on a ports export share and port-level export prices, measured by unit-values (export value relative to quantity). Specifically, I estimate:

$$ln(X_{ijt}^k/X_{ijt}) = \gamma_{ijt} + \delta^k + \beta_1 ln(p_{ijt}^k) + \epsilon_{ijt}^k \tag{4.15}$$

where, p_{ijt}^k is the unit-value of exports from state i to country j through port k, and β_1 is an estimate of the price elasticity $(1-\sigma)$. This estimating equation is derived from equation (9). I instrument for port-level prices using the internal shipping distance from the largest city in state state i to port k.[15] The results from estimating equation (14) are shown in Table 17.

In the first stage, I estimate that a 10% increase in the distance between i and k increases prices at k by roughly 2.5%. The first stage F-stat is roughly 12, indicating that distances are relevant in explaining prices. In the second stage, I estimate that a 1% increase in prices reduces the port's export share by roughly 4%. This produces an estimate of $\hat{\sigma} = 4.8$, which is consistent with estimates of trade elasticities in the literature (Simonovska and Waugh (2014)).

With an estimate of $\hat{\eta}_1 = 0.7$ from column (1) of Table 16, and an estimate of $\hat{\sigma} = 4.8$ from column (2) of Table 17, I calculate the tariff equivalence of hurricane wind speeds using equation (14). I estimate that a meter per second of hurricane wind speed at a port is roughly equivalent to a 0.184% tariff. To put this result another way, a storm like Hurricane Charley (51 meters per second of wind speed) has an equivalent effect on trade volume as a 9% ad-valorem tariff.

[15]The results are robust to measuring the shipping distance from 100 randomly chosen points within state i as well. Results available upon request.

TABLE 17. Response of export share to prices

Outcome:	First Stage $ln(p^k_{ijt})$	2SLS $ln(X^k_{ijt}/X_{ijt})$
$ln(d^k_i)$	0.255^{***}	
	(0.052)	
$ln(\hat{p}^k_{ijt})$		-3.805^{***}
		(0.829)
First-Stage Conditional F-Stat:	11.9	
N	692,004	692,004

The table presents the results of estimating equation (14). The first column displays the first stage results, where the dependent variable is the log of export price, and the second column displays the second stage results. Robust standard errors that allow for clustering at the state-of-exit level are shown.

State Level Results

Using the estimates from the port-level analysis, I analyze how hurricane intensity at ports influences aggregate exports from US states. This corresponds to the upper level of the nested CES demand function in equation (10). The θ_{ij} term, described in Section 3, is a measure of a trade flows exposure to port-level hurricane wind speeds. Port-level trade frictions can be aggregated into a "port-level hurricane exposure" index in the following expression:

$$\theta_{ijt} = [\sum_k (exp(\rho_1 wind_t^k)(\delta_{ijt}^k)^{\rho_2})^{1-\sigma}]^{\frac{1}{1-\sigma}} \tag{4.16}$$

which, using the identity in equation (14) can be expressed as:

$$\theta_{ijt} = [\sum_k (\hat{\epsilon}_{ijt}^k (exp(\hat{\rho}_1 wind_t^k))^{1-\hat{\sigma}}]^{\frac{1}{1-\hat{\sigma}}} \tag{4.17}$$

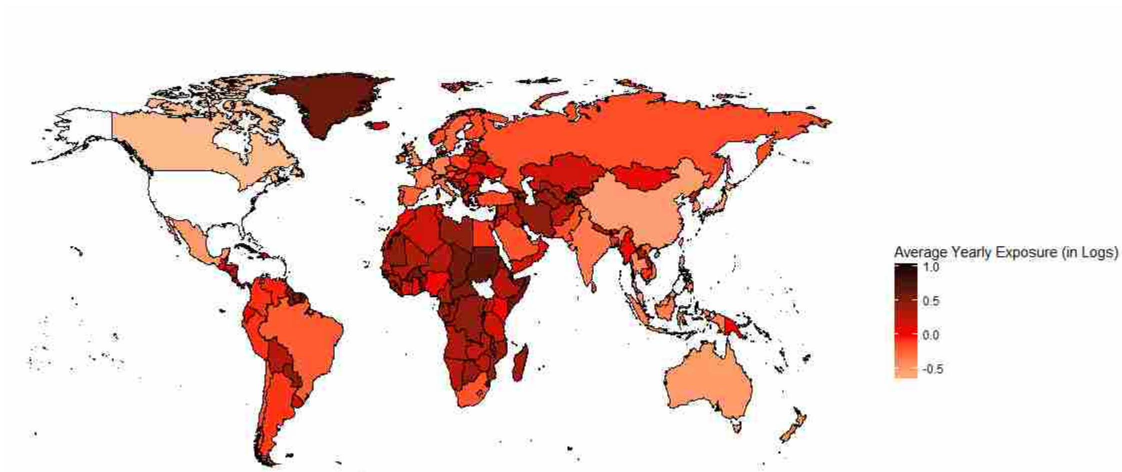
The assumption that the exogenous frictions (δ_{ijt}^k) can be captured in the residual of equation (12) is satisfied as long as port-level wind speeds are orthogonal to other trade frictions. The restriction of the sample used in the estimation of the parameters in the previous section, which omits exports from states in years in which they experienced strong hurricane wind speeds, also helps eliminate the potential for the residual to contain endogenous variation in production costs. I use an estimate of $\hat{\sigma} = 4.8$ and $\hat{\rho}_1$=0.175, which are discussed in Section 4.1, when calculating θ_{ijt}.

Figure 21 shows the heterogeneity across importing countries in θ_{ijt}. The figure displays each importers average annual θ_{ijt} (in logs). Canada, Mexico, and Western Europe, and China (all countries that import from a number of US states and numerous ports) have a relatively low level of average exposure. Sub-Saharan

African countries, Central American countries, and some West Asian countries are more highly exposed.

Figure 22 displays the heterogeneity in the average trade flow exposure to hurricane across exporting US states. Naturally, west coast states are relatively unexposed, as much of the exports from these states exit through West Coast ports. Some states in the interior of the USA are highly exposed to port-level hurricanes due to their reliance on Gulf and East Coast ports to export goods abroad.

FIGURE 21. Exposure of Imports to Hurricane Activity at US Ports



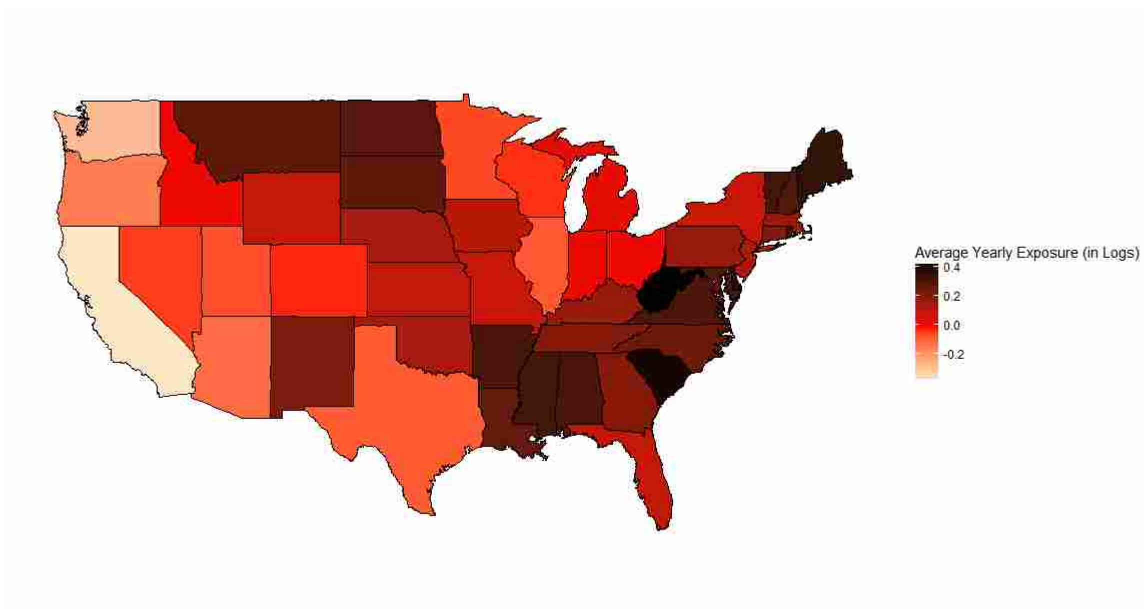
This figure shows the average level of trade flow hurricane exposure (θ_{ijt}) for all importing countries in the sample.

I use the variable θ_{ijt} to estimate how a trade flows hurricane exposure index influences trade intensity between exporting states and importing countries. Taking the log of equation (10) in Section 2.4 results in:

$$ln(X_{ijt}/X_{jt}) = \gamma_{it} + \xi_{jt} + \alpha_{ij} + (1-\phi)ln(\theta_{ijt}) + \epsilon_{ijt} \tag{4.18}$$

where, γ_{it}, ξ_{jt}, and α_{ij} are exporter-year, importer-year fixed effects, and exporter-importer fixed effects, respectively. Because θ_{ijt} is a generated regressor based on

FIGURE 22. Trade Flow Hurricane Exposure by US State



This figure shows the average trade flow hurricane exposure (θ_{ijt}) for each state in the sample.

estimates produced from equation (11), I cluster bootstrap the entire two-stage procedure (estimating equation (11), calculating θ_{ijt}, and estimating equation (18)) when estimating $(1 - \phi)$.

The results from estimating equation (18) are presented in Table 18. In column 1, I estimate a 1% increase in a trade flows hurricane exposure index reduces trade intensity by roughly 3%. In column 2, I include a one year lead and one year lag of the hurricane exposure variable. I find that neither the lead term of lag term are statistically significant. Using the results in the table, I estimate that $\phi = 4.32$, which is consistent with estimates of trade elasticities in the trade literature (Simonovska and Waugh 2014).

TABLE 18. Parameter Estimates

	Dependent: $ln(\frac{X_{ijt}}{X_{jt}})$	
	(1)	(2)
$ln(\theta_{ijt-1})$		0.006
		(0.014)
$ln(\theta_{ijt})$	-3.31^{***}	-3.32^{***}
	(0.189)	(0.204)
$ln(\theta_{ijt+1})$		-0.00005
		(0.002)
N	71,242	71,242
R^2	0.584	0.584
Adjusted R^2	0.569	0.569
Exporter-importer FE	Y	Y
Exporter-year FE	Y	Y
Importer-year FE	Y	Y

The table displays the results of estimating equation (16) using a bootstrap procedure with 10,000 replications. exporter-year, importer-year, and exporter-importer fixed effects are included in the estimating equation. The explanatory variable is the log of θ_{ijt}, which is defined in equation (20), along with leads and lags of this variable.

4.5 Welfare Analysis

In this Section I calculate the change in consumer welfare under counterfactual scenarios with different port-level hurricane wind speeds. Given the quasi-linear utility function assumed in equation (1), changes in consumer welfare from an increase in the price of goods sent through a port can be inferred from the compensating variation. In the case of a negative economic change, the compensating variation is the minimum amount of money the consumer would be need to be given in order to be indifferent about the change. For a positive economic change, the compensating variation is the maximum amount a consumer would be willing to pay to in order to have the change occur.

I calculate the compensating variation given by the following formula:

$$CV = [U(C_j^*) - U(C_j^{*'})] - [P_j C_j^* - P_j^{'} C_j^{*'}] \tag{4.19}$$

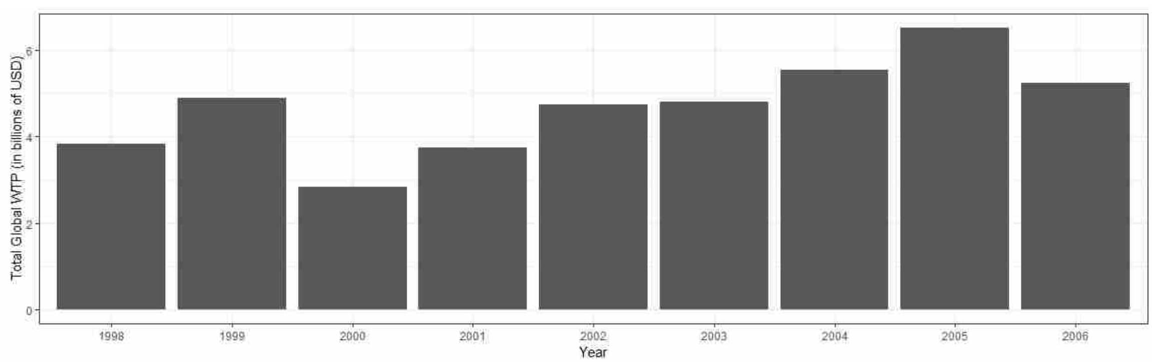
where C_j^* is the optimal consumption bundle in country j and P_j is the price index faced by consumers in country j. This price index is given by:

$$P_j = [\sum_i \beta_{ij} c_i^{\gamma} [\sum_k (e^{\rho_1 wind^k} (\delta_{ij}^k)^{\rho_2})^{1-\sigma}]^{(1-\phi)/(1-\sigma)}]^{1/(1-\phi)} \tag{4.20}$$

with $\gamma = (1-\sigma)(1-\phi)$. $P_j^{'}$ is the price index faced by consumers in country j under a counterfactual situation when hurricane wind speeds at port k were $wind'^k$. Given this change in wind speed, the price of goods sent from i to j through port k changes, resulting in a change in consumption. Due to the exogeneity of the wind speed experienced at a port, the term δ_{ij}^k is an exogenous parameter and is captured, along with the β terms, in the residual from equation (11) and (18).

