# The Resilience of International Trade

Evidence from Hurricane Katrina\*

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#### Abstract

As evidenced by recent Hurricanes Harvey, Irma and Maria, natural disasters are omnipresent, increasing in their destructive force and potentially devastating for local or even regional economic activity. In this study, I analyze the dynamics and spatial distribution of the trade effects resulting from natural disasters. I develop a spatial framework of international trade and apply the resulting spatial econometric model to monthly U.S. port-level trade data. Contributing to the existing literature, I estimate the dynamic evolution of trade effects caused by Hurricane Katrina differentiating these disruptions at the local port level. The estimates point to the static and dynamic resilience of international trade. While ports closest to Katrina's epicenter experience significant short-run reductions, international trade handled by nearby ports rises in response to this disaster. Moreover, the estimates are the first to point to the permanence of the disaster-induced trade disruptions causing persistent increases in trade at the port of Panama City eight years post treatment. Distance to Katrina's epicenter is estimated to be the primary determinant of the counteracting short-run and long-run trade effects and exports are shown to be more sensitive to this distance than imports. Overall, the analysis illustrates the potential disparity between aggregate and local trade effects and underlines the significance of infrastructure networks to reduce the devastation inflicted by natural disasters.

**JEL codes**: (F14, F18, Q54, R40)

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### 1 Introduction

Natural disasters pose a constant threat to human life and economic activity. Whether we consider recent earthquakes in Japan, Ecuador, Italy, or Mexico, floods in India or Bangladesh, or hurricanes in the U.S. and Caribbean, the devastation arising from these and other disasters is omnipresent. According to the Centre for Research on the Epidemiology of Disasters (CRED), the global community has experienced an average of 384 natural disasters per year, over the last decade. As a result, close to 200 million people have been victimized yearly and annual average damages are estimated around \$162 billion and increasing over time [CRED, 2015].

A variety of case studies indicate that this devastation not only encompasses the tragic loss of human life, but also the impairment of entire regional economic structures [Vigdor, 2008, Grenzeback et al., 2008. Upon the strike of a largely unanticipated natural disaster, housing, employment, and infrastructure, among others, are found to be in complete disarray. As international trade has grown and gained economic significance, its global presence has exposed it to the destruction and tragedy originating from natural disasters. The displacement of workers, destruction of product and capital, and impairment of infrastructure paramount to the facilitation of international trade can lead to substantial delays and/or rerouting of traded products. As such, natural disasters represent infrequent and uncertain trade costs, but yet have the potential to be immensely taxing, particularly at the local level. While the majority of commercial policies and academic research on trade is geared towards more common trade barriers, such as tariffs and transportation costs, relatively little attention has been paid to the linkages between trade and natural disasters. The existing studies suggest that natural disasters cause heterogeneous responses across countries, industries, firms and products and relatively small and short-lived disruptions of aggregate international trade [Gassebner et al., 2010, Oh and Reuveny, 2010, Ando and Kimura, 2012, Martineus and Blyde, 2013, a finding that is shown to not hold at a more disaggregated local level.

In this study, I build on this small strand of the economic literature and provide a novel analysis of the natural disaster induced trade effects at the regional and port level. To this end, I develop a simple model of port-level trade that allows me to capture the dynamic and spatial variation of natural disaster-induced trade effects, while accounting for the spatial correlations present in local trade flows. The resulting spatial econometric model is applied to U.S. port level trade data from August 2003 to August 2013. Identification of the spatial heterogeneity in natural disaster induced trade effects is based on the exogenous variation in trade caused by Hurricane Katrina. Evaluations of the treatment effects at the aggregate or regional level produce statistically insignificant estimates that are consistent with the findings of the previous trade literature [Parsons, 2014].

In contrast to these aggregate estimates, I also investigate trade disruptions at the disaggregated local port level. The empirical results provide novel evidence of statistically significant trade disruptions. While the port-specific treatment effects vary over time and strongly depend on the port's distance to Katrina's epicenter, other potential determinants, such as harbor type, entry restrictions and access capacity are found to be insignificant predictors of the disaster's impact. While the directly affected ports of New Orleans, Louisiana, and Gulfport, Mississippi, exhibit economically and statistically significant reductions in trade, the nearest neighboring ports of Mobile, Alabama, and Panama City, Florida, experience substantial and statistically significant increases in trade; a finding that is true both across the value of trade and the number of traded products. Regardless of whether the positive or negative trade disruptions are considered, I find that the impact of Hurricane Katrina exponentially vanishes as distance to its epicenter rises. Importantly, disruptions in exports are estimated to be more sensitive to distance than those of imports. Driving the resilience of international trade, this spatial distribution of counteracting trade effects leads to profound short-run disruptions at the local port level, but negligible effects in aggregate.

In addition to this static spatial analysis, I also consider the dynamic changes of these natural disaster-induced trade effects. The case study of Hurricane Katrina provides important insights into the evolution of the spatially heterogeneous trade effects. Differentiating the monthly impacts across first to sixth order contiguous ports, I find that the duration of the experienced trade effects is largely port specific. While some ports recover fairly quickly, others are exhibit

persistent long-run changes to their respective trade throughput. Trade facilitated through the port of New Orleans, for example, experiences drastic short-run reductions and recovers within the first six to twelve month post treatment. In contrast, U.S. imports facilitated through the port of Gulfport, for example, are shown to only partially recover resulting in permanent reductions of imports relative to pre Hurricane Katrina levels. The directly adjacent ports reflect similar heterogeneous dynamics. While the port of Panama City experiences an immediate and persistent increase in trade, the port of Mobile shows a long-run increase in trade triggered by Hurricane Katrina.

The estimation of these spatially heterogeneous and dynamic trade effects delivers novel evidence in support of the *static* and *dynamic* resilience of international trade as defined by Rose [2007]. In his study, the author describes *static* resilience as the ability of the economic system to maximize output based on the remaining, after-shock resources and *dynamic* resilience as the speed of recovery of the economy post natural disasters. Based on these definitions and the empirical results obtained in this study, the static resilience of trade is founded in the ability of international carriers to use the remaining local infrastructure to provide alternative channels of trade facilitation - a finding that is of particular interest to policy makers in developing countries which continue to experience significant reductions in output growth due to natural disasters. The dynamic resilience of trade is shown to be driven by port-specific recovery as well as permanent alterations to carriers' port calls.

Conducting these analyses, my research contributes to the existing literature in several ways. To the best of my knowledge, this study is the first to identify the spatial heterogeneity of natural disaster-induced trade effects and consider their short-run and long-run spatial distribution. The empirical findings offer insights into the dynamic response of the international transport sector and domestic infrastructure network to local trade disruptions and point to the importance of these mechanisms in mitigating aggregate repercussions. As such, the estimated spatial and dynamic variation in trade effects presented in this study provide supporting evidence of

<sup>&</sup>lt;sup>1</sup>Rose and Wei [2013] develop an input-output type model to simulate the macroeconomic effects of a hypothetical port shutdown and illustrate several mechanisms of resiliency, most important of which is the ability to reroute international and domestic trade.

the static and dynamic resilience of international trade and identify the specific channels that empower this pliancy.

The remaining parts of the paper are organized as follows: Section 2 presents an overview of the evolution of natural disasters and their devastating consequences, while also providing detailed background information on Hurricane Katrina and its specific effects. Section 3 offers a literature review focused on research pertaining to trade cost, its linkages to natural disasters and the resulting trade disruptions. To analyze the dynamic spatial variation in trade effects, I develop a theoretical framework and derive the resulting empirical specification in section 4. The U.S. port level trade data employed in this study are summarized in Section 5, while the empirical results are discussed in section 6. Section 7 concludes this study and points to the significance of the empirical results as well as areas of further inquiry.

# 2 Institutional Background

As Blonigen and Wilson [2013] point out, international trade has been growing for decades and has exhibited a growth rate much larger than that of world Gross Domestic Product (GDP). The growing importance and global presence of international trade have led to its exposure to the destruction and challenges originating from a host of natural disasters in all corners of the world. According to CRED, natural disasters frequently occur across all continents and cause significant human losses and economic damages. In fact, CRED reports that over the last 20 years 6,457 weather-related disasters were recorded worldwide and that these natural disasters have claimed over 600,000 lives in total [CRED, 2015]. Table 1 is based on the data presented in CRED's annual disaster statistical report of 2014 and provides continental averages concerning the frequency, number of overall victims and economic damages caused by all types of natural disasters over the time period from 2004 through 2013.

These data demonstrate that natural disasters are, indeed, frequent and global events. More importantly, the statistics show that recent natural disasters have caused substantial human and economic losses with roughly 200 million people affected annually and economic damages

reaching a staggering \$162 billion per year, on average. However, the data presented in Table 1 also reveal that the human and economic impacts of natural disasters vary greatly across continents. While an annual average of 69 natural disasters affected over 27 million people in Africa, natural disasters of similar average frequency in America and Europe affected only 9.82 and 0.64 million people, respectively. In contrast, average annual economic damages due to these natural disasters range from \$67.97 billion in America and \$13.45 billion in Europe to \$0.58 billion in Africa. Out of all continents, Asia is most affected with an annual average of over 160 million victims and over \$75 billion in economic damages caused by an average 156 natural disasters per year [Guha-Sapir et al., 2015].

Table 1: Average Continental Disaster Impact

Continent	Frequency	Victims (mil.)	Damages (2014 \$ bil.)
Africa	69	27.86	0.58
America	91	9.82	67.97
Asia	156	160.71	75.27
Europe	54	0.64	13.45
Oceania	14	0.19	5.26
Global	384	199.23	162.53

The data presented mark the 2004 through 2013 averages across all types of disasters.

Sources: Centre for Research on the Epidemiology of Disasters, Annual Disaster

Statistical Review 2014

In addition to these average impacts of natural disasters, their historical trends and the evolution of the resulting human losses and economic damages are of considerable interest as well. When considering these dynamic developments of natural disasters, several key aspects, such as changes in exposure or destructive force, come into play. While Kunkel et al. [1999] report that recent demographic trends have led to an increasing population and property density in heavily disaster stricken regions, research by Emanuel [2005] points out that the power dissipation of tropical cyclones, for example, has doubled over the last century. Data collected by CRED and published in the International Disaster Database (EM-DAT), give insight into the efficacy of these observations. Figures 1.1-1.4 display the annual global frequency of natural disasters and the resulting global economic damages, the overall number of victims affected and

the number of deaths caused by these catastrophes.

Figure 1.1 shows that the period from 1960 to about 2000 saw a sharp ten-fold increase in natural disasters, whereas the most recent decade suggests a downward trend concerning their frequency. Nonetheless, the most recent hurricanes in the U.S. have pointed to the omnipresence of these disastrous events. Matching the historical increase in natural disaster frequency, Figures 1.2 and 1.3 illustrate that annual global economic damages and the number of people affected by these disasters are also increasing over the sample period from 1960 to 2000. However, these positive trends are more gradual and exhibit much larger volatility compared to the steep and rather smooth increase concerning the frequency of natural disasters. The recent reduction in disaster frequency is accompanied by a decline in the number of affected people, whereas economic damages do not reflect this downturn. This finding supports the arguments made by Kunkel et al. [1999] and Emanuel [2005] that even less frequent disasters can cause significant overall losses due to increases in economic vulnerability and a rise in the destructive force of the most recent natural disasters. Despite these dispiriting findings, the lethality of natural disasters, depicted in Figure 1.4, encouragingly does not match the historic rise in their frequency, but appears to be rather disaster-specific instead.

The combination of larger populations subjecting themselves to the potential havoc of natural disasters, the growth of and increasing dependence on international trade and the rise in the destructive force of these natural disasters suggest potentially intensifying disruptions of international trade and global supply chains. While some empirical studies consider the average effect of natural disaster on aggregate trade, this study identifies the dynamic and spatially heterogeneous trade effects at a more disaggregated local level via the variation caused by a single event, Hurricane Katrina. Hurricane Katrina is widely recognized for its immense devastation that caused tremendous hardship in human life and economic outcomes. Until most recently, according to Grenzeback et al. [2008], Katrina was the costliest and most destructive natural disaster ever experienced by the U.S.<sup>2</sup> causing over 1,800 deaths and an estimated \$149 billion

<sup>&</sup>lt;sup>2</sup>While Grenzeback and Lukman's assessment is based on nominal values, Pielke Jr et al. [2008] show that in normalized terms Hurricane Katrina actually caused the second largest losses in U.S. history behind the Great Miami storm of 1926. Furthermore, Hurricane Harvey has been reported to have caused more economic

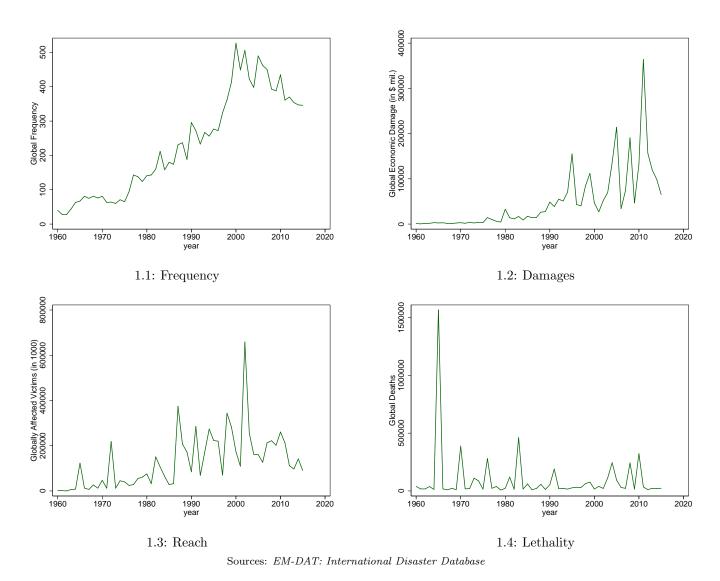


Figure 1: Global Disaster Trends (1960-2015)

in direct and indirect economic losses [Hallegatte, 2008].

As depicted in Figure 2, Hurricane Katrina originated around the Bahamas and made its first landfall as a Category 1 hurricane in Florida on August 25th of 2005. After causing modest disruptions in Florida, the windstorm moved to the Gulf of Mexico, where it rapidly intensified and developed into a Category 5 hurricane at its peak. Its second landfall occurred in the state of Louisiana on August 29th, 2005, with sustained winds of 125 mph. Upon this second landfall, the havoc caused by Hurricane Katrina was felt along the majority of the U.S. Gulf Coast severely affecting the coastal regions of Louisiana and Mississippi.

damages than Katrina.

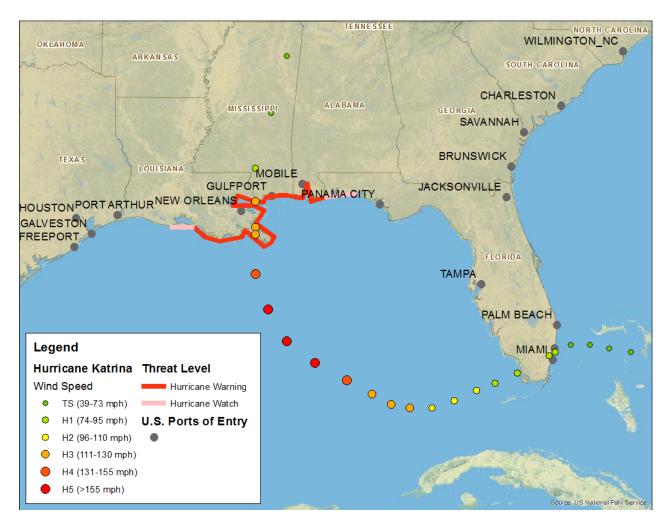


Figure 2: Geographical Movement and Strength of Hurricane Katrina

In addition to the tragic loss of human life, Hurricane Katrina's wreckage extended across the entire regional economic structure and even to the national level. Based on early estimations, Holtz-Eakin [2005] argued that the effects of Hurricane Katrina were expected to lower U.S. output growth by 0.5 percentage points in the short-run, whereas recovery efforts were expected to reverse this effect by 2006. The underlying causes for this initial decline in the growth of aggregate income range from extensive reductions in employment and housing due to the

flooding of New Orleans<sup>3</sup>, the destruction of physical capital<sup>4</sup>, and trade disruptions caused by the severe impairment of the regional infrastructure. According to Grenzeback et al. [2008], the infrastructure of the U.S. coastal region of Louisiana, Mississippi and Alabama experienced substantial ruination encompassing damages to road, rail and port networks. Taking account of the specific damages, the authors point to the destruction of bridges, specific railways, the ports of New Orleans and Gulfport and Interstate 10, as well as the loss of electricity and closing of major waterways as the main factors determining this wreckage of the coastal infrastructure and potentially causing severe local trade disruptions.

Despite this detriment to the regional infrastructure, Parsons [2014] finds that aggregate U.S. imports were unaffected by the destructive force of Hurricane Katrina in the long-run. Upon providing supporting evidence of this aggregate finding, I evaluate the significance of trade disruptions at the regional and local levels. I find statistically significant local trade effects that are offsetting in aggregate and evidence the substantial resilience of international trade to natural disasters, even to those as monumental as Hurricane Katrina.

