Impacts of disease in shrimp aquaculture on U.S. capture fishery prices

Tess Petesch, Master of Environmental Management 2017
Advisor: Martin Smith, PhD
Nicholas School of the Environment, Duke University

Abstract

Shrimp is one of the most traded seafood commodities in the world, and aquaculture now contributes more to global shrimp production than capture fishing. Since the 1970s, the shrimp culture industry has been simultaneously characterized by rapid growth due to falling production costs as well as severe losses from disease outbreaks. Previous research confirms that farmed and wild shrimp are substitutes and shrimp markets around the world are well integrated. We seek to determine if prices of wild shrimp in the U.S. Gulf of Mexico fishery reflect supply shocks in aquaculture attributed to acute disease epidemics. Analysis relies on U.S. farmed shrimp import data between 1990 and 2016 from three major producers: Ecuador, Thailand, and Indonesia. After testing country-level price indices for cointegration, we use structural break tests to determine if significant price changes coincide with anecdotal disease crises. We attempt to further characterize the shrimp market by testing if disease outbreaks correspond with changes in relative prices of larger, more valuable shrimp compared to smaller shrimp.

Executive Summary

Shrimp is one of the most traded seafood commodities in the world and the U.S is the top importer of the crustacean. Although the U.S. has productive and valuable shrimp fisheries, 94% of shrimp is imported, most of which is farmed (Food and Water Watch, 2016). Despite high demand, wild shrimp prices have fallen significantly in concert with the rise of aquaculture due to the integrated nature of shrimp markets. Between 1990-2007, the real price of shrimp fell from \$16/kg to \$7/kg (Asche, 2008).

Growth in aquaculture is driven by technical innovation, rising demand for seafood, and poor fishery management. Production methods in aquaculture differ from those in fishing—costs have fallen in aquaculture as technology has improved whereas fisheries cannot become much more cost competitive due to high vessel maintenance, diesel, and labor costs. Thus, falling shrimp prices potentially hurt fisheries more than culture producers. Additionally, available biomass limits growth in catch in fisheries. However, a major constraint in aquaculture, and perhaps a reprieve for capture fisheries, is disease.

Since the 1970s, the shrimp culture industry has been simultaneously characterized by rapid growth as well as severe losses from disease outbreaks like White Spot Syndrome. The Global Aquaculture Alliance estimated losses to the global shrimp culture industry from disease of about 22% per year, amounting to about \$1 billion annually (Flegel, 2008). More recently, an outbreak of Early Mortality Syndrome devastated Thailand's shrimp industry, where culture production fell by 47% between 2013 and 2014 (Dubik, 2017).

We seek to determine if prices of wild shrimp in the U.S. Gulf of Mexico fishery reflect supply shocks in aquaculture attributed to acute disease epidemics. Analysis relies on U.S. farmed shrimp import data between 1990 and 2016 from three major producers: Ecuador, Thailand, and Indonesia. After testing country-level price indices for cointegration, we use structural break tests to determine if significant price changes coincide with anecdotal disease crises. We attempt to further characterize the shrimp market by testing if disease outbreaks correspond with changes in relative prices of larger, more valuable shrimp compared to smaller shrimp.

Results of Johansen cointegration tests indicate that the Thai, Indonesian, Ecuadorian, and U.S. Gulf of Mexico shrimp markets are integrated. The integrated nature of shrimp markets suggests that U.S. shrimpers benefit less from disease in farmed shrimp than would be the case absent integration. Further, weak exogeneity tests reveal no price leader, though Gulf prices appear more responsive to the culture industry in Thailand than Ecuador or Indonesia. Structural breaks line up with the approximate timing of disease and technological changes. Disease may have played a role in prices, but it appears that genetic improvements in disease resistance in the early 2000s may have been a more important factor in the price determination process. Last, while prices of larger shrimp in Thailand do not appear to grow more relative to prices of small shrimp during times of disease, they do appear to fall more than prices smaller shrimp when developments in disease resistance took place in the early 2000s. Thus, it is possible that lowering the risk of disease induces an optimization response among culture producers in which harvest cycles are extended in order to capture price premiums associated with larger shrimp.

I. Introduction

Shrimp is the second most traded seafood commodity in the world after salmon. Roughly 15% of internationally traded seafood is shrimp, over half of which comes from aquaculture (FAO, 2015). The U.S is the top importer of shrimp in the world, importing $6.7 billion worth in 2014 (NMFS, 2015). U.S. consumers eat about 4 pounds of the crustacean per capita each year, representing over a quarter of seafood consumed (Consumer Reports, 2015).

The U.S. has highly productive and valuable shrimp fisheries, valued at $681.4 million in 2014 (NMFS, 2014), but 94% of shrimp consumed is imported, most of which is farmed (Food and Water Watch, 2016). Despite high demand, shrimp prices have fallen significantly in concert with the rise of aquaculture. U.S. dockside prices fell from $2.10/lb. in 2000 to $1.26/lb. in 2003, a period coinciding with dramatic growth in farmed shrimp imports (Keithly, 2008).

The shrimp culture industry took off in the 1970s and has grown exponentially since then, surpassing output from capture shrimp fisheries for the first time in 2007 (FAO, 2015). From 1970 to 2008, the industry observed an average annual growth rate of 18% (FAO, 2010), mounting to a worth of $19.4 billion in 2012 (Portley, 2016). Driven mostly by aquaculture, U.S. imports of shrimp grew at an average annual rate of 7.7% between 1984 and 2002 (Vinuya, 2007). U.S. capture fisheries remain valuable, but the market share of domestic shrimp in U.S. markets fell from 43% in 1980 to 12% in 2011 (Mukherjee & Segerson, 2011). Falling market share reduces the domestic fishery's ability to control prices and influence market dynamics (Asche et al. 2012). Between 1990 and 2007, the real price of shrimp fell from $16/kg to $7/kg (Ashe, 2008).

Rapid growth in shrimp aquaculture is credited to rising demand and falling production costs due to technical innovation. Meanwhile, capture shrimp landings have plateaued or even declined due to factors such as biological limits, poor management, and competition with aquaculture (FAO, 2015). Opportunities to become more cost competitive in fisheries are limited by the nature of production, which includes considerable labor, vessel maintenance, and diesel fuel components. Fisheries face high search costs in pursuit of a scarce resource and face stringent management measures, particularly in the U.S. However, one major constraint in shrimp aquaculture, and perhaps a reprieve for capture fisheries, is episodic disease.

Disease is the primary cause of mortality in intensive shrimp culture systems (Naylor et al. 1998), and is continually the most significant problem reported by farmed shrimp producers in every world region (Anderson, 2015). White Spot Syndrome Virus (WSSV) was a major epidemic in the 1990s, originating in Asia and spreading to the Americas later in the decade. Globally, the shrimp culture industry lost an estimated 40% of production to WSSV in 1996 (Walker & Mohan, 2009). More recently, an outbreak of Early Mortality Syndrome (EMS) devastated Thailand's shrimp industry, where culture production fell by 47% between 2013 and 2014 (Dubik, 2017).

Disease is a serious obstacle for those affected, but it might represent an opportunity to gain from higher prices for capture fishers and culture producers who avoid disease. The FAO contends that recent disease outbreaks in aquaculture led to significant and unexpected upward pressure on shrimp prices, creating new opportunities for struggling capture producers (FAO SOFIA, 2014). U.S. shrimp import prices jumped 17% between 2011 and 2013, largely attributed to the fall in Asian farmed shrimp production due to EMS (Anderson, 2015).

Ample research confirms that farmed shrimp are substitutes for wild-caught shrimp and that shrimp markets across the globe are well integrated (Smith et al. 2012, Kennedy et al. 2005, Keithly et al. 1993, Vinuya 2007). The more integrated the markets for shrimp, the less U.S. shrimp fisheries can mediate the negative impacts of supply shocks through higher prices. Integration suggests that negative supply shocks in one producer are quickly compensated for by other producers. Therefore, the price effects of even a large disease outbreak in one region would be masked to some extent due to the competitive nature of the market. The growth trends in the farmed shrimp industry also mute the effects of disease at aggregated levels. Nonetheless, large shocks can transmit effects across integrated markets. The sheer magnitude of viral disease losses in farmed shrimp motivates this investigation of price impacts.

We analyze U.S. farmed shrimp import data between 1990 and 2016 from three major producers: Ecuador, Indonesia, and Thailand in addition to U.S. Gulf of Mexico wild shrimp fishery data. This paper contributes to the literature by examining the impact of exogenous disease outbreaks on prices received in a capture fishery. Results contribute to growing research describing the impacts of aquaculture on fisheries.

We also test the hypothesis that disease affects relative prices of small and large shrimp, which is consistent with producers dynamically optimizing by adjusting harvest cycles when faced with disease. Qualitative evidence shows that disease results not only in losses due to mortality, but a tendency to harvest smaller shrimp, which are of lower value (Anderson, 2015). Using the Thai data, we examine whether the prices of large and small shrimp change relative to each other during disease epidemics. Disease might slow growth rates and/or incentivize producers to shorten harvest cycles to mitigate risk of losing an entire pond to disease, which would be reflected in a smaller supply of big shrimp on the market, more small shrimp, and a larger ratio of large shrimp prices to small shrimp prices. The size question sheds light on whether Gulf producers might gain from selling more big shrimp when culture producers face acute disease epidemics.

Results of the Johansen cointegration tests indicate that the Thai, Indonesian, Ecuadorian, and U.S. Gulf of Mexico shrimp markets are integrated. Further, weak exogeneity tests reveal no price leader. In absence of any producers insulated from market woes, I analyze all four shrimp price time series together within an error correction model framework and use unknown structural break tests to identify the points in time where prices change most significantly. If structural breaks line up with qualitative disease information, there is evidence that disease was important for prices. The goal is to find if the inclusion of qualitative disease information improves our ability to quantify how prices adjust among producers responding to one another in this market.

Impulse response functions, which visually represent the error correction model, reveal that Gulf prices are more responsive to the culture industry in Thailand than in Ecuador or Indonesia. Results also indicate that EMS may have played a role in prices, but it appears that improvements in disease resistance in the early 2000s, a period of low and falling prices, may have been a more important factor in the price determination process than disease. Last, while prices of larger shrimp in Thailand do not appear to grow more relative to prices of small shrimp during times of disease, they do appear to fall more than those of smaller shrimp when the developments in disease resistance took place. Thus, it is possible that lowering the risk of disease induces producers to lengthen harvest cycles in order to capture higher profits associated with the larger shrimp. Before a more detailed account of the methods and results, we provide a detailed background on disease in shrimp aquaculture and a literature review to motivate this analysis.

II. Background

Technical innovations in shrimp culture have reduced production costs, increased outputs, and decreased sale prices but also facilitated the spread of disease. Early shrimp cultivation utilized extensive systems and larvae were generally obtained from tidal flow or by hand collection. The eyestalk ablation technique came to prominence in the 1980s and expedited maturation of female broodstock. Producers also started using hatcheries to obtain post-larvae (Flegel, 2008). The combination of water aeration and inputs of chemicals and commercial feed supported higher stocking densities and a transition to more intensive cultivation (Naylor et al. 1998). Gradually increasing stocking densities coincided with larger production volumes particularly in Asia, but disease also became increasingly problematic. Most shrimp culture takes place in open-air pond systems where disease spreads quickly.

Disease results from a complex interaction of the animal, its environment, and the pathogen (Lightner et al. 1998). Shrimp diseases can cause a range of losses, sometimes reaching 100% mortality at a given production site, but effects vary across different species, genetic strains, and over life stages within a species. Diagnosis is complicated by the multiplicity of interacting agents including pathogens, toxicants, and environmental extremes. Compounding the problem, shrimp aquaculture has grown so rapidly that pathogens were often introduced before diagnostic tools could adequately identify them (Flegel, 2008). Modern intensive culture systems deliver ideal conditions for the proliferation of pathogens since they are cultivated with few to no breaks in production cycles and confined to high density ponds with limited water exchange (Cock et al., 2009). Trade is also implicated in the spread of pathogens across the globe. Before the 1990s, there was relatively little trade in shrimp and fewer disease problems. The introduction of the WSSV from Asia to the Americas in 1999 devastated Ecuador's industry recovering from a separate disease outbreak earlier in the decade (Lightner, 2003).