Using this set up, I calculate how much consumers would have been willing to pay to avoid the hurricane activity over the sample period. Setting hurricane wind speeds equal to zero in each year and summing the compensating variation across all importers produces the numbers in Figure 23. The total willingness to pay to avoid hurricane activity over the sample period varies from year to year. The most intense hurricane years correspond to the largest willingness to pay figures. For example, the figure shows that consumers would have been willing to pay over $6 billion to avoid all hurricane activity in 2005.

FIGURE 23. Total Willingess to Pay



This figure shows the total global willingess to pay to have avoided all hurricane activity each year. The top panel shows the willingness to pay in nominal terms, while the bottom panel shows the willingness to pay as a fraction of aggregate global GDP.

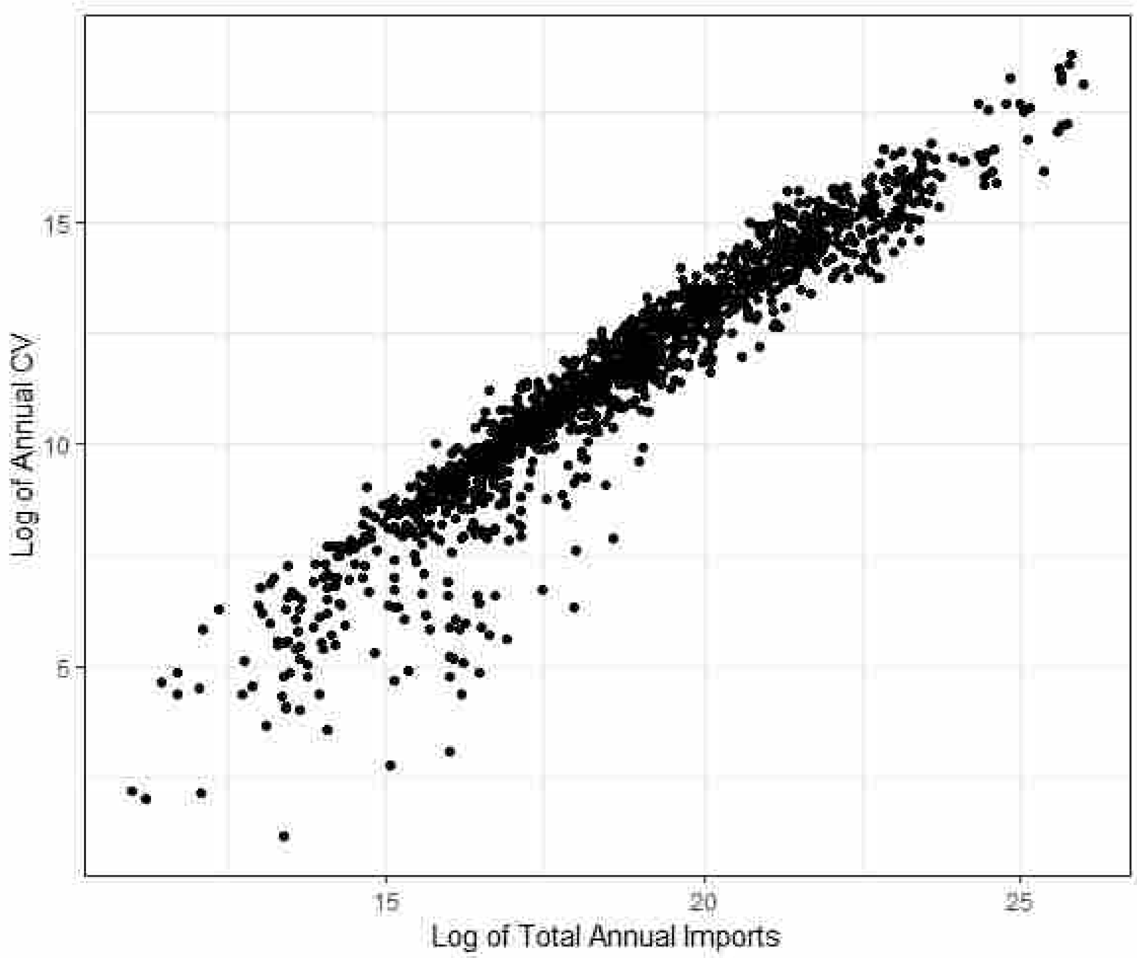
Next, I use the model to calculate the compensating variation under an increase in hurricane intensity. I base the simulations on estimates from Knutson et al. (2010), who estimate that Atlantic Basin hurricanes will increase in intensity by between 2% and 11% over the next century. If all hurricanes over the sample period were 2% stronger, the average annual compensating variation is $560,000, which is roughly 100 times larger than the average GDP per capita. The average importer of US goods would need to be compensated roughly $3.1 million per year to be indifferent about an 11% increase in hurricane intensity.

Table C4, in the appendix, displays the average annual compensating variation by country for a 6.5% increase in hurricane intensity. This is the median increase in Atlantic Basin hurricane intensity predicted in Knutson et al. (2010). Naturally, countries that do the most trade with the US have the largest compensating variation. The top five countries in terms of average annual compensating variation are Canada, Mexico, UK, Brazil, and Japan. Figure 24 displays the relationship between total annual imports from the US and annual compensating variation for a 6.5% increase in hurricane intensity. The figure shows a clear positive correlation between trade intensity with the US and the compensating variation associated with the 6.5% increase in hurricane intensity.

4.6 Conclusion

This paper analyzes the impact hurricanes have on exports from US states, focusing specifically on the effect these storms have on exporters that did not experience any physical destruction due to the storm. There is a growing literature on the effect of hurricanes on economic activity and damage, but little attention has been paid to the extent to which these storms disrupt trade through their effect on transport networks. Using detailed data on trade flows that include the origin of shipments, the customs port of exit, and the import country, I show that hurricane activity around US ports of exit have an effect on the share of exports from a state to a country through the affected port, and as a result affect average consumer welfare.

FIGURE 24. Total Imports and Compensating Variation



This figure shows the relationship between the annual compensating variation under a 6.5% increase in hurricane intensity, and total annual imports. Each point represents a importer-year pair.

The response of trade flows to historic hurricane driven port-level disruptions sheds light on how trade flows may respond to increased hurricane intensity due to climate change. Mitigation strategies involving upgrading port-level infrastructure may make ports better substitutes for each other when hurricanes strike. The willingness to pay figures calculated in this study also provide insights into the value of early warning systems that would facilitate coordination between exporters and importers during hurricane seasons.

This paper also provides avenues for future research. For example, with product-level data it would be beneficial for policy makers to know which products drive the relationships found in this study. Exploring the extensive margin effects of trade in response to climate change may also be a fruitful avenue for future research. Finally, future work can expand upon the work in this paper by examining how changes in sea-level rise and hurricane rainfall are project to influence the flow of global trade.

CHAPTER V

CONCLUSION

Trade liberalization over the past several decades has reduced tariffs, quotas, and other formal trade barriers faced in international markets. However, informal and non-tariff barriers remain an obstacle. For example, a large body of evidence suggests that non-tariff trade barriers, such as shipping distances, national borders, and currency unions, have a substantial effect on trade flows (Anderson and Van Wincoop 2004). In this dissertation, I analyze two unique non-tariff barriers: natural disasters and rules of origin. While there are fundamental differences in how these trade barriers arise, an understanding of how they influence trade flows is crucial to designing effective trade policy.

In the first essay, I find that restrictive rules of origin reduce the effectiveness of development-oriented trade policy. Using firm-level data on Bangladeshi apparel exporters, I estimate that the revision of the rules of origin for the EU's EBA agreement increased firm-level export growth by roughly 16% on the intensive margin, and led to firms expanding their product scope by roughly 9%. I also find that larger firms gained market share at the expense of smaller firms. Finally, I find that the initial rules of origin, which required the use of locally sourced textiles, were equivalent to a 6% export tariff. The preference depth of the EBA is roughly 13%, however, the rules of origin effectively cut that preferential margin in half.

In the second essay, I find that hurricanes are a major source of trade disruption at US ports. I estimate that the export volume from hurricane-affected ports remains below average for roughly 10 months after a storm, and this results in large cumulative losses in trade volume over time. However, I also find that surrounding ports absorb diverted trade. The results of this study highlight the importance of contingency planning in the face of natural disasters. Policy aimed at facilitating re-routing trade from hurricane-affected regions to less-affected regions can mitigate global trade disruptions.

In the third essay, I find that hurricane activity around US ports-of-exit result in welfare loss for global consumers. Specifically, I estimate the parameters of a nested-CES model of trade using hurricane tracking data and data on US export shipments, and then calculate consumers willingness to pay to avoid hurricane activity. For example, I find that consumers would have been willing to pay $6 billion to have avoided all of the hurricane activity during the 2005 Atlantic hurricane season. Typically, when estimating the costs of climate change, the indirect effects of climatic disasters are not considered. Thus, the results of this study provide new insights into the costs of stronger hurricanes due to climate change.

The research in this dissertation open new avenues for study. For example, the welfare effects of hurricanes may differ across traded products. It may be more difficult to re-route certain products because they require specific port-level infrastructure. For example, shipping agricultural products may require the use of grain elevators, which are not readily available at all ports. Given data restrictions, I am unable to examine product-level heterogeneity. Future work should also study how intermediate input sectors respond to rules of origin liberalization. So far, there has been little evidence that restrictive rules of origin have resulted in backwards-linkages within export sectors (Brenton and Imagawa 2005). However, the losses to intermediate input sectors when rules of origin are revised to allow for more imported content has not been analyzed.

APPENDIX A

APPENDIX FOR CHAPTER 1

A1 Theoretical Framework

In this section I outline a model of trade that extends the multi-product firm model in Bernard, Redding, and Schott (2011) (BRS hereafter), and incorporates elements from Demidova, Kee and Krishna. (2012), and Eaton and Kortum 2002, and abstracts away from the intermediate good sector. This is done due to data limitations, and due to the relative size of the final goods apparel sector compared to the textile sectors in LDCs.

In the model, firms decide whether to enter an export market, which products to supply, and whether to export while invoking the rules of origin or export without invoking the rules of origin. Invoking the rules of origin is costly, but doing so grants a firm access to preferential tariff rates under a preferential trade agreement. Products are imperfect substitutes, and each firm can produce a differentiated variety of each product. Production requires labor and an intermediate input, and competition is monopolistically competitive.

Demand

Following BRS, there is a representative consumer in each country $j \in J$ who has CES utility over a continuum of products. The continuum of products is normalized to the interval [0,1].

$$U_j = [\int_0^1 C_{jk}^{\eta} dk]^{1/\eta} \tag{A.1}$$

Here, k indexes products, and η is the elasticity of substitution across products. C_{jk} is a consumption index. The consumption index also takes the CES form, and depends on the varieties consumed:

$$C_{jk} = [\sum_{i=1}^{J} \int_{\omega \in \Omega_{ijk}} (\lambda_{ijk}(\omega) c_{ijk}(\omega))^{\rho} d\omega]^{\frac{1}{\rho}} \tag{A.2}$$

where ω indexes varieties of product k, Ω_{ijk} is the set of all products available in country j from country i, and $\lambda_{ijk}(\omega)$ represents a "product attribute", as in BRS. The product attribute term encompasses product quality (which may be the same in all j), as well as idiosyncratic taste variation that differs across j's. The fact that the product attribute term is country specific means that product attributes enter the utility of consumers in different countries differently. In this sense, the $\lambda_{ijk}(\omega)$ term is similar to the demand-shock term in Demidova, Kee and Krishna. (2012), but allows for variation across products as well.

Defining $\sigma \equiv \frac{1}{1-\rho} > 1$ as the elasticity of substitution across varieties within products, the corresponding price index is:

$$P_{jk} = [\sum_{i} \int_{\omega \in \Omega_{ijk}} (\frac{p_{ijk}(\omega)}{\lambda_{ijk}(\omega)})^{1-\sigma} d\omega]^{1/(1-\sigma)} \tag{A.3}$$

<u>Firms</u>

There is an unbounded measure of potential firms, each of which can supply a horizontally differentiated variety of each of the continuum of products. Firms are differentiated by their ability, ϕ. To enter the domestic market, firms must pay a fixed entry cost, f_e. After paying the fixed entry cost firms observe their ability, which is drawn from a continuous distribution $g(\phi)$, with CDF $G(\phi)$. Because I work with data containing information only on exports, I assume that all firms who export have already paid the fixed entry cost and observed their productivity. Ultimately, this assumption does not affect the model going forward, however, it abstracts away entry into the domestic market.[1]

Firms are also differentiated by their product attributes, λ_{jk}. Product attributes, which are drawn from a known distribution $z(\lambda)$ and are independently and identically distributed across the continuum of products.[2] Product attributes are drawn separately for each destination and product pair. This captures the idiosyncrasies in apparel product demand documented in Demidova, Kee and Krishna. (2012), Kee and Krishna (2008).

Production

To see how restrictive rules of origin influence the production of final goods, consider the simple production function for a firm with productivity ϕ:

$$q_k = f(\phi, L, X_k) \tag{A.4}$$

Here, production of product k requires only labor (L) and a single intermediate good (X_k). This single intermediate good is produced in a perfectly competitive global market, where producers of the intermediate good may also differ in terms of productivity. Following Eaton and Kortum (2002), producers of the final good search for the lowest price of this intermediate good, paying

[1] It should be noted that the "domestic market" in the case of the Bangladeshi apparel industry mainly consists of factory seconds. Given that the vast majority of apparel produced by Bangladeshi apparel firms is exported and the lack of domestic retail stores there are few firms that produce exclusively for the domestic market (Lopez-Acevedo and Robertson. 2016).

