ABSTRACT

SAKI, ZAHRA. An Investigation of U.S. Textile and Apparel (TAP) Industry Competitiveness. (Under the direction of Dr. Marguerite M. Moore).

This dissertation topic presents a series of related manuscripts, published and unpublished, that examine sources of export competitive advantage for U.S. textile and apparel (TAP) categories. The first manuscript presented in Chapter 1 provides the baseline research for all subsequent analyses (Chapters 2-4) and as such provides the majority of the supporting literature. Unique analytical approaches are required for each of the four analyses and are therefore presented in each respective Chapter. The prevalent timeframe for the analyses covers a 21-year period (1996-2016). However, deviations from this scope occur in several analyses in order to further investigate outcomes indicated by the original 21-year dataset.

The first analysis identifies sources of U.S. TAP advantage based on the Normalized Revealed Comparative Advantage (NRCA) index demonstrating original use of this measure in the industry context (Chapter 1). The UN COMTRADE system provides data for the analysis which are used to calculate NRCA. The analysis indicates six U.S. TAP categories with advantages in NRCA from most to least advantage: cotton fiber (HS 5201), artificial filament tow (HS 5502), nonwovens (HS 5603), cotton yarn (HS 5205), carpet (HS 5703) and worn clothing (HS 6903).

The second analysis examines each of the six TAP categories revealed in the previous study in greater depth. Trend analyses using linear and non-linear regression models are applied to the NRCA data over the 21-year period. Simple linear regression models are initially fit for the six TAP categories. Five out of six initial models indicated outliers which were removed and refit using the simple linear approach for a second time. The models were fit a third time using a quadratic approach which indicated improvement in fit for all categories except the cotton fiber.

Additional analysis suggests a seven-year cyclical trend for the cotton fiber. Insights into the trends for each TAP category are discussed.

The third study (Chapter 3) undertakes time-series analysis using *Autoregressive Integrated Moving Average* (ARIMA) models to forecast NRCA for each of the six TAP categories. The analysis also serves the purpose of identifying additive outliners and permanent level shifts among the 21-year scope. Results suggest short-term increases in NRCA for cotton yarn, artificial filament tow and nonwovens and slight declines for worn clothing and the cotton fiber while the carpet forecast suggested little change. Limitations associated generating the time-series analysis for a limited scope are presented.

The final analysis (Chapter 4) presents an interactive visual tool designed to facilitate deeper analyses of global trade data based directly upon export values in contrast to the previous three analyses which utilize NRCA to examine the concept of competitive advantage. The tool was developed using the R *Shiny* application to develop a user interface that facilitates manipulation of time in years, HS Code, frequency of export and destinations countries. Further examination of findings from the previous studies are facilitated by the tool. Corresponding visual outputs in the form of Sankey Diagrams are presented for interpretation.

Over the course of these inter-related studies several conclusions and implications emerge. The global dynamics associated with trade in textiles and apparel with regard to the rise of China and India are suggested among several outcomes across the different studies. Though category specific findings vary, of particular interest is the potentially cyclical nature of U.S. export advantage in the cotton fiber and, from a different perspective, rising volume of worn clothing exports. Limitations and future research directions are presented as appropriate within each analysis.

An Investigation of U.S. Textile and Apparel (TAP) Industry Competitiveness

by
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DEDICATION

To my lovely parents and inspiring sisters for their unconditional love and support.

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CHAPTER 1

REVEALED COMPARATIVE ADVANTAGE FOR U.S. TEXTILES AND APPAREL

Introduction

Comparative advantage of industries can be difficult to understand in the dynamic global trade environment. Increasingly integrated supply chains, rapid product development, increases in information technology, and foreign direct investment (FDI) as a transactional flow (Narula & Dunning, 2000) contribute to today's complex global markets. Advantages are vulnerable to imitation, even those generated through technology are less likely to be sustainable in the long-term (Erin, Cassill, & Oxenham, 2004; McEvily & Chakravarthy, 2002).

U.S. Textile and Apparel (TAP) manufacturing is commonly used as an example of domestic decline under globalization (Abernathy, F. H., Volpe, A., & Weil, 2006; Shelton, R. K., & Wachter, 2005). During the study period, the U.S. TAP trade deficit increased from negative $46.8 billion in 1996 to negative $124.4 billion in 2016 (Appendix A.1). Despite this decline, U.S. policymakers recently initiated efforts to renew domestic TAP manufacturing through the 2016 Advanced Functional Fabrics of America Program (AFFOA)[1].

Recent research into TAP competitiveness from the revealed comparative advantage perspective focuses on countries outside of the U.S. (Chaudhary, 2016; Hossain, Dechun, Zhang, & Van, 2017; Ignjatijević & Raičević, 2016; Tripa, Cuc, & Oana, 2016; Van Zyl & Matswalela, 2016). Existing empirical research into the competitive position of the U.S. within the global TAP industry was carried out well over a decade ago (i.e., Kilduff & Chi, 2006a, 2006b). To establish an updated understanding of the U.S. competitive position, comprehensive analysis of

[1] Available at https://obamawhitehouse.archives.gov/the-press-office/2016/04/01/fact-sheet-obama-administration-announces-new-revolutionary-fibers-and

domestic TAP industry performance in the long and short terms is needed. The purpose of the study is to identify U.S. TAP products and categories that indicate export comparative advantage in both the long and short-terms, and their respective country destinations based on longitudinal trade data.

The research employs *Revealed Comparative Advantage* (RCA) and its variant *Normalized Revealed Comparative Advantage* (NRCA) to examine U.S. TAP competitiveness across products in both the long-term (1996-2016) and the short-term (2010-2016). Created by Balassa (1965), the RCA index facilitates discovery of a country's comparative export advantage at various levels of specification and is widely applied in the academic literature (Amador, Cabral, & Maria, 2011; Deb & Sengupta, 2017; French, 2017; Huo, 2014; Suwannarat, 2017). The RCA evolved since its introduction, spurring variants designed to overcome limitations of the original index. Yu et al. (2009) introduced *Normalized Revealed Comparative Advantage* (NRCA) to provide a stable mean across sectors, countries, and distribution over time. Three objectives address the research purpose:

Research Objective 1 (RO1): To determine RCA and NRCA among U.S. TAP categories (two-digit harmonized code) over a 21-year period (1996-2016) and subsequently identify categories that indicate advantage over a minimum of three consecutive years between 2010 and 2016.

Research Objective 2 (RO2): To determine NRCA among U.S. TAP sub-categories (four-digit harmonized code) over a 21-year period (1996-2016) and subsequently

identify sub-categories that indicate comparative advantage over a minimum of three consecutive years between 2010 and 2016.

Research Objective 3 (RO3): To determine major export destinations (countries) for the top sub-categories that indicate comparative advantage over a minimum of three consecutive years between 2010 and 2016 based on NRCA at the four-digit harmonized code level.

The research provides insight into TAP competitiveness at the product category level (i.e., two-digit harmonized code) and the product sub-category level (i.e., four-digit harmonized code). The approach facilitates identification of specific products that attain comparative advantage, which contrasts with existing TAP research that typically utilizes industry level data (i.e., SIC, NAICS). Product level findings provide stakeholders, including practitioners and policymakers, with comparatively precise evidence to identify opportunities and invest resources. From an academic perspective, this study contributes to the work on RCA identification, by incorporating the NRCA into the design. The NRCA allows greater flexibility for analysis because it assumes a normal distribution. This research is the first to apply NRCA to TAP industry analysis.

Literature Review

Revealed Comparative Advantage (RCA). Empirical and conceptual work that examines trade competitive advantage, within and outside of TAP, using RCA and its variants constitutes the framework for this research. Balassa (1965) recognized limitations associated with the classical theory of comparative advantage. To address these limitations, he introduced

RCA, partially based on Liesner's (1958) Relative Export Performance Index designed to measure impacts of trade barrier removal. The RCA *reveals* comparative advantage retrospectively, through examination of trade data, which embodies the effects of cost and non-price factors. The RCA is defined as the share of commodity *j* in the export of country *i* (numerator) to the share of commodity *j* in the export of world (denominator). RCA values range from zero to +∞, values below one indicate a country's comparative disadvantage, while values of one suggest neutral advantage and values above one indicate comparative advantage.

$$RCA = \frac{E_j^i / E^i}{E_j / E} \tag{1.1}$$

Where E_j^i stands for the country *i* export of commodity *j*, E_j refer to the export of commodity *j* by all countries in the world, E^i is the country *i* export of all commodities, and E is the export of all commodities by all countries.

Dunning (1979), incorporates the RCA concept in three different domains to determine the ownership advantages of five countries (i.e., U.S., Japan, U.K., Sweden, West Germany) in different product categories, grouped as more and less technology intensive sectors; RCA in export RCA(x)(similar to Balassa's index), RCA in international production (RCA(A)), and RCA in portfolio resource transfers (RCA(P)). Indices are calculated by dividing the share of export, outward foreign direct investment, and resource endowments of a particular country in a particular industry by its share of the total for the five countries.

Revealed Comparative Advantage (RCA) Variants. Since the introduction of RCA, researchers have modified the index for their research purpose(s). Yeats (1985) identified limitations associated with application of the RCA to rank a single country's industries in terms of comparative advantage. In an empirical study that applied RCA to three industries among 47

countries, he demonstrated that using RCA creates unreliable ordinal and cardinal rankings, due to the dependency of RCA on its distribution.