Due to shrimp's commercial significance, seven of the nine major crustacean diseases listed by the World Animal Organization are viral diseases of shrimp (Lightner, 2011). Regulation and consumer demands limit options to treat shrimp diseases using drugs. And since crustaceans lack immune systems akin to those of vertebrates, vaccines are not effective (Lightner et al., 2012). Thus, farmers rely primarily on seed stock quality, nutrition, and environmental management measures such as improved sanitation, exclusion practices, and biosecurity measures to control disease. Starting in the early 2000s, the widespread use of a Specific Pathogen-Free (SPF) stock also offered better control over viral diseases (Lightner, 2011).

The Global Aquaculture Alliance estimated in 2001 that disease caused losses to the global shrimp culture industry of about 22% per year, amounting to about $1 billion annually (Flegel, 2008). Major shrimp diseases in the 1990s include White Spot Syndrome Virus (WSSV), Yellow-head Virus (YHV), and Taura Syndome. WSSV was first detected in Taiwan in 1992 and had reached most of Southeast Asia by 1996 (Cock et al., 2009). It is highly lethal and contagious, causing mortality within one to three days after infection. Attempts to reduce mortality induced by viral diseases like TSV and WSSV were largely unsuccessful since they cannot be treated, so appropriate management measures were critical to prevent the spread of the disease. However, the new industry had little experience managing disease before the 1990s.

Over 40% of global farmed shrimp production was lost to WSSV in 1996, the peak of the disease (Lightner et al. 2012). The WSSV epidemic spread from Asia to the Americas in the later 1990s, hitting Ecuador in 1999 shortly after industry was recovering from an outbreak of Taura Syndrome (TSV) which appeared in 1992. Monetary losses to WSSV were estimated at around $1 billion annually and $15 billion in total (Lightner et al. 2012). YHV and TSV were important too, with total losses estimated at $500 million and $2-$3 billion, respectively (Lightner et al. 2012).

Table 1. Shrimp diseases and estimated monetary losses

Disease - Region	*Year of emergence*	*Estimated losses*	*Source*
YHV - Asia	1991	$0.5 billion	Lightner et al. 2012
TSV - Americas	1991-1992	$1 - $2 billion	Lightner et al. 2012
TSV - Asia	1992	$0.5 - $1 billion	Lightner et al. 2012
WSSV - Asia	1992-1993	$6 billion	Lightner et al. 2012
WSSV - Americas	1999	$1 - $2 billion	Lightner et al. 2012
IMNV - Asia	2006	$1 billion	Lightner et al. 2012
EMS - Asia	2009	$5 billion (Thailand only)	The Fish Site, 2016

Genetic improvement increases profitability in agriculture and aquaculture. But unlike terrestrial agriculture species, shrimp have relatively short domestication histories (Stentiford et al., 2012). In absence of effective vaccines, the economic importance of diseases like TSV and WSSV in the 1990s motivated producers to invest in breeding research in pursuit of disease resistant or disease tolerant strains and replace wild stocks (Cock et al., 2009). According to Lightner et al. 2012, a paradigm shift occurred about five years after the introduction of Specified Pathogen Free (SPF) *P. vannamei* in Asia during the late 1990s. The predictable performance of the SPF stock was a key contributor to the recovery of the industry following the viral epidemics in the 1990s. Shrimp cultivators benefited from the predictability of disease resistant stocks and the reduced need for antibiotic and chemical inputs. Nevertheless, disease resistance may be negatively associated with other advantageous traits like fast growth rates (Cock et al., 2009).

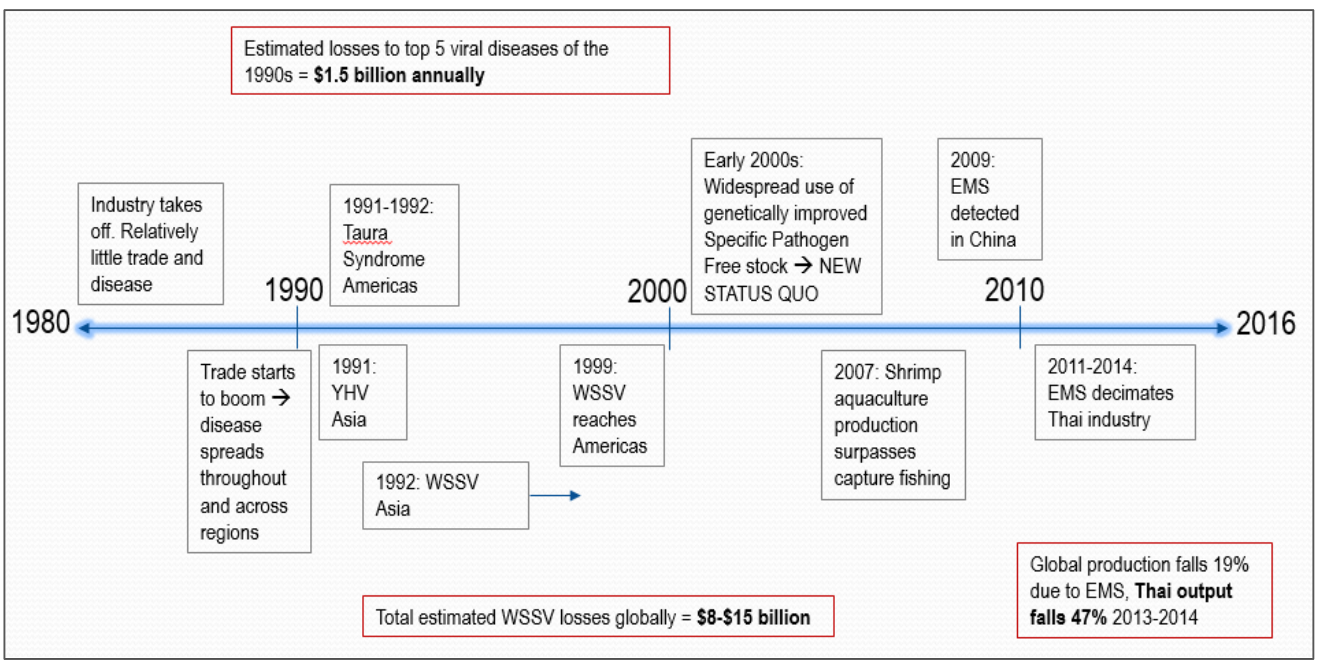

Figure 1. Shrimp disease timeline

In the early 2000s, global competition and low prices replaced disease as culture producers' principal concern (Flegel, 2008). This period of booming production and falling prices continued for years and culture output surpassed wild shrimp output for the first time in 2007 (FAO, 2015). Disease-related anxiety rose again when Early Mortality Syndrome (EMS) was first reported in China in 2009, which experts believe spread due to the transportation of live feeds (Zorriehzahra, 2015). EMS spreads quickly and generally affects shrimp before they are able to reproduce. Like WSSV, EMS cannot be treated. Outbreaks typically occur in the first 30 days after restocking a pond and mortality rates can exceed 70% (Zorriehzahra, 2015). EMS caused production worldwide to fall about 19% between 2010 and 2013 (Zorriehzahra, 2015). It appeared in Thailand in 2011, causing losses of 20% to 70% per year. Annual losses are estimated at over $1 billion in several Asian countries (Zorriehzahra, 2015). Interestingly, Indonesia has not suffered from EMS, which is largely attributed to routine cleaning practices and live animal import restrictions (Zorriehzahra, 2015). Thailand incurred losses estimated at $5.01 billion (The Fish Site, 2016), but Indonesia's exports rose significantly during this period.

III. Relevant literature

Aquaculture influences economic outcomes in capture fisheries through several mechanisms. Aquaculture adds to markets a steady supply of seafood products at low prices. Per capita availability of crustaceans increased from 0.4 kg in 1961 to 1.8 kg in 2013 due largely to the rising production of shrimp aquaculture (FAO, 2016). Keithly et al. (1993) conclude that U.S. capture shrimp prices in 1988–1989 would have been about 70% higher in absence of aquaculture. Consumer expectations also adjust to the introduction of product forms with increased quality and consistency and reductions in price uncertainty and risk.

Anderson (2007) discusses the downward pressure on wild fishery prices induced by the rise of aquaculture, highlighting trends in globalization, vertical integration, concentration, and the introduction of new product forms. High demand and increasing efficiency, control, and consistency combine to widen the gap between capture and aquaculture production. Producers who consistently deliver high quality product at a stable or declining price gain market share. More supply is concentrated in fewer species, and diversity must result from marketing of specific attributes such as size, color, and texture, over which aquaculture offers greater control than fishing.

Production methods of wild and farmed shrimp vary significantly, with aquaculture mirroring agriculture closely while fishing costs contain high labor, vessel maintenance, and diesel components. Aquaculture inputs are dominated by capital, e.g. feed and fingerlings. The labor component in capture fisheries presents reduced opportunities to improve costs relative to capital intensive aquaculture (Anderson, 2007). Opportunities to increase catch are also limited by the available biomass. Thus, competition between fisheries and aquaculture is more burdensome on capture fisheries, which cannot cut costs or increase output.

The effect of aquaculture on wild seafood prices depends on their substitutability and the degree of integration across global markets. In integrated markets, consumers do not distinguish between products based on point of origin or production method in purchasing decisions. The previous section highlights the economic magnitude of disease in farmed shrimp and supports speculation that disease shocks might lead to higher shrimp prices than would otherwise be observed. However, extensive research finds that shrimp markets are well integrated, which means that impacts of disease on prices are likely muted to some extent.

Vinuya (2007) uses import data from Japan, the U.S., and the European Union to test if price movements provide evidence of an integrated market for shrimp. He finds that prices in all three markets are strongly linked. Results hold at disaggregated levels such as wholesale markets in specific cities, confirming the law of one price in shrimp markets. Thus, analysis of U.S. prices is likely to be a strong representation of the global market.

Smith et al. (2012) verify the integrated nature of farmed shrimp and U.S. capture fishery prices. Smith et al. (2017) find that the consequences of supply shocks in the Gulf, such as those resulting from hypoxic dead zones, are not mitigated via increased prices due to compensation from rising farmed shrimp imports. Kennedy et al. 2005 confirm that shrimp imports negatively impact U.S. wild caught shrimp prices. Since frozen farmed shrimp imports are substitutes for U.S. wild caught shrimp, falling U.S. shrimp landings are not observable in U.S. shrimp prices. Gillig, Capps and Griffin (1998) also find that ex vessel prices in the U.S. shrimp fisheries were influenced by imports, but the smallest size class was more responsive than larger shrimp to imports. This suggests that shrimpers might gain from landing larger shrimp. Finally, Bene et al. 2000 use Johansen cointegration tests to confirm that imports of wild brown shrimp from French Guiana were substitutes for cultured shrimp from Thailand between 1986 and 1993.

Integrated markets tend toward stable relative prices in the long run, but this does not preclude prices from deviating from each other in the short run. Integration only indicates that prices are related in the long run due to arbitrage or substitutability. Our analysis adds to the literature on shrimp market integration and adds a new element identifying if disease in farmed shrimp impacts price trends. In a sub-analysis, we also examine if relative prices of large and small shrimp reflect a tendency of producers to harvest smaller shrimp during times of higher disease prevalence.

IV. Data

Analysis is based on U.S. farmed shrimp imports from three major exporting countries: Ecuador, Thailand, and Indonesia. U.S. imports came mostly from Thailand until 2011's EMS outbreak. Imports from Ecuador also make up a significant portion of imports as it is the biggest farmed shrimp producer in the Americas. China, Thailand, Vietnam, Indonesia, and India are the largest Asian producers, and imports from India and Vietnam have grown significantly in the last decade (Anderson, 2015). Future analysis will encompass more than the three producers presented here.