[2] These assumptions simplify the calculations going forward by letting firms profit-maximize over each product separately. Ultimately, they do not change the models predictions on how firms respond to rules of origin liberalization.

$p_{x,k} = min_{m \in J}(p^m_{x,k})$, where m denotes global producers of the intermediate good, with potentially $m = i$. In this sense, $p_{x,k}$ can be thought of as the lowest global price for input X inclusive of any potential trade costs associated with importing the good from other countries. Rules of origin that place limits on where inputs can be sourced will restrict the set of potential prices over which firms can search for a minimum. The restriction on the set of prices over which firms can search will result in the lowest input price being greater than or equal to the unrestricted price.

To further solidify this concept, I assume $f(\phi, L, X_k)$ is Cobb-Douglas. This results in a marginal cost for a firm with productivity ϕ producing good k of:

$$c_k(\phi, w, P_{x,k}) = \frac{\Gamma w^{\alpha} p^{\beta}_{x,k}}{\phi} \tag{A.5}$$

where w is the wage, and Γ is a constant[3], and α and β are output elasticities. Wages are assumed to be constant across products, and are normalized to one going forward.

Exporting to country j involves paying iceberg trade costs, $\tau_j > 1$. Trade costs include transport costs, tariffs, and other trade barriers which vary by country. If a firm invokes the rules of origin for country j, it's products are exposed to lower tariff rates. I define τ^{PTA}_j and τ^{MFN}_j as the trade costs associated with the preferential trade agreement (PTA) associated with invoking the rules of origin, and the non-rules of origin trade costs (MFN) associated with exports that do not meet the rules of origin standards and to which MFN tariffs are applied. Because firms invoking the rules of origin face lower tariffs, $\tau^{PTA}_j < \tau^{MFN}_j$.

[3] $\Gamma = (\frac{\alpha}{\beta})^{\beta} + (\frac{\alpha}{\beta})^{-\alpha}$

To invoke the rules of origin, firms can only source the intermediate input from specific countries. This restricts the set of global prices over which firms can search for the lowest $p_{x,k}$, resulting in firms paying $\bar{p}_{x,k} \geq p_{x,k}$ for the input.[4]Normalizing wages to one, the total cost functions for firms that invoke rules of origin (PTA), and those that do not (MFN) are shown below:

$$TC_{jk}^{PTA}(\phi, \lambda) = (F_j + f_{jk} + d_j + \Gamma \frac{\tau_{jk}^{PTA} \bar{p}_{x,k}^{\beta} q_{jk}(\phi, \lambda)}{\phi \lambda_{jk}}) \tag{A.6}$$

$$TC_{jk}^{MFN}(\phi, \lambda) = (F_j + f_{jk} + \Gamma \frac{\tau_{jk}^{MFN} p_{x,k}^{\beta} q_{jk}(\phi, \lambda)}{\phi \lambda_{jk}}) \tag{A.7}$$

Along with the marginal costs of producing and exporting discussed above the total cost of exporting a product to country j also depends on several fixed costs. First, regardless of how a firm decides to export its product it must pay a market-entry fixed cost F_j. This accounts for factors like market research, or any cost associated with learning about destination market j. For any product the firm decides to export, there are additional fixed costs associated with advertising, setting up distributors for the product, and so on. These fixed costs are captured by the f_{jk} term. This term is product specific because some products may require different types of advertising, or have different general product standards required in country j. Finally, if a firm decides to export the product while invoking the rules of origin, it must document that the rules of origin were satisfied. Previous

[4]Demidova, Kee and Krishna. (2012) estimate that the cost of using woven textiles made in Bangladesh for the production of apparel is roughly 15% higher than importing it from other countries.

research has shown that this documentation cost is high for many firms in LDCs (Brenton 2006). The term d_j captures this fixed cost.[5]

The firm's profit maximization problem results in choosing a price for each product separately, and under monopolistic competition this results in a price that is a constant mark-up over the marginal cost. The price set for product k, with attributes λ_{jk}, by a firm with productivity ϕ choosing to either meet, not meet, the rules of origin are given by:

$$p_{jk}^{PTA}(\phi, \lambda) = \frac{\tau_{jk}^{PTA} \bar{p}_{x,k}^{\beta}}{\chi \phi \lambda_{jk}}$$

$$p_{jk}^{MFN}(\phi, \lambda) = \frac{\tau_{jk}^{MFN} p_{x,k}^{\beta}}{\chi \phi \lambda_{jk}}$$

where $\chi = \frac{\rho}{\Gamma}$ and is a constant. As can be seen in the pricing rules above, the higher a firms productivity (ϕ) the lower the price it will charge for good k. Similarly, the more attractive a firms variety of product k is in country j (λ_{jk}) the lower the optimal price. Given these pricing rules, export revenue and profits for firms invoking the rules of origin (PTA) and those not meeting the rules of origin (MFN) are as follows:

$$r_{jk}^{PTA}(\phi, \lambda) = (\tau_{jk}^{PTA} \bar{p}_{x,k}^{\beta})^{(1-\sigma)} \frac{1}{\sigma} E_{jk} (P_{jk} \chi)^{\sigma-1} \phi^{\sigma-1} \lambda_{jk}^{\sigma-1} \tag{A.8}$$

$$\pi_{jk}^{PTA}(\phi, \lambda) = r_{jk}^{PTA}(\phi, \lambda) - f_{jk} - d_j \tag{A.9}$$

[5]This fixed cost can be thought of as gaining legal insight into documenting the rules of origin for country j. It is not product specific, however, allowing it to vary by product would not change the predictions of the model.

$$r^{MFN}_{jk}(\phi,\lambda) = (\tau^{MFN}_{jk} p^{\beta}_{x,k})^{(1-\sigma)} \frac{1}{\sigma} E_{jk}(P_{jk}\chi)^{\sigma-1}\phi^{\sigma-1}\lambda^{\sigma-1}_{jk} \tag{A.10}$$

$$\pi^{MFN}_{jk}(\phi,\lambda) = r^{MFN}_{jk}(\phi,\lambda) - f_{jk} \tag{A.11}$$

where, E_{jk} is the total expenditure in country j on product k. Given the competitive nature of the global apparel industry, I assume a firm is unable to influence the price index for any product.[6] This gives rise to:

Proposition 1: The Preference Utilization Criterion. *In order for any firm, ϕ, to find it profitable to export a product, λ, under the PTA the following condition must hold:* $\frac{\tau^{MFN}_j}{\tau^{PTA}_j} > (\frac{\bar{p}_{x,k}}{p_{x,k}})^{\beta}$

The proof of this proposition is clear when comparing equations (8) and (10), above. If the condition does not hold, the slope of the PTA profit function is less than the slope of the MFN profit function and $r^{PTA}_{jk} < r^{MFN}_{jk}$ for any level of firm ability and product appeal.[7] Going forward, I assume this condition holds.

Proposition 1 highlights an important trade-off. It relates the preference depth to the restrictiveness of the rules of origin. The larger deeper the preferences relative to the sourcing constraints imposed by the rules of origin, the more utilized the trade agreement. Conversely, the proposition can explain why trade agreements with deep preferences have low utilization rates. As preferences deepen, or as rules

[6] Although the price index is treated as exogenous in this paper, the price index can be endogenenized. Essentially, the endogeneity of the price index results in predictions similar to those found in Bombarda and Gamberoni (2013). When the rules of origin are liberalized, high productivity incumbents lower their prices and the overall price index in j falls. This reduces the profitability of low productivity incumbents and forces them out of the market. Empirically, I do not find support for this prediction in the data.

[7] Note that this condition is consistent with the empirical work in Demidova, Kee and Krishna. (2012), where it is estimated that sourcing woven textiles locally costs 15% more than importing them.

of origin become less restrictive, utilization rates increase as lower productivity firms find it more profitable to use the preferential tariffs.

Product-level profitability

Given this set up, only products with desirable enough attributes will allow a firm of ability ϕ to generate enough revenue to cover the product fixed cost of exporting to country j. Furthermore, only products with the most desirable attributes will allow firms to invoke the rules of origin because the fixed costs and marginal costs are higher. Therefore, within a firm, there is endogenous sorting of exported products between those exported using the rules of origin and those that are not. I define two zero-profit product attribute cutoffs, $\lambda_{jk}^{MFN}(\phi)$ and $\lambda_{jk}^{PTA}(\phi)$ to capture the endogenous thresholds above which a product will be exported without using the rules of origin, and when they will be exported using the rules of origin, respectively.

The zero-profit product attribute cutoff $\lambda_{jk}^{MFN}(\phi)$ is the lowest level of product attributes that are sufficient to generate enough profits to export a product without invoking the rules of origin. That is, it is the minimum level of product attributes for a firm with ability ϕ that allow the firm to export the product profitably to country j. The second zero-profit product attribute cutoff $\lambda_{jk}^{PTA}(\phi)$ is the lowest level of product attributes for a firm with productivity ϕ that allows the firm to profitably export the product to country j while invoking the rules of origin. The zero-profit product attribute cutoffs are defined as:

$$r_{jk}^{MFN}(\phi, \lambda_{jk}^{MFN}(\phi)) = \sigma f_{jk} \tag{A.12}$$

$$r_{jk}^{PTA}(\phi, \lambda_{jk}^{PTA}(\phi)) = \sigma(f_{jk} + d_j) \tag{A.13}$$

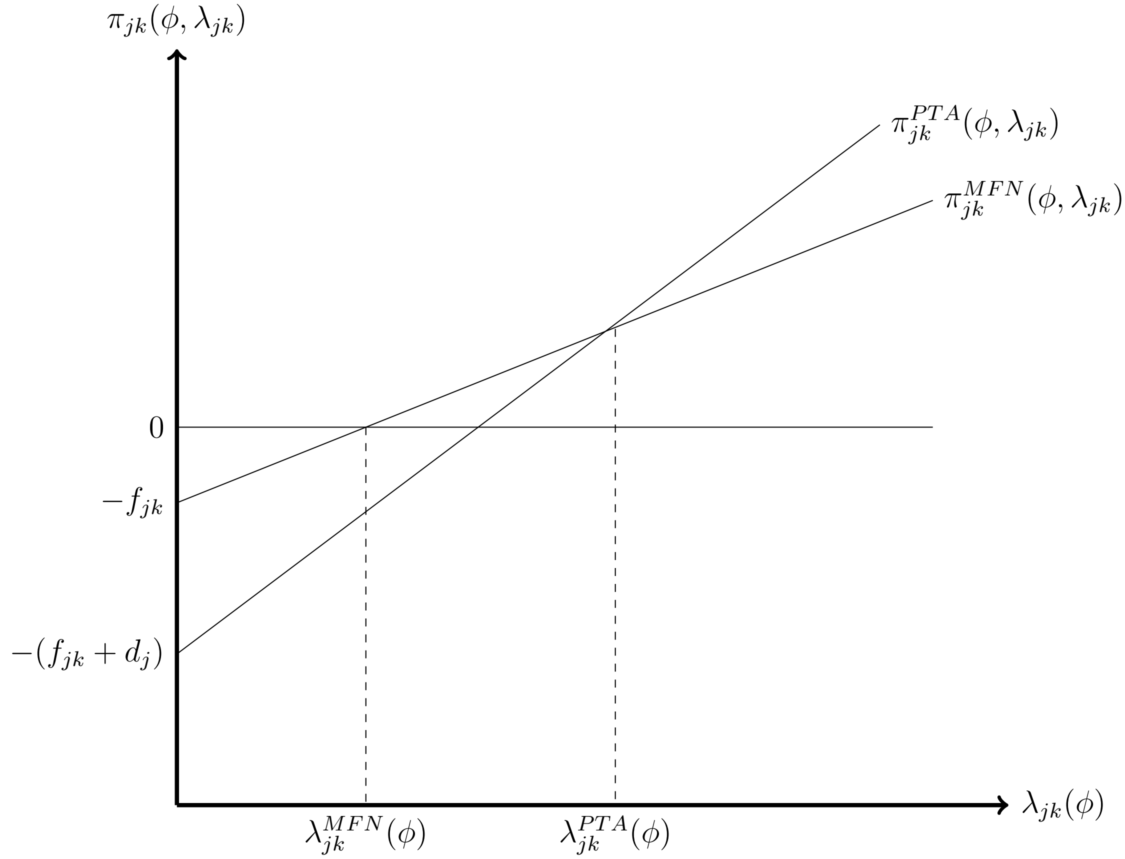
Equations (12) and (13) highlight how the fixed costs of invoking the rules of origin affect the range of products a firm of ability ϕ is able to export to country j. The higher the documentation costs, the higher the zero-profit cutoff for product attributes necessary for exporting under the preferential trade agreement. The equations also show how both zero-profit cutoffs for product attributes increase as the elasticity of substitution increases. That is, as the varieties of product k become more substitutable competition increases and firms must export products with better attributes in order to cover the fixed exporting costs.

Products with $\lambda_{jk} < \lambda_{jk}^{MFN}(\phi)$ will not be able to generate enough revenue to cover the fixed cost of exporting a product to country j, even without invoking the rules of origin. Products with attributes $\lambda_{jk} \in [\lambda_{jk}^{MFN}(\phi), \lambda_{jk}^{PTA}(\phi))$ will be profitable to export to country j without invoking rules of origin, but not profitable enough to export to j under the preferential trade agreement. Finally, products with $\lambda_{jk} > \lambda_{jk}^{PTA}(\phi)$ will be profitable to export to country j while invoking the rules of origin. Thus, within a firm, there is sorting across products based on how attractive the product is in country j. This is shown graphically in Figure A1.