Both Vollrath (1991) and Laursen (2015) investigated RCA asymmetry. Vollrath developed three RCA variants: *Relative Trade Advantage*, *Relative Export Advantage* and *Relative Competitiveness*. Among these measures, relative export advantage is the logarithm of the original RCA, which resolves the asymmetry problem. However, Vollrath pointed out that this approach is ineffective among countries with zero exports in a given commodity. Laursen (2015) applied RCA to 22 sectors of 22 countries for a 20-year time period (1987-2006) and ranked RCA values within country and year. Through this work, Laursen suggested econometric adjustment to skewed RCA distributions, which resulted in a symmetric version of RCA, *Revealed Symmetric Comparative Advantage* (RSCA). RSCA is defined as (RCA-1)/(RCA+1) and ranges from -1 to +1. De Benedictis and Tamberi (2001) demonstrated problems interpreting RSCA in a study that compared it to RCA and an additional variant, concluding that RSCA does not improve upon previous indices.

Proudman and Redding (2000) introduced the *Weighted RCA* (WRCA) to normalize RCA distribution across sectors. The WRCA is defined as the RCA value of a specific sector in a given country divided by its average RCA in all manufacturing sectors. Despite WRCA capability for generating a constant mean over time, researchers criticize the index for its inability to account for asymmetry (Benedictis & Tamberi, 2001; R. Yu et al., 2009). Moreover, De Benedictis and Tamberi (2001) in their comparative study of RCA indices found that WRCA was more difficult to interpret than RCA limiting its applicability in analysis. Hoen and Oosterhaven (2006) proposed *Additive RCA* (ARCA) to remedy limitations of RCA, which they attributed to the index's multiplicative nature. Using data from an earlier study (Hoen, A. R., &

de Mooij, 2001) they calculated RCA and ARCA for multiple sectors and demonstrated that ARCA generates a normal symmetric distribution around zero. Yu et al. (2009) suggest ARCA usefulness for comparison across commodities, but caution the index may be ineffective for comparison across countries due to its lack of constant value.

Normalized Revealed Comparative Advantage (NRCA). The term *Normalized RCA* was initially surfaced in the work of Dunning (1979) and was defined as the ratio of export RCA to foreign direct investment RCA as an indicator of the enterprise's ownership advantages. However, Dunning's application of NRCA in this instance is not comparable to the measure applied in this study which focuses on relative export advantage rather than enterprise ownership advantage which is consistent with the more recent work of Yu et al. (2009). In an effort to provide an index with stable means across commodities and countries, as well as stable distributions over time Yu et al. (2009) introduced *Normalized Revealed Comparative Advantage* (NRCA). The NRCA is defined as:

$$NRCA = \frac{E_j^i}{E} - \frac{(E_j * E^i)}{(E * E)} \tag{1.2}$$

Where E_j^i stands for the country *i* export of commodity *j*, E_j refer to the export of commodity *j* by all countries, E^i is the country *i* export of all commodities, and E is the export of all commodities by all countries.

The NRCA is symmetric around zero and deviations from zero indicate a country's comparative advantage or disadvantage. Though the NRCA is relatively new, initial empirical application suggests stability of the index across countries, commodities and over time (Ahmad, Qayum, & Iqbal, 2017; Deb & Sengupta, 2017; R. Yu, Cai, Loke, & Leung, 2010).

RCA Application in Textiles. Application of RCA and its variants to textile and apparel competitiveness is evident in the academic literature from the 2000s. Among this research,

studies focus on contexts outside of the U.S. TAP, researchers predominantly use RCA and Vollrath Competitiveness Measures to examine export competitiveness (Abbas & Waheed, 2017; Hatab & Romstad, 2014; Hossain et al., 2017; Shafaei, Shahriari, & Moradi, 2009; Yasmin & Altaf, 2014).

A number of researchers exclusively use RCA to investigate TAP competitiveness. Chi, et al. (2005) employed RCA to determine the relative advantage of U.S. technical textiles among trade partners with varying levels of economic development. Kathuria (2008, 2013) uses RCA to examine India's competitiveness in garment exports. The 2008 enquiry focused on India's trade with China and used two and four-digit HS codes for the analysis, while the 2013 enquiry focused on India's trade with Bangladesh using HS codes. In both studies, the author applied Spearman Rank Correlation Coefficients to analyze changes in RCA over time.

In a recent enquiry, using data ranging from 2003 to 2013, Kathuria (2018) examined the competitive position of Indian garment exports using RCA, Dynamic RCA and RSCA. Kathuria's findings indicate a shift of the textile trade within Asia from India to lower-cost countries such as Bangladesh and Vietnam. He points out that India however gains from competitive advantage associated with value-added product production capability. Havrila and Gunawardana (2003) examined comparative advantage among the Australian textile and clothing industry based on two and three-digit SITC codes, using RCA and Vollrath measures. The data suggested comparative advantage in three areas: *special textile products, floor coverings,* and *fur clothing*. As an outcome, the researchers suggested product differentiation through quality and design as sources of export advantage for Australian goods. Erdumlu (2009) demonstrated use of RCA and Vollarath's indices to determine Turkish competitiveness among its cotton spinning industry in a multiple country comparison. Recent examples of research using RCA and Vollrath

measures, apply the indices to competitiveness of textiles and apparel in Egypt and Romania (Hatab & Romstad, 2014; Karaalp & Yilmaz, 2012; Tripa et al., 2016).

A series of studies using RSCA by Kilduff and Chi (2006a, 2006b) investigate the U.S. textile complex based on factor endowment classifications that included four subsectors: textile machinery, man-made fibers, apparel, and textiles. To relate the findings to factor endowment classifications, they employed disaggregated data in the second study. As expected, this study's results agreed with factor proportions theory, which asserts that developed countries are stronger in capital-intensive sectors while less developed countries are stronger in labor-intensive sectors.

Data and Methodology

Data. Product-level trade data based on the 1996 revision of the Harmonized Commodity Description and Coding System (HS) from the United Nations Commodity Trade database (UN COMTRADE) is used for this study. The dataset includes Chapters 50-67 of the *Harmonized Tariff Schedule of the United States 2016*, which consist of textiles, textile articles, footwear, etc.

Measures and Analyses. To address RO1, the RCA and NRCA are calculated for the two-digit level HS codes to determine export comparative advantage for the textile categories (i.e., Chapters 50 – 67) and subsequently provide the basis for identifying products with relative short-term export comparative advantage. The RCA values range from zero to infinity with a neutral point of one, while NRCA values range from -1 to +1 with a neutral point of zero. Further, the values for RCA and NRCA are ranked within each year and an accompanying nonparametric rank correlation test (i.e., Spearman Rank Correlation) is applied to evaluate the consistency between RCA and NRCA indices. The Spearman test facilitates measurement of dependency between two ranked variables.

To address RO2, NRCA at the four-digit HS code levels is generated to identify specific textile sub-categories (i.e., 169) with export comparative advantage and also sub-categories with relative short-term export comparative advantage. As suggested by Vollrath (1991) a given country may indicate relative comparative advantage among more specific niche categories that are not evident at higher levels of aggregation. Bilateral trade data are employed to identify export destinations for sub-categories that indicate U.S. export comparative advantage in the short-term (RO3).

Results and Discussion

Aggregated Export Comparative Advantage of TAP. RCA and NRCA at the two-digit level for the textile categories (i.e., Chapters 50 – 67) are presented in table 1.1 and 1.2, respectively. Codes definition is available in Appendix A.2. Because the calculated NRCA values are extremely small, they are multiplied by $10^{\wedge 6}$ for ease of presentation. The RCA and NRCA indices that suggest advantage over three consecutive years (2010-2016) include three codes: 52 - cotton, 56 - wadding, felt and nonwovens, special yarns; twine, cordage, ropes and cables and articles thereof, and 59 - textile fabrics; impregnated, coated, covered or laminated; textile articles of a kind suitable for industrial use. The nonparametric rank correlation test to evaluate the relative rankings of RCA and NRCA (1996-2016) indicates a positive Spearman's Rho (ρ= 0.4542, *p*-value <.001) that suggests correlation between RCA and NRCA. Table 1.3 presents RCA and NRCA ranking comparisons for seven selected years. Positive correlation between RCA and NRCA rankings demonstrate that when the competitiveness of a single industry and a single country is of interest, RCA will perform just as well as its variants. However as suggested by different researchers (Ahmad et al., 2017; Deb & Sengupta, 2017; R. Yu et al., 2010). NRCA, provides a preferable measure of competitiveness due to its symmetry

and stability across commodities, countries and over time. In particular, NRCA consistency over time is useful for forecasting competitiveness using time series analysis.

Based on the analysis, cotton (HS 52) emerges as the sole category that maintained consistent comparative advantage over the full 21 years. With the exception of a sharp decline in 1999, attributed to the 1998 U.S. drought[2], cotton ranked first among all TAP exports in terms of relative advantage. The two additional categories that indicate export advantage include HS 65 (i.e., wadding, felt and nonwovens; special yarns, etc.) and HS 59 (i.e., textile fabrics; impregnated, coated, covered or laminated, etc.). The two-digit RCA and NRCA for the latter two codes are difficult to interpret due to the diversity of products classified within each category. Therefore, investigation of the sub-categories within each code (i.e., disaggregation) is necessary to pinpoint TAP products with export advantage.