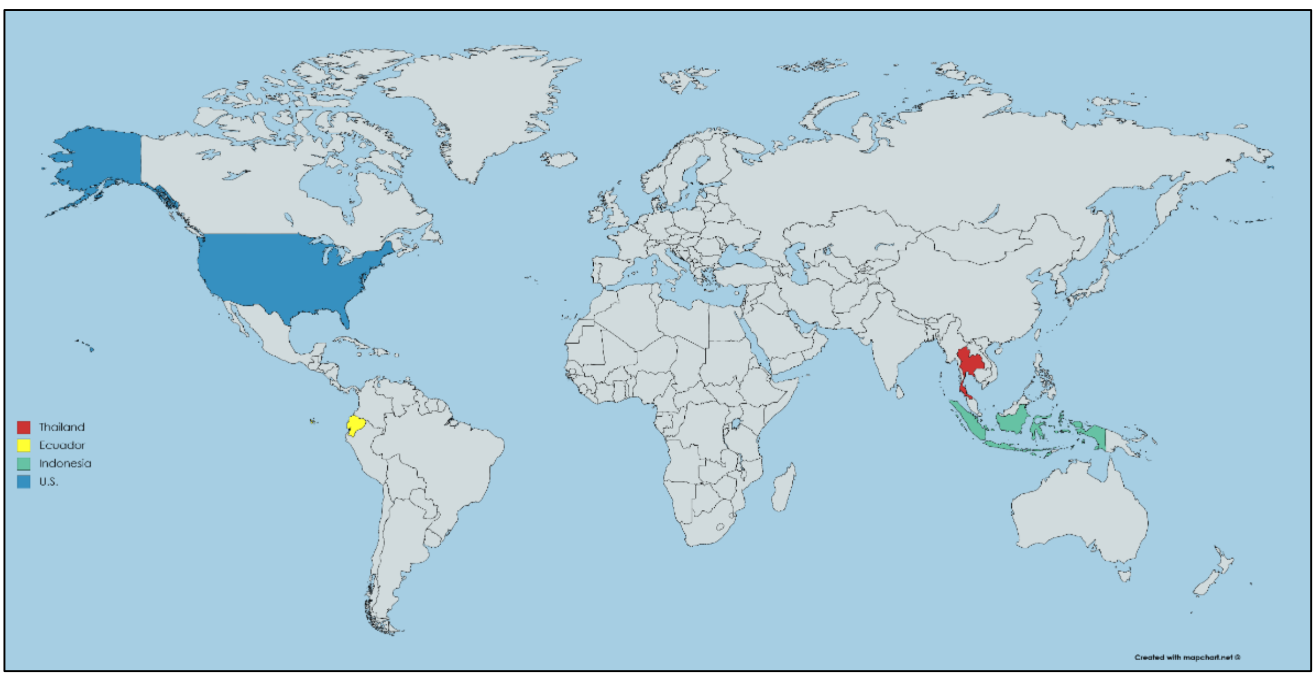

Figure 2. Map of shrimp producers analyzed

The dataset contains 307 months of import prices and quantities for 9 size classes of farmed shrimp from the three countries. The data span from July 1990 to January 2016, which were the publicly available months at the start of this analysis on NOAA's Fisheries trade statistics site (NMFS, 2017).

We also use 258 months of data for the Gulf of Mexico shrimp fishery from Smith et al. 2012, spanning from July 1990 to December 2011.

Shrimp size is measured by the number of shrimp per pound, thus, a lower count indicates larger shrimp. We use data for nine size categories ranging from under 15 shrimp per pound to over 70 per pound. Larger sizes are more valuable per pound. However, prices for different size classes tend to move with one another over time. With nine size categories and three countries, there are 27 price variables among the three culture exporters. Analysis hinges on prices instead of quantity outcomes because the disturbances resulting from diseases would be obscured using quantity data. Quantity falls in disease countries could be evident, but supply from the U.S. fishery is largely determined by a myriad of environmental and management factors, so prices are the preferred unit of analysis.

We create a separate Fisher index for each country (Tveteras et al. 2012) and use the Fisher index for the Gulf of Mexico shrimp fishery from Smith et al. 2012. The challenge in selecting the proper index is to account for regional variation and different product forms (i.e. size classes). The Fisher measures relative price changes over time compared to a base year to track the extent to which shrimp are becoming more or less expensive. The Fisher index is the geometric average of two other price indices: the Laspayres index and the Paasche index. Laspeyres assumes that quantities are fixed to a base period, constructed as follows:

$$I_L = \sum p_{it}(q_{i0})/p_{i0}(q_{i0})$$

Where p is price, q is quantity, i indexes the shrimp size category, and t is the month/year. The Laspeyres index assumes that the quantity of shrimp imported in the base period is relevant to all future years in the time series. This is problematic because we know that shrimp consumption in the U.S. grew rapidly throughout this time period. We also want to account for item substitution bias. If the price of a good with high weighting increases but prices remain stable for a good with a low weighting, consumers likely respond to the price increase of the first good by substituting it with the second. The Laspeyres Index would overestimate overall inflation in this example. An alternative index is the Paasche index, which updates relevant quantities each month:

$$I_P = \sum p_{it}(q_{it})/p_{i0}(q_{it})$$

The Paasche index differs from Laspeyres because it is responsive to changes in both prices and quantities. While the Laspeyres likely overestimates inflation by not accounting for adjustments in consumption trends, such as the availability of more diverse product forms over time, the Passche may understate inflation because it does not attribute changes in quantities to price changes in instances where demand is not perfectly inelastic. The Fisher Index acts as a compromise between these two indices which tend to bias the calculation in opposing directions. It is the geometric mean of the Laspeyres and the Paasche:

$$I_F = \sqrt{(I_L * I_P)}$$

Since we have updated prices and quantities throughout the times series (with some missing months), there is no reason to favor Laspeyres over Paasche. As technological improvements have driven down the production costs for the shrimp aquaculture industry, the Laspeyres index would underweight the impact of an expanding supply of shrimp and might make shrimp appear too expensive. On the other hand, the Paasche index would understate prices by ignoring behavioral responses to price changes. As the base price (p_{i0}) and quantity (q_{i0}), I use the average price and average monthly import quantity for the first full year of data, which is 1991.

A challenge that arises is how to treat re-imports. In 2012, the trade data starts to distinguish shrimp raised in cold and warm water. Shrimp raised in cold water, which tend to be of smaller size, are likely not reared in the tropical countries examined in this paper. They may be exported from cold water countries to Ecuador, Thailand, or Indonesia for processing and re-exported to the U.S. Had the data included this temperature distinction from the beginning of the series, we would have dropped those observations from the dataset, since their origin is unknown we cannot know the diseases to which they were exposed. Since 2012, cold water shrimp only represent at most 7% of average imports from these three countries, thus we hope their presence in the data does not have strong implications for results.

The case may be that countries with disease ramp up processing industries and import more cold water shrimp to compensate for losses, which would skew our results. But the data reveal that the percentage of cold water shrimp imports from the three countries went down from 7% in 2012 to 0% in 2015, a period coinciding with significant losses from EMS. We proceed acknowledging the limitations of our narrow three-country scope and the problem with re-imports.

4.1 Descriptive statistics

Figure 3 shows average yearly import quantities. Imports from Thailand are highest in most years but they also vary more than imports from Indonesia and Ecuador. Thai imports fell approximately 17% in 1997, a year when WSSV was problematic. Ecuadorian imports declined 24% in 1999 and then 63% in 2000, corroborating the arrival of WSSV in the late 1990s, and the graph also shows some evidence of Ecuador's early 1990s Taura Syndrome outbreak around 1994. Losses to disease in the 1990s are likely masked partially by industry growth during this time. The highest growth rates in imports from all three countries appear to have occurred between 2003 to about 2010, which was a relatively disease free period due to improved management and widespread use of the SPF stock. Average yearly import growth rates from 2003 to 2010 for Ecuador, Indonesia, and Thailand were 12%, 20%, and 16%, respectively. The most dramatic drop in the figure appears in the Thai series in 2011 continuing to 2014, which is when EMS hit. 2014 imports from Thailand fell nearly 80% from 2010 levels.

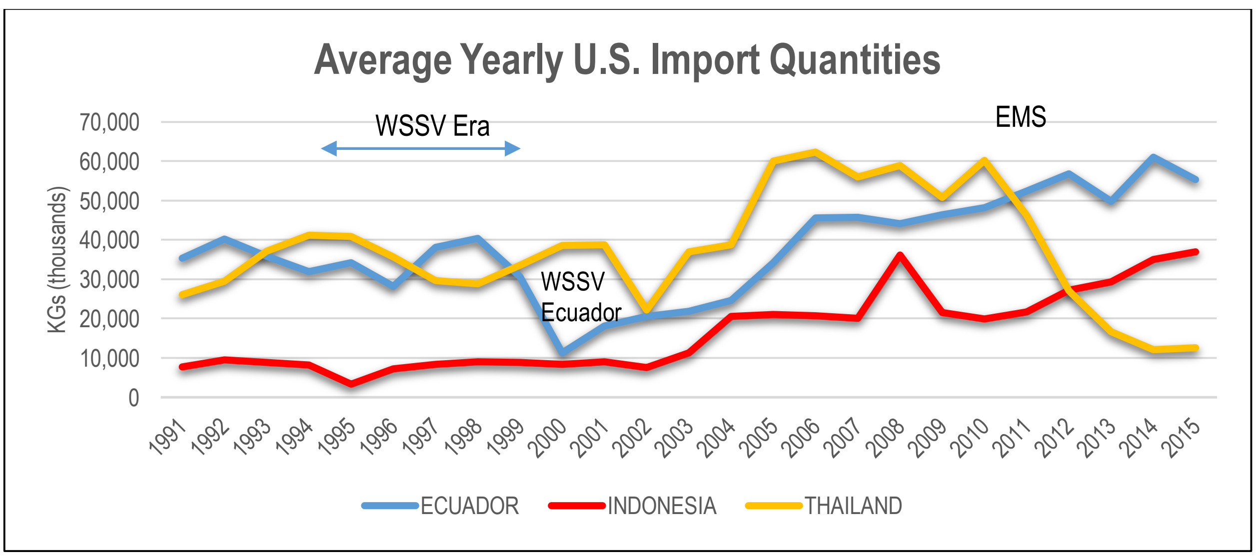

Figure 3. U.S. Import Quantities

The Fisher indices in Figure 4 largely follow the import quantity trends in Figure 3 as theory would predict. Prices for all four producers seem to move together, suggesting integration across producers. Prices are rising in the 1990s, which could be driven by rising demand, losses to disease, or both. Prices in Ecuador rise significantly around their WSSV outbreak in the late 1990s. Prices for all four producers appear to fall steadily during the 2000s when disease was less problematic and production boomed. Interestingly, we see evidence of the impacts of hurricane Katrina and the 2010 Gulf oil spill on the shrimp fishery reflected in the Gulf price index, which rises shortly after both of these events. Finally, prices for all three culture producers appear to rise markedly following the spread of EMS to Thailand.

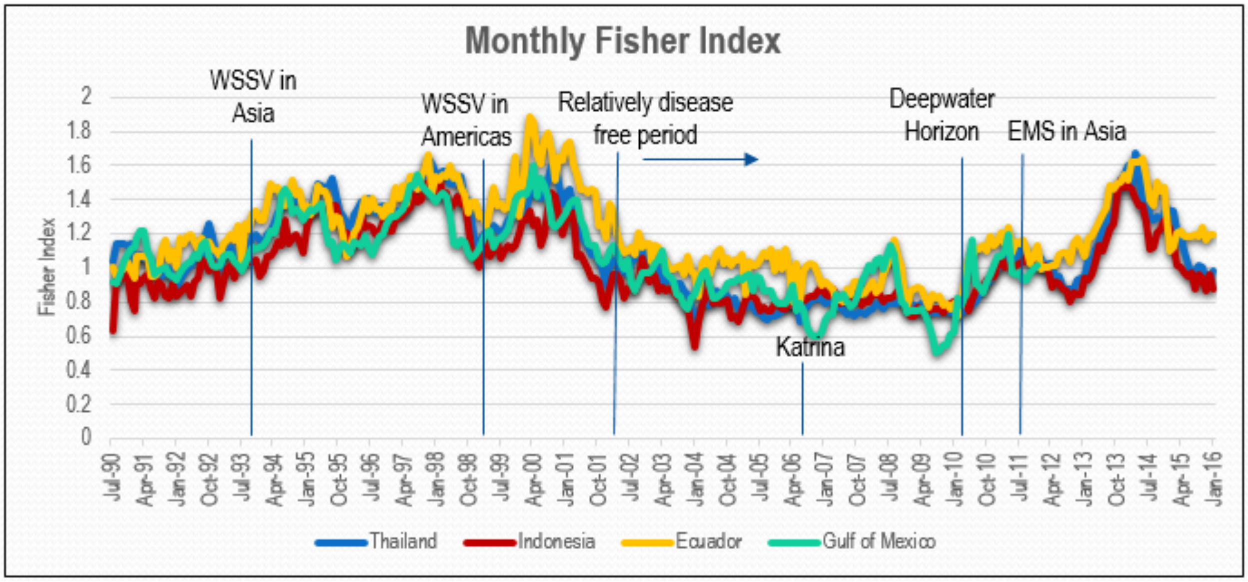

Figure 4. Fisher index by producer

Figure 5 of Thailand's log prices by size category confirms a high correlation between price and size of shrimp. Prices by shrimp size category appear to move in concert with one another as expected. Figure 1A in Appendix A shows that the mid shrimp size categories make up most U.S. imports by weight. It also shows, however, that the medium size categories are most volatile. The fall in the share of larger shrimp imports in the early 2000s (Figure 2A) may reflect a shift from the larger *P. Monodon* stock toward the smaller *P. Vennamei* stock, which offered better control over disease.