Using the zero-profit cutoffs above, the relative revenue for a firm of ability ϕ, between using the rules of origin and not using the rules of origin can be expressed as:

$$\lambda^{PTA}(\phi) = \lambda^{MFN}(\phi)(\frac{f_{jk} + dj}{f_{jk}})^{\frac{1}{\sigma-1}}(\frac{\tau_{jk}^{PTA}\bar{p}_{x,k}^{\beta}}{\tau_{jk}^{MFN}p_{x,k}^{\beta}}) \tag{A.14}$$

FIGURE A1. Zero-Profit Cutoffs



Note: This figure displays the zero-profit cutoffs for product attributes, described by equations (12) and (13).

From equation (14), the more restrictive the rules of origin are for intermediate input sourcing the higher the zero-profit cutoff for exporting under the PTA. It can also be seen in equation (14) that the higher the unrestricted minimum price of the intermediate input ($p_{x,k}$), the lower the zero profit cutoff for using the PTA. The intuition here is that if the price of the intermediate input is high the export market will be less competitive in general. Lower competition in the export market will allow firms to export products with worse attributes while using the PTA.

Firm-level profitability

A firm's profitability in market j is determined by the revenue across all of the products it sells in the market. In order to enter market j, firms must pay a fixed cost F_j. Only after paying F_j do firms observe their product attributes for the market, λ_{jk}. Because product attributes are distributed independently across the continuum of products, the law of large numbers implies that the expected revenue across the continuum of products is equal to the expected revenue for each product. The expected profit for each product k exported to country j is equal to the probability of drawing a value of product attributes above either $\lambda_{jk}^{MFN}(\phi)$ or above $\lambda_{jk}^{PTA}(\phi)$, multiplied by the expected profit (π_{jk}^{MFN}, or π_{jk}^{PTA}), conditional on supplying the product. A firm's expected profit in each market j is given by:

$$\begin{aligned}\Pi_j(\phi) = &\int_{\lambda_{jk}^{MFN}(\phi)}^{\lambda_{jk}^{PTA}(\phi)} [r_{jk}^{MFN}(\phi, \lambda_{jk}(\phi)) - \sigma f_{jk}] z(\lambda) d\lambda + \\ &\int_{\lambda_{jk}^{PTA}(\phi)}^{\infty} [r_{jk}^{PTA}(\phi, \lambda_{jk}(\phi)) - \sigma (f_{jk} + d_j)] z(\lambda) d\lambda - F_j\end{aligned} \tag{A.15}$$

The higher a firm's ability, the higher the probability of drawing a value of product attributes that is attractive enough to supply the product to country j while invoking origin $[1 - Z(\lambda_{jk}^{PTA}(\phi))]$. This is because high overall ability can make up for low product attributes in the product-level profit equations. The probability that a firm with ability ϕ will be able to profitably supply a product to country j without invoking origin is given by $[Z(\lambda_{jk}^{PTA}(\phi)) - Z(\lambda_{jk}^{MFN}(\phi))]$. Thus, similar to what is shown in Demidova et al (2012), there is endogenous sorting across firms between those that export under the PTA and those that do not. Given that the expected profit from exporting is increasing in firm ability, there exists some level of ability at which the expected profit is equal to zero:

$$\Pi_j(\phi^*) = 0 \tag{A.16}$$

A firm with an ability above ϕ^* will pay the fixed cost F_j and observe their product attributes for market j because the expected profits cover the fixed cost of market research. If a firm pays F_j but finds that all of their product attributes are too low to be profitably exported, they exit without exporting any products to country j.

Using equations (12) and (13) for a firm of ability ϕ^*, it can be shown that the zero-profit cutoff for firm ability, equation (16), can be expressed as:

$$\int_{\lambda^{MFN}(\phi^*)}^{\lambda^{PTA}(\phi^*)} [(\frac{\lambda_{jk}(\phi)}{\lambda^{MFN}(\phi^*)})^{\sigma-1} - 1]\sigma f_{jk} z(\lambda) d\lambda + \int_{\lambda^{PTA}(\phi^*)}^{\infty} [(\frac{\lambda_{jk}(\phi)}{\lambda^{PTA}(\phi^*)})^{\sigma-1} - 1]\sigma f_{jk} z(\lambda) d\lambda = F_j \tag{A.17}$$

The values $\lambda^{MFN}(\phi^*)$, and $\lambda^{PTA}(\phi^*)$ are implicitly defined in equation (17) as functions of fixed costs and the elasticity of substitution (σ), and as in BRS, they are independent of ϕ^*. These represent the minimum level of product attributes necessary to profitably export to j while invoking the rules of origin and while not invoking the rules of origin.

Finally, using equations (12) and (13) the relative revenue between exporting product k using the rules of origin and not using the rules of origin, for a firm of ability ϕ^*, can be expressed as:

$$\lambda^{PTA}(\phi^*) = \Theta\lambda^{MFN}(\phi^*) \qquad \Theta = (\frac{f_{jk} + d_j}{f_{jk}})^{\frac{1}{\sigma-1}}(\frac{\tau_j^{PTA}\bar{p}_{x,k}^{\beta}}{\tau_j^{MFN}p_{x,k}^{\beta}}) \tag{A.18}$$

Thus, the expected profit for a firm with ability ϕ can be expressed as:

$$\begin{aligned}\Pi(\phi) = \int_{\lambda^{MFN}(\phi^*)}^{\Theta\lambda^{MFN}(\phi^*)} [(\frac{\lambda_{jk}(\phi)}{\lambda^{MFN}(\phi^*)})^{\sigma-1} - 1]\sigma f_{jk} z(\lambda) d\lambda + \\ \int_{\Theta\lambda^{MFN}(\phi^*)}^{\infty} [(\frac{\lambda_{jk}(\phi)}{\Theta\lambda^{MFN}(\phi^*)})^{\sigma-1} - 1]\sigma f_{jk} z(\lambda) d\lambda - F_j\end{aligned} \tag{A.19}$$

<u>Rules of Origin Liberalization</u>

In this section, I discuss how liberalizing the rules of origin associated with an existing trade agreement with destination j affects between-firm reallocation of exports, and within-firm reallocation of product-level exports for firms in country i. Liberalizing the rules of origin corresponds to expanding the set of intermediate input prices over which firms can search for a minimum. That is, liberalizing the rules of origin reduces $\bar{p}_{x,k}$.

Generally, liberalizing rules of origin has a similar effect on exporting firms as reducing other non-tariff trade barriers in the context of heterogeneous firm models. In a small exporting country, with a sufficiently slack labor market, a reduction in $\bar{p}_{x,k}$ (i) increases export profits for incumbent firms; (ii) increases the range of products that are profitable to export for incumbent firms; and (iii) induces entry into the export market by low productivity firms. I offer proofs for these propositions in the appendix of this paper. A reduction in $\bar{p}_{x,k}$ also increases the utilization of trade preferences, as firms with lower productivity begin to export under preferential tariffs rather than MFN tariffs. The increase in utilization rates is clear in Figure 3.

Proposition 2: *Rules of origin liberalization results in entry of new firms into the export market.*

Proof: I assume product attributes have a Pareto distribution, $Z(\lambda) = 1 - (\frac{\lambda}{\lambda_{min}})^{-k}$. With the minimum level of product attributes necessary to cover the fixed costs given by $\lambda^*_{jk}(\phi^*)$, the Pareto distribution takes the form: $Z(\lambda_{jk}) = 1 - (\frac{\lambda_{jk}}{\lambda^{MFN}_{jk}(\phi^*)})^{-k}$. Here, I retain the usual assumption that $k > \sigma - 1$ required for trade flows to be finite. Proof of Proposition 2: Equation (19) can be rewritten as:

$$\begin{aligned}&\sigma f_{jk} \int_{\lambda^{MFN}(\phi^*)}^{\lambda^{PTA}(\phi^*)} [(\frac{\lambda_{jk}(\phi)}{\lambda^{MFN}(\phi^*)})^{\sigma-1} - 1](\frac{\partial(1-(\frac{\lambda_{jk}(\phi)}{\lambda^{MFN}(\phi^*)})^{-k})}{\partial\lambda})\partial\lambda + \\ &\sigma f_{jk} \int_{\lambda^{PTA}(\phi^*)}^{\infty} [(\frac{\lambda_{jk}(\phi)}{\lambda^{PTA}(\phi^*)})^{\sigma-1} - 1](\frac{\partial(1-(\frac{\lambda_{jk}(\phi)}{\lambda^{MFN}(\phi^*)})^{-k})}{\partial\lambda})\partial\lambda - F_j\end{aligned} \tag{A.20}$$

Working in parts, the first half of the equation results in:

$$k\sigma f_{jk} \int_{\lambda^{MFN}(\phi^*)}^{\theta\lambda^{MFN}(\phi^*)} [(\frac{\lambda_{jk}(\phi)}{\lambda^{MFN}(\phi^*)})^{\sigma-1} - 1](\frac{\lambda_{jk}(\phi)}{\lambda^{MFN}(\phi^*)})^{-k-1}\partial\lambda \tag{A.21}$$

Where, $\lambda^{PTA}(\phi^*) = \theta\lambda^{MFN}(\phi^*)$ from equation (18) in the text. Equation (A2) can be rearranged and integrated into:

$$\sigma f_{jk}[\frac{(\frac{\lambda_{jk}(\phi)}{\lambda^{MFN}(\phi^*)})^{\sigma-k-1}}{\sigma-k-1} + \frac{(\frac{\lambda_{jk}(\phi)}{\lambda^{MFN}(\phi^*)})^{-k}}{k}]_{\lambda^{MFN}(\phi^*)}^{\theta\lambda^{MFN}(\phi^*)} \tag{A.22}$$

When evaluated at the limits, this becomes:

$$\sigma f_{jk}[\frac{\theta^{\sigma-k-1}}{\sigma-k-1}+\frac{\theta^{-k}}{k}]+\sigma f_{jk}[\frac{1}{\sigma-k-1}+\frac{1}{k}] \tag{A.23}$$

Defining, $\sigma[\frac{1}{\sigma-k-1}+\frac{1}{k}]=C$ to save notation, equation (A6) can be expressed as:

$$\sigma f_{jk}[\frac{\theta^{\sigma-k-1}}{\sigma-k-1}+\frac{\theta^{-k}}{k}]+f_{jk}C \tag{A.24}$$

Next, working from the second half of equation (A1), produces:

$$\sigma(f_{jk}+d_j)[\frac{(\frac{\lambda_{jk}(\phi)}{\theta\lambda^{MFN}(\phi^*)})^{\sigma-k-1}}{\sigma-k-1}+\frac{(\frac{\lambda_{jk}(\phi)}{\theta\lambda^{MFN}(\phi^*)})^{-k}}{k}]_{\theta\lambda^{MFN}(\phi^*)}^{\infty} \tag{A.25}$$

Where the identify in equation (18) has been used again to replace $\lambda^{PTA}(\phi)$. When (A6) is evaluated at it's limits, the resulting expression is:

$$-(f_{jk}+d_j)C \tag{A.26}$$

Combining equations (A4) and (A6) results in the expression:

$$\sigma f_{jk}[\frac{\theta^{\sigma-k-1}}{\sigma-k-1}+\frac{\theta^{-k}}{k}]-d_jC \tag{A.27}$$

From equation (18) in the text, θ is an increasing function of $\bar{p}_{x,k}$. A relaxation of the rules of origin reduces $\bar{p}_{x,k}$. Thus, to see how $\Pi(\phi^*)$ responds to a revision of the rules of origin, it is sufficient to show that the derivative of (A8) with respect to θ is positive. Differentiating (A8) with respect to θ results in:

$$\frac{\partial\Pi}{\partial\theta}=\sigma f_{jk}[\theta^{\sigma-k-2}-\theta^{-k-1}] \tag{A.28}$$

The expression in the brackets is greater than zero if and only if:

$$\frac{1}{\theta^{k+2-\sigma}} > \frac{1}{\theta^{k+1}} \iff \theta^{k+1} > \theta^{k+2-\sigma}$$

Because $\sigma > 1$, this is true. An increase in Θ results in an increase in $\Pi(\phi^*)$, and because expected profits are strictly increasing in firm ability, this results in an increase in ϕ^*. Thus, because $\frac{\partial \Theta}{\partial \bar{p}_{x,k}} > 0$, liberalizing the rules of origin (i.e. reducing $\bar{p}_{x,k}$) reduces the zero-profit cutoff for firm ability. Intuitively, a relaxation of the rules of origin increases the expected profits from exporting to country j for all firms by reducing the prices they charge, and increasing the probability of drawing desirable enough product attributes in market j. Thus, lower ability firms are able to enter the export market.