## 3 Literature Review

Within the international economics literature it has been widely recognized that trade costs are an integral determinant of international trade. In fact, regardless of whether Krugman's 'New Trade Theory' [Krugman, 1980], the 'New-New Trade Theory' initially introduced by Melitz [2003], the gravity model [see, for example, Anderson and van Wincoop, 2003] or recent work on the classical model by Deardorff [2014] is considered, most theoretical derivations point to the significance of trade costs in the determination of the level and composition of international trade. In this section, I present a literature review concerning the micro- and macroeconomic

<sup>&</sup>lt;sup>3</sup>Studies by Dolfman et al. [2007] and Vigdor [2008] show that Hurricane Katrina resulted in significant reductions of employers and employment (between 70,000 and 95,000 lost jobs) and the long-term displacement of over 150,000 people. Elliott and Pais [2006] as well as Masozera et al. [2007] find significant heterogeneity across the individually experienced losses and illustrate that this heterogeneity systematically varied by socioeconomic factors, such as race, class and income. In addition to these labor market effects, Vigdor [2008] reports that the New Orleans' availability of housing declined from 215,000 units in 2000 to 106,000 units in the aftermath of Hurricane Katrina.

<sup>&</sup>lt;sup>4</sup>Holtz-Eakin [2005] estimate physical capital damages to total between \$70 billion and \$130 billion.

effects of natural disasters, linkages to trade costs and resulting trade disruptions.

Trade costs manifest themselves in variety of ways and many of their facets have been analyzed in the trade literature. Brander and Spencer [1984], for example, study the effects of tariffs on international trade, whereas Clausing [2001] and Frankel and Rose [2002] focus on the impact of preferential trade agreements and monetary unions, respectively. Other studies have considered the trade effects of national borders [McCallum, 1995, Anderson and van Wincoop, 2003], cultural and linguistic differences [Egger and Lassmann, 2012] or transportation costs [Hummels and Skiba, 2004, Hummels, 2007, Friedt and Wilson, 2015, Friedt, 2016], for example.

While these types of barriers are relatively constant factors in the determination of international trade, trade disruptions caused by natural or man-made disasters represent rather irregular elements of overall trade costs. Nevertheless, these events can have significant long-term impacts on trade. Glick and Taylor [2010], Li and Sacko [2002], or Anderton and Carter [2001], for example, study the impacts of war and militarized conflict on international trade and find that the effects are generally long-lasting, lower the level and growth of international trade, impose large externalities on impartial countries, and vary by the level of uncertainty, duration and hostility. Alternative causes of man-made trade disruptions include acts of terrorism [see, for example, Egger and Gassebner, 2015] as well as economic sanctions [Caruso, 2005]. In general, the empirical evidence concerning the trade effects of these alternative disasters varies by the severity of the event and the time horizon under consideration. Despite the fact that there is a large volume of studies providing theoretical and empirical analyses of the effects of trade costs on international trade, the consequences of natural disasters on trade have received very little attention.

Within the literature on natural disasters, many non-trade, microeconomic and macroeconomic aspects have been considered. On the microeconomic side, these issues include, for example, the natural disaster induced effects on labor markets [Belasen and Polachek, 2008], housing prices [Hallstrom and Smith, 2005], consumption volatility [Auffret, 2003] or supply chains [Altay and Ramirez, 2010]. The general findings of this strand of the literature provide evidence of large economic distortions that exhibit significant heterogeneity across economic

agents and over time. This variation in economic impacts is a reoccurring theme throughout the natural disaster's literature [see, for example, a survery by Cavallo and Noy, 2009] and applies to macroeconomic and trade related studies as well.

On the macroeconomic side, several studies have focused on primary issues, such as the effect of natural disasters on inflation [Noy, 2009], financial flows [Rasmussen, 2004, Yang, 2008] or output growth. While Yang [2008] finds a statistically significant increase in international financial flows for developing countries in response to natural disasters, evidence concerning their impact on output growth is rather mixed. Skidmore and Toya [2002], for example, find that a rise in the frequency of natural disasters causes an increase in the growth of aggregate income due to the substitution of investment towards human capital. Contrary to this finding, Strobl [2011] provides evidence of a very localized increase in output growth that is canceled out at the state level and leads to a negligible effect of natural disasters on the growth of aggregate output. In response to this variation concerning the effects on output growth, the literature has turned towards a more disaggregated analysis differentiating between developing and developed countries [see, for example, Strömberg, 2007, Crespo Cuaresma et al., 2008, Noy, 2009, Noy and Vu, 2010, Strobl, 2012 and identifying a variety of key factors determining the macroeconomic impact of natural disasters. Kahn [2005], Toya and Skidmore [2007], Raschky [2008] and Nov [2009], for example, show that countries with higher levels of democracy, government stability and education, greater openness, a more complete financial system, better investment climate and less inequality, in addition to higher income, experience fewer losses from natural disasters, on average.<sup>5</sup>

Of course, a potential explanation for this variation in disaster-induced aggregate economic outcomes may be the underlying heterogeneity of impacts at the regional level. While research by Burrus Jr et al. [2002] illustrates that output, employment and indirect business taxes in

<sup>&</sup>lt;sup>5</sup>The definition of losses varies across these studies. Kahn [2005], Toya and Skidmore [2007] and Raschky [2008] measure the effects on deaths and damages due to natural disasters, whereas Noy [2009] captures losses by estimating the effects on output growth via an interaction term with the disaster variable. Although these studies yield very similar results overall, their conclusions pertaining to the effects of governments vary. Specifically, Noy [2009] finds that larger governments dampen the reduction in output growth, whereas Toya and Skidmore [2007] provide evidence indicating that larger governments increase the lethality of disasters.

directly affected regions decline in response to hurricanes, Xiao and Nilawar [2013] demonstrate that income and employment in directly neighboring regions experience a short-run increase. Rose et al. [1997] and Lin et al. [2012] add that the effects of natural disasters vary not only geographically, but also across local industries.

Although international trade and its disruptions due to natural disasters can act as a significant catalyst for the discussed regional and aggregate variation in economic outcomes, research in this area is very limited. In a seminal study, Gassebner et al. [2010] analyze the effects of natural disasters on aggregate international trade. In general, the authors find that governance and economic size matter to the degree of devastation on the import side, while exports experience a negative shock regardless of country characteristics. Research by Oh and Reuveny [2010] complements these findings showing that political risk is another important factor in the determination of trade effects caused by natural disasters. In contrast to these general analyses, studies by Andrade da Silva and Cernat [2012] and Meng et al. [2015] distinguish between the trade effects of natural disasters on developing versus developed countries. In general, the authors show that the estimated trade effects vary by economic and geographical size of the affected country as well as across imports and exports. Further disaggregation of these trade effects has provided evidence that the resulting trade disruptions, in fact, vary across the time horizons under consideration [Ando and Kimura, 2012, Parsons, 2014], the type of trade flow [Chang, 2000], industries and firms [Ando and Kimura, 2012, Martineus and Blyde, 2013] as well as product groups [Martineus and Blyde, 2013] and can lead to a change in trade composition [Ando and Kimura, 2012, Pelli and Tschopp, 2013].

Although this relatively small strand of the economic literature on natural disasters has provided substantial insights into the variation of natural disaster induced impacts on trade, little is known about the spatial heterogeneity of these trade effects.<sup>6</sup> The spatial econometric analysis presented in this study provides supporting evidence of the *static* and *dynamic* resilience of international trade by estimating the short-run and long-run spatial distribution of

<sup>&</sup>lt;sup>6</sup>The study by Martincus and Blyde [2013] exploits geo-referenced data on Chile to estimate the short-run impact of local infrastructure disruptions on trade and is perhaps most closely related to the present study.

trade disruptions caused by Hurricane Katrina. The results offer an intuitive explanation for the generally small or even positive aggregate effects of natural disasters on trade and output. In addition, the empirical results point to the significance of infrastructure networks to dampen the economic devastation caused by natural disasters. Since, developing countries continue to experience reductions in output growth due to natural disasters, the specific resiliency channels identified in this research are of particular interest to international policy makers and one of the important remaining gaps in the literature as established by Cavallo and Noy [2009]. Based on these findings, my research contributes to both the trade and natural disaster literature in several ways. First, to the best of my knowledge, this study is the first to identify the spatial heterogeneity of natural disaster induced trade effects. Second, the empirical findings offer insights into the dynamic responses of the international transport sector and domestic infrastructure network to these local disruptions. Third, the results concerning the spatial and dynamic variation in trade effects presented in this study provide supporting evidence of the static and dynamic resilience of international trade and identify the specific channels that empower this resiliency.

#### 4 Model

As the CRED data indicate, natural disasters inflict substantial damages to human life and economic activity. However, the empirical findings in the literature suggest that, while these devastations appear to be locally intensive in the short-run, they are rather negligible at the national level and insignificant in the long-run [Parsons, 2014]. To test the validity of these findings and provide novel insights with regards to disaster-induced trade effects at a more disaggregated local level, I develop a simple model of port throughput. This framework allows me to identify the port-specific local trade disruptions arising from natural disasters, while accounting for the potential spatial correlations arising from disaggregated geo-spatial data.

Following common practice, I assume that aggregate U.S. trade at time t, denoted as  $X_t$ , is a function of exogenously given U.S. income,  $Y_t$ , and national trade cost factors,  $\tau_t$ . That

is, aggregate U.S. trade is given by  $X_t = X(Y_t, \tau_t)$ . Based on aggregated international carrier and freight forwarder port choices, each U.S. port of entry and exit facilitates a share,  $\alpha_{pt}$ , of aggregate U.S. trade, where each individual share is assumed independent of aggregate trade and the sum of shares across all ports must equal one,  $\sum_{p=1}^{P} \alpha_{pt} = 1 \quad \forall t$ . Naturally, each port's share in aggregate trade is assumed to depend on port-specific characteristics,  $c_p$ , port-specific trade costs,  $f_{pt}$ , and the strategic consideration of every other ports' trade share,  $\alpha_{-pt}$ . Each port's throughput of U.S. trade,  $x_{pt}$ , is, therefore, given by the following expression:

$$x_{pt} = \alpha(c_p, f_{pt}, \alpha_{-pt}) X(Y_t, \tau_t). \tag{1}$$

Unlike previous studies [see, for example, Parsons, 2014, Egger and Gassebner, 2015], natural disasters do not represent a part of national trade costs applied equally across all ports of entry and exit, but are rather assumed to be a port-specific cost factor that varies with the geo-spatial location of a given port in reference to the disaster's epicenter. This disaggregated specification allows for spatial heterogeneity in the disaster-induced trade effects. Specific to the present study,  $f_{pt}$  indicates the timing of Hurricane Katrina for each of the given sample ports at various distances to its epicenter. The dependence on this variable is intended to capture the resulting port-specific trade effects and give insights into their dynamic spatial heterogeneity as well as the hypothesized resilience of international trade.

While this theoretical framework is fairly abstract, it lends itself well for the derivation of a more complex stochastic model of port-specific trade flows and captures all of the essential elements to evaluate the disaster-induced local trade effects. The main trade cost component of interest, of course, includes a set of interacted dummy variables,  $f_{p,t^*\pm s}$ , each indicating a specific month before or after Hurricane Katrina for a given port of entry or exit. The specific timing of Hurricane Katrina's landfall in August of 2005 is indicated via  $t^*$ . Intuitively,  $f_{p,t=t^*+1}$  indicates the disaster induced trade disruption at port, p, one month following Hurricane Katrina's landfall and allows for the identification of the potential static and dynamic resilience of international trade. Furthermore, the stochastic version of equation 1 includes port

and time-specific fixed effects,  $a_p$  and  $a_t$ , in order to capture the time-invariant port-specific characteristics and port-invariant macroeconomic trends in national income and trade costs.

As indicated by equation 1, U.S. port-level trade flows and the unobservables influencing these transactions,  $u_{pt}$ , are potentially correlated across ports of entry and exit. To address this issue and control for spatial correlations arising from port competition,  $\alpha_{-pt}$ , I adopt the flexible spatial autocorrelation (SAC) model presented by LeSage and Pace [2009]. This specification nests the spatial autoregression (SAR) model, which allows for spatial spillover effects,  $\rho W ln(x_{pt})$ , as well as the spatial error (SEM) model, which controls for unobservable spatial correlations in the error term,  $u_{pt} = \lambda W u_{pt} + \epsilon_{pt}$ . Given this specification of the stochastic component,  $\epsilon_{pt}$  is a normally and independently distributed random error, while  $\rho W ln(x_{pt})$  and  $\lambda W u_{pt}$  consist of the spatial correlation coefficients,  $\rho$  and  $\lambda$ , as well as spatial weight matrix W. There are various weight matrices available when considering the final spatial econometric specification [see, for example, Ord, 1975, LeSage and Pace, 2009]. Since the distances between ports are non-uniform, a natural choice for the spatial weights may be an inverse distance measure which proposes that the spatial correlation across ports declines exponentially with the distance between a pair of ports [Cliff, 1969, Griffith, 1996, Getis, 2009]. An alternative may be a row normalized contiguity or nearest neighbor matrix indicating each port's neighboring facilities irrespective of their distance [LeSage and Pace, 2009].

Combining this stochastic structure with the theoretical model given by equation 1 yields the following log-linearized empirical model;

$$\ln(x_{pt}) = \beta_0 + \rho W \ln(x_{pt}) + \sum_{r=1}^R \sum_{p=2}^P \beta_{pr} f_{p,t^*-r} + \sum_{r=1}^S \sum_{p=2}^P \beta_{ps} f_{p,t^*+s} + a_p + a_t + u_{pt}$$

$$u_{pt} = \lambda W u_{pt} + \epsilon_{pt},$$
(2)

where 2 years of port-specific pre-treatment, R = 24, and 8 years of port-specific post treatment, S = 96, effects are considered. Given this specification, the SAR model is obtained when  $\rho > 0$ 

<sup>&</sup>lt;sup>7</sup>The empirical results presented in section 6 and the Appendix are consistent across all weight matrix specifications including inverse distance based on nautical distances as well as contiguity and nearest neighbor matrices of order four through ten.

and  $\lambda = 0$ , while the SEM model is nested via  $\rho = 0$  and  $\lambda > 0$ . Alternatively, the SAC model assumes  $\rho > 0$  and  $\lambda > 0$ . The parameters of interest capturing the direct and indirect dynamic and spatially distributed trade effects caused by Hurricane Katrina are given by  $(I - \rho W)^{-1}\beta_{ps}$ . These parameters, along with pre-treatment indicators,  $(I - \rho W)^{-1}\beta_{pr}$ , are evaluated in relation to the month of Hurricane Katrina's landfall,  $t^*$ , and a given port of reference, p = 1.

#### 5 Data

The data used to estimate the empirical model specified by equation (2) have been obtained from various sources. The main variable of interest is given by U.S. containerized trade concerning both exports and imports at the container seaport of entry and exit level. These data are available through the USA Trade Online database by the U.S. Census Bureau and cover the entirety of U.S. bilateral trade facilitated through U.S. ports of entry and exit at monthly frequency. The time period considered in this study extends from August of 2003 to August of 2013. While USA Trade Online includes a variety of ports with vastly different trade volumes, the selection of ports included in this analysis is based on economic significance. That is, only the largest forty ports of entry and exit have been included in the sample.<sup>8</sup> At the time of Hurricane Katrina's landfall, these forty ports account for roughly 98% and 96% of total U.S. containerized imports and exports, respectively.

The key variables of interest distinguishing the systematic variation in trade disruptions caused by Hurricane Katrina are based on longitudinal and latitudinal coordinates obtained from the World Port Index (WPI) compiled by the National Geospatial-Intelligence Agency and nautical port-to-port distances published by the U.S. Department of Commerce in collaboration with the National Oceanic and Atmospheric Administration (NOAA) and the National Ocean Service. The distinction in local treatment effects is based on the spatial distribution of U.S. ports and their nautical distances from the epicenter of Hurricane Katrina's landfall, which has

<sup>&</sup>lt;sup>8</sup>Due to the need to control for spatial correlations and their unique locations, the ports of Honolulu, HI, and Ranier-Falls, MN, have been excluded from this sample.

<sup>&</sup>lt;sup>9</sup>The port-to-port nautical distance matrix is presented in Table 12 in the Appendix.

been approximately located around Waveland and Bay St. Louis, Mississippi. Based on the selection of ports under consideration and their geographic locations, the ports of New Orleans, LA, and Gulfport, MS, have been identified as those closest to the epicenter in the western and eastern directions, respectively, while the port of Mobile, AL is the only other sample port still within the hurricane warning zone. Other second or higher order contiguous ports are located in Florida and Texas or more remote U.S. states. The respective nautical epicenter distances of ports located in these and other states are presented in Tables 2 and 3.

To gain preliminary insights into the spatial and dynamic distribution of trade disruptions caused by Hurricane Katrina, a summary detailing the cross-sectional, spatial and time dimensions of the data is provided in Tables 2 and 3 as well as Figures 3.1 through 4.6. In particular, Tables 2 and 3 provide the average port throughput of total exports and imports over a two year span pre and post Hurricane Katrina. Column (1) of each table presents the nautical distances between a given port and the estimated epicenter of Hurricane Katrina, whereas columns (2) and (3) present the two year average trade flows pre and post its landfall. These data reveal that the majority of ports experienced an increase export and import throughput over this time period. The exceptions to this rule are the first order contiguous ports of New Orleans and Gulfport on the import side and Gulfport on the export side which exhibit substantial reductions in trade. Another irregularity that stands out from the general trend is given by the port of Panama City which experienced a twenty fold increase in imports and immense 198 fold increase in exports. Indicatively, as depicted by Figures 3.1 and 3.2, this port is a third order contiguous port just east of the hurricane warning zone, fortunately spared from its devastation and clearly benefiting from its proximity to the negatively disrupted ports.