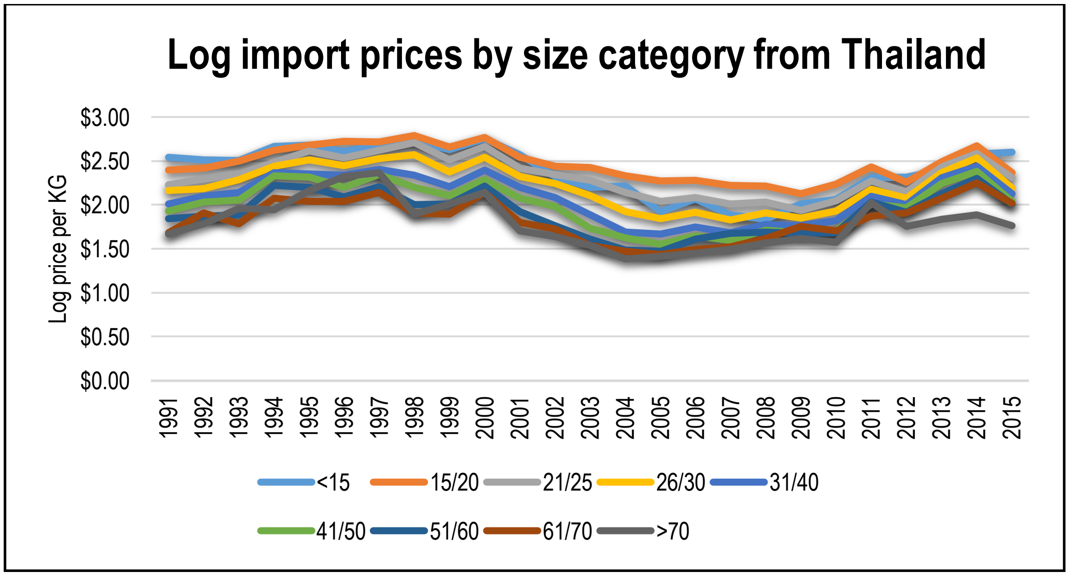

Figure 5. Log import prices by size category from Thailand

V. Methods

We employ a series of statistical concepts to determine the relationship among shrimp aquaculture prices in Ecuador, Indonesia, and Thailand, as well as the U.S. capture shrimp fishery in the Gulf of Mexico. The procedure broadly includes: (1) stationarity, or unit root tests, (2) cointegration analysis, and (3) structural break tests.

Stationarity Tests. Standard OLS regression techniques with time series data require stationarity, i.e. means and auto-covariances must be finite and cannot change to an excessive degree over time. Stationarity allows for temporal dependence between random variables in a stochastic process. Before selecting the right model, the first step is to determine if shrimp prices are stationary.

Prices are often nonstationary due to the presence of a trend, which may be deterministic or stochastic. Stochastic processes can be eliminated by taking the first difference across the series. A deterministic process involves a unit root in the moving-average process and requires more complex handling.

First, we use the Augmented Dickey-Fuller (1981) and Phillips-Perron (1988) to test for the presence of a unit root (non-stationarity). We add the Generalized Least Squares Detrended Dickey-Fuller (GLS-ADF) and Kwiatkowski, Phillips, Schmidt and Shin (1992) stationarity tests because they have higher power than ADF and PP (Elliot et al. 1996). We suspect nonstationarity in levels (i.e. not I(0)), so we also run the tests on first difference of each series to see if they are I(1). It is important to identify the lagged difference (I(d)) that ensures the error term is serially uncorrelated. A serially correlated error term induces bias, but over specifying a lag reduces the power of the test. Optimum lag lengths can be chosen based on the Akaike Information Criteria (AIC), among other criterion. The Stata package used in this analysis automatically selects a default lag based on sample size using the Schwert (1989) criteria.

The ADF indicates whether our Fisher index follows a unit root process. In other words, it tests it if the series has a time-invariant mean, variance, and auto-covariance. The null hypothesis is that the variable contains a unit root, and thus follows a nonstationary process. Rejection of the null hypothesis indicates that the variable is stationary. When variables are nonstationary in levels but stationary in first differences, as we expect to find in shrimp prices, cointegration analysis can provide a valid framework for estimation and inference.

Developed in the late 1980s, the Phillips-Perron test modifies the test statistics in the ADF to account for potential serial correlation and heteroscedasticity in the residuals (Phillips & Perron, 1988). PP uses the same specifications as the ADF with the same asymptotic distribution and critical values. Thus, rejection of the null hypothesis indicates stationarity. Advantages of this test include (1) robustness to heteroscedasticity in errors, (2) inherent correction for serial correlation and (3) no requirement to specify lag length.

The GLS-ADF test, proposed by Elliot et al. (1996), transforms the given series via a generalized least squares (GLS) regression prior to fitting the model in the ADF test. The GLS detrended version of ADF increases power to detect nonstationarity when the unit root is close to one, particularly in the presence of an unknown trend (Elliot et al. 1996).

Kwiatkowski, Phillips, Schmidt and Shin (1992) offer another test to complement ADF and PP. KPSS considers the observed times series as the sum of a deterministic time trend, random walk, and stationary time trend. In this test, the absence of a unit root is not evidence of stationarity and only implies trend-stationarity. The distinction matters as it is possible for a series to be nonstationary and trend-stationary. In the case of a shock, a trend-stationary series eventually reverts toward the mean trend. In other words, the trend is not affected by the shock. KPSS reverses the test hypotheses relative to ADF, so rejecting the null in the ADF should coincide with a failure to reject the null hypothesis in KPSS, though not necessarily since the test statistics are constructed differently. Unlike ADF, KPSS is associated with high rates of Type I error, i.e. tends to over-reject the null hypothesis of stationarity.

Table 2. Stationarity test hypotheses

Test	Null hypothesis (H_0)	Alternative hypothesis (H_A)
Augmented Dickey-Fuller (1979) and GLS-ADF	Series contains unit root (Non-stationarity)	Series does not contain unit root (Stationarity)
Phillips-Perron (1987)	Series contains unit root (Non-stationarity)	Series does not contain unit root (Stationarity)
KPSS (1992)	Series does not contain unit root (Trend/level stationarity)	Series contains unit root (Trend/level non-stationarity)
Johansen (1) Max. eigenvalue (2) Trace	 (1) No cointegration (2) No cointegration or rank (Π) = r0	 (1) Cointegrated series (2) r0 < rank (Π) $\leq$ n

Cointegration. Time series analysis of market integration suits well to markets that vary by geographic region and product form. Cointegration was developed by Engle and Granger (1987) to verify long run equilibrium relationships, or co-movements, in two series with stochastic properties. We expect to find cointegration among shrimp prices parallel to Smith et al. 2012 and others. Cointegration means that if markets become dissimilar, consumers shifting purchasing patterns until prices converge. Even where prices fluctuate relative to each other in the short run, cointegration can verify long run trends in nonstationary prices. If prices are stationary, ordinary regression analysis of series on lagged values is sufficient. The conventional estimator is a vector autoregressive model (VAR). In the presence of unstable residuals over time, VAR is not appropriate because the model's error term must account for serial correlation of a point in time with all previous data points. Luckily, in cointegrated markets, a regression of one I(1) price series on another produces stationary residuals. But in absence of a common stochastic trend, regressing one I(1) series on another produces results subject to spurious correlation.

We move on from analyzing the stationarity of shrimp prices in isolation to Johansen's test, a multivariate generalization of the ADF. The definition of cointegration requires existence of a linear combination of first difference stationary variables that is covariance stationary. If this is the case, we can estimate parameters using vector error correction models (VEC) with Johansen's (1995) normalization specifications. The Johansen test inspects linear combinations of variables for unit roots using a maximum likelihood estimator. Unlike Engle and Granger, Johansen (1990) offers a test permitting analysis of more than two time series variables.

Cointegration analysis requires that all the price series are integrated of the same order. With n price variables, the VEC estimates at most $n-1$ cointegrating vectors. We perform bivariate and multivariate Johansen tests on all possible bivariate and multivariate combinations of the four price variables. Confirmation of a long term trend in prices allows us to proceed with tests to determine if disease explains deviations from price trends. In an integrated shrimp market, the results of disease in the short run dissipate as other producers compensate for supply shocks in the disease country.

Johansen proposed two tests, both likelihood ratio tests, to identify if series are integrated of the same order and thus share a long term relationship. These tests are based on a null hypothesis that there are at most r cointegrating vectors. The rank, r, determines how many linear combinations of the variables are stationary. If there are n price series and there is one common stochastic trend, we expect r to confirm n-1 cointegrating vectors. The first of Johansen's tests is the maximum eigenvalue test, which tests the null hypothesis of no cointegration against the alternative that there are exactly $r+1$ cointegrating vectors. The null hypothesis is that the largest eigenvalue is zero vs. the alternative that the next largest eigenvalue is zero. Thus, we first test the null that the rank of the matrix is zero against the alternative that it is one. In the presence of more than two variables, it next tests the null that the rank of the matrix is one against the alternative that it is two, and so on.

The second of Johansen's tests is the trace test, which tests if r=0. The alternative hypothesis is that there are more than r cointegrating vectors, $r(0) < \text{rank}(\Pi) \leq n$, where n is the maximum number of possible cointegrating vectors. If this null hypothesis is rejected, the succeeding null hypothesis is that $\text{rank}(\Pi) = r0 + 1$ and the alternative hypothesis is $r0 + 1 < \text{rank}(\Pi) \leq n$. A rank of n-1 in a multivariate system with n price series implies that there is one stochastic trend driving price behavior in the market.

Assuming the price indices are cointegrated, the VEC model quantifies the short run dynamic adjustment process that takes place when one series deviates from the long run trend. The VEC model is fit to the first differences of nonstationary variables and includes a lagged error correction term. For a model of two variables, the error correction term is the lagged residual from the cointegrating regression of one series on the other in levels. The residual is zero when variables are in equilibrium with their long-run relationship. In the case of more than two variables, there is a vector of error correction terms whose length equals the number of cointegrating relationships among the variables. To identify each cointegrating vector, one variable is set equal to one and the others are estimated via regression on each variable in levels.

The VEC is a representation of the VAR model where the first differences of the cointegrated variables are regressed on themselves in levels as the exogenous variables. Within the VEC, we would like to identify whether the disease dummy variables play a key role in price auto and cross-determination. Running a VAR model on the first differences of I(1) series is possible, but it is suboptimal if series are cointegrated because the VAR quantifies only short-run responses. We want to capture long term tendencies. If variables are cointegrated, the VAR in first differences is inappropriate because it does not contain the error correction term. Only in the case of no cointegration is the VAR in first differences consistent.

Before Johansen's rank test, we find the optimal lag order of the autoregressive process to eliminate serial correlation based on the following criteria: Akaike information criterion (AIC), Hannan–Quinn information criterion (HQIC), Schwarz Bayesian information criterion (SBIC), and the sequential likelihood-ratio (LR). We select the lag based on which order the majority of the criterions indicate. In most cases, the AIC and LR agree with each other at a higher order than the HQIC and SBIC and we select this lag. We run a series of post-estimation tests to ensure the model is well-specified (See Appendix C for details).

Before proceeding with structural breaks tests, we test for weak exogeneity to determine if any of the shrimp producers are price leaders. Price leadership would suggest that disease shocks elsewhere could not influence prices received by the leader. We hypothesize that Thailand might be a price leader due to the magnitude of their shrimp industry. If Thailand is a price leader, we would alter the specifications employed to represent this market in the structural break tests. We would test bivariate relationships for structural breaks in the presence weakly exogenous actors. In absence of a price leader, the model should include all four producers simultaneously. To test for weak exogeneity, we test the significance of the adjustment parameters in each cointegrating equation for each producer estimated by the VEC model. Failure to reject that the adjustment parameter in each cointegrating equation is zero signifies that the producer is not a price leader.