Proposition 3: *Rules of origin liberalization results in an increase in the range of products that incumbent firms export to country j.*

To see this, the zero-profit condition for product attributes of a firm with productivity ϕ and the same cutoff for a firm of ability ϕ^* can be expressed as:

$$\begin{aligned} \lambda_{jk}^{MFN}(\phi) &= \frac{\phi^*}{\phi}\lambda_{jk}^{MFN}(\phi^*) \\ \lambda_{jk}^{PTA}(\phi) &= \frac{\phi^*}{\phi}\lambda_{jk}^{PTA}(\phi^*) \end{aligned} \tag{A.29}$$

The fall in ϕ^* that results from the rules of origin liberalization decreases the zero profit cutoffs for product attributes for incumbent firms. Lower values of ϕ^* mean the average rival's products are less attractive, thus product market competition falls. Since the terms $\lambda_{jk}^{PTA}(\phi^*)$ and $\lambda_{jk}^{MFN}(\phi^*)$ are implicitly defined as fuctions of the fixed costs and elasticity of substitution, as show in equation

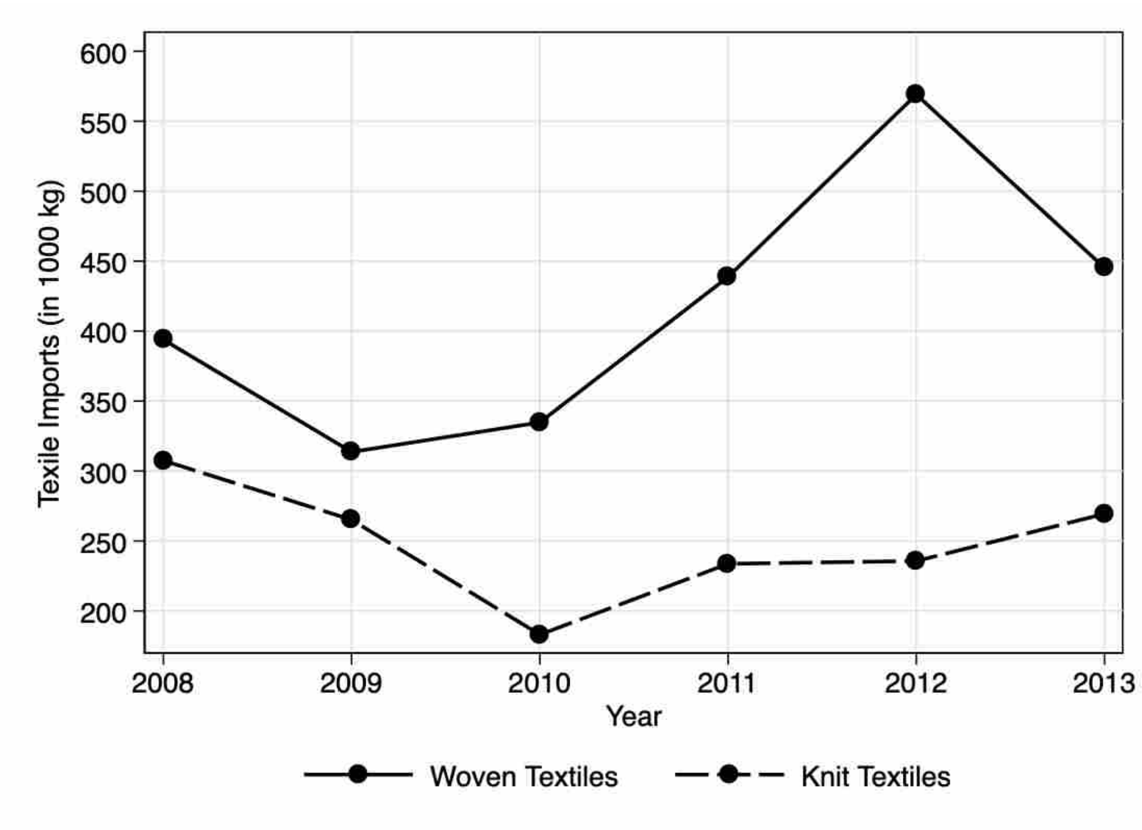
(17), they are independent of ϕ^*. As $\lambda_{jk}^{MFN}(\phi)$ falls, some products that were not profitable to export prior to the rules of origin change become profitable to export. Similarly, as $\lambda_{jk}^{PTA}(\phi)$ falls, the firm is able to export a wider range of its products using the rules of origin.

Proposition 4: *Rules of origin liberalization results in an increase in product-level revenue for products sold under the PTA for incumbent firms, but does not change the product-level revenue for firms exporting without invoking the rules of origin.*

This can be seen directly from the firm-product level revenue functions. A reduction in $\bar{p}_{x,k}$ increases the revenue for firms exporting product k under the rules of origin because $\sigma > 1$. For firms exporting k without invoking the rules of origin, a change in $\bar{p}_{x,k}$ has no effect on revenue. Higher productivity firms will export product k using the rules of origin, thus product-level revenue should increase more for high productivity firms. The increase in product-level revenue for high ability firms outweighs the lack of change in product-level revenue for low ability exporters, thus the average product-level revenue for incumbent exporters will increase.

A2 Additional Tables and Figures

FIGURE A2. Imports of Textiles in Bangladesh



Note: This figure displays trends in import quantity (measured by weight) of textiles into Bangladesh. The data are from the CompuStat database. Woven textiles are indicated with the solid line and knit textiles are indicated with the dashed line.

TABLE A1. Dynamic Responses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Export Revenue			Product Scope			Firms		
	Woven DD	Knit DD	DDD	Woven DD	Knit DD	DDD	Woven DD	Knit DD	DDD
$EU_j * WOVEN_k * (YEAR_t = 2008)$			-0.02			0.011			-0.052
			(0.076)			(0.040)			(0.041)
$EU_j * WOVEN_k * (YEAR_t = 2009)$			-0.02			0.015			-0.004
			(0.045)			(0.030)			(0.022)
$EU_j * WOVEN_k * (YEAR_t = 2011)$			0.04			0.048*			0.037
			(0.050)			(0.025)			(0.029)
$EU_j * WOVEN_k * (YEAR_t = 2012)$			0.23***			0.078**			0.062**
			(0.064)			(0.033)			(0.028)
$EU_j * WOVEN_k * (YEAR_t = 2013)$			0.17***			0.159***			0.057*
			(0.059)			(0.048)			(0.031)
$EU_j * (YEAR_t = 2008)$	0.03	0.05		0.135***	0.124***		0.116***	0.169***	
	(0.051)	(0.057)		(0.033)	(0.027)		(0.018)	(0.037)	
$EU_j * (YEAR_t = 2009)$	0.05	0.07**		0.040*	0.025		0.043***	0.047***	
	(0.032)	(0.032)		(0.023)	(0.021)		(0.015)	(0.016)	
$EU_j * (YEAR_t = 2011)$	0.09**	0.05*		-0.001	-0.048***		0.004	-0.033***	
	(0.042)	(0.028)		(0.020)	(0.018)		(0.027)	(0.010)	
$EU_j * (YEAR_t = 2012)$	0.18***	-0.05		-0.059**	-0.136***		-0.070***	-0.133***	
	(0.050)	(0.040)		(0.026)	(0.022)		(0.024)	(0.014)	
$EU_j * (YEAR_t = 2013)$	0.22***	0.05*		-0.075**	-0.234***		-0.106***	-0.164***	
	(0.052)	(0.029)		(0.036)	(0.034)		(0.026)	(0.018)	
Constant	15.74***	15.60***	15.67***	2.452***	2.248***	2.310***	6.226***	6.888***	6.586***
	(0.014)	(0.009)	(0.007)	(0.006)	(0.007)	(0.003)	(0.006)	(0.007)	(0.004)
Observations	60,122	76,689	136,811	14,676	22,105	36,781	1,349	1,268	2,617
Firm-HS8 FE	x	x	x						
Firm-Dest FE				x	x	x			
Dest-HS8 FE							x	x	x
Dest-Year FE	x	x	x	x	x	x	x	x	x
HS2-Year FE	x	x	x	x	x	x	x	x	x
Dest-HS2 FE	x	x	x	x	x	x	x	x	x
Errors Cluster	HS8	HS8	HS8	Firm	Firm	Firm	HS8	HS8	HS8

Note: This table presents the results from estimating the woven and knit difference-in-difference (DD) specifications for each margin, as well as the triple-difference (DDD) for each margin. The point estimates of the woven DD and knit DD are displayed in the top panels of Figures 6, 7, and 8, and the DDD estimates are shown graphically in the bottom panel of the figures.

TABLE A2. Total Market Share Reallocation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Total Enter	Dest. Adders	Prod. Adders	Brand New	Total Exit	Prod Droppers	Dest Droppers	Complete Exit	Net Entry	Incumbent
Quantity Share										
$EU_j * WOVEN_k * POST_t$	0.13***	0.00	0.10***	0.03	-0.10***	-0.06	0.00	-0.04*	0.03	-0.03
	(0.033)	(0.003)	(0.033)	(0.024)	(0.035)	(0.037)	(0.002)	(0.021)	(0.032)	(0.032)
Constant	0.30***	0.00*	0.19***	0.11***	0.32***	0.27***	0.00***	0.05***	0.62***	0.38***
	(0.009)	(0.000)	(0.009)	(0.005)	(0.010)	(0.010)	(0.000)	(0.005)	(0.016)	(0.016)
Observations	2,577	2,577	2,577	2,577	2,577	2,577	2,577	2,577	2,577	2,577
R-squared	0.663	0.005	0.466	0.241	0.603	0.525	0.004	0.114	0.014	0.014
Value Share										
$EU_j * WOVEN_k * POST_t$	0.12***	0.00	0.11***	0.01	-0.09***	-0.06	0.00	-0.03*	0.027	-0.027
	(0.032)	(0.003)	(0.033)	(0.022)	(0.034)	(0.036)	(0.002)	(0.020)	(0.032)	(0.032)
Constant	0.29***	0.00**	0.19***	0.10***	0.31***	0.27***	0.00***	0.05***	0.61***	0.39***
	(0.009)	(0.000)	(0.009)	(0.005)	(0.010)	(0.010)	(0.000)	(0.004)	(0.017)	(0.017)
Observations	2,577	2,577	2,577	2,577	2,577	2,577	2,577	2,577	2,577	2,577
R-squared	0.644	0.005	0.455	0.231	0.582	0.511	0.005	0.107	0.013	0.013

*** p<0.01, ** p<0.05, * p<0.1

Note: This table displays the results of estimating the regression model laid out in equation (16).

TABLE A3. Incumbent Market Share Change

	(1) Quartile 1	(2) Quartile 2	(3) Quartile 3	(4) Quartile 4
Quantity Share				
$EU_j * WOVEN_k * POST_t$	0.02	-0.04	-0.07*	0.09**
	(0.032)	(0.033)	(0.039)	(0.041)
Constant	0.15***	0.18***	0.27***	0.40***
	(0.014)	(0.014)	(0.015)	(0.019)
Observations	21,939	21,939	21,939	21,939
R-squared	0.036	0.013	0.003	0.033
Value Share				
$EU_j * WOVEN_k * POST_t$	0.01	-0.03	-0.07*	0.09**
	(0.029)	(0.032)	(0.039)	(0.039)
Constant	0.14***	0.18***	0.26***	0.42***
	(0.014)	(0.015)	(0.015)	(0.019)
Observations	1,939	1,939	1,939	1,939
R-squared	0.030	0.015	0.002	0.025

This table displays the results of estimating the regression model laid out in equation (16) for each quartile of firm productivity, measured by number of products sold. Errors allow for clustering at the product-level.

APPENDIX B

APPENDIX FOR CHAPTER 2

B1 Additional Tables and Figures

TABLE B1. Monthly Averages by Port

Port	log(exports)	wind	hurricane climate quintile
Albany	17.20131	0.8388381	2
Alexandria Bay	19.93169	0.6859769	2
Annapolis	13.6074	1.365101	3
Baltimore	20.79946	1.29553	3
Bangor	17.89856	1.004414	2
Baton Rouge	19.23846	1.761013	4
Beaumont	19.27963	1.754932	4
Birmingham	12.8052	1.095344	3
Boston	18.45465	1.14908	3
Brunswick	18.94229	1.85274	4
Buffalo	21.93616	0.6799816	1
Calais	18.21979	1.045205	2
Champlain-Rouses	20.45644	0.6962099	2
Charleston	21.25035	1.948115	4
Chattanooga	12.03405	0.8504208	2
Chicago	21.77064	0.3298515	1
Cincinnati	19.24793	0.6400509	1
Cleveland	21.15142	0.6362604	1
Corpus Christi	19.84956	1.28419	3
Crisfield	14.42603	1.222473	3
Dallas-Fort Wort	21.10103	0.7530294	2
Detroit	22.54031	0.5531176	1
Duluth	16.85369	0	1
Durham	17.30638	1.612546	4
Eastport	16.54776	1.045205	2
Fort Pierce	15.18885	2.405482	5
Freeport	18.69063	1.587227	3
Galveston	18.69793	1.705415	4
Gramercy	20.27636	1.96511	5
Gulfport	18.29631	1.903062	4
Houston	22.29336	1.530683	3
Indianapolis	17.94848	0.5926813	1
Jacksonville	20.31716	1.970891	5
Key West	14.48015	2.009889	5
Lake Charles	18.93357	1.695209	4
Louisville	17.94035	0.6599665	1
Memphis	18.8341	0.7221258	2
Miami	20.5261	2.126832	5
Milwaukee	15.50878	0.2692804	1
Minneapolis	18.84541	0	1
Mobile	19.17812	1.816498	4
Nashville	16.67976	0.7163472	2
New Orleans	21.98254	2.064237	5
New York	21.67811	1.257715	3
Newark	20.77479	1.227784	3
Newport News	16.92774	2.106913	5
Norfolk-Newport	21.25	2.058256	5
Ogdensburg	16.83582	0.6598525	1
Orlando	17.88129	2.231504	5
Owensboro	11.76208	0.6680749	1
Panama City	17.37863	1.678284	4
Pascagoula	18.84136	1.859909	4
Perth Amboy	16.52191	1.298945	3
Port Arthur	19.01382	1.769221	4
Port Canaveral	15.99246	2.274203	5
Port Everglades	20.47385	2.212663	5
Port Huron	21.8126	0.549471	1
Port Lavaca	17.11367	1.427843	3
Portland	15.60277	1.000197	2
Portsmouth	16.39185	1.039657	2
Providence	15.96998	1.173563	3
Rochester	14.86119	0.7019463	2
San Antonio	17.12203	0.9306885	2
Savannah	21.23123	1.760068	4
Tampa	19.13794	2.069941	5
Texas City	19.49174	1.705415	4
Toledo	17.96567	0.5711506	1
Tulsa	14.45684	0.4880415	1
Washington	19.77979	1.331695	3
West Palm Beach	18.5011	2.361719	5
Wilmington	18.94336	2.36558	5