Table 2: U.S. Port of Entry - Export Summary Pre & Post Hurricane Katrina

Ports	(1) Dist. to	(2) Pre	(3) Post	(4) Share	(5) Share	(6) Rank	(7) Rank
1 01 65	Epicenter	(\$ mil.)	(\$ mil.)	Pre (%)	Post (%)	Pre	Post
Gulfport, MS	15.66	85.59	49.24	0.824	0.363	18	24
New Orleans, LA	40.44	222.06	251.18	2.137	1.850	14	15
Mobile, AL	113.67	9.41	17.09	0.091	0.126	28	29

Continued on next page

Table 2 – Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ports	Dist. to	$\overset{\circ}{\text{Pre}}$	Post	Share	Share	Rank	Rank
	Epicenter	(\$ mil.)	(\$ mil.)	Pre (%)	Post $(\%)$	Pre	Post
Panama City, FL	237.67	0.16	31.79	0.002	0.234	41	27
Tampa, FL	428.67	4.53	7.65	0.044	0.056	31	31
Port Arthur, TX	481.44	1.25	3.41	0.012	0.025	40	35
Galveston, TX	486.44	6.53	6.79	0.063	0.050	30	32
Freeport, TX	529.44	15.38	18.61	0.148	0.137	27	28
Houston, TX	530.44	936.62	1,402.18	9.012	10.329	4	4
Corpus Christi, TX	595.44	1.61	1.91	0.015	0.014	36	40
Miami, FL	703.00	459.73	487.85	4.424	3.594	9	10
Port Everglades, FL	718.00	247.39	378.39	2.380	2.787	12	12
West Palm Beach, FL	759.00	60.84	87.74	0.585	0.646	21	20
Jacksonville, FL	1015.00	118.33	167.22	1.139	1.232	17	17
Brunswick, GA	1041.00	3.61	2.52	0.035	0.019	33	39
Savannah, GA	1096.00	549.61	834.52	5.288	6.147	8	7
Charleston, SC	1125.00	759.97	889.41	7.312	6.552	6	6
Wilmington, NC	1220.00	41.93	61.66	0.403	0.454	24	23
Newport News, VA	1458.00	764.62	1,025.70	7.357	7.556	5	5
Baltimore, MD	1584.00	210.27	276.79	2.023	2.039	15	13
Chester, PA	1624.00	58.17	105.29	0.560	0.776	22	19
Philadelphia, PA	1639.00	75.71	110.22	0.728	0.812	20	18
Perth Amboy, NJ	1642.00	1.32	3.96	0.013	0.029	39	34
Newark, NJ	1650.00	241.53	384.27	2.324	2.831	13	11
New York, NY	1662.00	1,135.75	1,596.33	10.928	11.759	2	2
Boston, MA	1900.00	50.27	73.22	0.484	0.539	23	21
Portland, ME	1940.00	3.60	2.86	0.035	0.021	34	38
Detroit, MI	3645.00	202.64	216.74	1.950	1.597	16	16
Port Huron, MI	3707.00	16.44	13.52	0.158	0.100	26	30
Chicago, IL	4278.00	25.68	34.13	0.247	0.251	25	25
San Diego, CA	4309.00	9.01	3.08	0.087	0.023	29	37
Long Beach, CA	4381.00	1,038.09	1,419.06	9.989	10.453	3	3
Los Angeles, CA	4382.00	1,280.06	1,644.61	12.317	12.115	1	1
Port Hueneme, CA	4456.00	2.12	3.31	0.020	0.024	35	36
San Francisco, CA	4712.00	4.06	5.37	0.039	0.040	32	33
Richmond, CA	4723.00	1.43	1.46	0.014	0.011	38	41
Oakland, CA	4767.00	575.55	668.37	5.538	4.923	7	8
Portland, OR	5330.00	84.62	65.60	0.814	0.483	19	22
Seattle, WA	5486.00	451.02	505.86	4.340	3.726	10	9
Tacoma, WA	5511.00	255.11	273.14	2.455	2.012	11	14

Source: U.S. Census Bureau USA Trade Online dataset

Table 3: U.S. Port of Entry - Import Summary Pre & Post Hurricane Katrina

Ports	(1) Dist. to Epicenter	(2) Pre (\$ mil.)	(3) Post (\$ mil.)	(4) Share Pre (%)	(5) Share Post (%)	(6) Rank Pre	(7) Rank Post
Gulfport, MS	15.66	190.94	116.85	0.550	0.271	17	22
New Orleans, LA	40.44	259.18	223.57	0.747	0.518	16	17
Mobile, AL	113.67	37.12	69.44	0.107	0.161	27	26
Panama City, FL	237.67	4.17	86.71	0.012	0.201	37	25
Tampa, FL	428.67	10.72	18.87	0.031	0.044	34	33
Port Arthur, TX	481.44	8.06	7.20	0.023	0.017	35	37
Galveston, TX	486.44	20.67	27.72	0.060	0.064	30	31
Freeport, TX	529.44	26.84	11.38	0.077	0.026	29	35
Houston, TX	530.44	999.29	1,433.85	2.881	3.322	10	10
Corpus Christi, TX	595.44	0.99	3.00	0.003	0.007	40	40
Miami, FL	703.00	821.43	850.75	2.368	1.971	11	12
Port Everglades, FL	718	428.57	531.95	1.236	1.232	14	14
West Palm Beach, FL	759.00	58.28	47.90	0.168	0.111	26	28
Jacksonville, FL	1015.00	85.63	119.77	0.247	0.277	22	21
Brunswick, GA	1041.00	131.40	88.36	0.379	0.205	21	24
Savannah, GA	1096.00	1,110.64	1,705.11	3.202	3.950	9	9
Charleston, SC	1125.00	$2,\!001.17$	$2,\!463.87$	5.769	5.708	4	4
Wilmington, NC	1220.00	71.40	113.37	0.206	0.263	25	23
Newport News, VA	1458.00	1,660.56	$2,\!158.80$	4.787	5.001	6	6
Baltimore, MD	1584.00	785.69	1,043.14	2.265	2.417	12	11
Chester, PA	1624.00	142.21	185.40	0.410	0.430	19	19
Philadelphia, PA	1639.00	266.94	389.88	0.770	0.903	15	15
Perth Amboy, NJ	1642.00	1.91	0.86	0.005	0.002	39	41
Newark, NJ	1650.00	$4,\!474.18$	$5,\!512.94$	12.899	12.772	2	2
New York, NY	1662.00	610.09	733.90	1.759	1.700	13	13
Boston, MA	1900.00	158.19	222.42	0.456	0.515	18	18
Portland, ME	1940.00	3.32	3.07	0.010	0.007	38	39
Detroit, MI	3645.00	13.59	19.43	0.039	0.045	33	32
Port Huron, MI	3707.00	5.34	6.01	0.015	0.014	36	38
Chicago, IL	4278.00	16.03	17.28	0.046	0.040	31	34
San Diego, CA	4309.00	74.63	165.40	0.215	0.383	23	20
Long Beach, CA	4381.00	$3,\!491.18$	$4,\!236.57$	10.065	9.815	3	3
Los Angeles, CA	4382.00	10,929.78	$13,\!532.80$	31.510	31.352	1	1
Port Hueneme, CA	4456.00	73.77	27.89	0.213	0.065	24	30
San Francisco, CA	4712.00	28.13	28.58	0.081	0.066	28	29
Richmond, CA	4723.00	14.89	8.86	0.043	0.021	32	36
Oakland, CA	4767.00	$1,\!488.80$	$1,\!832.66$	4.292	4.246	8	8
Portland, OR	5330.00	138.78	253.46	0.400	0.587	20	16
Seattle, WA	5486.00	1,917.51	$2,\!231.22$	5.528	5.169	5	5
Tacoma, WA	5511.00	1,537.71	1,899.13	4.433	4.400	7	7

Source: U.S. Census Bureau USA Trade Online dataset

Columns (4) and (5) of these tables present the shares of each port's throughput relative to average total trade prior to and in the aftermath of Hurricane Katrina. Based on these data, each port has been ranked before and after Katrina's landfall, with lower numbers representing larger market shares in U.S. trade. These rankings for exports and imports are given in columns (6) and (7) of Tables 2 and 3, respectively and point to spatial variation in trade disruptions. While the majority of ports experience minor changes in rank, ports closest to the epicenter demonstrate rather large relative adjustments. Gulfport, for example, exhibits a 6 and 5 point drop in export and import ranking, respectively, whereas the port of Panama City, for example, experiences a 14 and 12 point increase concerning these rankings. In contrast, the port of New Orleans, LA, displays rather small losses in export and import trade shares that results in a common one point drop in the respective rankings. While the former findings suggests that ports located closest to a disaster's epicenter tend to encounter significant negative or positive trade disruptions relative to other ports located at greater distances, the latter points to very idiosyncratic effects. Overall, the data presented in these tables provide supporting evidence of the local variation of trade disruptions across ports and point to the importance of modeling the disaggregated trade effects induced by natural disasters.

Building on this initial summary, Figures 3.1 and 3.2 provide insights into the short-run spatial distribution of the cross-sectional observations. In both figures, the geo-referenced ports are scaled by their one month pre and post Hurricane Katrina trade values. Overlaying the two trade values, a negative change in containerized trade is indicated by a larger red circle (i.e. Gulfport), while a positive change in trade is represented by a larger green circle (i.e. Panama City). Matching the previous medium-run observations, ports within or just outside of the hurricane warning zone experience the largest changes in trade after the landfall of Hurricane Katrina. Regardless of whether exports or imports are considered, the port of Panama City clearly indicates increases in trade post Hurricane Katrina, while the ports of Gulfport and New Orleans tend to exhibit the largest losses in trade. In contrast, the geo-referenced ports at greater distances appear to experience relatively small or no visible changes in trade.



3.1: Port Exports



3.2: Port Imports

Figure 3: Trends in Aggregate, Regional and Local US Exports and Imports

To investigate the spatial variation and duration of local trade effects, the trends of U.S. trade at the national, regional and local level are considered next. Figures 4.1 and 4.2 illustrate that aggregate U.S. exports and imports exhibit positive overall growth, albeit large seasonal variations. The vertical red line indicates August, 2005, the month during which Hurricane Katrina occurred. Both figures demonstrate that compared to common seasonal variation, the aggregate trade effects of Hurricane Katrina appear negligible and without any long-term impact. To explore the apparent disconnect between these aggregate observations and significant trade disruptions indicated in Tables 2 and 3 as well as Figures 3.1 and 3.2, the analysis continues at the disaggregated regional trade level. Figures 4.3 and 4.4 present regional trade shares and reveal slight variations from the aggregate conclusions. That is, Figure 4.3 shows that U.S. exports facilitated through ports located in the U.S. Gulf Coast (including Alabama, Louisiana, Mississippi and Texas) faced a sharp but temporary decline, while the adjacent Lower Atlantic region (including Florida, Georgia, North Carolina, South Carolina and Virginia) responded with an apparent increase in relative exports. <sup>10</sup> In addition to that, Figure 4.3 reveals that the share of exports held by the remaining U.S. regions remains rather stable during this period. In contrast, to this preliminary evidence of small short-run trade disruptions at the regional export level, Figure 4.4 presents a much less noticeable impact of Hurricane Katrina on regional U.S. imports, where we observe very slight reductions in the U.S. Gulf Coast and no visible effects on the Lower Atlantic or other regions.

Given these mixed findings at the regional level, a visual representation of the disaster induced trade disruptions at the local level is offered by Figures 4.5 and 4.6. Again, the timing of Hurricane Katrina is given by the vertical red line, but now marks a point of significant disruptions regarding local export and import trade shares across the more narrowly defined first, second and third order contiguous ports located in the U.S. Gulf Coast and Florida. Indeed, Figures 4.5 and 4.6 provide supporting evidence that natural disasters cause negative trade disruptions at the immediately affected ports, whereas positive trade effects are encountered by ports with close proximity. Interestingly, the depicted trade time paths post Hurricane Katrina

 $<sup>^{10}</sup>$ These regional definitions follow the categorization by the U.S. Energy Information Administration.

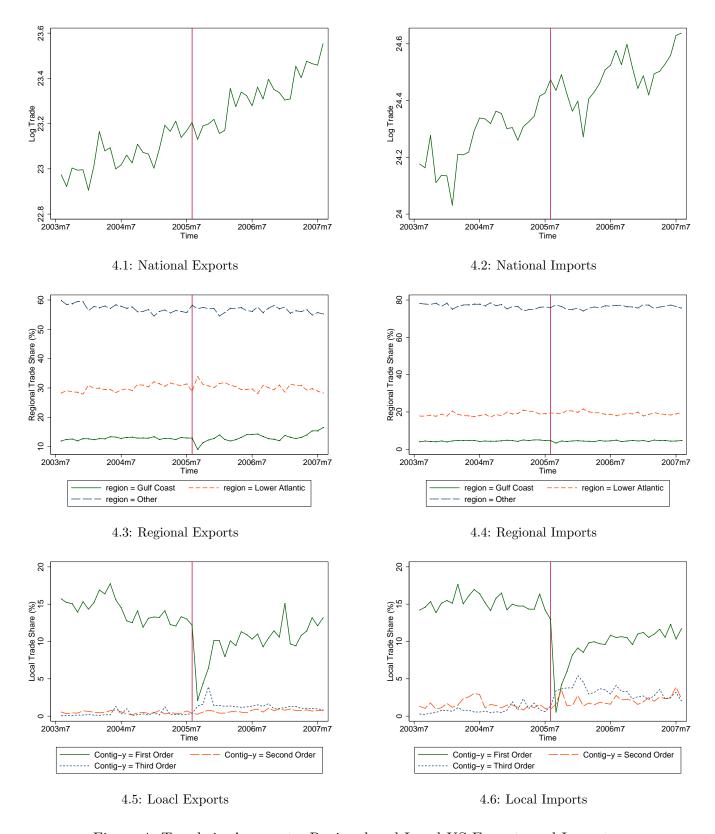


Figure 4: Trends in Aggregate, Regional and Local US Exports and Imports

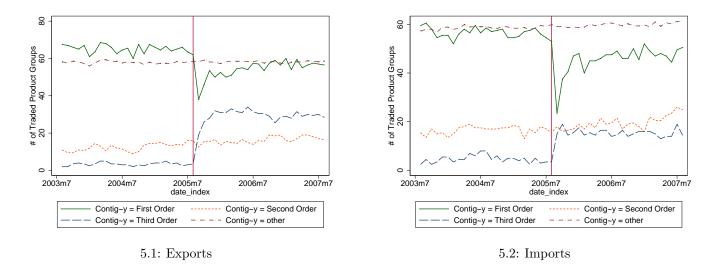


Figure 5: Trends in the Number of Traded Products

further suggest that the recovery of local trade is much slower than indicated by regional or national comparisons. While exports appear to recover to pre-disaster levels within the first two years, import trade shares exhibit long-lasting positive and negative trade disruptions.

Uncovering this initial evidence concerning the spatial and time heterogeneity of disaster induced trade effects, raises the question of the specific mechanisms driving the prolonged recovery of local trade. To this end, I provide Figures 5.1 and 5.2 which depict the number of two-digit HS traded product groups pre and post Hurricane Katrina. Both figures reveal dramatic and long-lasting reductions in the number of imported and exported products at the first order contiguous ports which coincide with a significant and permanent increase in the number of exported and imported products at the third order contiguous ports. Complementing the spatial heterogeneity in trade effects, second order contiguous ports, however, reveal no visual treatment effects concerning the number of traded products. In line with the negligible aggregate trade effects, higher order contiguous ports exhibit no change concerning their average trade composition in response to this natural disaster. These observations offer first insights into the port-specific short-run and long-run recovery of local trade and suggest that both the local patterns and composition of trade are subject to natural disasters. Overall, this summary of the data provides strong preliminary evidence of the spatial and dynamic heterogeneity of disaster induced trade effects and resilience of international trade.

### 6 Results

In this section, I present the empirical findings obtained from a variety of analyses culminating in the estimation of equation 2. The aggregate average treatment effects on U.S. trade are given in Table 4. Controlling for a time trend, port-specific fixed effects and seasonal variation, the results illustrate that Hurricane Katrina had no statistically significant impact on U.S. containerized exports or imports over the two years following the shock. This finding is robust across various model specifications<sup>11</sup> and in line with previous findings [Parsons, 2014].

Taking a closer look at this insignificant aggregate outcome, shown in Table 4, I turn towards a regional analysis. In this case, I differentiate treatment effects across ports located in the U.S. Gulf Coast and Lower Atlantic, the regions closest to Hurricane Katrina's epicenter, from other U.S. regions. Still, the results, given in columns (1) through (5) of Table 5, display insignificant trade effects for both regions across all export and import estimations. That is, controlling for port and time specific fixed effects, as well as potential spatial correlations, Hurricane Katrina appears to have had no discernibly different impact on trade across the U.S. Gulf Coast and Lower Atlantic regions relative to all others. Again, this finding is robust to variations in estimation technique as well as spatial weights specifications and points to the intraregional resilience of trade.