Establishing a long run equilibrium relationship between prices implies a short run dynamic adjustment process, since the series cannot diverge far before correction by market forces. Impulse response functions (IRFs), visual representations of the VEC, are useful to determine the degree and duration of shocks affecting a responding series. IRFs allow us to estimate, for example, how long it took for prices in the Gulf to converge back to the long run equilibrium after a disease shock in Thailand, assuming that disease impacts prices.

Structural break tests. A structural break is when a time series changes abruptly in time. Structural break tests test for parameter constancy or homogeneity. We are interested in finding if shrimp prices reveal structural breaks and if they coincide with times of disease outbreaks identified in Section II.

We test for unknown structural breaks using a specification including all four series and a specification excluding the Gulf because the data for the Gulf ends at the end of 2011, which is not ideal for identifying EMS. The data on Ecuador, Indonesia, and Thailand ends in January 2016, so we want to see if structural breaks occur later in these series.

We test each possible break date (each month) throughout the series using a rolling dummy procedure. We run an iteration of a VAR model in first differences with a dummy variable for each date throughout the series. With 307 observations, this results in 306 iterations. We compare each iteration and identify the best fitting model using Akaike's Information Criterion. The best fitting iteration contains the dummy covariate with the most significant break date. After the first round, we repeat the procedure but include a dummy of the previously identified break date in all iterations in order to find the second most important break date. We repeat the procedure four more times to come up with the top six break dates, in order of importance. We use the VAR model in first differences as a second best alternative because Stata does not permit the inclusion of exogenous covariates in the VEC model. The VEC model is preferable but the rolling dummy procedure is not viable with the VEC model in Stata. The VAR is acceptable in this context since we are looking to explain short run adjustments in response to disease outbreaks. We also present the results of the unknown structural break test on OLS specifications of all bivariate and multivariate combinations of the four variables in Appendix B but acknowledge that OLS is not ideal for this type of data.

An issue with the structural break test is that it has lower power to detect a break at either end of a time series, which is not ideal in this case for testing the impacts of diseases like YHV and Taura Syndrome which fall early on in the series, and EMS, which arrives at the end of the data. Not all break dates are easily testable because of insufficient observations on opposite sides of each possible break.

The results of the structural break test are limited by the fact that there is likely some degree of chronic disease impacting production throughout the whole time series. Production may not decline, but industry growth rates are slower than they would be otherwise. In times of fairly severe losses, we might only observe stagnant, slight declines, or slowly rising production quantities. Identifying the outbreaks is challenging because the whole time period is marked by dramatic growth. Thus, technological improvements in farmed shrimp mask disease impacts on prices to some extent. However, we hypothesize that the acuteness of the EMS outbreak in Thailand may lead us to find a break around this time, contingent on the the test's power to detect breaks toward the end of the time series.

Size-based analysis. This portion of the analysis examines if disease covariates based on our qualitative information are significant determinants of the relationship between prices of larger shrimp relative to smaller shrimp. Shrimp size and value are positively correlated, and the most valuable ponds require the most time before harvest, increasing the risk and magnitude of monetary losses to disease-induced mortality the longer the harvest cycle. The stochastic optimization revealed in shorter harvest cycles is detailed in Reed et al.'s (1986) analysis of the forestry industry's response to exogenous increases in forest fire risk. Elevated forest fire risk (or disease risk in this case) effectively increases the discount rate and shortens the rotation length.

Using only the shrimp price data from Thailand, we examine bivariate combinations of log prices of one of the four smallest shrimp size categories with one of the four largest shrimp size categories. We use OLS to estimate log prices of the larger size class regressed on the smaller shrimp log price with dummy variables. OLS is adequate only if the prices of the two size classes share a stochastic trend. Thus, we only present results of the bivariate relationships where the Johansen test confirms cointegration ($r = 1$, i.e. a stationary linear combination of the two variables). The Johansen rank test is impossible with missing data points, so the only possible relationships are between either the <15, 21-25, or 26-30 count regressed on the 41-50 or 51-60 count categories. Of the six possible bivariate combinations, five were cointegrated.

We construct our dummy covariates for these regressions largely based on the information presented in the background section, checking that the import data support the qualitative findings. We are limited in that our research does not yield exact outbreak months, when outbreaks are most intense, or when disease starts to reside. We use a dummy covariate for the year 1997 because both our data and research confirm that this was a year of substantial losses to diseases in Thailand. WSSV and YHV combined to reduce Thai shrimp culture production by 30% in 1997, adding up to $600 million in losses (Chanratchakool, 2002). The EMS covariate turns on in August 2011, as per an article on Shrimp News International and stays on through the end of 2014 since production recovered starting in 2015.

We also include a dummy covariate to test the impacts of the paradigm shift in disease resistance beginning in the early 2000s. Use of the SPF stock became an industry wide best practice about 5 years after its introduction in the late 1990s according to Lightner et al. 2012. Import quantities show visible signs of recovery starting in 2003, so we assume it was this year that the paradigm shift resulting from the breeding innovation intensified. The 2003 dummy covariate turns on in January 2003 and stays on throughout the rest of the time period.

VI. Results

Stationarity tests. Results of the stationarity tests are in Appendix B Table 1B. The four tests provide mixed evidence on the stationarity of the Fisher indices in levels. The ADF indicates stationarity in levels for a few series while KPSS rejects stationarity in levels for all four price series. However, all four tests confirm first-difference stationarity across the board. We proceed with cointegration analysis under the assumption the variables are not I(0), but are I(1).

We also run stationarity tests on log prices of all size categories of shrimp from Thailand for the size-based analysis and find similar results. The four tests yield mixed results for log prices in levels, with KPSS rejecting stationarity in levels for all size categories. All nine log price variables are first difference stationary.

Cointegration analysis. Variables are cointegrated if each is an I(1) process but the linear combination of the variables is an I(0) process. The rank, or number of cointegrating equations, should be one less than the number of variables if they are cointegrated. Thus, with two cointegrated series, we should fail to reject the null hypothesis that there is one cointegrating equation. We report whether the eigenvalues used to compute the trace statistics are indicative of cointegration in Appendix B Table 3B. Interestingly, the Johansen test does not identify cointegration in all bivariate combinations of the Fisher indices. All pairwise combinations that include Indonesia's Fisher index do not yield a rank of one. However, the rank test including all four Fishers results in a failure to reject a rank of three (Table 3), indicative of cointegration.

Table 3. Johansen cointegration rank test results – Gulf, Ecuador, Indonesia, and Thailand Fishers

Max rank	Trace parms	Critical LL	Eigenvalue	Statistic	Value
0	20	1455	.	110.5	47.21
1	27	1478	0.161	65.48	29.68
2	32	1496	0.136	28.02	15.41
3	35	1509	0.0942	**2.6849***	3.760
4	36	1510	0.0104		

Note: * indicates failure to reject null hypothesis of respective max rank

In the weak exogeneity tests, we reject the null hypothesis that that the adjustment parameter is zero in each of the three cointegrating equation of the VEC model for all four Fishers. Finding that no producer, including Thailand, is a price leader, we confirm that these markets are integrated and no one is insulated from the impacts of price shocks. This result means that modeling separate bivariate relationships is incorrect, and we should include all actors in one model when we test for structural breaks. The significance of the adjustment parameters also provides further evidence that residuals are unstable and OLS is not a suitable estimator.

Table 4. Weak exogeneity test results

	chi2 test statistic (3 parameters)	P-value
Thailand	14.06***	0.0028
Indonesia	14.37***	0.0024
Ecuador	19.56***	0.0002
Gulf	20.55***	0.0001

Note: *** indicates rejection of null hypothesis at 1% level that the adjustment parameter in the cointegrating equation is 0 (reject null that the series is exogenous)

After determining the presence of a cointegrating relationship among the four shrimp price series, parameters of interest in the VEC model are the β's and the adjustment coefficients (α) in the cointegrating equations. We present VEC model results of specifications including all four price variables and results excluding the Gulf in Appendix B. Since we cannot include exogenous disease covariates in the VEC model, we also present VAR specifications including dummy covariates for the year 1997, EMS, and the use of the SPF stock starting in 2003. Also included is a covariate for the 2010 Gulf oil spill in the specification including the Gulf. We expect the disease and oil spill coefficients to be positive because these events should restrict supply and raise prices. The innovation dummy is expected to be negative because it reflects a time when costs declined and thus supply increased. Results indicate that these covariates are not statistically significant determinants of shrimp prices after controlling for the relationships among prices over time.

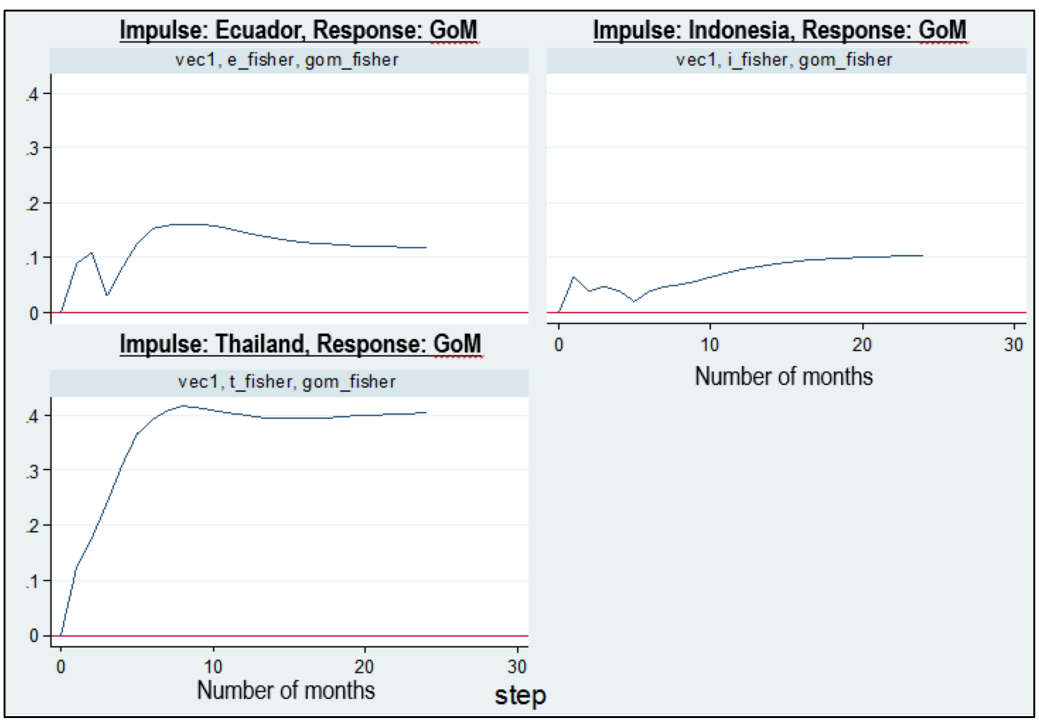

Figure 6. Impulse response functions (VEC model)

The IRFs of the VEC model shown in Figure 6 reveal that Gulf prices are most sensitive to the market in Thailand and least responsive to Indonesia's market. All functions appear to level out at around 10 months, however. IRFs of VEC models do not always display a die out of the effects of a shock over time because the variables are not mean reverting, as they are in a VAR model. That shocks in Thailand are most important for Gulf prices is unsurprising since most shrimp imports come from Thailand. The dataset is somewhat limiting because Thailand is most negatively affected by EMS, which comes at the very end of the time series for the Gulf. Therefore, we do not have the best data to explore the effects of the most affected exporter during its worst disease crisis.

Structural break tests. The most significant break dates are listed in order of significance based on the AIC in Table 5. Figure 7 displays a graphical representation of the breaks laid over the Fisher indices. The first break occurs in 1992 when the Gulf is included, which could signify the effect of rising prices in 1990s due to the variety of viral diseases hitting the culture industry. Several breaks pop up in 2003, when the culture industry became more resilient to disease due to the SPF stock. Prices appear to have fallen precipitously with the expansion farmed shrimp imports to the U.S. at this time. Five of six breaks occur in the early 2000s for the specification excluding the Gulf while two of six breaks occur in this time period when the Gulf is included. In the model including the Gulf, two breaks occur in 2005, the year Hurricane Katrina hit in August. NOAA (2007) estimated losses to Louisiana's seafood industry due to Katrina at $1.3 billion. Hurricane Katrina disrupted shrimp supply through destruction of shrimp vessels and processing facilities (Buck, 2005).