TABLE B2. Main Results

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	Dependent: $ln(X_{pt})$			
	(1)	(2)	(3)	(4)
			Cumulative Effect	Cumulative Effect
$wind_{kmy+8}$	0.114 (0.176)	0.114 (0.197)	0.114 (0.176)	0.114 (0.197)
$wind_{kmy+7}$	−0.128 (0.194)	−0.128 (0.204)	−0.014 (0.262)	−0.014 (0.283)
$wind_{kmy+6}$	−0.048 (0.198)	−0.048 (0.174)	−0.062 (0.328)	−0.062 (0.333)
$wind_{kmy+5}$	−0.324 (0.198)	−0.324 (0.214)	−0.386 (0.383)	−0.386 (0.396)
$wind_{kmy+4}$	0.008 (0.200)	0.008 (0.193)	−0.378 (0.432)	−0.378 (0.440)
$wind_{kmy+3}$	0.038 (0.199)	0.038 (0.234)	−0.340 (0.476)	−0.340 (0.499)
$wind_{kmy+2}$	−0.088 (0.199)	−0.088 (0.261)	−0.428 (0.516)	−0.428 (0.563)
$wind_{kmy+1}$	0.125 (0.202)	0.125 (0.222)	−0.303 (0.554)	−0.303 (0.605)
$wind_{kmy}$	−0.268 (0.202)	−0.268 (0.228)	−0.571 (0.590)	−0.571 (0.647)
$wind_{kmy-1}$	−0.566*** (0.202)	−0.566** (0.255)	−1.137* (0.623)	−1.137 (0.695)
$wind_{kmy-2}$	−0.509** (0.201)	−0.509** (0.210)	−1.646** (0.655)	−1.646** (0.726)
$wind_{kmy-3}$	−0.599*** (0.190)	−0.599*** (0.190)	−2.245*** (0.682)	−2.245*** (0.751)
$wind_{kmy-4}$	−0.467** (0.193)	−0.467** (0.200)	−2.712*** (0.709)	−2.712*** (0.777)
$wind_{kmy-5}$	−0.667*** (0.194)	−0.667*** (0.189)	−3.379*** (0.735)	−3.379*** (0.799)
$wind_{kmy-6}$	−0.392** (0.193)	−0.392** (0.180)	−3.772*** (0.760)	−3.772*** (0.819)
$wind_{kmy-7}$	−0.348* (0.189)	−0.348** (0.171)	−4.120*** (0.783)	−4.120*** (0.837)
$wind_{kmy-8}$	−0.522*** (0.194)	−0.522*** (0.166)	−4.642*** (0.807)	−4.642*** (0.853)
$wind_{kmy-9}$	−0.584*** (0.195)	−0.584*** (0.210)	−5.226*** (0.830)	−5.226*** (0.879)
$wind_{kmy-10}$	−0.366* (0.197)	−0.366** (0.168)	−5.592*** (0.853)	−5.592*** (0.895)
$wind_{kmy-11}$	−0.329* (0.199)	−0.329 (0.231)	−5.920*** (0.876)	−5.920*** (0.924)
$wind_{kmy-12}$	−0.567*** (0.196)	−0.567*** (0.216)	−6.487*** (0.898)	−6.487*** (0.949)
$wind_{kmy-13}$	−0.323* (0.193)	−0.323* (0.194)	−6.810*** (0.918)	−6.810*** (0.968)
$wind_{kmy-14}$	−0.351* (0.192)	−0.351 (0.214)	−7.161*** (0.938)	−7.161*** (0.992)
$wind_{kmy-15}$	−0.486*** (0.181)	−0.486** (0.201)	−7.647*** (0.955)	−7.647*** (1.012)
$wind_{kmy-16}$	−0.209 (0.170)	−0.209 (0.167)	−7.856*** (0.970)	−7.856*** (1.026)
$wind_{kmy-17}$	−0.394** (0.159)	−0.394*** (0.152)	−8.249*** (0.983)	−8.249*** (1.037)
$wind_{kmy-18}$	−0.495*** (0.154)	−0.495*** (0.138)	−8.744*** (0.995)	−8.744*** (1.046)
$wind_{kmy-19}$	−0.293* (0.150)	−0.293** (0.134)	−9.037*** (1.006)	−9.037*** (1.055)
$wind_{kmy-20}$	−0.305** (0.153)	−0.305** (0.142)	−9.342*** (1.018)	−9.342*** (1.064)
$wind_{kmy-21}$	−0.226 (0.152)	−0.226* (0.133)	−9.567*** (1.029)	−9.567*** (1.073)
$wind_{kmy-22}$	−0.118 (0.151)	−0.118 (0.107)	−9.686*** (1.040)	−9.686*** (1.078)
$wind_{kmy-23}$	−0.111 (0.154)	−0.111 (0.147)	−9.797*** (1.052)	−9.797*** (1.088)
$wind_{kmy-24}$	−0.014 (0.157)	−0.014 (0.126)	−9.811*** (1.063)	−9.811*** (1.095)
N	8,444	8,444	8,444	8,444
R^2	0.011	0.011	0.011	0.011
errors	port	sHAC(300,12)	port	sHAC(300,12)
	All columns control for port-month and port-year fixed effects			

Note: The table presents the results of estimating equation 2, in text. The variable "wind" controls for the maximum sustained wind speed from a hurricane experienced at a port in a given month. The dependent variable is the log of total port level exports. Columns 3 and 4 display the cumulative effect. Errors allow for clustering at the port level in columns 1 and 3. Errors allow for spatial clustering up to 300 miles and autocorrelation over 12 months in columns 2 and 4.

TABLE B3. Bilateral Results

.

	(1)	(2)	(3)	(4)
VARIABLES	coef	se	coef	se
$wind_{kmy+8}$	0.001	(0.0006)	-0.001	(0.0007)
$wind_{kmy+7}$	-0.001	(0.0010)	-0.001	(0.0005)
$wind_{kmy+6}$	-0.000	(0.0009)	-0.001	(0.0009)
$wind_{kmy+5}$	0.000	(0.0009)	-0.001	(0.0007)
$wind_{kmy+4}$	-0.000	(0.0006)	-0.001	(0.0006)
$wind_{kmy+3}$	-0.000	(0.0006)	-0.000	(0.0005)
$wind_{kmy+2}$	-0.001	(0.0008)	0.001*	(0.0005)
$wind_{kmy+1}$	0.001	(0.0008)	0.000	(0.0008)
$wind_{kmy}$	-0.002**	(0.0008)	-0.002**	(0.0008)
$wind_{kmy-1}$	-0.002***	(0.0008)	-0.002**	(0.0011)
$wind_{kmy-2}$	-0.003**	(0.0012)	-0.003***	(0.0010)
$wind_{kmy-3}$	-0.004***	(0.0010)	-0.004***	(0.0009)
$wind_{kmy-4}$	-0.003***	(0.0010)	-0.004***	(0.0010)
$wind_{kmy-5}$	-0.003***	(0.0010)	-0.003***	(0.0009)
$wind_{kmy-6}$	-0.003***	(0.0011)	-0.003***	(0.0007)
$wind_{kmy-7}$	-0.004***	(0.0009)	-0.003***	(0.0008)
$wind_{kmy-8}$	-0.004***	(0.0011)	-0.003***	(0.0008)
$wind_{kmy-9}$	-0.003***	(0.0010)	-0.002***	(0.0007)
$wind_{kmy-10}$	-0.003***	(0.0008)	-0.002***	(0.0006)
$wind_{kmy-11}$	-0.003***	(0.0009)	-0.002***	(0.0007)
$wind_{kmy-12}$	-0.003***	(0.0009)	-0.002***	(0.0007)
$wind_{kmy-13}$	-0.003***	(0.0009)	-0.002***	(0.0007)
$wind_{kmy-14}$	-0.001	(0.0010)	-0.001**	(0.0007)
$wind_{kmy-15}$	-0.001	(0.0011)	-0.001	(0.0008)
$wind_{kmy-16}$	-0.001	(0.0011)	-0.002***	(0.0008)
$wind_{kmy-17}$	-0.002**	(0.0007)	-0.002***	(0.0006)
$wind_{kmy-18}$	-0.004***	(0.0008)	-0.002***	(0.0005)
$wind_{kmy-19}$	-0.002***	(0.0007)	-0.002***	(0.0005)
$wind_{kmy-20}$	-0.001	(0.0006)	-0.001***	(0.0005)
$wind_{kmy-12}$	-0.002***	(0.0004)	-0.001**	(0.0005)
$wind_{kmy-22}$	-0.001*	(0.0005)	-0.001*	(0.0004)
$wind_{kmy-23}$	-0.002***	(0.0005)	-0.002***	(0.0005)
$wind_{kmy-24}$	-0.000	(0.0006)	-0.001	(0.0004)
Constant	14.726***	(0.0204)	19.241***	(0.0159)
Observations	252,069		252,069	
r2_within	0.00161		.	

Note: The table presents the results of estimating equation 2, in text. The variable "wind" controls for the maximum sustained wind speed from a hurricane experienced at a port in a given month. The dependent variable is the log of total port level exports. Columns 3 and 4 display the cumulative effect. Errors allow for clustering at the port level in columns 1 and 3. Errors allow for spatial clustering up to 300 miles and autocorrelation over 12 months in columns 2 and 4.

TABLE B4. Response by hurricane climate percentile

	(1)	(2)	(3)	(4)	(5)
$wind_{kt} * (PCT = 1)$	-0.002	-0.001	-0.003	-0.003	-0.003
	(0.0028)	(0.0028)	(0.0037)	(0.0039)	(0.0039)
$wind_{kt} * (PCT = 2)$	-0.001	-0.000	-0.002	-0.003	-0.004
	(0.0074)	(0.0083)	(0.0083)	(0.0083)	(0.0083)
$wind_{kt} * (PCT = 3)$	0.002	0.000	0.001	0.001	0.001
	(0.0037)	(0.0021)	(0.0028)	(0.0029)	(0.0029)
$wind_{kt} * (PCT = 4)$	0.000	0.000	-0.001	-0.001	-0.002
	(0.0024)	(0.0025)	(0.0025)	(0.0026)	(0.0027)
$wind_{kt-1} * (PCT = 1)$		-0.010**	-0.010**	-0.010**	-0.010**
		(0.0041)	(0.0042)	(0.0043)	(0.0042)
$wind_{kt-1} * (PCT = 2)$		0.005	0.003	0.002	0.000
		(0.0042)	(0.0041)	(0.0037)	(0.0039)
$wind_{kt-1} * (PCT = 3)$		-0.009**	-0.009**	-0.009**	-0.009**
		(0.0038)	(0.0039)	(0.0038)	(0.0038)
$wind_{kt-1} * (PCT = 4)$		-0.003	-0.003	-0.004	-0.004
		(0.0024)	(0.0025)	(0.0027)	(0.0028)
$wind_{kt-2} * (PCT = 1)$			-0.003	-0.003	-0.003
			(0.0063)	(0.0062)	(0.0062)
$wind_{kt-2} * (PCT = 2)$			-0.015**	-0.015**	-0.017**
			(0.0063)	(0.0064)	(0.0068)
$wind_{kt-2} * (PCT = 3)$			-0.005**	-0.005**	-0.005**
			(0.0022)	(0.0022)	(0.0023)
$wind_{kt-2} * (PCT = 4)$			-0.006**	-0.006**	-0.006**
			(0.0025)	(0.0025)	(0.0025)
$wind_{kt-3} * (PCT = 1)$			-0.011	-0.011	-0.011
			(0.0077)	(0.0073)	(0.0073)
$wind_{kt-3} * (PCT = 2)$			-0.009	-0.009	-0.010
			(0.0074)	(0.0070)	(0.0074)
$wind_{kt-3} * (PCT = 3)$			-0.001	-0.001	-0.001
			(0.0030)	(0.0030)	(0.0031)
$wind_{kt-3} * (PCT = 4)$			-0.008**	-0.008**	-0.008**
			(0.0031)	(0.0030)	(0.0030)
$wind_{kt-4} * (PCT = 1)$				-0.001	-0.001
				(0.0044)	(0.0043)
$wind_{kt-4} * (PCT = 2)$				-0.015***	-0.017***
				(0.0052)	(0.0050)
$wind_{kt-4} * (PCT = 3)$				0.002	0.002
				(0.0017)	(0.0018)
$wind_{kt-4} * (PCT = 4)$				-0.002	-0.002
				(0.0035)	(0.0035)
$wind_{kt-5} * (PCT = 1)$					0.005
					(0.0058)
$wind_{kt-5} * (PCT = 2)$					-0.011
					(0.0101)
$wind_{kt-5} * (PCT = 3)$					0.001
					(0.0022)
$wind_{kt-5} * (PCT = 4)$					-0.003
					(0.0025)
Constant	18.853***	18.889***	18.929***	18.940***	18.952***
	(0.0018)	(0.0023)	(0.0037)	(0.0045)	(0.0055)
Observations	9,496	9,403	9,255	9,190	9,126
r2_within	0.000138	0.00190	0.00542	0.00668	0.00816

Note: This table displays the results of estimating equation (10) for ports in different hurricane climate percentiles. The omitted category are ports in the fifth percentile. The results are all relative to the effects at ports in the fifth (highest) percentile, which are estimated but not shown in the table. If multiplied by 100, the coefficients can be interpreted as semi-elasticities. All columns contain port-month and port-year fixed effects. All columns allow for errors clustering at the port level.