[2] *Outlook for U.S. agricultural exports* (1998). Available at http://usda.mannlib.cornell.edu/usda/ers/AES//1990s/1998/AES-12-03-1998.asc

Table1.1

RCA for Textile Categories at Two-Digit Harmonized Code Level

		Year										
HSCodes	Descriptions*	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
50	Silk	0.096	0.072	0.084	0.075	0.081	0.097	0.122	0.145	0.114	0.111	0.200
51	Wool	0.075	0.068	0.081	0.086	0.092	0.091	0.099	0.105	0.091	0.092	0.103
52	Cotton	1.050	1.070	1.088	0.757	1.086	1.204	1.282	1.502	1.813	1.761	1.809
53	Veg. Fiber	0.073	0.066	0.075	0.058	0.099	0.109	0.164	0.107	0.084	0.051	0.067
54	Man-made Filament	0.512	0.560	0.583	0.661	0.686	0.616	0.658	0.616	0.620	0.591	0.586
55	Man-made Staple	0.543	0.510	0.515	0.549	0.557	0.598	0.708	0.753	0.799	0.855	0.837
56	Wadding	0.772	0.855	0.854	0.840	0.948	0.979	1.088	1.176	1.301	1.389	1.432
57	Carpet	0.684	0.649	0.745	0.717	0.805	0.808	0.832	0.800	0.876	0.946	0.968
58	Special Woven Fabric	0.674	0.700	0.742	0.973	0.918	0.996	1.076	0.842	0.980	0.908	0.799
59	Fabric for Industrial Use	0.725	0.869	0.874	0.919	0.801	0.907	0.975	1.144	1.117	1.062	1.064
60	Knitted Fabric	0.447	0.491	0.471	0.500	0.492	0.630	0.774	1.007	1.169	1.275	1.064
61	Apparel, Knitted	0.444	0.420	0.445	0.486	0.516	0.454	0.374	0.332	0.274	0.238	0.192
62	Apparel, not-Knitted	0.395	0.415	0.428	0.344	0.303	0.226	0.204	0.173	0.149	0.128	0.106
63	Worn Clothing	0.569	0.601	0.553	0.504	0.526	0.481	0.458	0.386	0.379	0.383	0.380
64	Footwear	0.163	0.162	0.153	0.151	0.141	0.135	0.118	0.112	0.098	0.103	0.106
65	Headgear	0.486	0.469	0.381	0.360	0.352	0.404	0.328	0.317	0.329	0.349	0.317
66	Umbrella	0.079	0.102	0.083	0.097	0.095	0.100	0.089	0.075	0.076	0.089	0.094
67	Feather	0.227	0.233	0.243	0.238	0.216	0.230	0.216	0.226	0.227	0.239	0.235

Table1.1 Continued

HSCodes	Descriptions*	Year									
		2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
50	Silk	0.152	0.126	0.102	0.088	0.077	0.050	0.044	0.039	0.046	0.037
51	Wool	0.078	0.074	0.096	0.081	0.063	0.061	0.071	0.059	0.054	0.047
52	Cotton	1.769	1.827	1.628	1.856	2.262	1.694	1.500	1.386	1.339	1.335
53	Veg. Fiber	0.064	0.072	0.087	0.071	0.049	0.046	0.038	0.048	0.039	0.043
54	Man-made Filament	0.524	0.519	0.436	0.487	0.465	0.466	0.461	0.459	0.450	0.422
55	Man-made Staple	0.824	0.924	0.916	0.914	0.888	0.916	0.939	0.868	0.804	0.747
56	Wadding	1.241	1.259	1.237	1.327	1.266	1.289	1.301	1.219	1.131	1.072
57	Carpet	0.934	1.007	0.901	0.899	0.902	0.944	0.905	0.846	0.810	0.774
58	Special Woven Fabric	0.615	0.529	0.568	0.576	0.520	0.496	0.465	0.455	0.458	0.397
59	Fabric for Industrial Use	1.040	0.968	0.922	1.004	0.951	1.018	1.014	1.025	1.040	0.955
60	Knitted Fabric	0.985	0.905	0.573	0.562	0.488	0.455	0.440	0.402	0.387	0.321
61	Apparel, Knitted	0.125	0.114	0.118	0.115	0.099	0.094	0.089	0.086	0.081	0.086
62	Apparel, not-Knitted	0.084	0.087	0.090	0.100	0.097	0.103	0.094	0.089	0.081	0.079
63	Worn Clothing	0.389	0.373	0.366	0.370	0.375	0.379	0.382	0.357	0.332	0.309
64	Footwear	0.096	0.104	0.103	0.105	0.103	0.096	0.084	0.078	0.079	0.080
65	Headgear	0.321	0.371	0.329	0.318	0.312	0.341	0.293	0.280	0.297	0.319
66	Umbrella	0.086	0.093	0.062	0.064	0.073	0.078	0.070	0.072	0.076	0.075
67	Feather	0.234	0.249	0.220	0.197	0.165	0.138	0.138	0.132	0.121	0.130

Extreme Disadvantage  Extreme Advantage

* Note: Full description of codes are available in appendix A.2

Table 1.2

NRCA for Textile Categories at Two-Digit Harmonized Code Level

		Year										
HS Codes	Descriptions**	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
50	Silk	-69.3	-65.9	-50.9	-44.7	-41.0	-37.3	-28.7	-22.9	-22.9	-22.8	-18.2
51	Wool	-399.1	-376.5	-292.0	-239.2	-207.0	-200.0	-164.3	-128.9	-113.8	-96.5	-83.0
52	Cotton	44.4	54.1	65.0	-155.4	48.3	116.6	140.4	235.3	328.3	260.3	253.0
53	Veg. Fiber	-49.1	-50.9	-52.4	-50.4	-44.7	-40.0	-35.6	-34.3	-30.4	-26.7	-22.6
54	Man-made Filament	-390.7	-332.1	-295.0	-202.9	-190.0	-210.8	-160.2	-152.0	-129.4	-119.2	-106.1
55	Man-made Staple	-327.5	-314.8	-279.1	-224.9	-203.2	-168.5	-103.1	-71.3	-49.3	-31.5	-31.8
56	Wadding	-64.6	-37.3	-35.7	-35.0	-9.7	-3.8	14.2	26.0	36.9	46.2	48.4
57	Carpet	-84.3	-98.5	-59.3	-60.3	-32.3	-29.4	-22.9	-24.0	-12.6	-5.2	-2.8
58	Special Woven Fabric	-59.5	-54.0	-44.2	-4.1	-11.8	-0.6	10.5	-17.9	-1.9	-8.3	-16.6
59	Fabric for Industrial Use	-83.5	-36.5	-34.5	-20.4	-49.6	-22.4	-5.2	25.2	17.4	8.2	7.6
60	Knitted Fabric	-148.0	-135.7	-141.5	-122.8	-136.7	-94.1	-52.1	1.3	27.4	39.5	8.5
61	Apparel & Clothing Knitted	-888.9	-1018.6	-932.6	-838.4	-696.9	-778.7	-830.3	-800.0	-750.7	-732.9	-770.5
62	Apparel & Clothing not-Knitted	-1416.4	-1317.6	-1262.1	-1333.7	-1287.9	-1400.9	-1359.9	-1213.8	-1054.6	-996.7	-932.1
63	Worn Clothing	-175.0	-152.6	-175.4	-186.6	-155.3	-173.7	-170.8	-194.3	-172.7	-171.7	-158.4
64	Footwear	-938.0	-879.4	-838.7	-772.6	-681.3	-713.8	-640.7	-552.1	-481.5	-454.4	-425.2
65	Headgear	-30.0	-27.2	-31.7	-32.4	-33.1	-29.9	-30.7	-27.1	-24.2	-21.4	-21.7
66	Umbrella	-24.2	-21.1	-24.9	-20.4	-17.9	-18.0	-14.6	-12.8	-11.6	-10.8	-10.5
67	Feather	-24.9	-23.2	-23.8	-24.1	-22.1	-22.3	-20.2	-16.4	-13.8	-12.8	-12.6

Table 1.2 Continued

HS Codes	Descriptions**	Year									
		2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
50	Silk	-16.1	-14.7	-15.9	-15.1	-12.9	-13.2	-12.6	-12.1	-12.0	-14.0
51	Wool	-80.5	-62.3	-59.7	-60.0	-62.8	-59.0	-56.1	-58.2	-64.4	-81.5
52	Cotton	211.8	198.9	161.2	241.0	357.0	197.3	143.0	102.6	96.0	109.0
53	Veg. Fiber	-19.4	-14.9	-16.4	-18.6	-17.4	-16.9	-17.3	-16.9	-23.9	-22.5
54	Man-made Filament	-114.3	-98.1	-123.6	-107.6	-109.2	-109.4	-110.4	-118.2	-132.4	-167.4
55	Man-made Staple	-32.6	-11.7	-14.3	-14.6	-19.0	-13.7	-9.8	-22.9	-38.1	-57.0
56	Wadding	25.4	25.5	26.9	34.7	26.6	29.1	30.7	24.6	16.8	11.1
57	Carpet	-5.3	0.5	-7.7	-7.5	-6.5	-3.7	-6.3	-11.0	-14.9	-20.6
58	Special Woven Fabric	-30.3	-32.3	-29.1	-24.7	-24.9	-26.9	-28.6	-30.8	-34.0	-45.9
59	Fabric for Industrial Use	4.6	-3.3	-9.0	0.4	-5.3	1.9	1.5	2.9	5.0	-6.9
60	Knitted Fabric	-1.9	-10.7	-56.9	-56.3	-62.7	-69.6	-73.8	-85.1	-103.3	-143.8
61	Apparel & Clothing Knitted	-852.8	-744.2	-875.0	-786.0	-762.8	-817.2	-858.3	-864.6	-1042.1	-1080.8
62	Apparel & Clothing not-Knitted	-880.6	-785.5	-893.6	-757.8	-726.6	-733.1	-763.5	-840.0	-1038.2	-1127.3
63	Worn Clothing	-148.0	-141.5	-178.7	-161.3	-149.9	-157.4	-164.7	-185.6	-218.8	-273.1
64	Footwear	-419.1	-387.8	-463.0	-432.5	-419.7	-456.0	-485.1	-558.0	-643.1	-699.4
65	Headgear	-20.4	-17.7	-22.4	-21.1	-21.0	-21.9	-25.0	-27.8	-32.9	-38.3
66	Umbrella	-11.0	-10.7	-16.1	-15.5	-14.5	-14.5	-14.8	-16.4	-19.1	-22.2
67	Feather	-13.6	-12.4	-17.7	-18.1	-20.6	-26.6	-28.1	-32.0	-40.4	-42.2

Extreme Disadvantage  Extreme Advantage

* Note: NRCA Values are multiplied by 10^6

** Note: Full description of codes are available in appendix A.2

Table 1.3

RCA and NRCA Ranking Comparison of TAP at Two-Digit Levels for 7 Years and Spearman Rank Correlation