#### 6.1 The Static Resilience of Trade

Based on the previous summary of the data, the insignificant regional findings come at no surprise. Instead, these results speak to the intraregional resilience of international trade offsetting

<sup>&</sup>lt;sup>11</sup>While columns (1) and (2) of Table 4 include traditional fixed effects and the Poisson Pseudo-Maximum Likelihood (PPML) [Santos Silva and Tenreyro, 2006] estimators, columns (3) through (5) present the results obtained from the Spatial Autoregression Model (SAR), Spatial Error Model (SEM), and Spatial Autocorrelation Model (SAC), respectively. Following LeSage and Pace [2009], the spatial weights underlying the latter estimations are chosen based on log-likelihood values and given by a fourth nearest neighbor weight matrix (m=4) for exports and 10th nearest neighbor weight matrix (m=10) for imports. Aggregate results involving alternative spatial weight matrices are given in Table 13 in the Appendix and provide consistently insignificant coefficient estimates.

<sup>&</sup>lt;sup>12</sup>While the U.S. Gulf Coast includes the states of Alabama, Louisiana, Mississippi, and Texas, the Lower Atlantic includes the states of Florida, Georgia, North Carolina, South Carolina, and Virginia. The control group consists of ports located in the Central Atlantic, Midwest, New England and West Coast regions.

<sup>&</sup>lt;sup>13</sup>See Panels A through C of Table 14 in the Appendix.

Table 4: Aggregate Trade Disruptions

	OLS	PPML	SAR	SEM	SAC
	(1)	(2)	(3)	(4)	(5)
Panel A: Exports					
Hurricane Katrina	0.132	-0.012	0.135	0.132	0.147
	(0.143)	(0.019)	(0.143)	(0.137)	(0.147)
Spatial-Weighting	None	None	m=4	m=4	m=4
Panel B: Imports					
Hurricane Katrina	-0.015	-0.040	-0.019	-0.015	-0.017
	(0.096)	(0.029)	(0.093)	(0.075)	(0.083)
Spatial-Weighting	None	None	m = 10	m = 10	m=10
Observations	1,960	1,960	1,960	1,960	1,960
Trend	Yes	Yes	Yes	Yes	Yes
Port FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No
Std. Errors	clustered	clustered	clustered	clustered	clustered

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

local port trade reductions through immediate rerouting of traded goods to nearby and within region facilities with available capacity. To better understand the cross-sectional dependencies across U.S. ports and provide evidence in support of the spatial econometric model specification, I test U.S. containerized trade for cross-port spatial correlations. A test for cross-sectional dependence based on Pesaran [2015] decisively rejects the null hypothesis of weak cross-sectional dependence in favor of stronger cross-port correlations. Building on this initial evidence and following Anselin [2001], I calculate Moran's I-statistic<sup>14</sup> for each month of the data. The results provide overwhelming evidence in support of spatial correlations over the entire sample period for both U.S. exports and imports.<sup>15</sup>

<sup>&</sup>lt;sup>14</sup>As shown by Anselin and Rey [1991] and Anselin and Florax [1995], Moran's test has power against any form of spatial dependence.

 $<sup>^{15}</sup>$ Following suggestions by Greene [2003], the average I-statistics of 1.189 and 1.284 with average p-values of 0.00001 and  $1.33 \times 10^{-9}$  for exports and imports, respectively, strongly reject the null hypothesis of no spatial correlation present in U.S. containerized trade. Across any time period the maximum p-values are 0.0005 and  $1.27 \times 10^{-7}$  for exports and imports, respectively. Furthermore, identical tests applied to annual U.S. port-level trade data provide robust evidence consistent with the presence of spatial correlation across U.S. ports of entry and exit regardless of the time horizon under consideration.

Table 5: Regional Trade Disruptions

	OLS	PPML	SAR	SEM	SAC
	(1)	(2)	(3)	(4)	(5)
Panel A: Exports					
Gulf Coast	0.022	0.056	0.047	0.050	-0.152
	(0.188)	(0.088)	(0.174)	(0.173)	(0.615)
Lower Atlantic	0.526	0.023	0.549	0.512	0.795
	(0.457)	(0.059)	(0.455)	(0.420)	(0.968)
Spatial-Weighting	None	None	m=4	m=4	m=4
Panel B: Imports					
Gulf Coast	-0.021	-0.008	0.055	0.080	0.055
	(0.198)	(0.136)	(0.193)	(0.171)	(0.226)
Lower Atlantic	0.328	0.035	0.381	0.297	0.380
	(0.308)	(0.047)	(0.301)	(0.232)	(0.348)
Spatial-Weighting	None	None	m=10	m=10	m = 10
Observations	1,960	1,960	1,960	1,960	1,960
Port FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Std. Errors	clustered	clustered	clustered	clustered	clustered

Robust standard errors in parentheses
\*\*\* p<0.01. \*\* p<0.05. \* p<0.1

To control for these cross-port spatial correlations of U.S. containerized trade, while investigating the static resilience of international trade, I estimate the port-specific, disaster-induced trade effects using the spatial autocorrelation model. Following LeSage and Pace [2009], I estimate the model for a variety of weight matrix specifications<sup>16</sup> and compare the resulting log-likelihood values, given in Table 15 in the Appendix. Whereas the four nearest neighbors matrix (m=4) is the preferred specification in the export case, imports are estimated using the ten nearest neighbors specification. As suggested by LeSage and Pace [2009], a log-likelihood ratio test based on these preferred weight matrix specifications strongly rejects the more restricted SAR and SEM models in favor of the more flexible SAC model in export case, while no such evidence is found in the import case.<sup>17</sup>

<sup>&</sup>lt;sup>16</sup>These specifications include a contiguity matrix, four through ten nearest neighbor weight matrices and an inverse distance weight matrix. The inverse distance matrix is build on the port-to-port distance matrix provided in Table 12 of the Appendix.

<sup>&</sup>lt;sup>17</sup>Nevertheless, the estimation results for both exports and imports are robust to the alternative spatial

The specific estimations of the preferred SAC model include port and time fixed effects, along with port-specific export or import treatment effects across various time horizons. While columns (1) and (2) of Tables 6 and 7<sup>18</sup> display the estimated direct and indirect export and import disruptions averaged over three months post Hurricane Katrina's landfall, columns (3) and (4) as well as (5) and (6) present average direct and indirect treatment effects over two and eight years following the disaster, respectively.<sup>19</sup>

Overall, these short-run, medium-run, and long-run treatment effects offer novel insights into the systematic spatial heterogeneity of the disaster-induced trade disruptions that are masked by aggregate estimations and evidence the static and dynamic resilience of international trade. That is, with respect to the excluded port of Tacoma, WA, nearly all treatment effects are statistically insignificant in the short and medium-run. Notable exceptions to this observation are the estimated trade effects for those ports closest to Hurricane Katrina's epicenter. The ports of Gulfport and New Orleans, for example, those closest to Katrina's epicenter, experience economically and statistically significant direct short-run reductions in both exports and imports ranging from 71% to 86%. The spatial heterogeneity of trade effects and resulting static resilience of trade is evidenced when extending the scope just beyond the hurricane warning zone, as depicted in Figures 3.1 and 3.2. In contrast to Gulfport and New Orleans, the port of Panama City experiences the largest and only statistically significant short-run increase in trade in response to Hurricane Katrina. Point estimates suggest a 650% and 9950% short-run increase for imports and exports, respectively, that partially offsets the economically significant reductions at the ports of Gulfport and New Orleans.

The dynamic resilience of trade is documented by the medium to long-run coefficient estimates and indicates two complementary mechanisms. The first of which is described as

model specifications and results are available upon request.

<sup>&</sup>lt;sup>18</sup>For expositional purposes, Tables 6 and 7 display the respective export and import direct and indirect treatment effects for ports nearest to Hurricane Katrina's epicenter located in Alabama, Florida, Louisiana, Mississippi, and Texas. The remaining port-specific treatment effects are presented in Tables 16 and 17 in the Appendix.

<sup>&</sup>lt;sup>19</sup>Following the discussion by LeSage and Pace [2014], the direct treatment effects can be interpreted as the Hurricane Katrina-induced disruptions off logged real U.S. containerized trade facilitated by the respective port of entry or exit. In contrast, the indirect effects should be seen as a secondary response of all other ports to Hurricane Katrina's direct impact on a given port.

long-term recovery and evidenced by the port of New Orleans. Here, the results illustrate a rapid recovery that leads to much smaller and largely insignificant direct treatment effects over the medium to long-run suggesting a complete export recovery in less than two years. This direct recovery, however, does not apply to all negatively affected ports. Gulfport, for example, continues to suffer the repercussions of Hurricane Katrina leading to statistically significant direct long-run trade reductions of 82% and 49% for exports and imports, respectively. Gulfport's misfortune, however, gives rise to the second mechanisms driving the dynamic resilience of trade. Permanent rerouting away from the severely damaged infrastructure of the port of Gulfport is evidenced by the persistent direct treatment effects of Panama City, which remain statistically and economically significant when extending the sample to the medium and long-run. The suggested permanence and remarkable consistency of these disaster-induced trade effects reflect the second mechanism of the dynamic resilience of trade and could speak towards the substantial switching costs for carriers choosing their ports of entry and exit from a larger available infrastructure network.

Interestingly, the port of Mobile exhibits insignificant export and import direct treatment effects in the short-run. However, when considering the medium to long-run, these estimated treatment effects increase and become statistically and economically significant for both exports and imports suggesting a 56% and 191% long-run increase, respectively.<sup>20</sup> An intuitive explanation for this initially surprising finding may be the fact that this port was located within the hurricane warning zone. Albeit being sparred from considerable damage, carriers may have avoided the entire hazard zone, including the port of Mobile, due to the uncertainty in the short-run. In the medium to long-run, however, the port's proximity to the severely damaged infrastructures of New Orleans and Gulfport, in particular, may have swayed carriers to consider the port of Mobile as a low-cost alternative and port officials to invest into additional capacity.<sup>21</sup>

<sup>&</sup>lt;sup>20</sup>In the medium- to long-run, there are some other ports that exhibit statistically significant variation post treatment. However these treatment effects may capture alternative port-specific events and are not indicative of the effects of Hurricane Katrina.

<sup>&</sup>lt;sup>21</sup>In general, the port-specific results are qualitatively and quantitatively very consistent when estimated via the SAR and SEM models or alternative weight matrix specifications and results are available upon request.

Table 6: Port-Specific Trade Disruptions - Exports

	Short	Run	Modiu	m-Run	Long-Run		
	Direct	Indirect	Direct	Indirect	Direct	Indirect	
	(1)	(2)	(3)	(4)	(5)	(6)	
Jacksonville, FL	-0.134	0.051	0.280	-0.000	0.134	0.077	
Jacksonvine, FL	(0.424)	(0.154)	(0.200)	(0.033)	(0.134)	(0.135)	
	,	,	, ,	,	, ,	, ,	
Palm Beach, FL	-0.221	0.077	0.309	0.002	-0.124	-0.074	
	(0.423)	(0.159)	(0.198)	(0.036)	(0.230)	(0.137)	
Port Everglades, FL	-0.046	0.022	0.357*	0.001	0.308	0.180	
	(0.419)	(0.143)	(0.203)	(0.039)	(0.234)	(0.142)	
Miami, FL	0.321	-0.141	0.005	-0.015	-0.780***	-0.465***	
	(0.522)	(0.216)	(0.258)	(0.029)	(0.246)	(0.178)	
Corpus Christi, TX	0.042	-0.024	-0.026	-0.001	1.561***	0.918***	
1	(0.414)	(0.143)	(0.196)	(0.020)	(0.231)	(0.196)	
Houston, TX	-0.350	0.120	0.316	-0.001	0.206	0.120	
110430011, 174	(0.441)	(0.178)	(0.206)	(0.036)	(0.235)	(0.139)	
Engan ant TV		-0.037	, ,	,	,	,	
Freeport, TX	0.100 $(0.429)$	(0.146)	0.140 $(0.201)$	0.002 $(0.023)$	-0.309 $(0.230)$	-0.184 $(0.142)$	
	,	,	, ,	,	,	, ,	
Galveston, TX	0.412	-0.105	-0.080	-0.005	0.208	0.120	
	(0.416)	(0.153)	(0.201)	(0.021)	(0.226)	(0.131)	
Port Arthur, TX	-1.075**	0.336	1.098***	0.008	0.430*	0.251*	
	(0.475)	(0.286)	(0.196)	(0.105)	(0.227)	(0.138)	
Tampa, FL	0.148	-0.093	0.389	-0.012	-0.369	-0.224	
	(0.519)	(0.195)	(0.255)	(0.043)	(0.245)	(0.159)	
Panama City, FL	4.610***	-1.306	5.198***	0.045	4.892***	2.880***	
<i>3</i> )	(0.438)	(0.863)	(0.197)		(0.234)	(0.465)	
Mobile, AL	0.145	-0.057	0.495**	-0.008	0.762***	0 444***	
WOODE, TL	(0.435)	(0.158)	(0.238)	(0.052)	(0.237)	(0.144)	
New Orleans I A	-1.714***	,	-0.048	,	,	,	
New Orleans, LA	(0.502)	0.521 $(0.396)$	(0.210)	-0.004 $(0.022)$	-0.139 $(0.233)$	-0.083 $(0.140)$	
G 10 15G	,	,	, ,	,	,	, ,	
Gulfport, MS	-1.239***	0.331	-0.659**	-0.022	-1.689***	-1.001***	
	(0.441)	(0.252)	(0.267)	(0.072)	(0.255)	(0.245)	
Spatial-Weighting	m=4	m=4	m=4	m=4	m=4	m=4	
Observations	240	240	1,920	1,920	4,800	4,800	
Port FE	Yes	Yes	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Another important finding is that Hurricane Katrina and the resulting direct short to medium-run disruptions at ports closest to its epicenter cause no statistically significant indirect network effects at other ports. In the long-run, however, the permanent changes in exports at the ports of Gulfport, Mobile and Panama City, in particular, trigger statistically significant indirect responses that are positively correlated with the primary impact. That is, the long-run increases in exports at the port of Panama City and Mobile are estimated to increase exports across all other ports as well. As one might expect, however, the magnitude of these indirect effects heavily depends on a given port's proximity to Mobile and Panama City and quickly vanishes with increasing orders of neighboring ports.

To address the evidenced short-run to long-run spatial heterogeneity in trade effects and gain a better understanding of the underlying factors driving the indicated static and dynamic resilience of international trade and persistence in trade effects, I conduct an additional analysis regressing the previously estimated port-specific treatment effects on time-invariant port characteristics, inverse distance and an access capacity measure.<sup>22</sup> To gain insights into the selection of ports for rerouting carriers, I restrict the analysis to include only those treatment effects that are obtained for ports outside of the hurricane warning zone, excluding Gulfport, New Orleans and Mobile from the sample. The available characteristics include harbor type as well as tidal and other entry restrictions. The legend key to these characteristics is given by Table 18 in the Appendix and shows that the respective reference groups are coastal breakwater ports for the available harbor types and ports without any tidal or other entry restrictions. Given these reference groups, negative point estimates on any of the included port characteristics imply that the presence of entry restrictions and specific harbor types other than coastal breakwater reduce the positive disaster induced treatment effects. Inverse distance is calculated as 1/(nautical distance to Katrina's epicenter), as presented in Tables 2 and 3, so that a positive coefficient implies that closer ports experience exponentially larger treatment effects.

To address the issue of uncertainty in the estimated dependent variable, I follow the sug-

<sup>&</sup>lt;sup>22</sup>Access capacity is measured as a port's maximum monthly throughput prior to Hurricane Katrina relative to the average throughput three month prior to the disaster.