Table 5. Structural break dates (VAR first difference rolling dummy procedure)

Round	*Including GoM*	*Excluding GoM*
1	March, 1992	August, 2003
2	February, 2011	June, 2011
3	August, 2002	June, 2003
4	October, 2005	April, 2003
5	September, 2003	August, 2003
6	September, 2005	February, 2001

We also observe the second most important break dates occurring in 2011 for the models including and excluding the Gulf. It is unclear if the February 2011 break is picking up on the effects of the Gulf oil spill or early warning signs of EMS. The Deepwater Horizon spill cost the Gulf's fishing industry an estimated $95 million in 2010 (Schleifstein, 2016). However, fishery closures also resulted in an abundance of large shrimp when the fishery reopened. The glut of shrimp in the Gulf upon resumption of fishing activities led to depressed prices. A June 2011 break occurs when we exclude the Gulf, which is consistent with anecdotes of EMS intensifying in Thailand around this time.

The structural break results highlight the importance of (1) technical innovation in disease resistance, (2) Katrina in the Gulf, and (3) EMS for culture prices. The rise of disease in the early 1990s may have also put upward pressure on prices. It appears the improved SPF stock may have been more important for explaining shrimp prices than disease, though EMS is also significant. Breaks largely fit with the qualitative research, but some sort of disease or event that might affect prices seems to be happening throughout the time period. Results are encouraging, but we cannot rule out alternative explanations for the observed price volatility.

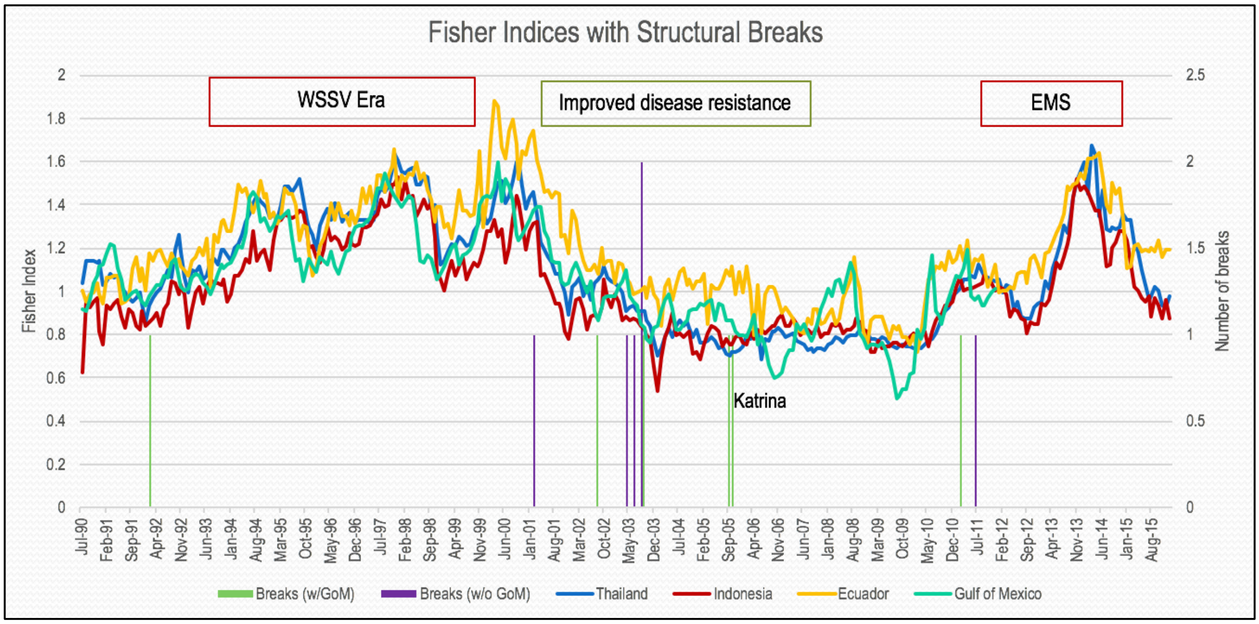

Figure 7. Graph of structural breaks with Fisher indices

Size-based analysis. We hypothesized that prices of large shrimp would increase more than prices of small shrimp when disease outbreaks occur because producers may optimize by shortening harvest cycles in response to heightened risk of disease. Table 6 displays the results of the pairwise combinations of log prices of larger shrimp regressed on log prices of smaller shrimp and several dummy covariates.

Table 6. Pairwise Size-based Regression Results - Thailand

	(1)	(2)	(3)	(4)	(5)
	ln_t_p_1	ln_t_p_3	ln_t_p_3	ln_t_p_4	ln_t_p_4
y1997	-0.0671**	-0.00524	0.0386*	-0.0166	0.0296
	(0.0312)	(0.0199)	(0.0227)	(0.0164)	(0.0194)
y2003	-0.167***	-0.0325	-0.170***	-0.0505***	-0.199***
	(0.0415)	(0.0211)	(0.0239)	(0.0158)	(0.0220)
ems	-0.0261	-0.103***	0.0115	-0.0526**	0.0688**
	(0.0478)	(0.0243)	(0.0296)	(0.0213)	(0.0281)
ln_t_p_6	0.766***	0.779***		0.857***	
	(0.0685)	(0.0385)		(0.0282)	
ln_t_p_7			0.581***		0.649***
			(0.0512)		(0.0461)
Constant	0.953***	0.805***	1.304***	0.539***	1.068***
	(0.148)	(0.0816)	(0.105)	(0.0597)	(0.0950)
Obs	307	307	307	307	307
R-squared	0.699	0.796	0.714	0.898	0.818

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

Estimates of the five specifications do not show consistent signs or significance for the 1997 and EMS dummy variables, all else equal. In two of the five regressions, the EMS coefficient is negative and significant, counter to expectations. However, in four of five specifications, the dummy covariate turning on in 2003 is negative and significant at the 1% level. This could indicate that producers do not react during times of more intense disease but do optimize in response to improved disease resistance by lengthening grow-out periods in pursuit of higher prices associated with larger shrimp. This result is interesting in light of the industry's shift away from the larger *P.monodon* toward the smaller sized but less risky *P.vennamai* stock in the early 2000s (Anderson, 2015). Considering this development, results provide even stronger indication that producers were lengthening grow-out cycles at this time.

Other explanations for these results are also conceivable. Supply shocks due to disease could affect size classes differently due to spatio-temporal dynamics of the system. Young shrimp in particular are reared at high stocking densities, which facilitates the spread of disease to more small shrimp (Naylor et al. 1998). If small shrimp are more vulnerable to disease, prices would reflect this if a disease cycle is fairly confined in time such that bigger shrimp are largely unaffected. It is also possible that producers of larger shrimp react to disease risks by expending more resources to manage risks in comparison to producers of smaller shrimp, and so smaller sized shrimp are more vulnerable to losses from disease.

Irrespective of why prices of large shrimp do not appear to grow disproportionally when disease strikes, the result indicates that Gulf producers do not appear able to gain from landing larger shrimp when disease outbreaks occur. In fact, developments in disease risk management might diminish opportunities for fishermen to gain from catching larger shrimp.

Conclusion

This analysis attempts to contextualize the economic interaction of capture fisheries and aquaculture with a focus on disease in aquaculture. We set out to determine if disease in farmed shrimp benefits the capture shrimp fishery in the U.S. Gulf of Mexico via increased prices. Using U.S. farmed shrimp import data from Indonesia, Ecuador, and Thailand, we confirm findings in the literature of integration in shrimp markets across culture and capture producers and separate geographic regions. The integrated nature of shrimp markets suggests that U.S. shrimpers benefit less from disease in farmed shrimp than would be the case in absence of integration. This research is informative as the U.S. considers trade protective measures to insulate its domestic seafood producers from global competition. Market integration suggests that trade restrictions primarily lead to changes in trade patterns with little price benefits for domestic producers (Keithly, 2008). In spite of antidumping duties in place on farmed shrimp from Thailand and Ecuador during much of the time period considered here, prices in the Gulf largely mirror those of the global culture market.

Ironically, aquaculture emerged to avoid mismanagement in fisheries, increase control, and minimize environmental shocks, yet we observe all of these problems in shrimp aquaculture, showcased by the burden of disease. We found a wealth of information highlighting dramatic losses incurred by the global culture industry from the viral diseases of the 1990s and the more recent outbreak of EMS. The impacts of disease cost the shrimp culture industry billions of dollars in lost production, jobs, and revenue. The integrated nature of shrimp markets and dramatic growth in shrimp aquaculture in the last few decades should mask the effects of disease on prices to some extent, but we find evidence that EMS impacted culture shrimp prices. However, extrapolation of this finding to Gulf prices is limited due to the availability of Gulf price data, which ends in 2011. Structural break tests reveal that the SPF stock innovation in aquaculture may have played a greater role in the price determination process than disease. This means that the genetic improvement's impact on disease management may have hurt Gulf shrimpers more so than disease has helped them.

We also investigate the relative prices of small and large farmed shrimp to shed light on whether culture producers dynamically optimize in response to higher disease prevalence. Results do not support this storyline but may substantiate the inversion of this theory. The prices of large shrimp compared to small shrimp fell after widespread use of the SPF shrimp stock in 2003, thus, producers may have responded to reduced disease risks afforded by the innovation by extending harvest cycles and growing more big shrimp to capture size-based price premiums.

Disease is a major constraint in aquaculture. Nonetheless, technical innovation and dramatic growth in aquaculture might reduce opportunities for capture fisheries to accrue price benefits from (1) disease in aquaculture, and (2) delayed season openings to improve the size composition of catch. The benefits of marketing campaigns to distinguish the U.S.'s wild shrimp from farmed shrimp on sustainability, health, and 'local' fronts might hold potential to help fishermen, but do not appear remarkably successful at this time. Absent prospects to cut production costs to compete with low cost aquaculture, the Gulf shrimp fishery's future may hinge on effective marketing efforts.

Future analysis should include other major culture producers like India, Vietnam, and China as well as an extension of the time series data from the Gulf of Mexico. The data is somewhat limiting because Thailand is most affected by EMS, which comes at the tail end of the time series for the Gulf. In the future we might regress the Fisher index on average prices for brown shrimp in the publicly available NOAA data and predict in the post-2011 period for the Gulf Fisher index. This is not ideal but would be one way to extend the time series. The size-based analysis here focused on Thailand, but other major culture producers are also candidates for this analysis. Enhanced temporal specificity on the disease and technical innovation information would also add clarity to results.