HS		1998		2001		2004		2007		2010		2013		2016	
Code	Descriptions**	RCA	NRCA	RCA	NRCA	RCA	NRCA	RCA	NRCA	RCA	NRCA	RCA	NRCA	RCA	NRCA
52	Cotton	1	1	1	1	1	1	1	1	1	1	1	1	1	1
56	Wadding	3	6	3	3	2	2	2	2	2	2	2	2	2	2
59	Fabric for Industrial Use	2	5	4	6	4	4	3	3	3	3	3	3	3	3
50	Silk	15	8	17	9	14	9	12	8	15	6	17	6	18	4
57	Carpet	4	10	5	7	6	7	5	5	5	4	5	4	4	5
66	Umbrella	16	3	16	4	18	6	15	6	18	7	16	7	15	6
53	Veg. Fiber	18	9	15	10	17	11	18	9	17	9	18	8	17	7
65	Headgear	12	4	11	8	10	10	10	10	10	10	10	9	9	8
67	Feather	13	2	12	5	12	8	11	7	11	8	11	10	11	9
58	Special Woven Fabric	5	7	2	2	5	5	7	11	6	11	6	11	7	10
55	Man-made Staple	8	13	8	12	7	12	6	12	4	5	4	5	5	11
51	Wool	17	14	18	14	16	13	17	13	16	13	15	12	16	12
60	Knitted Fabric	9	11	6	11	3	3	4	4	7	12	8	13	8	13
54	Man-made Filament	6	15	7	15	8	14	8	14	8	14	7	14	6	14
63	Worn Clothing	7	12	9	13	9	15	9	15	9	15	9	15	10	15
64	Footwear	14	16	14	16	15	16	14	16	13	16	14	16	13	16
61	Apparel & Clothing Knitted	10	17	10	17	11	17	13	17	12	18	13	18	12	17
62	Apparel & Clothing not-Knitted	11	18	13	18	13	18	16	18	14	17	12	17	14	18

Variable	by Variable	Spearman's	Prob>|ρ|
NRCA	RCA	0.4542	<.0001*

* Note: Spearman rank correlation test applied to 21-year time period, but this table demonstrates relative RCA and NRCA ranks for seven years

** Note: Full description of codes are available in Appendix A.2.

Disaggregated NRCA Insights and Destinations. Interpretation of the calculated NRCA at the four-digit level, identifies textile sub-categories with export comparative advantage over the full 21-year period, of which 22 sub-categories meet the requirement of three sustained years of advantage. However, 16 sub-categories are eliminated from consideration due to consistently small relative magnitudes that do not constitute appreciable sources of export advantage resulting in six final sub-categories (Table 1.4) (for codes definition see Appendix A.3). This reveals specific information about sources of advantage within the cotton and the nonwovens categories (i.e., HS 5201: Cotton; not carded or combed., HS 5205: cotton yarn, other than sewing thread, containing 85% or more by weight, not for retail sale, and HS 5603: nonwovens; whether or not impregnated, coated, covered or laminated). However, the sub-categories within HS 59, fabrics suitable for industrial use, did not suggest appreciable advantage over three consecutive years. Additionally, three sub-categories with export comparative advantage emerged: HS 5502 (artificial filament tow), HS 5703 (carpets and other textile floor coverings; tufted, whether or not made up) and HS 6309 (textiles; worn clothing and other worn articles). Top destination rankings for these sub-categories based on total export values (1996-2016) are presented in Table 1.5.

HS 5201 Cotton Fiber Not Carded or Combed. The HS 5201 sub-category indicated the largest NRCA magnitude among TAP products for the 21-year period, suggesting its superior competitiveness within the industry. Despite cotton's performance as the highest ranked TAP category, the analysis reveals two changes in NRCA over the examination period that warrant further investigation. Cotton exports enjoyed an upward trend until 2004 but indicated decline thereafter. This downturn began following Brazil's victory over the U.S. in a World Trade Organization dispute over unfair cotton subsidies, which resulted in the reduction of cotton

production in the U.S. (Summer, 2016). Subsequently, between 2009 and 2011 the data suggests an increase in relative export advantage. A likely explanation for this upturn is a global price increase for cotton during this period. Lucas (2016) explains that speculation between 2009 and 2011 increased worldwide cotton prices from a historical range of .55 - .60 cents to two USD per pound. A number of drivers may have contributed to cotton's export advantage over the 21-year period. These drivers include advantages associated with resources, technology and policy. U.S. advantage associated with land endowments and climatological factors over the study's time-period likely contributed to cotton's success. Additionally, technological advantages in the U.S., such as genetically engineered seeds, which lead to lower pesticide use and higher crop yield, contribute to export advantage. Moreover, Summer (2016) reports that institution of the U.S. Stacked Income Protection Plan (STAX) behaves as a subsidy and boosts competitiveness through a policy initiative.

Perhaps the most likely explanation of cotton's export performance is explained by Rivoli's (Rivoli, 2014) assertion that a confluence of forces contribute to the commodity's success. After comprehensive analysis of global cotton T-shirt consumption, Rivoli suggests that symbiotic relationships between institutions and ethical global business practices that build trust and political capital contribute to U.S cotton export success.

Table 1.4

TAP NRCA Four-Digit Level, Indicated a Minimum of Three Consecutive Years of Appreciable Comparative Advantage (2010-2016)

		Year										
HS Codes	Descriptions**	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
5201	Cotton Fiber	474.32	420.97	392.00	92.27	217.65	273.19	255.00	366.25	406.10	334.84	332.55
5502	Artificial Filament Tow	73.14	53.29	53.07	47.23	35.92	45.73	40.32	34.13	37.40	39.64	37.25
5603	Nonwovens	3.91	18.69	15.41	9.92	26.78	32.63	39.27	50.53	50.64	61.20	60.09
5205	Cotton Yarn	-102.75	-90.44	-75.10	-61.45	-44.77	-42.71	-32.39	-32.45	-14.37	1.69	5.98
5703	Carpet	-8.37	7.80	11.50	11.22	22.18	21.61	19.10	18.00	22.47	25.70	26.17
6309	Worn Clothing	23.11	22.84	17.54	13.01	15.24	12.79	13.69	15.00	15.49	13.20	10.89

		Year									
HS Codes	Descriptions**	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
5201	Cotton Fiber	293.19	269.48	237.20	326.33	400.89	277.48	241.65	189.75	198.94	239.33
5502	Artificial Filament Tow	40.76	45.10	61.84	50.86	44.47	50.92	52.98	51.94	47.55	50.07
5603	Nonwovens	39.51	39.46	41.84	45.75	39.32	42.85	44.10	40.45	36.44	33.56
5205	Cotton Yarn	11.12	17.85	20.24	15.74	50.69	18.85	7.87	12.02	13.06	20.09
5703	Carpet	17.13	24.97	22.68	24.73	22.07	23.23	20.43	19.05	16.50	17.20
6309	Worn Clothing	12.44	13.81	14.16	15.51	18.34	18.59	19.26	18.47	16.17	17.82

Extreme Disadvantage Extreme Advantage

* Note: NRCA Values are multiplied by 10^6

* *Note: Full description of codes are available in appendix A.3

Table 1.5

Top Destination of Six Sub-Categories

HS Code *					
5201	5502	5603	5205	5703	6309
Cotton Fiber	Artificial Filament Tow	Nonwovens	Cotton Yarn	Carpet	Worn Clothing
China (29.2%)	China (31.7%)	Rest of the world (25.3%)	Honduras (48.8%)	Canada (64.1%)	Rest of the world (45.9%)
Rest of the world (21.2%)	Rest of the world (26.5%)	Mexico (23.2%)	Dominican Republic (17.5%)	Rest of the world (15.5%)	Canada (13.8%)
Turkey (12.1%)	Belgium (11.3%)	Canada (19.3%)	Mexico (7.4%)	Mexico (8.5%)	Chile (8%)
Mexico (11.1%)	Indonesia (9.8%)	China (9.2%)	Canada (7.3%)	United Kingdom (2.6%)	Guatemala (7.1%)
Indonesia (6.9%)	Hong Kong, China (4.9%)	Belgium (6.2%)	El Salvador (5.8%)	Japan (2%)	Mexico (6.3%)
Vietnam (4.7%)	Russian Federation (3.9%)	United Kingdom (4.3%)	China (4.2%)	Australia (1.8%)	India (4.9%)
Kore. Rep. (4.3%)	Netherlands (3.3%)	Japan (4.2%)	Guatemala (4.1%)	Saudi Arabia (1.4%)	Japan (4.5%)
Thailand (4.1%)	Germany (3.1%)	Germany (3.2%)	Rest of the world (3%)	Hong Kong, China (1.4%)	Tanzania (3.6%)
Other Asia, nes (3.3%)	Egypt, Arab Rep. (2.8%)	Hong Kong, China (2.7%)	Colombia (1.3%)	China (1.4%)	Honduras (3.1%)
Pakistan (3.2%)	Korea, Rep. (2.7%)	Honduras (2.4%)	Venezuela (0.7%)	Singapore (1.3%)	Angola (2.7%)

Note: Values in Parenthesis shows the % of US export to each country from 1996 to 2016

* Note: Full description of codes are available in appendix A.3

China emerged as the dominant destination for U.S. cotton, accounting for more than 29 percent of export dollar value from 1996 to 2016. The average dollar value of Chinese cotton imports from the U.S. increased more than 360 percent after 2001. Structural changes within the Chinese textile industry including; joining the WTO in 2001 and the expiration of the Multi-Fiber Arrangement in 2005 likely encouraged this growth. After joining the WTO, China committed to increase its tariff rate quotas, decrease within and out-of-quota tariff rates, and eliminate its cotton export subsidies (Fang & Babcock, 2003). These commitments also contributed to the growth of U.S cotton comparative advantage until 2012, which marked the beginning of a decline of Chinese imports. At this time, the Chinese government enacted efforts to decrease cotton imports, potentially ending a period of stockpiling the fiber.