Table 7: Port-Specific Trade Disruptions - Imports

	Short-		Mediur		Long-	
	Direct (1)	Indirect (2)	Direct (3)	Indirect (4)	Direct (5)	Indirect (6)
Jacksonville, FL	0.228 $(0.360)$	-0.086 $(0.356)$	0.174 $(0.194)$	-0.025 (0.044)	0.558*** (0.162)	-0.052 $(0.069)$
Palm Beach, FL	0.026 $(0.378)$	-0.098 $(0.793)$	-0.351* (0.198)	0.018 $(0.067)$	-0.838*** (0.168)	0.067 $(0.097)$
Port Everglades, FL	0.198 $(0.348)$	-0.091 $(0.550)$	0.049 $(0.192)$	-0.012 $(0.037)$	-0.041 $(0.162)$	0.001 $(0.025)$
Miami, FL	-0.095 $(0.357)$	0.028 $(0.492)$	-0.132 $(0.193)$	0.003 $(0.044)$	-0.123 $(0.165)$	0.007 $(0.028)$
Corpus Christi, TX	-0.608* (0.358)	0.145 $(1.267)$	0.623*** (0.182)	-0.052 $(0.102)$	0.689*** (0.157)	-0.059 $(0.082)$
Houston, TX	-0.035 $(0.352)$	$0.030 \\ (0.332)$	0.194 $(0.201)$	-0.027 $(0.047)$	0.253 $(0.166)$	-0.026 (0.038)
Freeport, TX	-0.367 $(0.442)$	0.195 $(0.304)$	-0.774*** (0.186)	0.067 $(0.123)$	-0.655*** (0.161)	$0.060 \\ (0.078)$
Galveston, TX	-0.161 $(0.408)$	0.162 $(0.924)$	0.247 $(0.181)$	-0.021 $(0.051)$	0.445*** (0.156)	-0.038 $(0.057)$
Port Arthur, TX	0.060 $(0.347)$	-0.023 $(0.753)$	-0.058 $(0.199)$	-0.008 $(0.041)$	-0.621*** (0.168)	0.047 $(0.075)$
Tampa, FL	0.157 $(0.353)$	-0.016 $(0.280)$	0.390** (0.189)	-0.038 $(0.067)$	0.848*** (0.161)	-0.076 $(0.100)$
Panama City, FL	2.011*** (0.368)	-0.320 $(3.225)$	3.122*** (0.181)	-0.263 $(0.483)$	2.911*** (0.156)	-0.255 $(0.332)$
Mobile, AL	0.456 $(0.354)$	-0.045 $(0.911)$	0.433** (0.192)	-0.044 $(0.075)$	1.069*** (0.161)	-0.096 $(0.126)$
New Orleans, LA	-1.966*** (0.415)	0.304 $(4.555)$	-0.431** (0.203)	0.026 $(0.082)$	0.055 $(0.169)$	-0.009 (0.027)
Gulfport, MS	-1.794*** (0.403)	0.258 $(4.403)$	-0.729*** (0.201)	0.052 $(0.120)$	-0.666*** (0.170)	0.054 $(0.079)$
Spatial-Weighting Observations Port FE Time FE	m=4 240 Yes Yes	m=4 240 Yes Yes	m=4 1,920 Yes Yes	m=4 1,920 Yes Yes	m=4 4,800 Yes Yes	m=4 4,800 Yes Yes

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

gestions by Lewis and Linzer [2005] and estimate the Fitted Estimated Dependent Variable (FEDV) Model that accounts for both the noise in the estimation as well as the dependent variable.<sup>23</sup> The results presented in Table 8 support ex ante expectations. While harbor types, entry restrictions and even capacity play a very limited role in redirecting U.S. containerized exports and imports, the inverse of nautical distance to the epicenter has a statistically significant positive impact on all export and import treatment effects. This, of course translates into an exponential decline of the port-specific impact in absolute distance; a finding that increases in magnitude in the medium to long-run. Furthermore, regardless of the time horizon under consideration, export treatment effects tend to be much more sensitive to distance to Katrina's epicenter than import treatment effects. All of these findings are quite intuitive. In the short-run, distance may not be as important of a factor to handle rerouted trade immediately. Carriers may travel considerable distances to avoid being delayed and incur penalties. In the long-run, however, distance becomes the most prominent cost factor in the determination of port choice. Lastly, containerized exports facilitated via truck, rail or even inland waterway tend to command a higher cost per ton-mile than imports facilitated on international container carriers and are thus, significantly more sensitive to distance than imports.

To further explore this dependence on distance, offer insights for both positive and negative treatment effects alike, and gain a better understanding of the potential differences in this distance-dependence across export and import treatment effects, I develop and estimate a model interacting intraregional port groups with the inverse of nautical distance to Hurricane Katrina's epicenter. For the purposes of this estimation, I differentiate between *core* and *peripheral* ports and estimate average treatment effects over two years post Hurricane Katrina. The *core* is defined as those ports within Hurricane Katrina's warning zone, namely the ports of New Orleans, Gulfport, and Mobile. Whereas the *periphery* is defined as those ports located outside of this warning zone, but within the Gulf Coast and Lower Atlantic regions. The resulting

<sup>&</sup>lt;sup>23</sup>For robustness, I also estimate the model with heteroskedasticity robust standard errors as well as a weighted least squares regression, where the weights are set equal to the inverse of the original treatment effects' standard errors. As expected, the FEDV Model produces the most conservative estimates. Alternative estimation results are available upon request

Table 8: Influence of Port Characteristics on Direct Treatment Effects

	Short	-Run	Mediu	m-Run	Long	-Run
VARIABLES	Export	Import	Export	Import	Export	Import
	(1)	(2)	(3)	(4)	(5)	(6)
HT (=1)	-0.202	-0.044	-0.968**	0.119	-1.001*	-0.031
	(0.429)	(0.260)	(0.409)	(0.364)	(0.540)	(0.392)
HT (=2)	-0.097	-0.268	-0.308	0.300	-2.530**	0.480
	(0.747)	(0.436)	(0.704)	(0.635)	(0.930)	(0.675)
HT (=3)	-2.327***	-0.295	-0.827	-0.476	-1.476	-1.493*
	(0.823)	(0.480)	(0.747)	(0.707)	(0.987)	(0.732)
HT (=4)	-0.502	-0.041	-0.408	0.111	-0.569	0.053
	(0.758)	(0.445)	(0.708)	(0.650)	(0.934)	(0.680)
HT (=5)	-0.306	-0.129	-0.732*	0.112	-0.746	0.151
	(0.421)	(0.248)	(0.396)	(0.360)	(0.523)	(0.379)
HT (=6)	-1.477*	-0.328	-1.449*	-0.279	-1.532	-0.429
	(0.798)	(0.469)	(0.741)	(0.691)	(0.978)	(0.711)
ER - Tide	-0.435	0.027	-0.300	-0.181	-0.395	-0.389
	(0.267)	(0.160)	(0.253)	(0.233)	(0.334)	(0.244)
ER - Other	-0.264	-0.186	-0.708**	-0.174	-0.411	-0.073
	(0.330)	(0.197)	(0.311)	(0.282)	(0.410)	(0.298)
Inv. Distance	660.354***	245.576**	750.906***	450.815***	767.542***	458.256***
	(146.465)	(88.805)	(138.145)	(120.006)	(182.317)	(130.276)
Capacity	-0.002	0.000	0.014	-0.003	0.020	0.002
	(0.013)	(0.002)	(0.012)	(0.003)	(0.016)	(0.003)
Observations	37	37	37	37	37	37
R-squared	0.568	0.353	0.657	0.447	0.572	0.439
Std. Errors	FEVD	FEVD	FEVD	FEVD	FEVD	FEVD

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

direct marginal effects are presented in Figures 6.1 through 6.4 and illustrate the converted marginal export and import treatment effects for core and peripheral ports over distance.<sup>24</sup> Standard errors are calculated via the delta method.

Several key features of these graphs are important to point out. First, while ports in very close proximity reduce trade between 50% and 100%, the negative disruptions vanish exponentially as distance increases and become insignificant roughly 20 miles away from the

<sup>&</sup>lt;sup>24</sup>The conversion of the core and periphery point estimates into percentage changes in the value of trade is based on the following calculations:  $\Delta\%Core = (exp(\beta_{core}) * exp(\beta_{core-dist.} * (1/(Distance)) - 1) * 100$  and  $\Delta\%Periphery = (exp(\beta_{periphery}) * exp(\beta_{periphery-dist.} * (1/(Distance)) - 1) * 100$ , respectively.

epicenter two years after the disaster. To put this in perspective, while exports handled by the port of Gulfport, 15.7 nautical miles east of Katrina's epicenter, for example, are estimated to experience a statistically significant 63.8% average reduction, the average export effect at the port of New Orleans, 40.4 nautical miles west of Katrina's epicenter, for example, is estimated to yield a statistically insignificant 24% increase.<sup>25</sup> As illustrated by Figures 6.1 and 6.2, this finding is consistent across both exports and imports.

Second, the peripheral changes are economically and statically significant and substantially larger for exports than imports at close proximity. Although the estimated peripheral increases in exports appear very large, the underlying differences in average pre and post port throughput listed in Tables 2 and 3 are also quite sizable. Rerouting of traded products away from a fairly large port, like New Orleans, can result in dramatic throughput changes in smaller nearby ports, like Panama City, which is estimated to experience a statistically significant 14,562.2% increase in exports, 237.7 miles away from Katrina's epicenter.<sup>26</sup>

Third, marginal peripheral direct treatment effects decrease quickly, but vanish faster for exports than for imports as distance increases. In fact, both treatment effects, despite the initial size difference, approach zero roughly 450 miles away from the disaster epicenter. This finding provides further evidence in support of the hypothesis that exports tend to be more sensitive to distance than imports.<sup>27</sup>

# 6.2 Dynamic Local Analysis

Having provided considerable evidence in support of the static local resilience of international trade and some preliminary evidence supporting its dynamic resilience, I now turn towards

 $<sup>^{25}</sup>$ Calculations are based on the point estimates obtained from the SAC model.

<sup>&</sup>lt;sup>26</sup>A natural concern is the feasibility of such staggering increases and whether a port, like Panama City, can handle such shipments. The answer to this pressing question, lies within the presence of large sporadic pretreatment shipments as evidenced by Panama City, FL prior to Hurricane Katrina. Although these shipments are large and require sufficient capacity, their sporadic nature implies little influence on pre-treatment average port throughput. Thus, Panama City appears as a small port, but with considerable excess capacity prior to Hurricane Katrina, capable of handling tremendous short-run increases.

<sup>&</sup>lt;sup>27</sup>The actual export and import point estimates underlying these Figures are presented in columns (5) and (6) of Table 19 in the Appendix and are significant at the 1% level across all coefficients. For robustness empirical results from SAR and SEM model estimations are also presented in columns (1) through (4) and point to the consistency of the primary estimates.

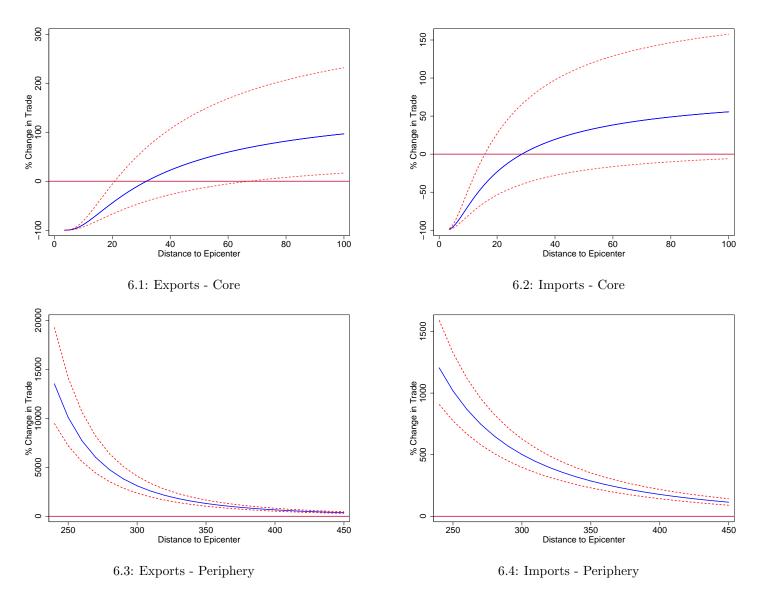


Figure 6: Direct Treatment Effects over Distance

the primary estimation of the dynamic and spatially heterogeneous trade effects induced by Hurricane Katrina. To this end, I estimate the empirical specification given by equation (2) over the entire sample period, R = 24 and S = 96. Given the preliminary port-specific short-run to long-run treatment effects presented in Tables 6 and 7, I focus this discussion around the ports closest to Hurricane Katrina, including Gulfport, New Orleans, Mobile and Panama City.<sup>28</sup> Since a tabular representation of these dynamic trade disruptions is quite convoluted,

<sup>&</sup>lt;sup>28</sup>As part of the robustness analysis, I also provide the dynamic treatment effects for ports at greater distances. The results are provided via Figures 10.1 through 17.2 in the Appendix and show no systematically statistically significant treatment effects resulting from Hurricane Katrina.

I use graphical representations of the estimated port-specific direct treatment effects instead. Figures 7.1 through 9.2 display port-specific monthly direct treatment effects in relation to August, 2005, the landfall of Hurricane Katrina, and relative to all sample ports excluding the ports of 6th order contiguity or less to Katrina's epicenter.

The vertical red line at 0 indicates Katrina's landfall. Given the empirical specification, each point on the graph can be thought of as a difference-in-differences estimator. That is, each point estimate post treatment reflects a month-port-specific treatment effect relative to that port's trade during the month of August, 2005, the time of Hurricane Katrina's landfall, and relative to the average change in trade across the excluded ports from August, 2005 to the given month under consideration. The flexibility of this specification allows for a clearer evaluation of the persistence of the disaster induced trade effects and facilitates dynamic cross-port comparisons.<sup>29</sup>

Figures 7.1 through 7.4, for example, display tremendous short-run trade disruptions at the ports of New Orleans and Gulfport, but also reveal that the duration and magnitude of these disruptions vary across imports and exports as well as across the individual ports. For both ports, imports, for example, suffer a larger short-run reduction than exports. This finding supports the previous conclusions and strengthens the claim that imports facilitated by container vessels are more easily rerouted than exports transported by train, truck or inland waterways. Relative to importing container vessels, these types of transportation modes are subject to significant rerouting barriers. This is particularly true for the port of New Orleans which is strategically located at the mouth of the Mississippi River and one of the main facilitator of bulk exports that have few transportation substitutes to the inland waterways. This route dependence of exports causes rather short-lived delays in export shipments and leads to smaller short-run export reductions than for imports.

While these short-run export/import comparisons are similar for both ports, a long-run cross port comparison reveals that imports for the port of Gulfport experience rather lasting

<sup>&</sup>lt;sup>29</sup>The presented trade effects are based on the SAC model and are robust to the use of the SAR or SEM models as well as various weight matrix specifications. Results are available upon request.

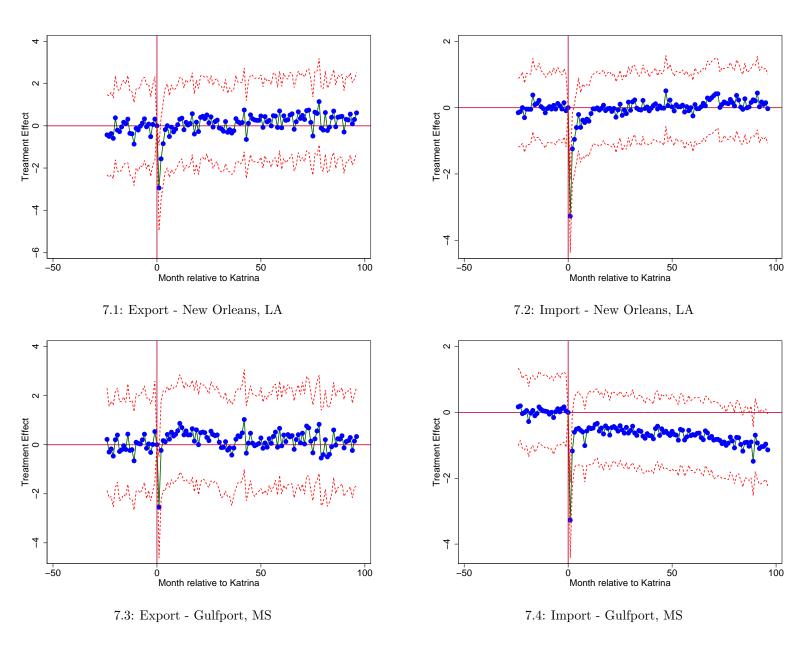


Figure 7: Dynamic Variation in Treatment Effects - New Orleans, LA & Gulfport, MS

reductions relative this port's exports as well as exports and imports of the port of New Orleans. In fact, while exports and imports handled by the port of New Orleans experience a rapid recovery over the first six to twelve month post treatment, depicted in Figures 7.1 and 7.2, Gulfport's merely partial recovery of imports is much more prolonged, as shown by Figure 7.4. These negative long-run effects, albeit only marginal significance at the 5% level, can be traced back to the substantial damages sustained by the infrastructure at the port of Gulfport and documented by Grenzeback et al. [2008].

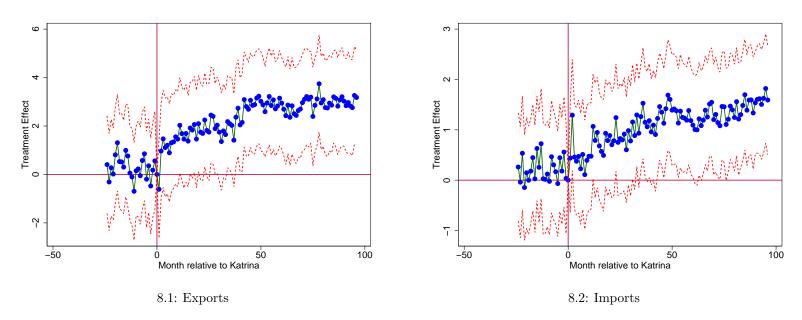


Figure 8: Dynamic Variation in Treatment Effects - Mobile, AL

Expanding the spatial scope of the analysis, I now consider the dynamic trade effects of Hurricane Katrina on the ports of Mobile, AL and Panama City, FL. Both of these ports are just outside of the disaster stricken region and, as the previous static port-specific analysis suggests, are the primary candidates for the evaluation of the static and dynamic resilience of international trade. The results for both of these ports are presented in Figures 8.1 through 9.2 and illustrate significant short-run as well as long-run disruptions across both exports and imports. However, the depicted responses are very idiosyncratic across the two ports. While the short-run effects on Mobile exports suggest a slight one month reduction relative to pretreatment export levels, the import trade effects at the port of Mobile are estimated to be

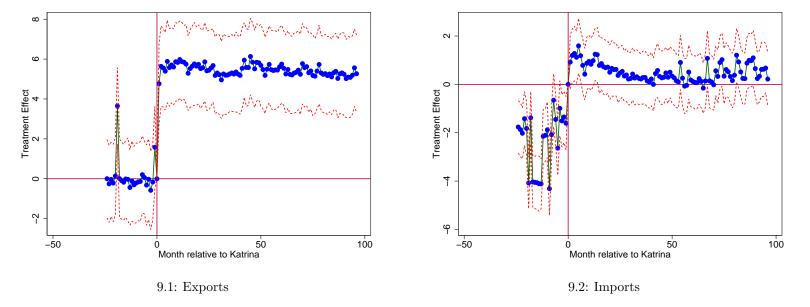


Figure 9: Dynamic Variation in Treatment Effects - Panama City, FL

positive and economically significant in the first month following treatment before tapering off to pre-treatment levels over the next four month. Contrary to these opposing short-run responses, Figures 8.1 and 8.2 also reveal that both exports and imports facilitated through Mobile start experiencing positive growth roughly two to five month post treatment. This disaster-induced growth in trade leads to statistically significant effects roughly 30 months post treatment.