TABLE B5. Response of Mineral Products

	(1) Salt, Sulfur, Stone	(2) Ores	(3) Mineral Fuel, Oil
$wind_{kmy}$	0.0005	-0.0028	-0.0051***
	(0.0009)	(0.0049)	(0.0010)
$wind_{kmy-1}$	-0.0005	0.0041	-0.0060***
	(0.0010)	(0.0037)	(0.0012)
$wind_{kmy-2}$	-0.0002	-0.0012	-0.0042**
	(0.0007)	(0.0046)	(0.0019)
$wind_{kmy-3}$	-0.0042***	0.0024	-0.0036***
	(0.0006)	(0.0060)	(0.0012)
$wind_{kmy-4}$	-0.0042**	0.0043	-0.0046*
	(0.0021)	(0.0052)	(0.0026)
$wind_{kmy-5}$	-0.0009	0.0118	-0.0050**
	(0.0010)	(0.0091)	(0.0021)
Constant	16.4904***	16.8614***	20.1057***
	(0.0054)	(0.0255)	(0.0069)
Observations	3,753	2,274	5,634

Note: This table displays the results of estimating equation (11) for products in the minerals category, estimated using PPML. All columns contain port-product-month and port-product-year fixed effects. All columns allow for errors clustering at the port level.

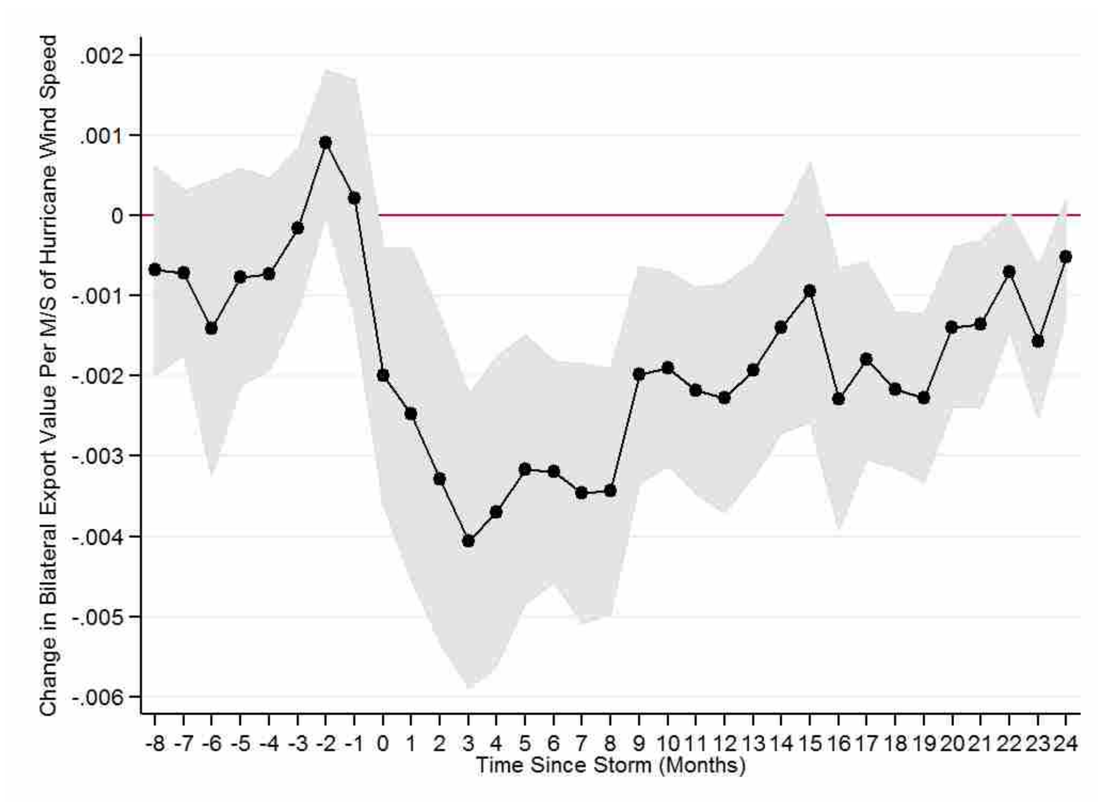
TABLE B6. Response of Neighbor Port

. 3

	Dependent: $ln(export_{pt})$				
	(Own)	(Neighbor)	(Cumulative Own)	(Cumulative Neighbor)	(Cumulative Diff)
$wind_{kmy+8}$	0.77 (0.78)	−0.67 (0.76)	0.77 (0.78)	−0.67 (0.76)	0.10 (1.09)
$wind_{kmy+7}$	0.64 (0.97)	−0.79 (0.95)	1.41 (1.24)	−1.46 (1.22)	−0.05 (1.74)
$wind_{kmy+6}$	0.49 (1.05)	−0.53 (1.07)	1.91 (1.63)	−2.00 (1.62)	−0.09 (2.30)
$wind_{kmy+5}$	0.01 (1.11)	−0.32 (1.10)	1.91 (1.97)	−2.31 (1.96)	−0.40 (2.78)
$wind_{kmy+4}$	0.85 (1.02)	−0.88 (1.01)	2.76 (2.22)	−3.19 (2.20)	−0.42 (3.13)
$wind_{kmy+3}$	0.86 (1.21)	−0.84 (1.13)	3.62 (2.53)	−4.03 (2.47)	−0.41 (3.54)
$wind_{kmy+2}$	−0.03 (1.08)	−0.02 (1.06)	3.59 (2.75)	−4.06 (2.69)	−0.47 (3.85)
$wind_{kmy+1}$	0.72 (1.09)	−0.61 (1.07)	4.31 (2.96)	−4.66 (2.90)	−0.35 (4.14)
$wind_{kmy}$	1.84 (1.17)	−2.14* (1.14)	6.15* (3.18)	−6.80** (3.11)	−0.65 (4.45)
$wind_{kmy-1}$	0.18 (1.01)	−0.73 (0.95)	6.33* (3.34)	−7.54** (3.26)	−1.20 (4.66)
$wind_{kmy-2}$	−0.07 (0.97)	−0.48 (0.94)	6.27* (3.48)	−8.02** (3.39)	−1.75 (4.85)
$wind_{kmy-3}$	−1.07 (0.96)	0.45 (0.93)	5.20 (3.61)	−7.57** (3.51)	−2.37 (5.03)
$wind_{kmy-4}$	−1.41* (0.83)	0.94 (0.81)	3.79 (3.70)	−6.63* (3.60)	−2.85 (5.17)
$wind_{kmy-5}$	−1.79** (0.71)	1.12 (0.70)	2.00 (3.77)	−5.52 (3.67)	−3.52 (5.26)
$wind_{kmy-6}$	−1.67** (0.75)	1.29* (0.70)	0.32 (3.84)	−4.23 (3.74)	−3.91 (5.36)
$wind_{kmy-7}$	−1.66** (0.65)	1.32** (0.65)	−1.33 (3.90)	−2.91 (3.79)	−4.24 (5.44)
$wind_{kmy-8}$	−1.92*** (0.69)	1.39** (0.66)	−3.25 (3.96)	−1.53 (3.85)	−4.78 (5.52)
$wind_{kmy-9}$	−2.19*** (0.74)	1.59** (0.71)	−5.44 (4.03)	0.07 (3.92)	−5.37 (5.62)
$wind_{kmy-10}$	−2.36*** (0.81)	1.99*** (0.77)	−7.80* (4.11)	2.06 (3.99)	−5.74 (5.73)
$wind_{kmy-11}$	−1.55** (0.72)	1.21* (0.70)	−9.34** (4.17)	3.27 (4.05)	−6.07 (5.81)
$wind_{kmy-12}$	−3.21*** (0.90)	2.65*** (0.87)	−12.55*** (4.26)	5.91 (4.14)	−6.63 (5.95)
$wind_{kmy-13}$	−2.09** (0.83)	1.73** (0.82)	−14.64*** (4.34)	7.65* (4.22)	−6.99 (6.06)
$wind_{kmy-14}$	−2.16** (0.94)	1.78** (0.90)	−16.80*** (4.44)	9.43** (4.32)	−7.37 (6.20)
$wind_{kmy-15}$	−1.41* (0.84)	0.89 (0.81)	−18.21*** (4.52)	10.32** (4.39)	−7.89 (6.31)
$wind_{kmy-16}$	−0.40 (0.72)	0.19 (0.70)	−18.61*** (4.58)	10.51** (4.45)	−8.10 (6.39)
$wind_{kmy-17}$	−0.45 (0.54)	0.09 (0.52)	−19.06*** (4.61)	10.60** (4.48)	−8.46 (6.43)
$wind_{kmy-18}$	−1.07** (0.54)	0.60 (0.54)	−20.13*** (4.64)	11.20** (4.51)	−8.94 (6.47)
$wind_{kmy-19}$	−0.63 (0.51)	0.36 (0.49)	−20.77*** (4.67)	11.56** (4.54)	−9.21 (6.51)
$wind_{kmy-20}$	−0.30 (0.45)	−0.01 (0.43)	−21.07*** (4.69)	11.54** (4.56)	−9.52 (6.54)
$wind_{kmy-21}$	0.01 (0.45)	−0.24 (0.44)	−21.06*** (4.71)	11.30** (4.58)	−9.75 (6.57)
$wind_{kmy-22}$	−0.52 (0.49)	0.43 (0.48)	−21.57*** (4.74)	11.73** (4.61)	−9.84 (6.61)
$wind_{kmy-23}$	0.27 (0.40)	−0.38 (0.40)	−21.30*** (4.76)	11.35** (4.62)	−9.95 (6.63)
$wind_{kmy-24}$	0.62 (0.45)	−0.63 (0.44)	−20.69*** (4.78)	10.72** (4.64)	−9.97 (6.66)
N	8,444	8,444	8,444	8,444	8,444

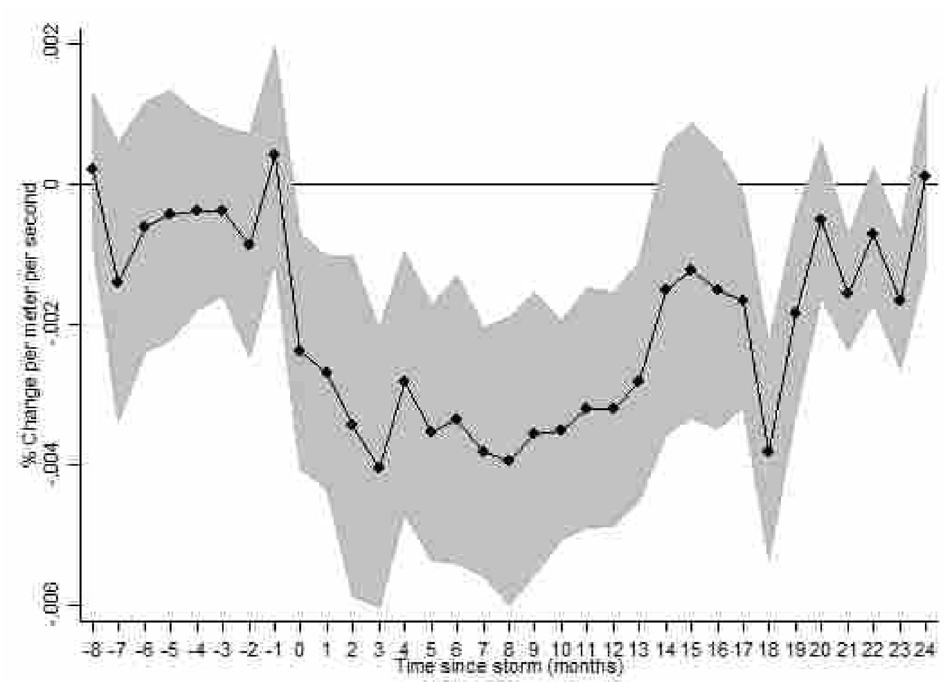
Note: This table displays the results of estimating equation (11). If multiplied by 100 the coefficients can be interpreted as partial elasticities. Columns 1 and 2 of the table correspond to the same regression, they are only broken apart for viewing ease. All columns control for port-month and port-year fixed effects. Errors in all columns allow for spatial clustering up to 300 miles and over 12 months and are in parentheses.

FIGURE B1. PPML Estimation



Note: This figure displays the results of estimating equation (10) in the text using psudo-poisson maximum likelihood estimation. Errors allow for clustering at the port-level.

FIGURE B2. Atlantic Basin Importers Excluded



Note: This figure displays the results of estimating equation (10) in the text excluding Atlantic basin importers from the sample.