The data suggest that while Chinese cotton imports from the U.S. are declining, Vietnamese imports are growing. In terms of U.S. dollar value, Vietnamese imports quadrupled from 2008 to 2016, totaling nearly 800 million dollars in 2016. Given the recent increase in Vietnamese, garment production, this finding is not surprising and is attributable to shifting comparative advantage to low cost countries of production.

HS 5502 Artificial Filament Tow. HS 5502 mainly used as cigarette filters, garment lining and lingerie represents the second largest source of export advantage over the 21-year period. Though, export comparative advantage of artificial filament tow (i.e., predominantly acetate fiber) suggested inconsistency between 1996 and 2016, overall the sub-category indicated advantage. The likely drivers of U.S. artificial filament tow's export success over the study period are the sustained availability of raw material (i.e, wood converted to cellulose acetate flake) and access to proprietary technology.

Over the study period, China represented the primary destination of U.S. exports of HS 5502. An upward trend in NRCA peaked in 2011 at which point the sub-category began to consistently decline. A similar trend is evident among other supplier countries to China. Upon investigation, this finding reveals a successful Chinese effort to produce artificial filament tow domestically. The major production input for artificial filament tow is cellulose acetate flake (HS 3912). Chinese imports of HS 3912 doubled from 2011 to 2016 (i.e., 106 to 226 million dollars). Therefore, China assumes a higher tier of the production process, which eliminates the need to import U.S. artificial tow and threatens U.S. competitiveness for the sub-category.

HS 5603 Nonwovens; whether or not impregnated, coated, covered or laminated. HS 5603 emerged as the single sub-category within HS 56 with export comparative advantage. Though this category enjoys a reputation for its unique competitiveness within the U.S., the results suggest steady export declines following 2006. In spite of this downturn, HS 5603 continues to rank highly among U.S. TAP products and occupied the third highest NRCA rank over the recent period (2012-1016). The U.S., Germany, European Union (EU), and China are the largest exporters of HS 5603. Among these, the steadily increasing Chinese export share poses a significant threat to U.S. export comparative advantage.

China represents the third largest market for U.S. nonwovens, despite decreases since the early 2000's. Chinese exports to the U.S. increased 4,000 percent from 2003 to 2016 (i.e., 5.7 to 248 million dollars). This export boost may explain the recent U.S. decline of nonwovens NRCA. Mexico and Canada rank second and third as export destinations, respectively behind the rest of the world. This finding likely reflects the impact of the regional trade agreement (NAFTA).

HS 5205 Cotton Yarn other than sewing thread, etc. The pattern of sustained advantage of Cotton yarn (HS 5205) emerged in 2005 and continued to increase as time progressed. This is likely due to the country of origin rule, specifically the yarn forward regulation, established in 1983 with the Caribbean Basin Initiative (CBI). The CAFTA-DR ultimately replaced the CBI in 2006. Additionally, increased foreign investment in U.S. spinning mills support this trend (e.g., Mercer, 2014). The CAFTA-DR countries account for more than 75 percent of U.S. cotton yarn exports over the past 21 years. Honduras and the Dominican Republic rank first and second, respectively, accounting collectively for around 67 percent over the full time period, reinforcing the impact of CAFTA-DR.

HS 5703 Carpet and other Textile floor coverings; tufted whether or not made up. HS 5703 sub-category emerged in the disaggregated analysis of NRCA. The NRCA for HS 5703 ranked between four and sixteen during the 21-year period, with limited appreciable increase. Chinese exports of HS 5703 increased more than 510 percent in value from 2003 to 2015, which likely influences the observed changes in U.S. carpet NRCA. Canada accounts for 65 percent of U.S. carpet exports followed by Mexico with 8 percent. Geographic proximity (e.g., relative shipping cost) along with NAFTA advantages likely support this trend.

HS 6309 Worn clothing. Worn clothing NRCA ranked between three and seven over the 21-year period, with observed increases in recent years. Note that the carpet sub-category and worn clothing ranked similarly overall, however worn clothing increased while carpet NRCA was flat. U.S. exports worn clothing to more than 70 countries (1996-2016). The single largest country market for U.S. worn clothing is Canada (14 percent overall). Additional investigation reveals that Canada acts as an intermediary for worn clothing and exports approximately 40 percent to four African countries: Kenya, Angola, Ghana and Tanzania.

Conclusions

This research incorporates the NRCA index for the first time within the TAP context to provide understanding of the U.S.'s export competitive position. The aggregated product level comparison of RCA and NRCA indicate consistent positive correlation and support application of NRCA to disaggregated product level analysis. The insights provided by the disaggregated findings reveal cotton fiber as, by far, the most important source of U.S. TAP advantage. Cotton fiber's advantage in the U.S. is driven by a number of factors; historical culture of cotton production in the U.S., availability of natural resources, and continued political supports. Artificial filament tow, the second most important source of comparative advantage is also driven by the availability of natural resources (wood). However, recent declines in exports to China, previously the largest importer of U.S. artificial filament tow, suggest fleeting advantage for the sub-category. Additional analysis suggests Chinese increases in acetate flake imports, which likely reflect Chinese manufacturing of artificial filament tow.

Nonwovens is the third largest contributor to U.S. TAP export advantage. Traditionally, nonwoven production is viewed as a stable source of domestic advantage due to its highly automated, capital-intensive production processes. However, NRCA indicates declines in U.S. export advantage for nonwovens. Vice versa, Chinese increases in global exports of nonwovens are likely a contributor to this phenomenon.

In terms of cotton yarn, observed exports of NRCA advantage are attributable to DR-CAFTA. Cotton yarn production tends to primarily serve domestic markets, and as such, operate as a part of integrated supply chains, which ultimately produce knit and woven fabrics. Due to the comparative nature of NRCA, cotton yarn production in other counties with active domestic textile industries may be overlooked because the index does not capture domestic consumption.

Geography and cultural preferences likely drive export advantage for carpet and other floor coverings. Canada is the largest importer of U.S. carpet, indicating strong demand in North America. Traditionally, carpet represents a U.S. TAP product that generates economic benefits including employment and contribution to GDP, etc. Despite the past importance of U.S. carpet production, the sub-category appears only to garner comparable export advantage to that of worn clothing. Export advantage of worn clothing is more of a challenge than an advantage. Sustained imports of cheap, poor-quality clothing and general over consumption in the U.S. market contribute to the sub-category's rank (6). NRCA reveals that worn clothing for select years is more competitive than the carpet sub-category. Given the level of economic benefits associated with worn clothing exports, the sub-category is unlikely to be a focus of the U.S. for economic renewal.

Limitations and Future Research

A limitation of *revealed comparative advantage* is the sole reliance on exports as an indicator of competitiveness. Though RCA and NRCA provide useful tools for comparing countries in terms of export advantage, they do not consider the impact of domestic influences and provide little information on the drivers of advantage. Competitiveness research from alternative perspectives including Dunning's (1995) work that considers the impacts of foreign direct investment (FDI) on a country's relative advantage in a given industry can augment the results of this study. Though access to FDI data is limited to aggregated data which poses challenges for more granular analysis at the product level. The results suggest current sources of TAP advantage, which present new questions regarding the reasons behind this advantage and further scrutiny for using these advantages in the future. Additional research into the sub-categories that incorporates conceptual perspectives beyond exporting (e.g., Porter, 2008) can

clarify the usefulness of these advantages. The diversity in the revealed sub-categories drives a need for focused analysis of these unique sources of advantage. Replicating the study in additional countries will facilitate interpretation of the results by providing a basis for comparison, which currently does not exist in the literature.

In terms of measurement, UN trade data, though widely used may include inconsistencies in export data driven by political bias. Despite this limitation, the UN provides the most comprehensive source of trade data to date. As a direct result of this research, additional NRCA analyses into the revealed sources of TAP advantage should be undertaken. Specifically, examination of NRCA trends among sub-categories and time series analysis along with the identification of disruptions (permanent level shifts) can provide directions for increased understanding of the revealed sources of export advantage as well as events that may influence these advantages.

CHAPTER 2

APPLICATION OF LINEAR AND NON-LINEAR MODELS TO TREND ANALYSIS OF U.S. TEXTILES AND APPAREL

Introduction

Building on insights from previous NRCA-based research for TAP products, the current analysis applies trend analyses to historical trade data using appropriate modeling approaches for the six top U.S. TAP export categories over the 21-year period spanning 1996-2016. Trend analyses are generated for cotton fiber (HS 5201), artificial filament tow (HS 5502), nonwovens (HS 5603), cotton yarn (HS 5205), carpet (HS 5703) and worn clothing (HS 6309) which indicated varying degrees of relative advantage in the previous analysis (Chapter 1). Various linear and non-linear models suggest trends among these TAP categories. The NRCA data for cotton fiber indicated a unique cyclical pattern for which additional analyses are undertaken.

Data and Methodology

Data for the most recent 21-year period is drawn from the United Nations Commodity Trade Database (UN COMTRADE). Normalized Revealed Comparative Advantage (NRCA) values are calculated for the period from 1996-2016 to detect trends among the TAP categories using linear and non-linear models. Initially simple linear regression (SLR) (equation 2.1) is applied to fit the NRCA values. In cases that SLR models indicate poorly distributed residuals, outlier analyses are performed, and significant data points are subsequently removed from the dataset and the SLR model is refit. Next, quadratic regression models were fit for each of the six TAP categories. In the case of cotton only, cyclical models were required to fit the data.

$$NRCA_t = \beta_0 + \beta_1 t + \varepsilon_t \tag{2.1}$$

Results

Simple linear regression (SLR) and modified SLR. Simple linear and modified simple linear regression model fits are presented in Figures 2.1-2.5 for cotton fiber, artificial filament tow, nonwovens, cotton yarn and carpet. The SLR for worn clothing did not indicate outliers and required no modification beyond the initial model (Figure 2.6).