In contrast to these varying and mild short-run responses as well as persistent growth rate changes of trade handled by the port of Mobile, exports and imports facilitated through the port of Panama City, depicted by Figures 9.1 and 9.2, experience immediate and large increases in response to Hurricane Katrina that are very persistent in the long-run. While imports reveal a economically significant but statistically insignificant increase post Hurricane Katrina<sup>30</sup>, Panama City's exports reflect an unparalleled economically and statistically significant upward jump that persists through the entire sample period.

Based on these estimated treatment effects across the ports of Gulfport, New Orleans, Mobile and Panama City, one can conclude that the static resilience of international trade and

<sup>&</sup>lt;sup>30</sup>Interpretation of the import effects is complicated by the fact that some imports appear to have been rerouted during August of 2005 in anticpation of Hurricane Katrina's landfall. A more appropriate comparison would consider the effects post August 2005 to those prior, clearly indicating a statistically significant difference.

resulting negligible aggregate trade effects are mainly driven by rerouted exports and imports through the port of Panama City. Moreover, the estimates show that the dynamic resilience of international trade in response to Hurricane Katrina is driven by the long-run recovery by the port of New Orleans and the persistent long-run increases in exports and imports at the ports of Mobile and Panama City that offset the permanent reductions experienced by port of Gulfport.

In contrast to these consistent and considerable short-run and long-run trade effects displayed by the ports of Gulfport, New Orleans, Mobile and Panama City, ports located at greater distances show no statistically significant responses to Hurricane Katrina. In fact, Figures 10.1 through 17.2 in the Appendix provide no evidence of any short-term or long-term responses in exports or imports that are distinguishable from pre-hurricane variation or can be directly linked to Hurricane Karina. In summary, these findings suggest that albeit significant disaster induced reductions in trade for those ports closest to the epicenter, a transport network, similar to that of the U.S., can offset the majority of trade reductions caused by a natural disaster, similar to Hurricane Katrina, within a small geographic region. The indicated mechanisms of the resilience of trade include rerouting and delaying of traded products within a narrow band of nearby ports leaving short-run and long-run trade effects unaffected at the aggregate level.

## 6.3 Disaggregated Analysis

To gain a better understanding of the underlying forces driving these dynamic disruptions in the value of trade, I redirect the focus of the analysis towards the effects at a more disaggregated product level. Specifically, I consider the effects of Hurricane Katrina on the number of products facilitated by a given port differentiating across several different product categories. Re-estimating the port-specific treatment effects over the short, medium and long-run on the number of traded products, I provide insights into the specific industries driving the static and dynamic resilience of international trade. Similar to the dynamic analysis, the results reported here focus on the direct effects on the primary ports of interest including Gulfport, New Or-

leans, Mobile and Panama City and are summarized in Tables 9 and 10 for exports and imports, respectively.  $^{31}$ 

The number of traded products for a given port-month pair is based on the 2 digit HS classification that consolidates individually traded products into 98 product groups. While column (1) of Tables 9 and 10 provides the treatment effects of Hurricane Katrina on the total number of traded products, columns (2) through (8) depict these trade effects for seven slightly more disaggregated product categories. The consolidation of the original 98 product groups into these seven product categories is based on sections and individual product group definitions obtained from Schedule B reported by the *U.S. Census Bureau*.<sup>32</sup> A legend providing the necessary details for each of these product categories is presented in Table 11. The estimation results at this disaggregated level are intended to disentangle the aggregate effects observed in column (1) and help identify whether the disaster induced trade disruptions are experienced across all industries or rather idiosyncratic.

When considering the aggregate effects on the number of traded products presented in column (1), it becomes clear that these results reflect the expected patterns. In the short-run, the ports of New Orleans and Gulfport experience economically and, in part, statistically significant reductions in the number of exported and imported products ranging from 15 to 33 lost product groups. Over time, however, these large initial reductions in the portfolio of traded products revert back towards pre-treatment levels. As expected, New Orleans experiences a more rapid recovery over the medium to long-run relative to the port of Gulfport. In the long-run the estimated treatment effects for New Orleans, for example, result in statistically significant reductions of the number of traded products by 4 and 5 for exports and imports, respectively, while Gulfport continues to suffer reductions of 4 and 7 exported and imported product groups.

<sup>&</sup>lt;sup>31</sup>The remaining short-run to long-run port-specific treatment effects of ports located at greater distances have been estimated and the results are available upon request. As expected, the majority of these treatment effects for more remote ports are again statistically insignificant and without any significant outliers or discernible patterns relative to the primary ports under consideration.

<sup>&</sup>lt;sup>32</sup>Schedule B is the official schedule of commodity classifications to be used by shippers in reporting export shipments from the United States.

Table 9: Port-specific Direct Treatment Effects on the Number of Exported Products

Ports	Total (1)	Category 1 (2)	Category 2 (3)	Category 3 (4)	Category 4 (5)	Category 5 (6)	Category 6 (7)	Category 7 (8)
Short-Run								
Panama City, FL	47.342***	0.003	3.546***	9.346***	5.746***	11.881	7.006***	8.784**
	(7.109)	(0.883)	(0.756)	(1.034)	(1.580)	(7.388)	(1.070)	(4.178)
Mobile, AL	1.920	-1.015	-0.403	1.130	0.668	0.643	0.283	0.022
	(5.975)	(0.935)	(0.917)	(1.224)	(1.013)	(2.929)	(0.937)	(1.474)
New Orleans, LA	-14.943***	-4.783***	0.044	-1.406	-0.132	-6.530*	-1.072	-0.309
	(5.026)	(0.952)	(0.938)	(1.000)	(0.891)	(3.724)	(1.273)	(1.415)
Gulfport, MS	-17.427**	-1.899	-3.149***	-2.789**	-1.545*	-1.492	-3.121**	-3.424***
	(7.514)	(1.261)	(0.753)	(1.130)	(0.837)	(4.246)	(1.245)	(1.098)
Medium-Run	,	,	, ,	, ,	,	· · ·	,	,
Panama City, FL	59.306***	2.093***	5.642***	12.053***	4.835***	15.056***	7.984***	9.810***
	(1.745)	(0.388)	(0.291)	(0.451)	(0.310)	(0.530)	(0.514)	(0.450)
Mobile, AL	8.456***	-0.748*	0.968**	2.986***	0.425	4.843***	2.989***	2.496***
	(1.786)	(0.399)	(0.397)	(0.679)	(0.357)	(0.668)	(0.644)	(0.733)
New Orleans, LA	-4.413***	-2.450***	0.102	-0.401	-0.810**	-0.542	-0.168	-0.536
	(1.491)	(0.404)	(0.303)	(0.430)	(0.320)	(0.513)	(0.451)	(0.414)
Gulfport, MS	1.022	-1.529***	-0.430	-0.416	-0.815**	3.970***	-1.534***	-1.434***
	(1.653)	(0.436)	(0.310)	(0.452)	(0.354)	(0.786)	(0.536)	(0.432)
Long-Run								
Panama City, FL	58.953***	3.337***	5.300***	12.248***	6.138***	14.456***	8.623***	9.341***
	(1.747)	(0.449)	(0.284)	(0.500)	(0.344)	(0.487)	(0.394)	(0.507)
Mobile, AL	9.878***	0.881**	2.044***	2.913***	1.069**	2.988***	2.985***	2.144**
	(2.052)	(0.449)	(0.320)	(0.745)	(0.503)	(0.520)	(0.471)	(0.903)
New Orleans, LA	-3.768**	-2.247***	0.156	-0.200	-0.202	-0.779	-0.015	-0.350
	(1.810)	(0.392)	(0.303)	(0.443)	(0.276)	(0.505)	(0.406)	(0.384)
Gulfport, MS	-4.134**	-1.731***	0.599**	-0.928**	-0.718**	2.311***	-1.916***	-2.310***
	(1.786)	(0.430)	(0.292)	(0.431)	(0.282)	(0.498)	(0.411)	(0.385)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial-Weighting	m=1	m=1	m=1	m=1	m=1	m=1	m=1	m=1

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Considering the adjacent ports, the estimated treatment effects on the aggregate number of traded products, once again, match the previous findings and provide supporting evidence of the static and dynamic resilience of trade. In the short-run the port of Panama City experiences substantial increases in the number of imported and exported products ranging from 28 to 47, respectively, while the port of Mobile exhibits no statistically significant impact across exports or imports. Expanding the time horizon under consideration emphasizes the expected persistence of the positive gains in the portfolio of products handled by the port of Panama City and the considerable growth in the number of exported and imported products for the port of Mobile. That is, the estimated average direct treatment effects over the first eight years after Hurricane Katrina suggest a statistically significant and persistent increase in the number of exported and imported products by 59 and 25 for the port of Panama City and 10 and 17 for the port of Mobile, respectively.

At the disaggregated level, the port of New Orleans experiences a relatively even reduction in imports with five out of seven product categories experiencing statistically significant short-run reductions. On the export side, however, we observe a very heterogeneous response concerning the number of traded products that is driven by decreases in Categories 1 and 5. This heterogeneity in treatment effects continues to persist for the number of exported products and also manifests itself for the number of imported products in the medium to long-run. While the number of traded products recovers over time and reverts to pre-treatment levels for the majority of product categories handled by the port of New Orleans, the remaining negative aggregate treatment effect is almost exclusively driven by permanent reductions in trade of Animal and Vegetable Products, shown in column (2) of Tables 9 and 10.

In contrast to New Orleans, the short-run effects for the port of Gulfport are fairly evenly spread across all imported and exported categories. The exception to this rule are exports of textiles which experience a statistically insignificant reduction in the short-run and surprising statistically significant increase in the number of exported products in the medium- to long-run. While this relatively even distribution of treatment effects persists in the medium to long-run for the number of exported products facilitated through Gulfport, the distribution of the

Table 10: Port-specific Direct Treatment Effects on the Number of Imported Products

Ports	Total (1)	Category 1 (2)	Category 2 (3)	Category 3 (4)	Category 4 (5)	Category 5 (6)	Category 6 (7)	Category 7 (8)
Short-Run								
Panama City, FL	27.965	2.756***	-1.246	0.395	3.946**	9.780***	3.405***	7.526
1 01101110 010, 1 1	(74.389)	(0.747)	(7.737)	(0.962)	(1.737)	(1.425)	(0.780)	(79.801)
Mobile, AL	-0.649	0.031	-1.745	-0.474	1.091	0.538	0.665	-2.659
11100110, 1111	(3.742)	(0.768)	(13.644)	(1.121)	(0.730)	(1.164)	(0.786)	(26.616)
New Orleans, LA	-33.139	-4.342***	-4.029	-6.855***	-1.838**	-5.811***	-4.729***	-4.273
,	(65.400)	(0.791)	(20.240)	(1.086)	(0.860)	(1.163)	(0.824)	(12.202)
Gulfport, MS	-9.929	-1.118	-1.478	-2.086	-1.611	-3.364	-1.897*	-0.392
1 /	(48.830)	(1.068)	(18.920)	(1.733)	(1.284)	(2.075)	(1.140)	(42.754)
Medium-Run	,	,	,	,	,	,	,	,
Panama City, FL	22.573***	3.307***	1.211***	1.371***	2.947***	7.339***	2.984***	3.585***
0 /	(1.414)	(0.380)	(0.303)	(0.428)	(0.271)	(0.494)	(0.554)	(0.568)
Mobile, AL	6.196***	-0.458	1.133***	0.208	0.506*	2.446***	1.758***	1.541***
	(1.467)	(0.388)	(0.300)	(0.407)	(0.282)	(0.515)	(0.429)	(0.506)
New Orleans, LA	-11.279***	-3.160***	-1.701***	-0.801*	-1.076***	-2.690***	-1.109***	-0.867**
	(1.457)	(0.397)	(0.300)	(0.446)	(0.288)	(0.495)	(0.378)	(0.398)
Gulfport, MS	-6.317***	-1.315**	-0.349	-1.577***	-0.947***	-1.364**	-1.873***	-0.845*
	(1.721)	(0.515)	(0.392)	(0.464)	(0.330)	(0.547)	(0.487)	(0.448)
Long-Run	, ,	,	,	,		,	,	,
Panama City, FL	25.463***	4.342***	2.375***	1.402***	3.610***	7.424***	2.464***	4.684***
	(1.890)	(0.384)	(0.390)	(0.484)	(0.285)	(0.616)	(0.427)	(0.411)
Mobile, AL	17.384***	0.429	2.358***	0.878**	1.944***	6.298***	3.295***	2.981***
	(1.572)	(0.333)	(0.267)	(0.385)	(0.289)	(0.508)	(0.346)	(0.380)
New Orleans, LA	-4.971***	-2.498***	-0.800**	-0.393	0.364	-0.714	-0.016	-0.657*
	(1.511)	(0.383)	(0.359)	(0.375)	(0.250)	(0.515)	(0.344)	(0.365)
Gulfport, MS	-6.855***	-2.974***	1.506***	-0.957**	-0.388	-1.139**	-3.075***	-0.558
	(1.518)	(0.531)	(0.329)	(0.376)	(0.253)	(0.470)	(0.348)	(0.356)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial-Weighting	m=1	m=1	m=1	m=1	m=1	m=1	m=1	m=1

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

trade disruptions becomes rather bimodal for the number of imported products. In particular, the estimates suggest that the sustained reduction in the number of imported products and incomplete overall long-term recovery appears to be mainly driven by the lack of imported Animal and Vegetable products and Bulk Products.

Turning the attention towards the positively affected ports of Panama City and Mobile, the estimated category-specific treatment effects suggest rather heterogeneous responses across industries. For Panama City, for example, all exported product categories but Animal and Vegetable Products and textiles reveal economically and statistically significant increases in the short-run. In the medium to long-run, aggregate increases in the total number of exported products are predominantly driven by changes in categories 3 (Mineral products, etc.) and 5 (Textiles), which increase by 77% to 80%, respectively, while Animal and Vegetable Products continue to be a disproportionately small contributor to the increase in exported products. A similar pattern is observed on the import side, where increases in the number of imported Textiles dominate the average changes of the product portfolio across all time horizons under consideration. Interestingly, Minerals and Plastics, rather than imported Live Animal and Vegetable Products, lag behind the other increasingly imported industries. The same holds true for the port of Mobile in the medium to long-run. Textiles are shown to be the main factor underlying Mobile's disaster induced export and import growth and the most prominent contributor to the changes in the local trade composition. Whereas exported and imported Live Animal and Vegetable Products as well as imported Minerals and Plastics (5%) tend to defy this growth at the port of Mobile.

Overall, these results provide considerable insights into the previously described trade disruptions caused by Hurricane Katrina. While the static and dynamic resilience of trade is evidenced for both the value of trade and number of traded products, the product-specific contributions to these offsetting trade disruptions in the short-run and overall recovery in the long-run are very heterogeneous across industries. High value containers of *Textiles*, for example, tend to be very resilient types of trade, whereas containerized trade of *Live Animals and Vegetable Products* or *Minerals and Plastics* appear to be less resilient and suffer dispropor-

tionately large disruptions from natural disaster. Given the fact that origin and/or destination changes in containerized shipments of *Live Animals and Vegetable Products* are rather costly, due to the required special handling and equipment and the fact that *Minerals and Plastics* are bulky, low value products, relative to shipments of *Textiles*, this finding is justifiable.

Table 11: Product Category Legend Key

Product Category	# of Products	Sections   included	Type of Products
1	15	1-3	Animal and Vegetable Products
2	9	4	Prepared Food Stuffs, Beverages, Spirits, Tobacco, etc.
3	16	5-7	Mineral, Chemical, Rubber and Plastic Products
4	9	8-10	Wood and Paper and products thereof, Leather, etc.
5	18	11, 12	Textiles, Footwear, Umbrellas, etc.
6	15	13-15	Bulk products including Stone, Plaster and Base Metals
7	14	16-19, 21	Work of Art, Manufactured products (i.e. Vehicles, etc.)

Source: Schedule B published by the U.S. Census Bureau

Notes: Excluded products groups include special classification provisions

## 7 Conclusion

The increasing presence and reliance of global economic output on international transactions has lead to the significant growth of international trade and its exposure to the omnipresent devastation caused by natural disasters. Frequent, yet uncertain calamities continue to cause tremendous human and economic hardship, but have been largely ignored in the trade literature. In the present study, I evaluate the impacts of Hurricane Katrina on U.S. trade and find that natural disasters represent significant barriers to international trade at the local port level. In conjunction with negligible aggregate treatment effects, the estimated dynamic and spatially heterogeneous trade disruptions point to the static and dynamic resilience of international trade.