APPENDIX C

APPENDIX FOR CHAPTER 3

C1 Spatial Spillovers

A potential concern with the estimates in Table 16 involves the spillover effect of hurricane wind speed across ports. In equation (11), I show that the exporter-importer-year fixed effect controls for the weighted sum of exporter-port-importer trade frictions, a method which is consistent if τ_{ijt}^{k} is uncorrelated with τ_{ijt}^{m} $\forall m \neq k$. This fixed effect is similar to the multilateral resistance terms of Anderson and Van Wincoop (2003). In the case of hurricanes, the share of exports from port k is likely affected by the wind speed experienced at neighboring port $m \neq k$. Thus, excluding the hurricane wind speed at surrounding ports from equation (16) potentially results in an biased estimate of η_1. Rather than omitting ports around port k and estimating equation (12) using a new sample, it is more informative to examine the spillover effects directly using a spatially weighted regressor. Including a weighted average of hurricane wind speeds around port k can provide insight into how substitutable ports are for each other. If ports are relatively good substitutes, an increase in wind speed at surrounding ports may lead to an increase in the export share from port k.

Using equation (11), it is possible to derive an equation that explains the trade share of exports from i to j though k as a function of wind speeds across all other ports k. Following Behrens et al., (2012), I linearize equation (10) around $\sigma = 1$, which results in the following expression:

$$
\begin{aligned}
ln\frac{X_{ijt}^{k}}{X_{ijt}} \approx -ln[n(k)] + \sum_{k} ln(\delta_{ijt}^{k})^{\rho_2(\sigma-1)} + (1-\sigma)\rho_1 wind_t^k + \\
(\sigma-1)\rho_{1.1}\frac{\sum_{k'\neq k} wind_t^{k'}}{n(k)} + ln(\delta_{ijt}^{k})^{\rho_2(1-\sigma)}
\end{aligned} \tag{C.1}
$$

where $n(k)$ is the cardinality of the set of ports. Given this expression, the term $\frac{\sum_{k'\neq k} wind_t^{k'}}{n(k)}$ can be thought of as the average hurricane wind speeds across all ports k'. Thus, the hurricane intensity at ports surrounding port k may influence the export share though port k in a way that is theoretically consistent.

To examine the relationship between hurricane wind speed at ports surrounding port k, and the share of exports through port k, I construct a weighting matrix that allows me to include a weighted average of hurricane intensity at ports surrounding k as a control variable in equation (12). I use an inverse-distance weighting matrix, that takes the following form:

$$
\begin{aligned}
w_{k,m} = \frac{1}{d_{k,m}} \qquad \text{if } \; d_{k,m} \in (\Delta_L, \Delta_H); \\
w_{k,m} = 0 \quad \text{ otherwise}
\end{aligned} \tag{C.2}
$$

where the entry in the weighting matrix associated with ports k and m is a function of the distance between the ports ($d_{k,m}$), and an upper Δ_H, and lower Δ_L bound, above and below which weights are zero. Weights across the diagonal (i.e., where $k = m$) are also set to zero so that the $wind_t^k$ variable can be separately included. This weighting matrix allows me to flexibly examine how trade is diverted around affected ports. I shift the interval (Δ_L, Δ_H) by five mile increments, and estimate estimate equation (16) as follows:

$$\ln(X^k_{ijt}/X_{ijt}) = \alpha_{ijt} + \nu^k + \eta_1 wind^k_t + WX_t\Gamma + \epsilon^k_{ijt} \tag{C.3}$$

where W is the weighting matrix, X is the vector of port-level hurricane wind speeds, and Γ is the coefficient. Here, as in equation (12), α_{ijt} is an exporter-importer-year fixed effect, and ν^k is a port fixed effect. When estimating equation (18) I allow for clustering of the errors at the state-of-exit level to roughly account for spatial autocorrelation across ports within a geographic region. The results of this estimation are presented in Table C1. Each column of Table C1 uses a different cutoff value for (Δ_L, Δ_H), shown in the column title. The coefficient on port-level hurricane wind speed does not change from the preferred estimates in Table 16 by a statistically significant amount in any column. The results of this exercise indicate that the coefficient η_1 in equation (12) is not underestimated by a large amount. The coefficient on spatially weighted wind speed variable $(spatialWind^k_t)$ describes how the export share from port k responds to the spatially weighted average wind speed at ports around k, within the (Δ_L, Δ_H) range. I find evidence that an increase in the spatially weighted average wind speed at ports between 10-15 miles from port k result in an increase in port k's export share by roughly 9%. A similar result is found when examining the effect of average wind speeds at ports between 15-20 miles from port k. These results indicate that the "trade diversion" effect is made up for by ports within 20 miles from port k.

C2 Additional Tables and Figures

TABLE C1. Parameter Estimates

	Export Share					
(Δ_L, Δ_H)	(<5)	(5-10)	(10-15)	(15-20)	(20-25)	(>25)
$wind_t^k$	-0.007^{***}	-0.008^{***}	-0.009^{***}	-0.009^{***}	-0.007^{***}	-0.007^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$spatialWind_t^k$	$3.44e(-6)^{**}$	0.010	0.093^{***}	0.109^{**}	0.019	-0.006
	(1.62e(-6))	(0.014)	(0.030)	(0.045)	(0.036)	(0.018)
N	732,473	732,473	732,473	732,473	732,473	732,473
Adjusted R^2	0.460	0.460	0.460	0.460	0.460	0.460

Errors clustered at state-of-exit level in all columns
Port FE included in all columns
Exporter-importer-year FE included in all columns

Note: This table displays the results of estimating equation (18). Each column uses a different cutoff range for (Δ_L, Δ_H) from equation (17). The cutoff value is given in the column title. Each column includes exporter-port-importer fixed effects, and exporter-importer-year fixed effects. Errors allow for clustering at the state of exit level (i.e. the state in which the port of exit is located). The dependent variable in all specifications is the log share of exports from i to j in year t that exited through port k. The variable $wind_t^k$ is the hurricane wind speed (in meters per second) experienced at port k in year t. The variable V1 is the weighted average of hurricane wind speeds at ports surrounding port k in year t, with weights as defined in equation (17).

TABLE C2. Port-level Results using PPML Estimation

	Dependent: $(\frac{X^k_{ijt}}{X_{ijt}})$		
	(1)	(2)	(3)
$wind^k_{t-1}$		0.005	
		(0.004)	
$wind^k_t$	-0.014^{***}	-0.013^{***}	-0.013^{***}
	(0.003)	(0.003)	(0.003)
$wind^k_{t+1}$		0.002	
		(0.002)	
$(wind^k_t)^2$			-0.0009^{**}
			(0.0004)
N	732,427	337,429	732,427
Pseduo-R^2	0.59	0.61	0.59
exporter-importer-year FE	Y	Y	Y
port FE	Y	Y	Y

Note: This table displays the results of estimating a version of equation (12) using PPML estimation. Instead of taking the log of the export share, the equation is left in levels and estimated using Pseudo-Poisson Maximum Likelihood. All columns allow for errors to cluster at the state-of-exit level.

TABLE C4. Average Annual Compensating Variation

	Country	Compensating Variation
1	Albania	15035.74
2	Algeria	665347.24
3	Andorra	9777.91
4	Angola	337900.05
5	Antigua and Barbuda	90004.21
6	Argentina	4016259.52
7	Armenia	35400.20
8	Aruba	315972.46
9	Australia	4681595.63
10	Austria	1501505.29
11	Azerbaijan	100049.10
12	Bahrain	336217.90
13	Bangladesh	154670.89
14	Barbados	308197.19
15	Belarus	25986.99
16	Belgium	8873313.95
17	Belize	147604.74
18	Benin	46155.54
19	Bermuda	286425.74
20	Bhutan	308.70
21	Bolivia	260460.05
22	Botswana	14281.35
23	Brazil	13589601.60

24	British Virgin Islands	62780.01
25	Bulgaria	92824.81
26	Burundi	5694.48
27	Cambodia	5319.96
28	Cameroon	74410.97
29	Canada	76901087.85
30	Cayman Islands	274233.28
31	Central African Republic	6343.57
32	Chad	59808.26
33	Chile	2983509.54
34	China	8121057.52
35	Colombia	4576113.35
36	Comoros	354.96
37	Costa Rica	3815182.93
38	Croatia	84161.81
39	Cuba	218634.60
40	Cyprus	109475.81
41	Czech Republic	344021.82
42	Denmark	926659.29
43	Djibouti	35685.84
44	Dominica	47831.98
45	Dominican Republic	3936466.08
46	Ecuador	1461954.59
47	El Salvador	2128079.22
48	Equatorial Guinea	138170.60

49	Eritrea	28648.92
50	Estonia	92683.14
51	Ethiopia	101000.03
52	Faroe Islands	4514.85
53	Fiji	2872.95
54	Finland	883186.94
55	France	8415851.68
56	French Polynesia	20473.69
57	Gabon	62091.80
58	Georgia	141281.75
59	Ghana	188174.61
60	Gibraltar	38205.32
61	Greece	760595.60
62	Greenland	2983.72
63	Grenada	70600.85
64	Guatemala	2371303.50
65	Guinea	55132.73
66	Guinea-Bissau	1100.95
67	Guyana	148700.06
68	Haiti	686626.13
69	Honduras	3686940.03
70	Hungary	341044.90
71	Iceland	161656.50
72	India	2159875.00
73	Indonesia	1084930.27

74	Iraq	355257.31
75	Ireland	3431714.57
76	Israel	2315590.26
77	Italy	5057320.43
78	Jamaica	1379027.63
79	Japan	11122764.09
80	Jordan	321389.30
81	Kazakhstan	253940.61
82	Kenya	133410.12
83	Kiribati	861.18
84	Kuwait	1508640.47
85	Latvia	112620.98
86	Lebanon	439196.09
87	Lesotho	2297.15
88	Liberia	54159.46
89	Libya	43518.21
90	Liechtenstein	5983.59
91	Lithuania	126986.19
92	Luxembourg	198386.43
93	Madagascar	21106.32
94	Malawi	15236.55
95	Malaysia	2186941.92
96	Maldives	3094.48
97	Mali	20241.40
98	Malta	91065.73

99	Marshall Islands	312.01
100	Mauritania	30941.22
101	Mauritius	11309.52
102	Mexico	42220273.83
103	Moldova	26759.12
104	Monaco	9432.56
105	Mongolia	5480.99
106	Morocco	370137.91
107	Mozambique	62355.54
108	Namibia	35962.72
109	Nauru	722.30
110	Nepal	9077.61
111	Netherlands	10689784.47
112	New Caledonia	15745.81
113	New Zealand	555821.65
114	Nicaragua	524579.79
115	Niger	30253.33
116	Nigeria	912396.39
117	Norway	821840.38
118	Oman	312735.27
119	Pakistan	513644.68
120	Palau	662.97
121	Panama	1499169.53
122	Papua New Guinea	13206.25
123	Paraguay	504614.79

124	Peru	1812973.44
125	Philippines	1295749.28
126	Poland	516527.21
127	Portugal	577391.32
128	Qatar	468022.48
129	Romania	248483.57
130	Rwanda	12131.18
131	San Marino	4882.20
132	Sao Tome and Principe	2647.39
133	Saudi Arabia	5822342.98
134	Senegal	47099.49
135	Seychelles	6927.75
136	Sierra Leone	27206.74
137	Singapore	4016918.55
138	Slovenia	83421.33
139	Solomon Islands	1206.98
140	Somalia	6131.48
141	South Africa	2217426.82
142	Spain	3661615.36
143	Sri Lanka	88342.53
144	Sudan	28782.99
145	Suriname	159017.32
146	Sweden	1772869.24
147	Switzerland	2299162.72
148	Tajikistan	37064.12

149	Tanzania	62939.29
150	Thailand	1610414.77
151	Togo	21263.11
152	Tonga	653.42
153	Trinidad and Tobago	1120462.16
154	Tunisia	193063.48
155	Turkey	2310098.99
156	Turkmenistan	71394.38
157	Turks and Caicos Islands	87819.36
158	Tuvalu	2.38
159	Uganda	29622.84
160	UK	17973096.76
161	Ukraine	291951.86
162	United Arab Emirates	2597582.86
163	Uruguay	410403.98
164	Uzbekistan	138743.00
165	Vanuatu	1082.74
166	Vietnam	228708.70
167	Zambia	18598.49
168	Zimbabwe	40830.83

TABLE C3. State-Level Summary Statistics

state	Ports Used	Trade Partners	Export Value
AL	18	54	$5155544
AR	17	40	$2447263
AZ	20	57	$8177820
CA	39	90	$21600000
CO	21	51	$3305682
CT	23	44	$2746711
DC	8	41	$1102541
DE	15	32	$2226366
FL	29	87	$7731516
GA	24	72	$6310920
IA	18	48	$3583540
ID	16	34	$2184857
IL	30	68	$9961322
IN	23	55	$7992768
KS	19	49	$3130171
KY	22	48	$6362149
LA	19	61	$10100000
MA	27	59	$5683843
MD	19	64	$2394358
ME	15	35	$1989326
MI	27	56	$14800000
MN	25	58	$4874079
MO	22	52	$3931695
MS	15	45	$2609422
MT	13	18	$682845
NC	27	66	$6191017
ND	11	22	$1579481
NE	15	39	$2262926
NH	18	39	$1489393
NJ	27	59	$4654805
NM	13	30	$2904838
NV	16	43	$1683390
NY	32	63	$6933172
OH	31	65	$9378888
OK	17	50	$1999971
OR	23	54	$5533999
PA	30	63	$5600732
RI	14	37	$1108325
SC	21	55	$6036263
SD	12	23	$1126730
TN	24	60	$6232756
TX	35	78	$25700000
UT	17	54	$2135340
VA	22	66	$4900596
VT	14	32	$3340602
WA	26	63	$15300000
WI	24	59	$4987160
WV	15	30	$2614629
WY	10	14	$1380832

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