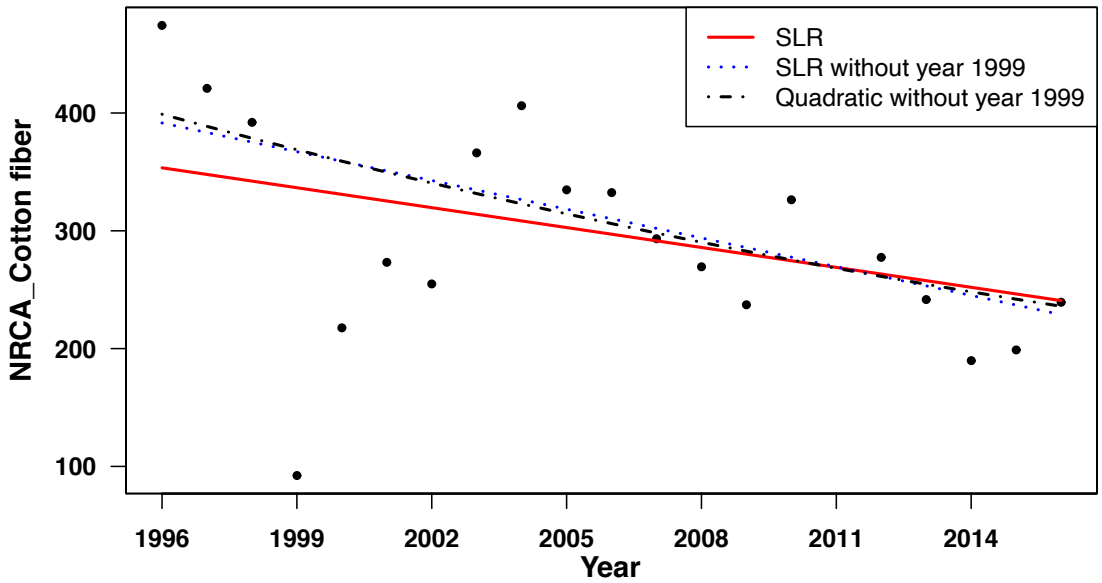


Figure 2.1. Linear regression models, NRCA U.S. cotton fiber.

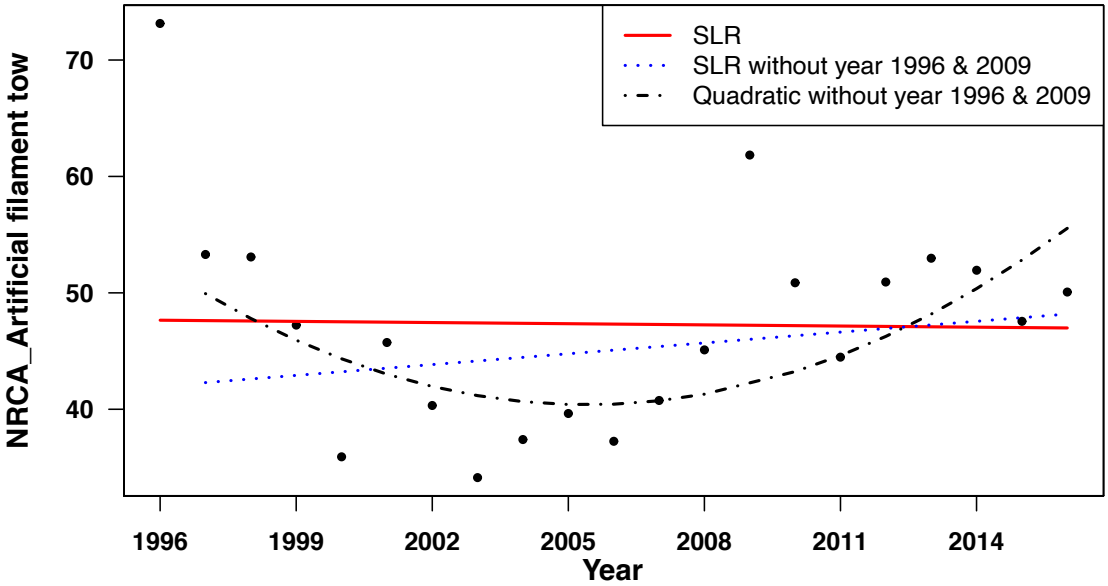


Figure 2.2. Linear regression models, NRCA U.S. artificial filament tow.

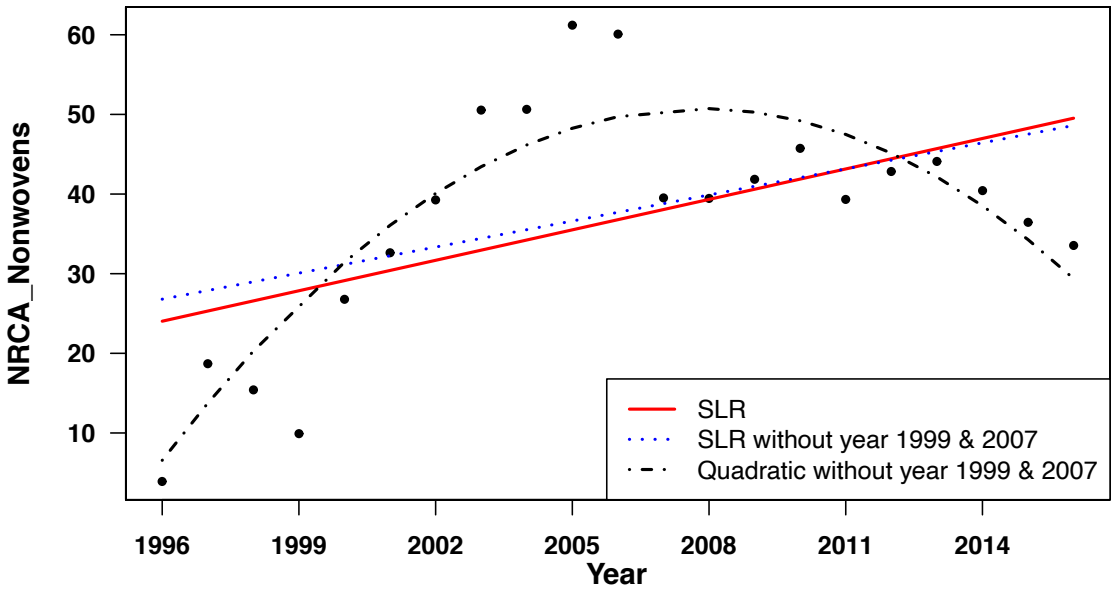


Figure 2.3. Linear regression models, NRCA U.S. nonwovens.

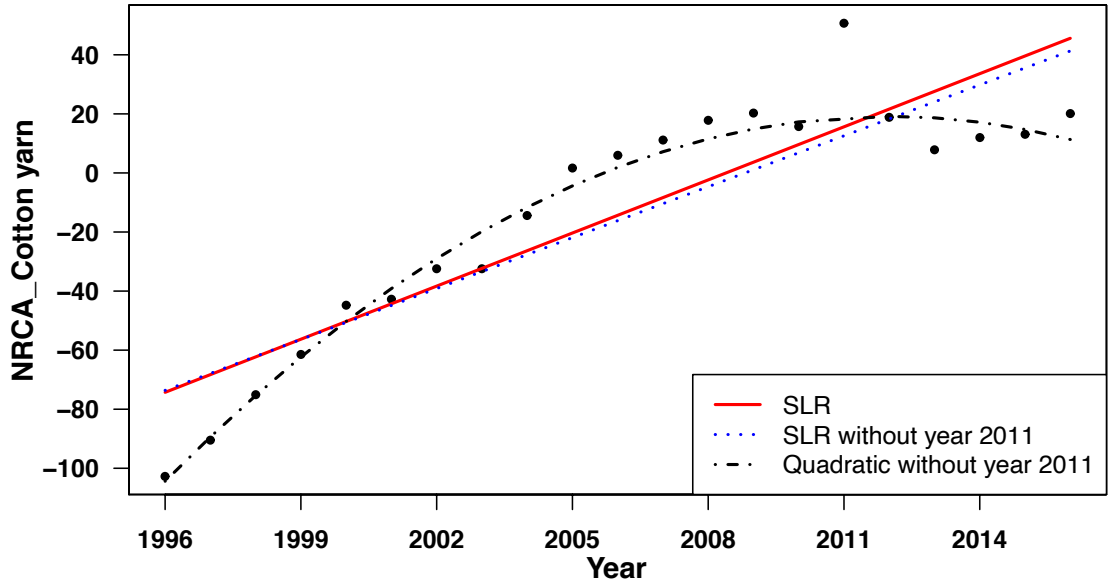


Figure 2.4. Linear regression models, NRCA U.S. cotton yarn.