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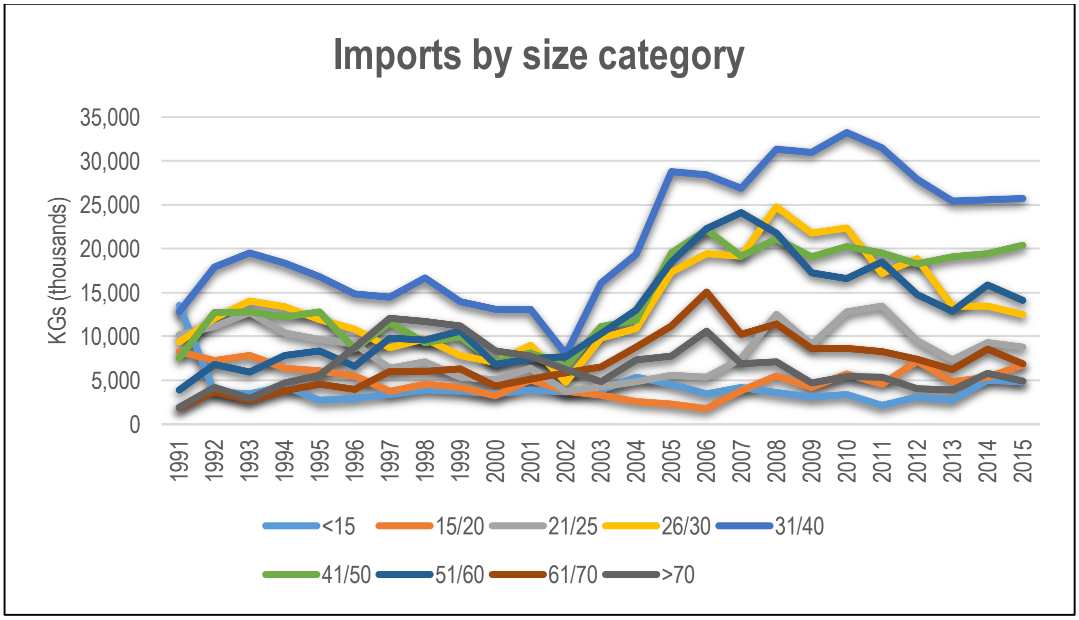
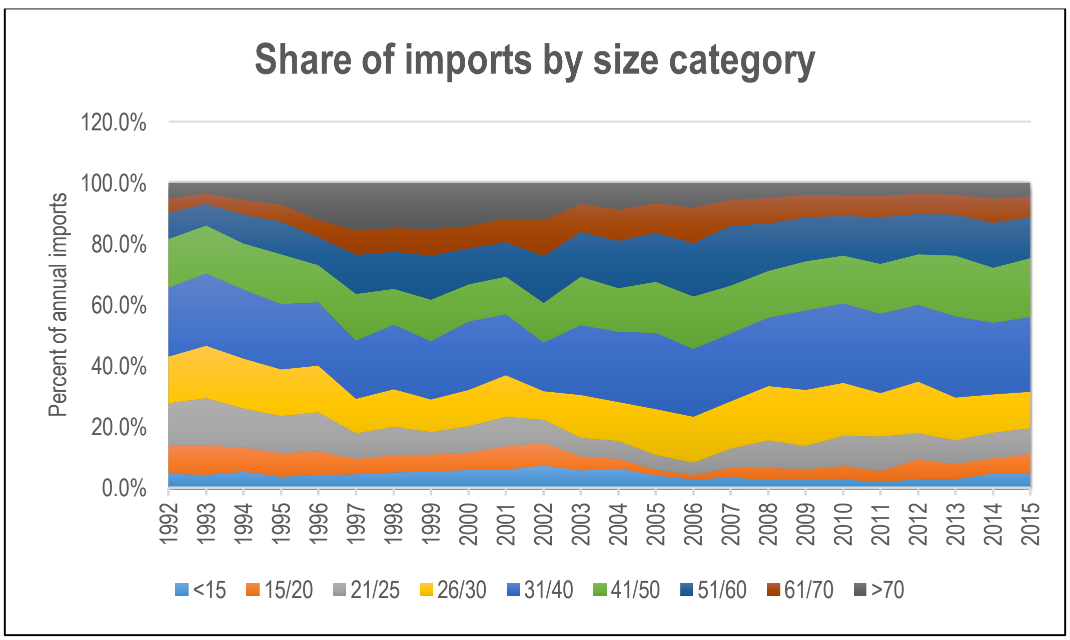
Appendix A. Figures



<u>**Figure 1A. Import quantities by size category from all three countries**</u>



<u>**Figure 2A. Share of imports by size category**</u>

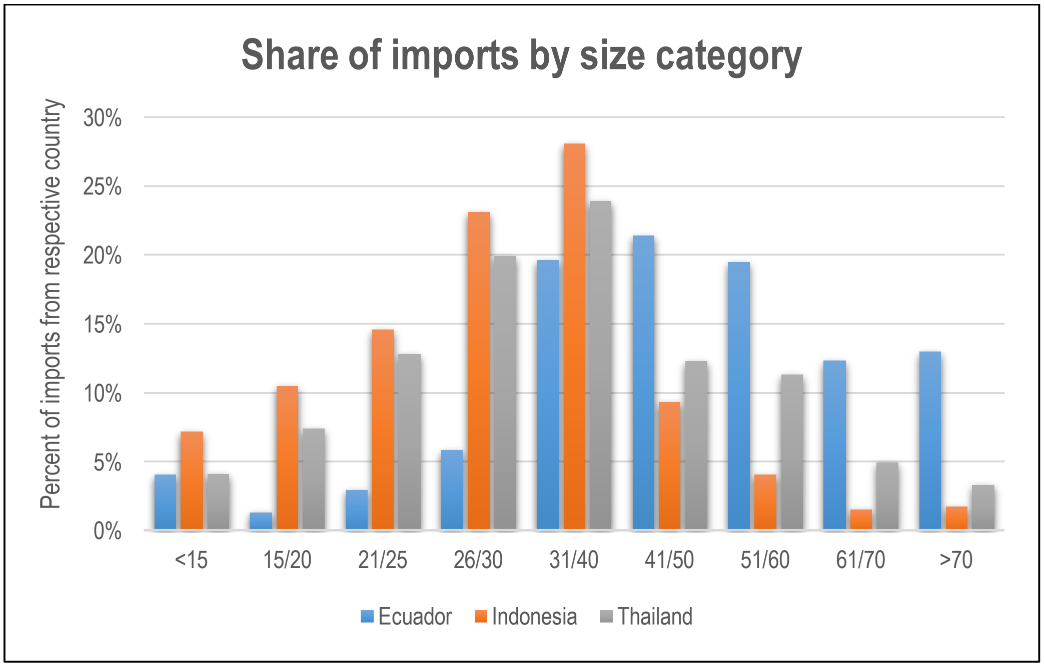


Figure 3A. Share of imports by size category

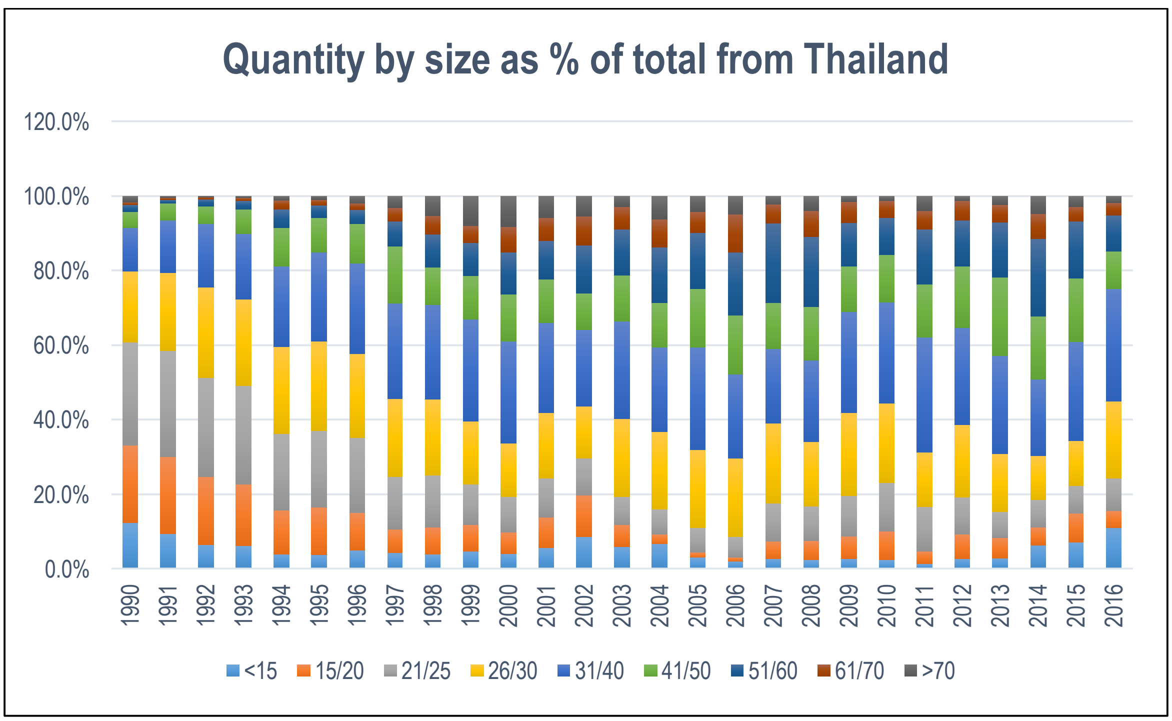


Figure 4A. Share of imports by size category - Thailand

Appendix B. Results

Table 1B. Fisher index stationarity test results

	ADF		ADF (linear trend)		PP		PP (linear trend)		KPSS		KPSS (no trend)		DFGLS	
	Levels	FD	Levels	FD	Levels	FD	Levels	FD	Levels	FD	Levels	FD	Levels	FD
Thailand (N=306)	-1.81**	-17.44***	-2.067	-17.41***	-1.99	-17.47***	-2.22	-17.44***	0.796***	0.075	2.0***	0.074	-1.98	-4.29***
Indonesia (N=306)	-2.89**	-18.2***	-3.14*	-18.17***	-2.84*	-18.38***	-3.09	-18.35***	0.708***	0.069	1.28***	0.113	-1.6	-2.97
Ecuador (N=306)	-3.2**	-21.79***	-3.34*	-21.76***	-2.66*	-22.98***	-2.8	-22.96***	0.701***	0.055	1.36***	0.06	-1.71	-8.47***
GoM (N=258)	-2.06	-13.84***	-2.88	-13.82***	-2.5	-13.81***	-3.19*	-13.79***	0.616***	0.047	2.77***	0.057	-2.28	-7.71***

Note: ***=1%, **=5%, *=10%. Rejection of null in ADF, PP, DFGLS indicates stationarity. Rejection of null in KPSS indicates non-stationarity.

Table 2B. Stationarity test results - log prices of Thai imports by size category

	ADF		PP		KPSS (lag 3)		DFGLS (lag 3)		N
Size	Levels	FD	Levels	FD	Levels	FD	Levels	FD	
<15	-5.22***	-28.82***	-4.49***	-35.44***	.922***	0.0302	-2.479	-10.91***	306
15/20	-3.81***	-25.03***	-3.15**	-25.76***					300
21/25	-2.75*	-22.63***	-2.42	-22.66***	0.736***	0.048	-2.13	-4.12***	306
26/30	-1.99	-18.14***	-2.04	-18.12***	0.81***	0.074	-1.86	-3.41***	306
31/40	-1.76	-16.95***	-1.86	-16.95***	0.89***	0.085	-1.74	-6.13***	306
41/50	-2.38	-23.6***	-2.02	-23.5***	0.931***	0.079	-1.63	-8.59***	306
51/60	-3.55***	-26.92***	-2.91**	-27.73***	0.913***	0.044	-2.09	-8.45***	306
61/70	-4.57***	-22.99***	-3.89***	-26.1***					304
>70	-6.36***	-25.67***	-5.97***	-30.16***					300

Note: ***=1%, **=5%, *=10%. Rejection of null in ADF, PP, DFGLS indicates stationarity. Rejection of null in KPSS indicates non-stationarity. Cannot run KPSS or DFGLS tests with gaps in data.

Table 3B. Johansen rank test results

	Indonesia	Ecuador	Gulf of Mexico	Thailand, Indonesia	Thailand, Ecuador	Indonesia, Ecuador	Thailand, Indonesia, Ecuador
Thailand	N	Y	Y				
Indonesia			N				
Ecuador	N		N	Y			
Gulf of Mexico	N	N		Y	Y	N	Y

Note: Y = rank 1 for bivariate, rank 2 with 3 covariates, rank 3 for 4 covariates

Table 4B. Error correction model results (including Gulf)

	D_gom_fisher	D_t_fisher	D_i_fisher	D_e_fisher
L._ce1	-0.157***	0.101***	0.0738*	0.231***
	-0.0415	-0.0306	-0.0384	-0.0561
L._ce2	0.140**	-0.117***	0.120**	-0.0051
	-0.0594	-0.0438	-0.0551	-0.0803
L._ce3	-0.0443	0.0528	-0.212***	0.0764
	-0.0645	-0.0476	-0.0598	-0.0873
LD.gom_fisher	0.223***	0.0659	0.0675	0.0524
	-0.0668	-0.0492	-0.0619	-0.0903
L2D.gom_fisher	0.0358	-0.0705	0.0159	-0.0897
	-0.0678	-0.05	-0.0628	-0.0916
LD.t_fisher	-0.0655	-0.0249	0.304***	0.0108
	-0.0965	-0.0711	-0.0895	-0.13
L2D.t_fisher	-0.106	-0.208***	0.0221	-0.172
	-0.0912	-0.0672	-0.0846	-0.123
LD.i_fisher	0.121	0.152**	-0.0865	0.00992
	-0.0815	-0.0601	-0.0756	-0.11
L2D.i_fisher	0.0108	0.0819	-0.163**	0.0843
	-0.0723	-0.0533	-0.067	-0.0977
LD.e_fisher	0.0756	0.0840**	0.0748	-0.153**
	-0.0521	-0.0384	-0.0483	-0.0704
L2D.e_fisher	0.0372	0.108***	0.0242	-0.0219
	-0.0487	-0.0359	-0.0452	-0.0659
Constant	-0.000233	-0.00031	-3.28E-05	-1.21E-05
	-0.00375	-0.00276	-0.00347	-0.00507
Observations	255	255	255	255