The mechanisms underlying this trade resiliency include considerable rerouting of both exports and imports and their rapid recovery due to product-specific path dependence that lead to statistically and economically significant gains in trade for those ports closest to the disaster stricken region and negatively disrupted ports. The local disruptions are shown to be port-

specific, of temporary nature for some ports and permanent for others, heterogeneous across industries and offsetting in aggregate. While the rerouting of exports and imports is shown to strongly depend on the distance between the affected and non-affected ports, port-specific characteristics, such as harbor type, entry restrictions, or available capacity play only a limited role in port choice. In conjunction, these empirical results illustrate the importance of a closely knit infrastructure network to mitigate aggregate repercussions resulting from natural disasters, even the ones as monumental as Hurricane Katrina. As developing countries continue to experience significant aggregate disruptions from natural disasters, the empirical evidence pertaining to the negating transport network effects of rerouting of internationally traded products are of considerable interest to global policy makers.

Interestingly, the empirical findings point to an east/west dichotomy concerning the significance and magnitude of the trade effects resulting from Hurricane Katrina. Further inquiry may consider the role of hinterland transportation networks and other infrastructure characteristics that drive this spatially heterogeneous response and resulting resilience of international trade.

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## 8 Appendix

Table 12: Distances between U.S. Ports of Entry

	1a	bie 12.	Distan	ces ben	ween o.	S. 1 OI t	S OI LIII	ыу		
	Tacoma, WA	Seattle, WA	Portland, OR	San Francisco, CA	Richmond, CA	Oakland, CA	Port Hueneme, CA	Los Angeles, CA	Long Beach, CA	San Diego, CA
Tacoma	0									
Seattle	25	0								
Portland, OR	387	362	0							
San Francisco	1039	1014	652	0	_					
Richmond	1050	1025	663	11	0					
Oakland	1064	1039	677	25	14	0				
Port Hueneme	1379	1354	992	340	329	315	0			
Los Angeles	1441	1416	1054	402	391	377	62	0		
Long Beach	1444	1419	1057	405	394	380	65	3	0	
San Diego	1538	1513	1151	499	488	474	159	97	94	0
Corpus Christi	6000	5975	5613	4961	4950	4936	4621	4559	4556	4462
Freeport	6160	6135	5773	5121	5110	5096	4781	4719	4716	4622
Galveston	6244	6219	5857	5205	5194	5180	4865	4803	4800	4706
Houston	6291	6266	5904	5252	5241	5227	4912	4850	4847	4753
Port Arthur	6423	6398	6036	5384	5373	5359	5044	4982	4979	4885
New Orleans	6864	6839	6477	5825	5814	5800	5485	5423	5420	5326
Gulfport	7135	7110	6748	6096	6085	6071	5756	5694	5691	5597
Mobile	7233	7208	6846	6194	6183	6169	5854	5792	5789	5695
Panama City	7426	7401	7039	6387	6376	6362	6047	5985	5982	5888
Tampa	7691	7666	7304	6652	6641	6627	6312	6250	6247	6153
Miami	8134	8109	7747	7095	7084	7070	6755	6693	6690	6596
Port Everglades	8161	8136	7774	7122	7111	7097	6782	6720	6717	6623
Palm Beach	8207	8182	7820	7168	7157	7143	6828	6766	6763	6669
Jacksonville	8463	8438	8076	7424	7413	7399	7084	7022	7019	6925
Brunswick	8545	8520	8158	7506	7495	7481	7166	7104	7101	7007
Savannah	8649	8624	8262	7610	7599	7585	7270	7208	7205	7111
Charleston	8751	8726	8364	7712	7701	7687	7372	7310	7307	7213
Wilmington	8902	8877	8515	7863	7852	7838	7523	7461	7458	7364
Newport News	9262	9237	8875	8223	8212	8198	7883	7821	7818	7724
Baltimore	9432	9407	9045	8393	8382	8368	8053	7991	7988	7894
Chester	9509	9484	9122	8470	8459	8445	8130	8068	8065	7971
Philadelphia	9524	9499	9137	8485	8474	8460	8145	8083	8080	7986
Perth Amboy	9744	9719	9357	8705	8694	8680	8365	8303	8300	8206
Newark	9759	9734	9372	8720	8709	8695	8380	8318	8315	8221
New York City	9771	9746	9384	8732	8721	8707	8392	8330	8327	8233
Boston	10157	10132	9770	9118	9107	9093	8778	8716	8713	8619
Portland, ME	10257	10232	9870	9218	9207	9193	8878	8816	8813	8719
Detroit	12146	12121	11759	11107	11096	11082	10767	10705	10702	10608
Port Huron	12208	12183	11821	11169	11158	11144	10829	10767	10764	10670
Chicago	12779	12754	12392	11740	11729	11715	11400	11338	11335	11241
								<u> </u>		

	Corpus Christi, TX	Freeport, TX	Galveston, TX	Houston, TX	Port Arthur, TX	New Orleans, LA	Gulfport, MS	Mobile, AL	Panama City, FL	Tampa, FL	Miami, FL
Corpus Christi	0										
Freeport	160	0									
Galveston	244	84	0								
Houston	291	131	47	0							
Port Arthur	423	263	179	132	0						
New Orleans	864	704	620	573	441	0					
Gulfport	1135	975	891	844	712	271	0				
Mobile	1233	1073	989	942	810	369	98	0			
Panama City	1426	1266	1182	1135	1003	562	291	193	0		
Tampa	1691	1531	1447	1400	1268	827	556	458	265	0	
Miami	2134	1974	1890	1843	1711	1270	999	901	708	443	0
Port Everglades	2161	2001	1917	1870	1738	1297	1026	928	735	470	27
Palm Beach	2207	2047	1963	1916	1784	1343	1072	974	781	516	73
Jacksonville	2463	2303	2219	2172	2040	1599	1328	1230	1037	772	329
Brunswick	2545	2385	2301	2254	2122	1681	1410	1312	1119	854	411
Savannah	2649	2489	2405	2358	2226	1785	1514	1416	1223	958	515
Charleston	2751	2591	2507	2460	2328	1887	1616	1518	1325	1060	617
Wilmington	2902	2742	2658	2611	2479	2038	1767	1669	1476	1211	768
Newport News	3262	3102	3018	2971	2839	2398	2127	2029	1836	1571	1128
Baltimore	3432	3272	3188	3141	3009	2568	2297	2199	2006	1741	1298
Chester	3509	3349	3265	3218	3086	2645	2374	2276	2083	1818	1375
Philadelphia	3524	3364	3280	3233	3101	2660	2389	2291	2098	1833	1390
Perth Amboy	3744	3584	3500	3453	3321	2880	2609	2511	2318	2053	1610
Newark	3759	3599	3515	3468	3336	2895	2624	2526	2333	2068	1625
New York City	3771	3611	3527	3480	3348	2907	2636	2538	2345	2080	1637
Boston	4157	3997	3913	3866	3734	3293	3022	2924	2731	2466	2023
Portland, ME	4257	4097	4013	3966	3834	3393	3122	3024	2831	2566	2123
Detroit	6146	5986	5902	5855	5723	5282	5011	4913	4720	4455	4012
Port Huron	6208	6048	5964	5917	5785	5344	5073	4975	4782	4517	4074
Chicago	6779	6619	6535	6488	6356	5915	5644	5546	5353	5088	4645

	Port Everglades, FL	Palm Beach, FL	Jacksonville, FL	Brunswick, GA	Savannah, GA	Charleston, SC	Wilmington, NC	Newport News, VA	Baltimore, MD	Chester, PA	Philadelphia, PA
Port Everglades	0										
Palm Beach	46	0									
Jacksonville	302	256	0								
Brunswick	384	338	82	0					I		
Savannah	488	442	186	104	0						
Charleston	590	544	288	206	102	0					
Wilmington	741	695	439	357	253	151	0				
Newport News	1101	1055	799	717	613	511	360	0			
Baltimore	1271	1225	969	887	783	681	530	170	0		
Chester	1348	1302	1046	964	860	758	607	247	77	0	
Philadelphia	1363	1317	1061	979	875	773	622	262	92	15	0
Perth Amboy	1583	1537	1281	1199	1095	993	842	482	312	235	220
Newark	1598	1552	1296	1214	1110	1008	857	497	327	250	235
New York City	1610	1564	1308	1226	1122	1020	869	509	339	262	247
Boston	1996	1950	1694	1612	1508	1406	1255	895	725	648	633
Portland, ME	2096	2050	1794	1712	1608	1506	1355	995	825	748	733
Detroit	3985	3939	3683	3601	3497	3395	3244	2884	2714	2637	2622
Port Huron	4047	4001	3745	3663	3559	3457	3306	2946	2776	2699	2684
Chicago	4618	4572	4316	4234	4130	4028	3877	3517	3347	3270	3255

	Perth Amboy, NJ	Newark, NJ	New York City, NY	Boston, MA	Portland, ME	Detroit, MI	Port Huron, MI	Chicago, IL
Perth Amboy	0							
Newark	15	0						
New York City	27	12	0					
Boston	413	398	386	0				
Portland, ME	513	498	486	100	0			
Detroit	2402	2387	2375	1989	1889	0		
Port Huron	2464	2449	2437	2051	1951	62	0	
Chicago	3035	3020	3008	2622	2522	633	571	0

Source: Department of Commerce, NOAA & National Ocean Service

Table 13: Aggregate Trade Disruptions - Various Spatial Weights

Model	Cont.	m=6	m=8	m=10	Inv. Dist.
	(1)	(2)	(3)	(4)	(5)
Panel 1: SAR					
Exports	0.125	0.140	0.137	0.137	0.132
	(0.141)	(0.143)	(0.141)	(0.140)	(0.142)
Imports	-0.015	-0.015	-0.015	-0.018	-0.015
	(0.094)	(0.094)	(0.093)	(0.092)	(0.094)
Panel 2: SEM	г				
Exports	0.132	0.132	0.132	0.131	0.131
Exports	(0.132)	(0.132)	(0.132)	(0.131)	(0.141)
T	,	,	` /	,	` /
Imports	-0.015	-0.015	-0.014	-0.015	-0.014
	(0.099)	(0.094)	(0.086)	(0.076)	(0.095)
Panel 3: SAC					
Exports	0.128	0.117	0.134	0.134	0.132
-	(0.145)	(0.133)	(0.138)	(0.137)	(0.142)
Imports	-0.015	-0.015	-0.015	-0.016	-0.015
•	(0.097)	(0.094)	(0.089)	(0.084)	(0.095)
Observations	1,960	1,960	1,960	1,960	1,960
Trend	Yes	Yes	Yes	Yes	Yes
Port FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 14: Regional Trade Disruptions - Various Spatial Weights

Model	Cont.	m=6	m=8	m=10	Inv. Dist.
Model	(1)	(2)	(3)	(4)	(5)
		(2)	(0)	(4)	(0)
Panel A: SAR					
A.1: Exports					
Gulf Coast	0.013	0.072	0.074	0.087	0.021
	(0.184)	(0.173)	(0.174)	(0.179)	(0.184)
Lower Atlantic	0.516	0.569	0.570	0.585	0.525
	(0.448)	(0.456)	(0.454)	(0.456)	(0.446)
A.2: Imports					
Gulf Coast	-0.026	-0.014	0.012	0.046	-0.022
	(0.193)	(0.191)	(0.184)	(0.184)	(0.193)
Lower Atlantic	0.321	0.334	0.352	0.373	0.327
	(0.299)	(0.304)	(0.304)	(0.303)	(0.300)
Panel B: SEM	[				
B.1: Exports					
Gulf Coast	-0.003	0.085	0.088	0.111	0.022
	(0.197)	(0.169)	(0.170)	(0.174)	(0.184)
Lower Atlantic	0.542	0.502	0.509	0.513	0.527
	(0.481)	(0.395)	(0.401)	(0.385)	(0.451)
B.2: Imports					
Gulf Coast	-0.035	-0.015	0.026	0.072	-0.022
	(0.205)	(0.192)	(0.174)	(0.162)	(0.195)
Lower Atlantic	0.336	0.326	0.313	0.294	0.329
	(0.319)	(0.297)	(0.270)	(0.235)	(0.303)
Panel C: SAC					
C.1: Exports	0.051	0.104	0.004	0.000	0.000
Gulf Coast	-0.051	-0.124	0.024	0.089	0.022
T A.1	(0.315)	(0.542)	(0.334)	(0.221)	(0.184)
Lower Atlantic	0.639	0.766	0.628	0.584	0.527
	(0.769)	(0.826)	(0.661)	(0.529)	(0.453)
C.2: Imports	0.055	0.040	0.014	0.005	0.000
Gulf Coast	-0.055	-0.049	-0.014	0.025	-0.022
T 4 . 1	(0.253)	(0.276)	(0.265)	(0.271)	(0.195)
Lower Atlantic	0.372	0.379	0.382	0.401	0.329
	(0.422)	(0.426)	(0.405)	(0.413)	(0.304)
Observations	1,960	1,960	1,960	1,960	1,960
Port FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	YEs	Yes	Yes	Yes

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 15: Spatial Weights Model Comparison

Spatial Weights	LL values	AIC	BIC
	(1)	(2)	(3)
Panel A: Expor	:ts		
A.1: SAC			
Contiguity	-4786.768	9657.535	9929.891
m=4	-4785.212	9654.423	9926.780
m=6	-4796.088	9676.176	9948.532
m=8	-4796.860	9677.719	9950.076
m = 10	-4797.071	9678.143	9950.499
Inverse Distance	-4795.827	9675.654	9948.010
A.2: SAR			
m=4	-4795.727	9673.454	9939.325
4 - 677.5			
A.3: SEM			
m=4	-4795.727	9673.453	9939.325
Danal D. Immar	<b>.</b>		
Panel B: Impor B.1: SAC	US		
Contiguity	-3495.382	7074.764	7347.120
m=4	-3496.293	7076.587	7348.943
m=4 $m=6$	-3488.008	7060.016	7332.372
m=0 $m=8$	-3483.682	7051.364	7323.720
m=0 $m=10$	-3476.835	7037.671	7310.027
Inverse Distance	-3499.642	7083.285	7355.641
inverse Distance	0100.012	1000.200	1000.011
B.2: SAR			
m=10	-3477.221	7036.443	7302.314
B.3: SEM			
m=10	-3477.221	7036.441	7302.313

Table 16: Port-Specific Trade Disruptions - Exports

	Short	Short-Run		m-Run	Long-Run		
	Direct	Indirect	Direct	Indirect	Direct	Indirect	
	(1)	(2)	(3)	(4)	(5)	(6)	
Seattle, WA	-0.032	0.000	0.051	0.001	-0.107	-0.062	

Table 16 – Continued from previous page

			ed from pro			
		t-Run	Mediu		_	-Run
VARIABLES	Direct	Indirect	Direct	Indirect	Direct	Indirect
	(1)	(2)	(3)	(4)	(5)	(6)
	()	( )	()	( )	()	( )
	(0.322)	(0.112)	(0.203)	(0.021)	(0.275)	(0.163)
Portland, OR	0.127	-0.046	-0.248	-0.004	-0.521**	-0.309*
	(0.307)	(0.110)	(0.192)	(0.031)	(0.256)	(0.164)
Oakland, CA	0.055	-0.019	0.095	-0.003	-0.082	-0.050
,	(0.388)	(0.133)	(0.193)	(0.021)	(0.227)	(0.138)
Richmond, CA	0.044	-0.020	0.114	-0.001	0.880***	0.517***
reformione, orr	(0.384)	(0.132)	(0.193)	(0.021)	(0.215)	(0.146)
San Francisco, CA	0.585	-0.168	-0.149	-0.003	-0.774***	-0.457***
San Francisco, CA	(0.385)	(0.172)	(0.203)	(0.024)	(0.218)	(0.153)
D + II CA	,	,	,	,	,	,
Port Hueneme, CA	-0.044	0.016	0.831***	0.004	1.007***	0.590***
	(0.413)	(0.141)	(0.202)	(0.081)	(0.233)	(0.156)
Los Angeles, CA	-0.142	0.034	0.177	-0.002	0.021	0.010
	(0.435)	(0.147)	(0.213)	(0.025)	(0.243)	(0.145)
Long Beach, CA	-0.155	0.038	0.231	0.000	-0.055	-0.035
	(0.416)	(0.143)	(0.190)	(0.028)	(0.215)	(0.128)
San Diego, CA	0.629	-0.176	-0.421**	-0.005	-0.935***	-0.553***
	(0.421)	(0.187)	(0.198)	(0.045)	(0.232)	(0.171)
Chicago, IL	-0.060	0.021	0.220	0.002	-2.054***	-1.209***
0 /	(0.412)	(0.143)	(0.191)	(0.029)	(0.226)	(0.229)
Port Huron, MI	-0.171	0.057	-0.286	-0.003	0.381	0.228
r ore rigidity, wir	(0.418)	(0.149)	(0.199)	(0.034)	(0.243)	(0.157)
Detroit, MI	-0.108	,	0.013	,	-0.556**	,
Detroit, MI	(0.428)	(0.147)	(0.203)	(0.019)	(0.237)	(0.145)
D 41 1 ME	,	,	,	,	,	,
Portland, ME	-0.506	0.149	-0.310 $(0.202)$	-0.004 $(0.036)$	-1.530***	-0.901*** (0.106)
	(0.421)	(0.173)	,	,	(0.231)	(0.196)
Boston, MA	-0.166	0.054	0.302	-0.000	0.141	0.083
	(0.436)	(0.152)	(0.210)	(0.034)	(0.243)	(0.144)
New York, NY	-0.218	0.075	0.257	-0.001	0.254	0.150
	(0.417)	(0.149)	(0.193)	(0.031)	(0.216)	(0.132)
Newark, NJ	-0.218	0.070	0.383*	-0.001	0.168	0.096
	(0.429)	(0.158)	(0.207)	(0.039)	(0.237)	(0.140)
Perth Amboy, NJ	-0.527	0.159	0.461**	-0.001	0.518**	0.303**
J , -	(0.439)	(0.185)	(0.211)	(0.049)	(0.240)	(0.146)
	. ,	. ,	. ,		·	. ,