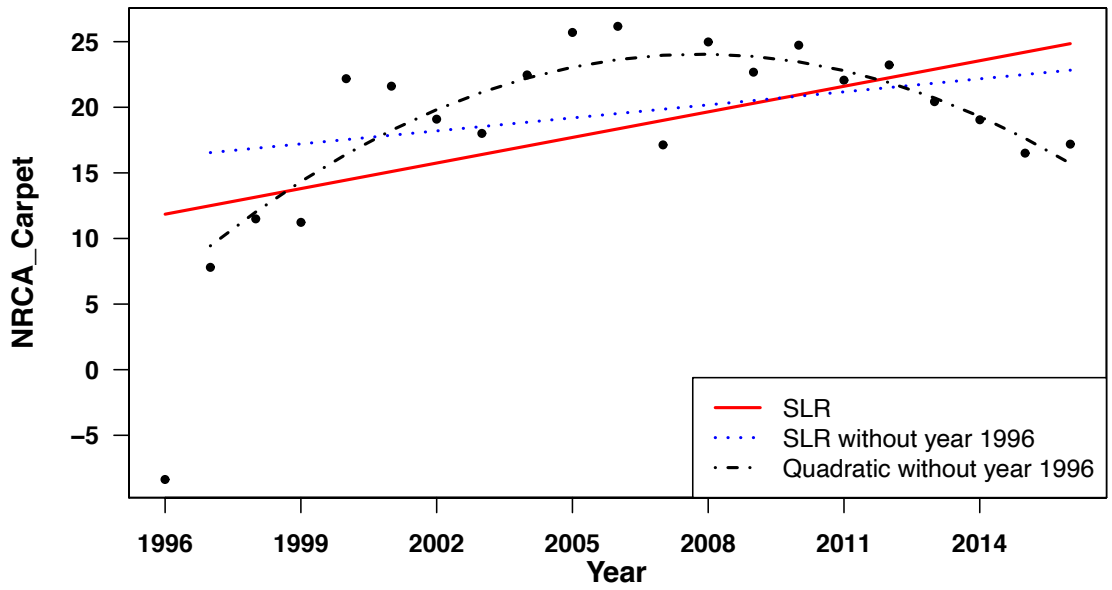


Figure 2.5. Linear regression models, NRCA U.S. carpet.

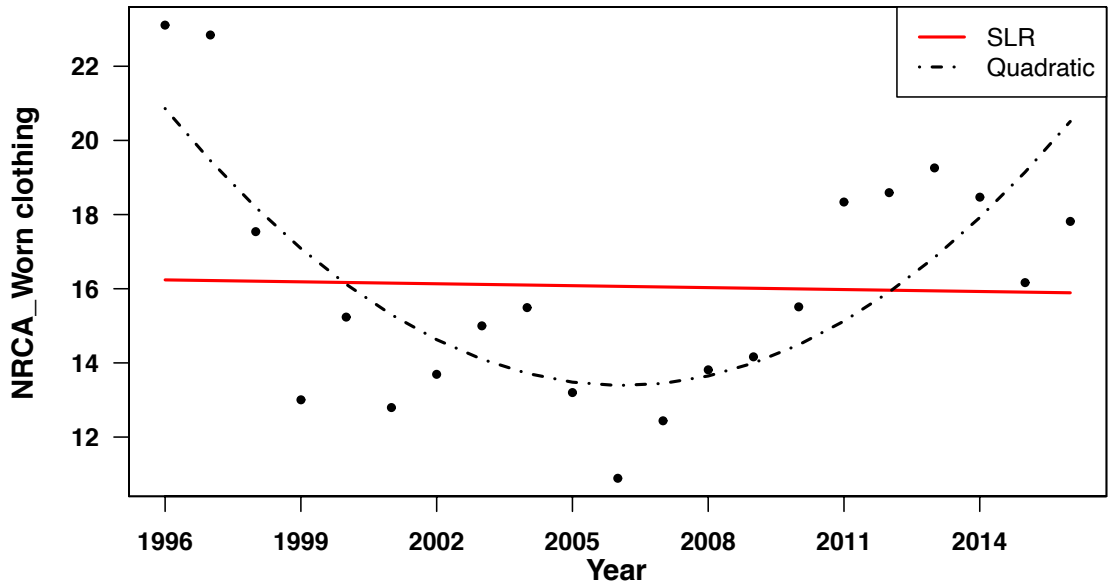


Figure 2.6. Linear regression models, NRCA U.S. worn clothing.

For three TAP categories including cotton fiber, artificial filament tow and cotton yarn, the adjusted-R^2 improved following outlier removal (Table 2.1). The observed residual pattern versus fitted value graphs suggest missing terms in the structural portion of the model (Appendix B.1). Therefore, quadratic models are applied to the modified data (i.e., outliers are excluded) to potentially improve fit.

Table 2.1

Summary of Fit for Simple Linear Models

HS Code	Metrics	SLR	SLR*	Quadratic*
5201 Cotton fiber * Exclude year 1999	R^2	0.144	0.378	0.381
	Adj.-R^2	0.099	0.344	0.308
	F-statistic (df)	3.20 (1,19)	10.9 (1,18)	5.23 (2, 17)
	P-value	0.089	0.004	0.017
5502 Artificial filament tow *Exclude year 1996, 2009	R^2	0.000	0.085	0.499
	Adj.-R^2	0.000	0.031	0.437
	F-statistic (df)	0.01 (1,19)	1.59 (1,17)	7.98 (2, 16)
	P-value	0.923	0.225	0.004
5603 Nonwovens * Exclude year 1999, 2007	R^2	0.279	0.23	0.799
	Adj.-R^2	0.242	0.185	0.773
	F-statistic (df)	7.38 (1,19)	5.08 (1,17)	31.77 (2, 16)
	P-value	0.014	0.03	<0.0001
5205 Cotton yarn * Exclude year 2011	R^2	0.795	0.808	0.981
	Adj.-R^2	0.784	0.798	0.978
	F-statistic (df)	73.5 (1,19)	76.1 (1,18)	429 (2, 17)
	P-value	<0.0001	<0.0001	<0.0001
5703 Carpet * Exclude year 1996	R^2	0.264	0.150	0.715
	Adj.-R^2	0.225	0.103	0.682
	F-statistic (df)	6.81 (1,19)	3.18 (1,18)	21.34 (2, 17)
	P-value	0.017	0.09	<0.0001
6309 Worn clothing *No outlier is detected	R^2	0.001	-	0.561
	Adj.-R^2	0.000	-	0.512
	F-statistic (df)	0.02 (1,19)	-	11.49 (2,18)
	P-value	0.887	-	0.0006

Quadratic regression models. According to Faraway (2014) adding polynomial terms to a regression model does not necessarily represent an underlying reality, however this addition

can facilitate better modeling of features. Quadratic models (equation 2.2) indicated improvement in R^2 and adjusted-R^2 metrics compared to those of simple linear regression (Table 2.1). Additionally, the *residual versus the fitted model plots* for all quadratic regression models indicate improvement over the SLR and modified SLR (Appendix B.1). The quadratic lines for each model are presented in figures 2.1 through 2.6 along with the SLR and modified SLR lines. The raw output for fitting different models using the R software is presented in Appendix B.2.

$$NRCA_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon_t \tag{2.2}$$

Non-linear models. Rises and falls in cotton fiber NRCA values over time suggest that a sinusoidal function with regression parameters that define the location (phase) and height (amplitude) of peaks provides a useful cyclical approach to fit the data. For the cyclical model periods for both seven and eight years are fit to the data (Figure 2.7). The results suggest that the seven-year model indicates most improvement in the adjusted R^2 (Table 2.2). Estimated parameters for the seven-year cyclical model are presented in equation 2.3.

$$NRCA = 297.11 + 94.59\, Sin\left(\frac{2\pi * year}{7}\right) - 1.24\, Cos\left(\frac{2\pi * year}{7}\right) \tag{2.3}$$

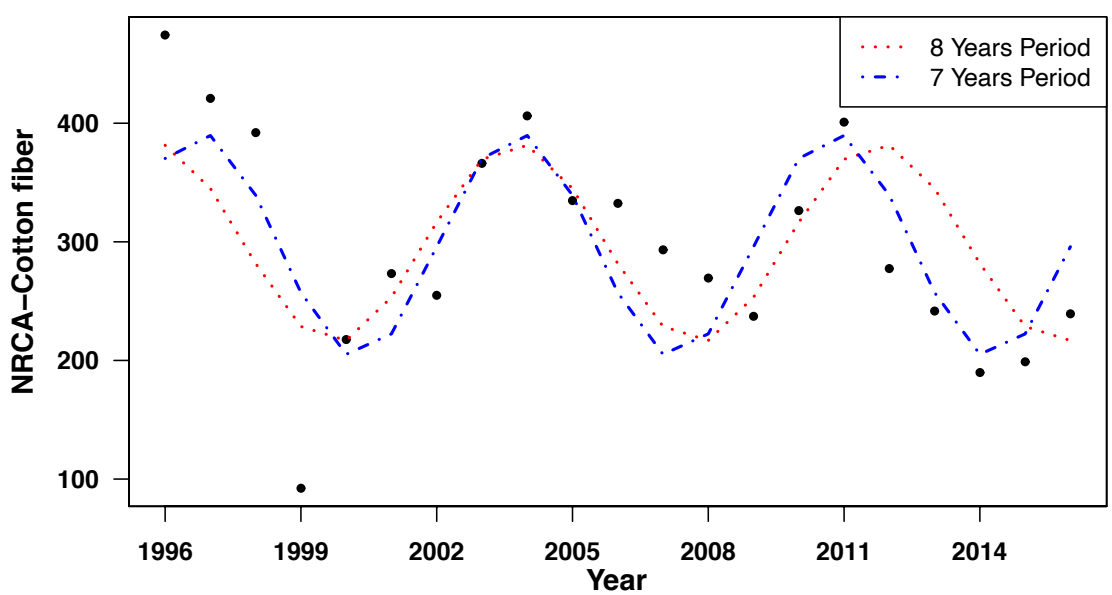


Figure 2.7. Cyclical models, NRCA U.S. cotton fiber.

Table 2.2
Summary of Fit for Cotton Fiber Cyclical Models

	Cyclical period 8	Cyclical period 7
R^2	0.46	0.55
Adj.-R^2	0.39	0.50
F-statistic (df)	7.55 (2,18)	11.17 (2,18)
P-value	0.0041	0.0007

Discussion

The findings related to each TAP category are discussed in terms of the six original categories with the exception of the cotton fiber (5201) and cotton yarns (5205) which represent the first and fourth highest ranked export categories in terms of NRCA (Chapter 1). Due to the logical relevance of the two cotton subcategories this portion of the discussion is integrated. The quadratic models suggested both positive and negative trends in NRCA among the TAP categories with the exception of cotton fiber.