Standard errors below estimates, *** p<0.01, ** p<0.05, * p<0.1

Table 5B. Error correction model results (excluding Gulf)

	D_t_fisher	D_i_fisher	D_e_fisher
L._ce1	-0.131***	0.140***	0.137*
	-0.0461	-0.0521	-0.0748
L._ce2	0.0931*	-0.227***	0.0127
	-0.0514	-0.0581	-0.0834
LD.t_fisher	-0.164**	0.211***	-0.0551
	-0.0656	-0.0741	-0.106
L2D.t_fisher	-0.159***	0.101	-0.0782
	-0.0608	-0.0688	-0.0986
LD.i_fisher	0.231***	-0.0121	0.092
	-0.0623	-0.0704	-0.101
L2D.i_fisher	0.136**	-0.125**	0.0582
	-0.0556	-0.0629	-0.0902
LD.e_fisher	0.0772*	0.0802*	-0.138**
	-0.0401	-0.0453	-0.065
L2D.e_fisher	0.0900**	0.0443	-0.0177
	-0.038	-0.043	-0.0617
Constant	-0.000385	-0.000169	-0.000196
	-0.00291	-0.00329	-0.00472
Observations	304	304	304

Standard errors below estimates, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6B. Vector autoregressive model in first differences (including Gulf)

	fd_gom_fisher	fd_t_fisher	fd_e_fisher	fd_i_fisher
L.fd_gom_fisher	-0.0162	0.167***	0.339***	0.119**
	-0.0621	-0.0493	-0.0777	-0.056
L2.fd_gom_fisher	-0.176***	0.0204	0.138*	0.0618
	-0.0626	-0.0497	-0.0784	-0.0565
L3.fd_gom_fisher	-0.111*	0.0936*	0.257***	0.0125
	-0.0631	-0.05	-0.0789	-0.0569
L.fd_t_fisher	0.102	-0.0895	0.157	0.418***
	-0.0917	-0.0727	-0.115	-0.0828
L2.fd_t_fisher	-0.0195	-0.262***	-0.121	0.0969
	-0.0898	-0.0712	-0.112	-0.0811
L3.fd_t_fisher	0.0256	-0.0507	0.0044	-0.00312
	-0.0865	-0.0686	-0.108	-0.078
L.fd_e_fisher	0.0503	0.0880**	-0.448***	0.0555
	-0.044	-0.0349	-0.055	-0.0397
L2.fd_e_fisher	-0.00172	0.106***	-0.290***	0.0256
	-0.0464	-0.0368	-0.058	-0.0418
L3.fd_e_fisher	-0.108**	-0.0229	-0.294***	-0.0307
	-0.0447	-0.0355	-0.056	-0.0404
L.fd_i_fisher	0.062	0.207***	0.0967	-0.346***
	-0.0715	-0.0567	-0.0895	-0.0645
L2.fd_i_fisher	-0.0157	0.114**	0.163*	-0.310***
	-0.0716	-0.0568	-0.0895	-0.0646
L3.fd_i_fisher	0.000968	0.0422	0.0747	-0.143**
	-0.0675	-0.0536	-0.0845	-0.061
gom_fisher	0.267***	-0.0746**	-0.172***	-0.0069
	-0.0394	-0.0313	-0.0493	-0.0356
t_fisher	-0.118**	0.0882**	-0.209***	-0.275***
	-0.0527	-0.0418	-0.066	-0.0476
e_fisher	-0.104***	0.0211	0.408***	-0.00934
	-0.0343	-0.0272	-0.0429	-0.031
i_fisher	-0.00435	-0.0457	0.00913	0.385***
	-0.0538	-0.0427	-0.0673	-0.0486
fd_1997	0.00679	0.0151	-0.0167	0.0363
	-0.039	-0.031	-0.0488	-0.0352
fd_ems	-0.0603	-0.0309	0.0281	-0.0256
	-0.0568	-0.0451	-0.0711	-0.0513
fd_oilspill	0.00772	0.00306	0.0506	-0.000562
	-0.0399	-0.0316	-0.0499	-0.036
fd_2003	0.00185	-0.0141	-0.0907	0.0396
	-0.0558	-0.0443	-0.0698	-0.0504
Constant	-0.0274	0.00423	-0.0866***	-0.0717***
	-0.0208	-0.0165	-0.026	-0.0187
Observations	254	254	254	254

Standard errors below estimates, *** p<0.01, ** p<0.05, * p<0.1

Table 7B. Vector autoregressive model in first differences (excluding Gulf)

	fd_t_fisher	fd_e_fisher	fd_i_fisher
L.fd_t_fisher	-0.259***	0.143	0.294***
	-0.0647	-0.0912	-0.0668
L2.fd_t_fisher	-0.220***	0.0521	0.114*
	-0.066	-0.093	-0.0681
L3.fd_t_fisher	-0.00551	0.0798	0.00148
	-0.0619	-0.0872	-0.0638
L.fd_e_fisher	0.128***	-0.388***	0.0952**
	-0.0365	-0.0514	-0.0377
L2.fd_e_fisher	0.120***	-0.247***	0.0716*
	-0.038	-0.0535	-0.0392
L3.fd_e_fisher	-0.00293	-0.266***	0.0113
	-0.0367	-0.0517	-0.0379
L.fd_i_fisher	0.334***	0.12	-0.267***
	-0.0572	-0.0805	-0.059
L2.fd_i_fisher	0.191***	0.113	-0.267***
	-0.0583	-0.0822	-0.0602
L3.fd_i_fisher	0.0863	0.034	-0.101*
	-0.0558	-0.0786	-0.0576
t_fisher	0.114***	-0.295***	-0.314***
	-0.0417	-0.0587	-0.043
e_fisher	-0.0289	0.350***	-0.00277
	-0.026	-0.0367	-0.0268
i_fisher	-0.0906**	0.0138	0.412***
	-0.0451	-0.0635	-0.0465
fd_1997	0.0264	0.00359	0.0452
	-0.0354	-0.0499	-0.0365
fd_ems	-0.00734	0.103**	0.0176
	-0.0355	-0.05	-0.0366
fd_2003	-0.00468	-0.0666	0.0462
	-0.0505	-0.0712	-0.0521
Constant	0.00201	-0.111***	-0.0736***
	-0.0167	-0.0236	-0.0172
Observations	303	303	303

Standard errors below estimates, *** p<0.01, ** p<0.05, * p<0.1

Table 8B. Unknown Structural Break Test Results – OLS Specifications

Y, X(→)	Thailand	Indonesia	Ecuador	Thailand, Indonesia	Thailand, Ecuador	Indonesia, Ecuador	Thailand, Indonesia, Ecuador
Thailand		Feb. 2004***	Nov. 1998***			March 2004***	
Indonesia	March 2004***		Nov. 1998***		March 2004***		
Ecuador	Feb. 1997***	March 2006***		Feb. 1997***			
Gulf of Mexico	July 2002***	July 2002***	Aug. 2000***	July 2002***	Aug. 2000***	Aug. 2000***	Aug. 2000***

*** $p<0.01$

Appendix C. Post estimation robustness checks

We test the robustness of our VEC and VAR specifications using several post estimation tests. We (1) test that the residuals show no serial correlation, (2) test that the residuals are normally distributed, (3) ensure that the number of cointegrating equations has been correctly specified.

Inference depends on the stationarity of the cointegrating equations, so we graph the predictions to examine if there are trends in the residuals. Predicted values should vary from actual values due to the volatile nature of the market, but residuals should not exhibit noticeable trends over time. If the number of cointegrating equations is correctly specified and the process is stable, the moduli of the eigenvalues in equations beyond the specified rank should be strictly less than one. If they are close to one, either the cointegrating equations are not stationary or the rank is too high. There is no theory to specify criteria for how far moduli should be from one, but results indicate that none exceed 0.85. This test uses the coefficient estimates from the VEC model to get estimates of the coefficients of the corresponding VAR model and computes eigenvalues of the companion matrix. None of the following graphs of the remaining eigenvalues approach the unit circle. This stability check indicates proper model specification. We also find stability of our VAR specifications in Tables 6B and 7B.

We test for error autocorrelation using the Lagrange Multiplier test discussed in Johansen (1995). Serial correlation in the residuals indicates an under-specification of lags, which biases parameter estimates (Gonzalo, 1994). However, over-specifying lags increases variance and reduces power. If we reject the null hypothesis of no serial correlation in the residuals, we adjust lags upward until we can no longer reject the null at the 5% level. Since we reject the null of no autocorrelation at lag three in the VEC including the Gulf, we try adjusting the lags upward only to find that autocorrelation is worse when we do this. Thus, we proceed with our initial VEC model specification with three lags. We reject the null of no autocorrelation in the VAR models shown in Tables 6B and 7B.

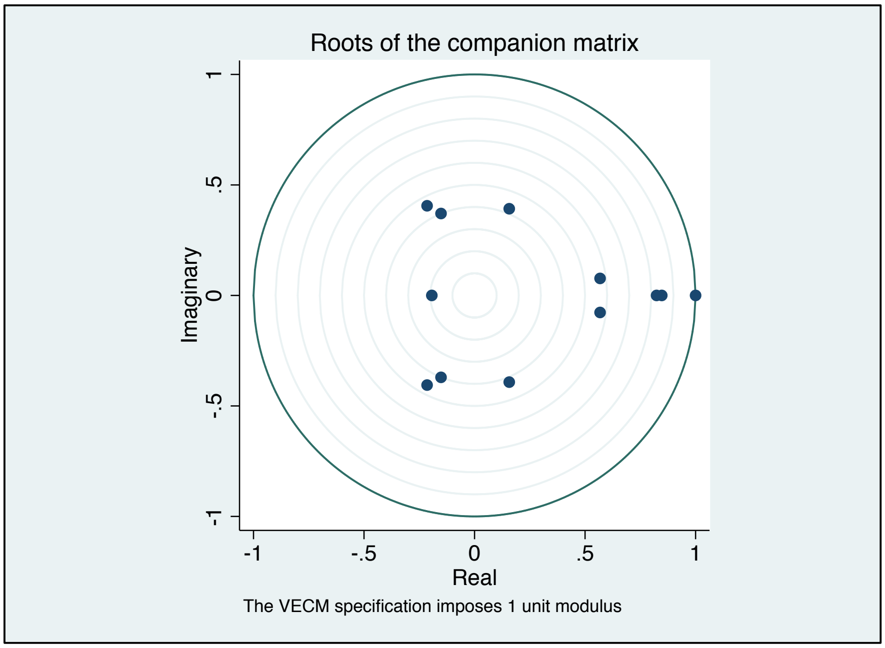


Figure 1C. Graph of eigenvalue moduli over unit circle for VEC of all four Fishers with 3 lags

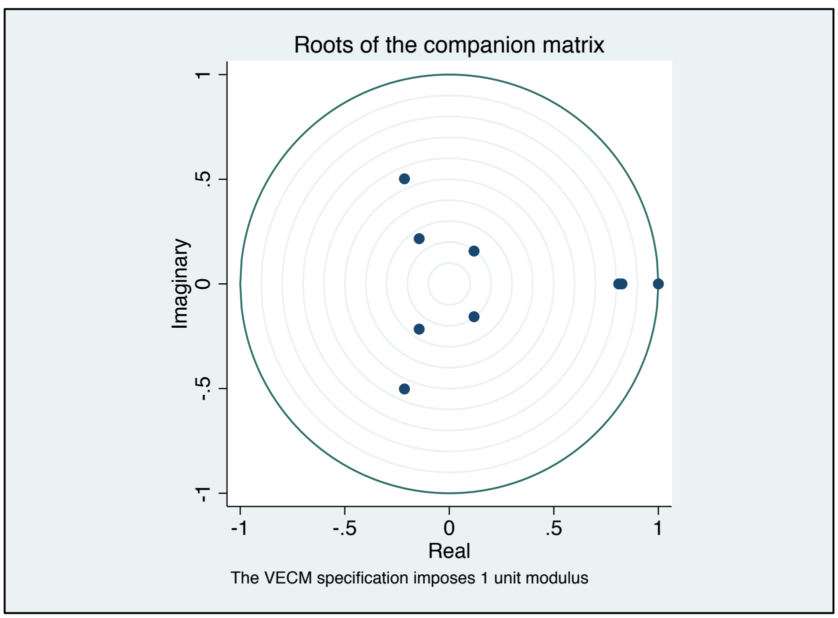


Figure 2C. Graph of eigenvalue moduli over unit circle for VEC of three Fishers (no Gulf) with 3 lags