 ${\bf Table}~16-{\it Continued~from~previous~page}$ 

	Short-Run		Mediu	n-Run	Long-Run		
VARIABLES	Direct	Indirect	Direct	Indirect	Direct	Indirect	
	(1)	(2)	(3)	(4)	(5)	(6)	
Philadelphia, PA	-0.114	0.049	0.350*	-0.001	-0.027	-0.017	
	(0.429)	(0.151)	(0.201)	(0.038)	(0.224)	(0.132)	
Chester, PA	-0.256	0.083	0.524***	0.000	0.230	0.133	
,	(0.423)	(0.151)	(0.201)	(0.052)	(0.229)	(0.136)	
Baltimore, MD	-0.108	0.028	0.207	-0.002	-0.038	-0.024	
Dardinore, WD	(0.417)	(0.141)	(0.206)	(0.029)	(0.238)	(0.143)	
NT 1 NT 174	,	,	,	,	,	,	
Newport News, VA	-0.023	0.003	0.222	-0.001	-0.030	-0.020	
	(0.403)	(0.137)	(0.197)	(0.028)	(0.229)	(0.137)	
Wilmington, NC	0.786*	-0.222	0.318	-0.000	0.700***	0.410***	
	(0.414)	(0.212)	(0.201)	(0.036)	(0.233)	(0.147)	
Charleston, SC	-0.178	0.055	0.093	-0.002	-0.368	-0.219	
,	(0.410)	(0.147)	(0.197)	(0.021)	(0.228)	(0.143)	
Savannah, GA	-0.180	0.053	0.340*	0.000	0.367	0.214	
20,000000000000000000000000000000000000	(0.404)	(0.140)	(0.193)	(0.038)	(0.223)	(0.135)	
Brunswick, GA	-0.888**	0.262	-0.263	-0.006	0.096	0.054	
Drunswick, GA	(0.433)	(0.202)	(0.207)	(0.034)	(0.235)	(0.140)	
Spatial-Weighting	m=4	m=4	m=4	m=4	m=4	m=4	
Observations	240	240	1,920	1,920	4,800	4,800	
Port FE	Yes	Yes	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	

Table 17: Port-Specific Trade Disruptions - Imports

	Shor	Short-Run		Medium-Run		Long-Run	
	Direct (1)	Indirect (2)	Direct (3)	Indirect (4)	Direct (5)	Indirect (6)	
Seattle, WA	-0.002 (0.323)	0.020 (0.309)	-0.067 (0.194)	0.010 (0.036)	-0.057 (0.166)	0.007 $(0.025)$	
Portland, OR	0.080 $(0.307)$	-0.016 $(0.363)$	0.352* $(0.184)$	-0.026 (0.060)	0.217 $(0.157)$	-0.017 $(0.033)$	
Oakland, CA	0.018 $(0.311)$	-0.031 $(0.924)$	0.020 $(0.180)$	-0.004 (0.034)	0.052 $(0.155)$	-0.004 $(0.024)$	

Table 17 – Continued from previous page

	Short-Run Medium-Run Long-Run						
VARIABLES	Direct (1)	Indirect (2)	Direct (3)	Indirect (4)	Direct (5)	Indirect (6)	
	(1)	(2)	(0)	(4)	(0)	(0)	
Richmond, CA	0.276 $(0.307)$	-0.085 (0.247)	-0.598*** (0.181)	0.048 (0.100)	-0.070 $(0.156)$	0.007 $(0.025)$	
San Francisco, CA	-0.382 (0.332)	0.012 $(1.810)$	-0.178 $(0.192)$	0.015 $(0.047)$	$0.206 \\ (0.166)$	-0.017 $(0.033)$	
Port Hueneme, CA	-0.286 $(0.354)$	-0.018 $(2.094)$	-1.013*** (0.186)	0.082 $(0.167)$	-0.658*** (0.160)	0.057 $(0.080)$	
Los Angeles, CA	-0.040 $(0.357)$	0.009 $(0.403)$	0.004 $(0.196)$	-0.001 $(0.033)$	0.087 $(0.169)$	-0.008 $(0.026)$	
Long Beach, CA	0.004 $(0.323)$	0.014 $(0.215)$	-0.019 (0.175)	0.002 $(0.030)$	-0.045 $(0.151)$	0.004 $(0.022)$	
San Diego, CA	0.554 $(0.337)$	-0.084 $(1.085)$	0.614*** (0.183)	-0.049 (0.100)	0.324** (0.158)	-0.026 $(0.043)$	
Chicago, IL	-0.380 $(0.331)$	0.095 $(0.327)$	0.020 $(0.177)$	-0.004 $(0.030)$	0.411*** (0.153)	-0.035 $(0.053)$	
Port Huron, MI	-0.286 $(0.341)$	0.076 $(0.320)$	-0.078 $(0.185)$	$0.005 \\ (0.035)$	0.010 $(0.159)$	-0.001 $(0.023)$	
Detroit, MI	$0.166 \\ (0.355)$	-0.032 $(0.518)$	0.136 $(0.189)$	-0.012 $(0.037)$	0.282* $(0.163)$	-0.027 $(0.039)$	
Portland, ME	0.067 $(0.349)$	-0.005 $(0.376)$	-0.502*** (0.187)	0.041 $(0.087)$	-0.993*** (0.163)	0.084 $(0.117)$	
Boston, MA	-0.174 $(0.363)$	0.067 $(0.215)$	0.123 $(0.195)$	-0.010 (0.038)	0.281* (0.168)	-0.025 $(0.040)$	
New York, NY	-0.102 $(0.331)$	0.051 $(0.240)$	-0.031 $(0.177)$	0.001 $(0.030)$	0.281* $(0.153)$	-0.026 $(0.039)$	
Newark, NJ	-0.062 $(0.347)$	0.009 $(0.477)$	0.007 $(0.188)$	-0.003 (0.036)	0.149 $(0.162)$	-0.014 $(0.030)$	
Perth Amboy, NJ	-0.082 (0.362)	-0.002 $(0.744)$	-0.536*** (0.191)	$0.041 \\ (0.091)$	0.706*** (0.165)	-0.065 $(0.084)$	
Philadelphia, PA	-0.123 (0.344)	$0.055 \\ (0.197)$	0.178 $(0.181)$	-0.015 $(0.042)$	0.211 $(0.157)$	-0.019 $(0.033)$	
Chester, PA	-0.175 $(0.345)$	0.064 $(0.226)$	0.070 $(0.184)$	-0.008 $(0.033)$	0.202 $(0.161)$	-0.021 $(0.034)$	
Baltimore, MD	-0.094	0.037	0.085	-0.008	0.227	-0.022	
Continued on next page							

Table 17 – Continued from previous page

	Short-Run		Mediur	n-Run	Long-Run	
VARIABLES	Direct	Indirect	Direct	Indirect	Direct	Indirect
	(1)	(2)	(3)	(4)	(5)	(6)
	(0.348)	(0.407)	(0.188)	(0.035)	(0.162)	(0.035)
Newport News, VA	-0.034	0.032	0.057	-0.004	0.117	-0.011
,	(0.337)	(0.293)	(0.180)	(0.033)	(0.156)	(0.026)
Wilmington, NC	-0.239	0.034	0.279	-0.024	0.889***	-0.078
	(0.346)	(0.998)	(0.185)	(0.052)	(0.159)	(0.104)
Charleston, SC	-0.070	0.021	0.010	-0.004	0.029	-0.003
	(0.338)	(0.291)	(0.182)	(0.034)	(0.157)	(0.023)
Savannah, GA	0.033	-0.014	0.213	-0.019	0.508***	-0.044
	(0.334)	(0.445)	(0.178)	(0.045)	(0.154)	(0.063)
Brunswick, GA	-0.355	0.024	-0.727***	0.055	-1.029***	0.088
	(0.354)	(1.179)	(0.192)	(0.120)	(0.164)	(0.119)
Spatial-Weighting	m=10	m=10	m=10	m=10	m=10	m=10
Observations	240	240	1,920	1,920	4,800	4,800
Port FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 18: Port Characteristics Legend Key

	Entrance Restrictions		
Harbor Type	Tide	Other	
0 - Coastal (Breakwater)	0 - No	0 - No	
1 - Coastal (Natural)	1- Yes	1- Yes	
2 - Coastal (Tide Gates)			
3 - Canal or Lake			
4 - River (Basin)			
5 - River (Natural)			
6 - River (Tide Gates)			

Source: 2015 WPI - National Geospatial-Intelligence Agency

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Table 19: Direct Treatment Effects over Distance

	SAR		SE	$\overline{\mathbf{M}}$	SAC	
VARIABLES	Export	Import	Export	Import	Export	Import
	(1)	(2)	(3)	(4)	(5)	(6)
Core (AL, LA, MS)	0.487***	0.471***	0.378**	0.349**	0.992***	0.619***
	(0.166)	(0.149)	(0.173)	(0.155)	(0.144)	(0.159)
Core Distance to Epicenter	-21.004***	-18.396***	-18.970***	-18.869**	-31.543***	-17.676***
	(3.981)	(3.600)	(3.306)	(3.712)	(3.618)	(3.483)
Periphery (GA, FL, SC, TX)	-1.867***	-1.198***	-1.934***	-1.167***	-2.307***	-1.302***
	(0.096)	(0.088)	(0.128)	(0.106)	(0.090)	(0.102)
Periphery Distance to Epicenter	1347.802***	861.833***	1387.983***	830.048***	1733.185***	929.147***
	(46.178)	(42.227)	(62.347)	(52.884)	(45.577)	(48.667)
Observations	1,960	1,960	1,960	1,960	1,960	1,960
Port FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Spatial-Weighting	Cont.	m=8	Cont.	m=8	Cont.	m=8

Robust standard errors in parentheses
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

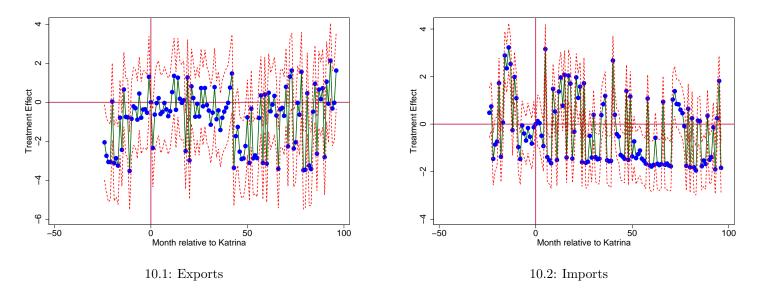


Figure 10: Dynamic Variation in Treatment Effects - Port Arthur, TX

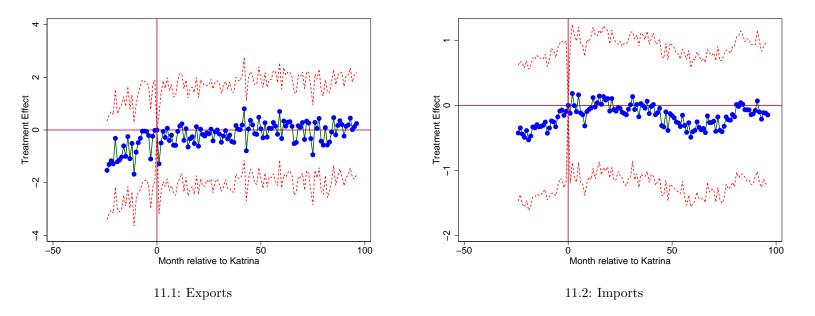


Figure 11: Dynamic Variation in Treatment Effects - Houston, TX

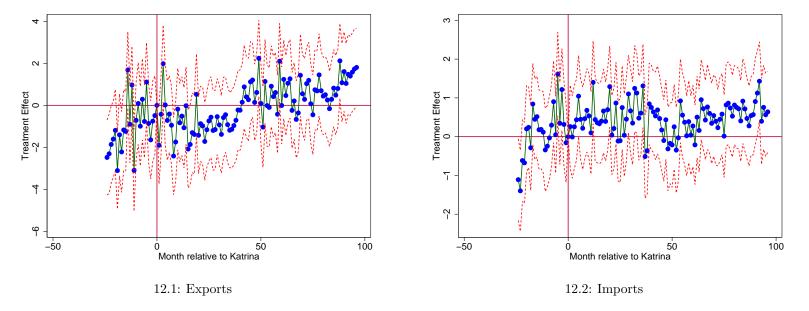


Figure 12: Dynamic Variation in Treatment Effects - Galveston, TX

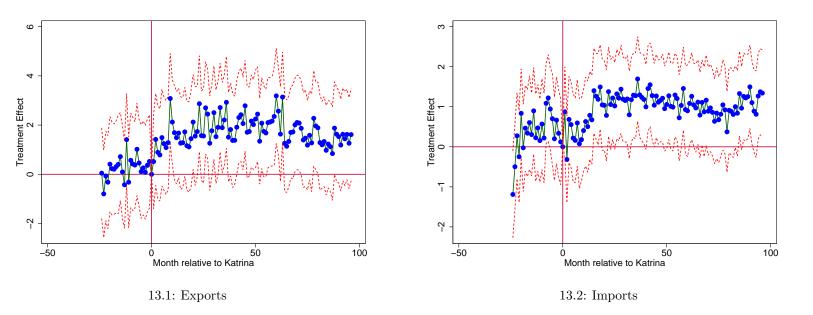


Figure 13: Dynamic Treatment Effects - Tampa, FL

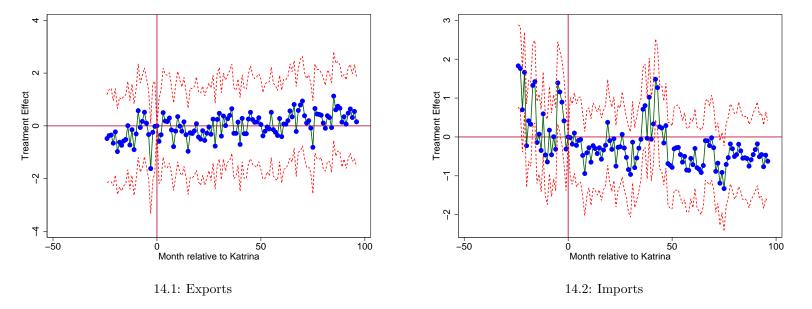


Figure 14: Dynamic Treatment Effects - Freeport, TX

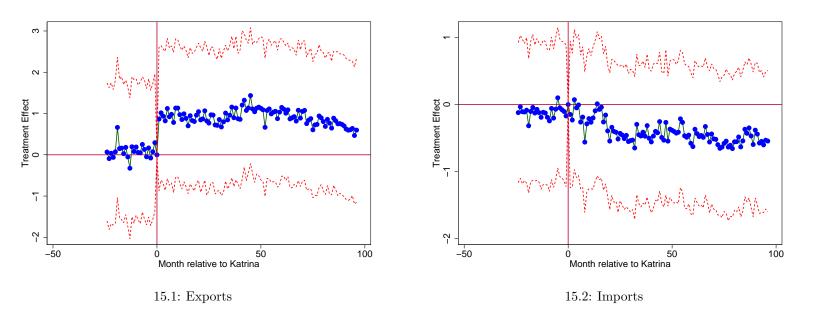


Figure 15: Dynamic Treatment Effects - Miami, FL

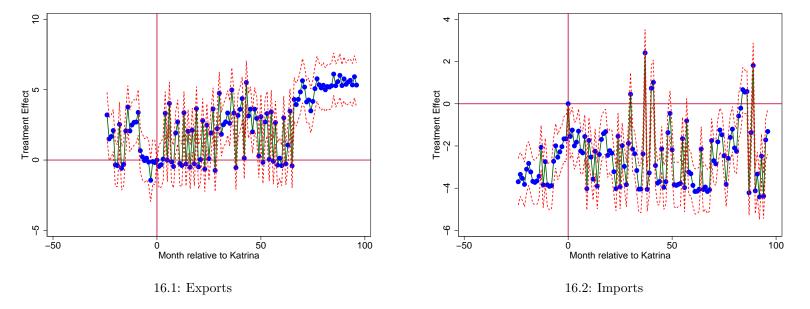


Figure 16: Dynamic Treatment Effects - Corpus Christi, TX

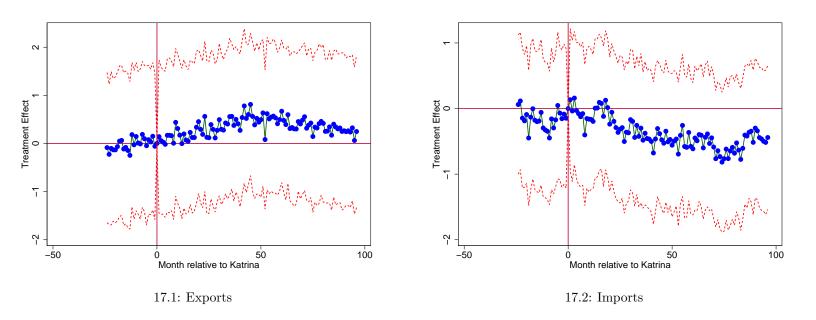


Figure 17: Dynamic Treatment Effects - Port Everglades, FL