Among the best fitting models for the TAP categories, the cyclical model for cotton was most unexpected. To further investigate this finding, additional analysis incorporating data prior to 1996 was undertaken. Unfortunately, export data for the U.S. cotton trade before 1991 was not recorded in the UN COMTRADE Database. Therefore, NRCA values were calculated from 1991 to 2016, for which U.S. cotton export data are available. A second cyclical model was fit for the 26-year period and did not support the findings of the first cyclical model for cotton (i.e., presence of seven-year cycle). However, this finding may have been affected by irregularities in the older data that were integrated into the 26-year model (Figure 2.8 and Table 2.3). During the analysis, the potential for missing country exports emerged in the data prior to 1996 (Appendix

B.3). For this reason, reliability of the earlier data is questionable and therefore may not discount the seven-year cycle indicated in the original cyclical model.

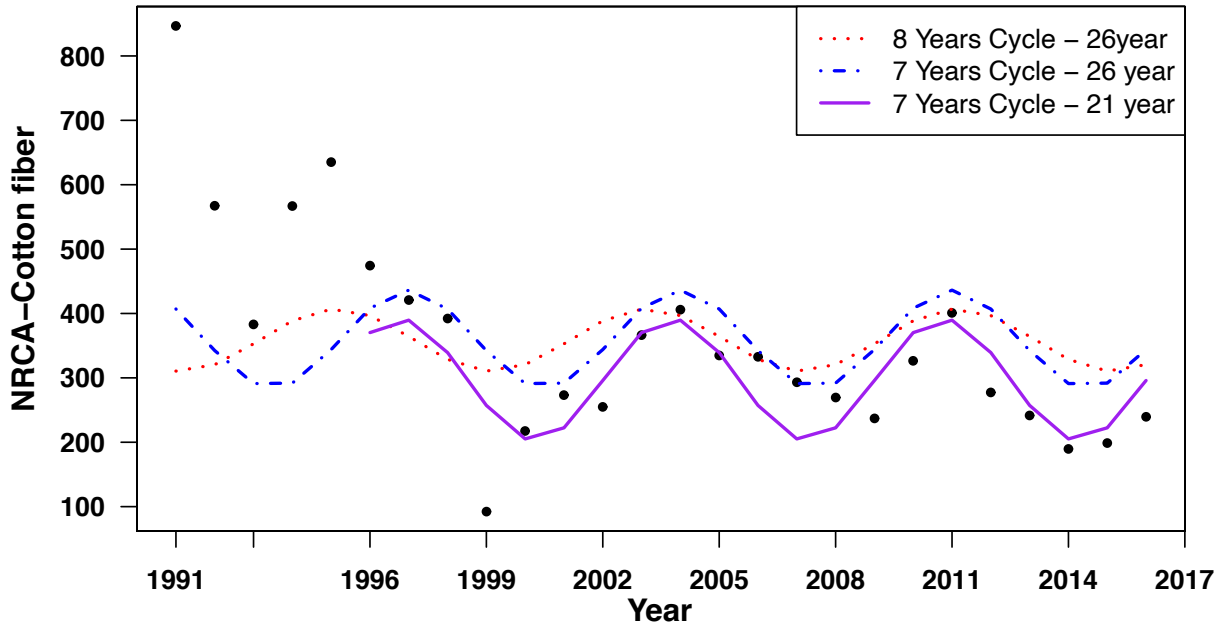


Figure 2.8. 26-Year and 21-year cyclical models for U.S. cotton NRCA.

Table 2.3
Summary of Fit for Cyclical Models using 26-Years Data for Cotton Fiber

	Cyclical period 8	Cyclical period 7
R^2	0.04869	0.1114
Adj.-R^2	0	0.03414
F-statistic (df)	0.5885(2,23)	1.442 (2,23)
P-value	0.5633	0.2571

Given the lack of clarity that arises from the expanded cyclical analyses, focusing on the original data (1996-2016) may provide additional insight into this finding related to cotton fiber. Among the countless potential factors that can drive the cyclical competitive position for U.S. cotton exports, changes in the business cycle (e.g., GDP) and cotton price represent logical areas for consideration. To investigate the potential impacts of GDP and price on NRCA over time a

multiple-linear regression model was fit for the 20-year dataset (with the outlier year for 1999 excluded) (Table 2.4). The results suggest that GDP does not impact NRCA over time ($t = 0.81$, $p. < 0.433$). However, after removing GDP, the resulting model indicates that price significantly impacts NRCA for U.S. cotton ($t = 3.30$, $p < 0.0042$). Further, this model indicates improvement in the adjusted R^2 compared to the cyclical modal (Table 2.4). Additional external factors including sociopolitical and natural impacts can also influence U.S. export advantage in cotton.

Table 2.4
Summary of Fit, Multiple Linear Regressions (MLR) for Cotton Fiber

	MLR (NRCA~Year+GDP+Price)	MLR (NRCA~Year+Price)
R^2	0.63	0.62
Adj.-R^2	0.57	0.58
F-statistic (df)	9.31 (3, 16)	13.93 (2, 17)
P-value	0.0008	0.0002

Stated previously, cotton yarn is best described by the quadratic model based on the R^2 criterion. This model indicated the highest R^2 (0.981, adjusted 0.978) among all of the TAP models suggesting a significant positive trend over the observed time period. Recent foreign investment in spinning mill capacity in the U.S. (Mercer, 2014) likely driven by government incentives and proximity to raw materials supported increases in cotton export advantage (NRCA) since the early 2000s. These policies encourage domestic spinning through rule of origin based trade advantages. For example, the *yarn-forward* standard which requires that the yarn spinning and all operations forward (i.e., weaving, knitting and apparel assembly occurs in either the U.S. and or the CAFTA-DR region[3].

[3] Retrieved from http://web.ita.doc.gov/tacgi/fta.nsf/FTA/CAFTA-DR?opendocument&country=CAFTA-DR

The second most important contributor to U.S. TAP export comparative advantage, artificial filament tow (HS 5502) is also best described by a quadratic model which suggests a decreasing trend until 2006, after which the line turned upward.

The quadratic model for the nonwoven category (HS 5603), suggests a negative trend after 2009. Specifically, the model suggests a consistent four-year decline beginning during 2013. Pointed out in Chapter 1, additional analysis reveals that Chinese trade in nonwovens likely impacted U.S. export performance for this TAP category. Though China continues to represent a significant export destination for U.S. nonwovens, the country steadily decreased imports. The reason for this reduction is the rise of Chinese domestic production of nonwovens, which is also driving an increase in U.S. imports from China for this category. The nonwovens category was commonly cited as a successful sub-sector in terms of global competitiveness among developed countries (Chi et al., 2005).

For carpets and other textile floor coverings (HS 5703), the quadratic model suggests a negative trend beginning during 2008. Additional analysis suggests that emergence of China and India, as low-cost producers, have changed the traditional trajectory of carpet exports which are historically localized. Prior to 2006, European countries (i.e., Belgium, The Netherlands and Germany) dominated global carpet exports, with the U.S. following closely behind. Similar to the dynamic observed in the nonwovens category between the U.S. – China, production advantage appears to have shifted east which suggests price is driving this trend. Further, this suggest advances in the sophistication of manufacturing in China and India.

In contrast to the trend associated with carpet NRCA, the quadratic model for worn clothing (HS 6309) suggests a significant, positive trend since 2006. Exponential increases in clothing consumption among the U.S. and other developed markets of North America and

Western Europe over the past two decades led to emergence and expansion of reverse supply chains for redistribution of used or unsold inventory. The implications of expanded exports of worn clothing are both far reaching and controversial for the U.S. and other developed nations. The merits of reverse clothing supply chains for apparel through which products are redistributed from developed to less developed markets remain controversial (Norris, 2015). Opponents of worn clothing trade, argue that it hampers economic progress among developing nations with a stake in apparel production, thereby circumventing gains in the per capita standard of living enjoyed by developing economies in the past such as South Korea and China (Brooks & Simon, 2012; Mhango & Niehm, 2005). Further, the environmental impacts of worn clothing exports are increasingly questioned by policymakers, academics and additional stakeholders. Brooks (2013) illustrates this sentiment by suggesting that the resources required to redistribute low value-added consumer products are inefficient and ultimately detrimental to the environment. Therefore, increases in relative export advantage for worn clothing does not appear to be a productive strategic focus for future trade expansion.

CHAPTER 3

FORECASTING U.S. TEXTILE COMPARATIVE ADVANTAGE USING AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODELS AND TIME SERIES OUTLIER ANALYSIS

Introduction

Forecasting represents an important area of enquiry in business and academic research. Practitioners in sales, marketing, supply chain and other fields advocate the importance of forecasting for business success (Bendato, Cassettari, Mosca, Mosca, & Rolando, 2015; Dalrymple, 1987; Fildes & Hastings, 1994). Additionally, economic forecasting has always been an integral part of policymaking for individual countries (Sims, 1986).

In 1786 Playfair first illustrated the historical economic performance of England using import and export data (Tufte, 2001, p.32). Much later, the field of economics introduced the theory of comparative advantage to predict trade patterns among countries. In 1965 Balassa developed a new approach to compare and predict trade patterns from a global perspective. His index referred to as *Revealed Comparative Advantage* (RCA) provides an indicator of competitiveness based on historical trade data. Since its introduction, researchers modified RCA (Hoen & Oosterhaven, 2006; Vollrath, 1991) to overcome various shortcomings of the index. One of the most recent modifications, known as *Normalized Revealed Comparative Advantage* (NRCA) (R. Yu et al., 2009) claims stable distribution over time and enables application of time-series analysis to comparative advantage.

Recent policies and initiatives encourage U.S. TAP domestic manufacturing. This trend emphasizes the need to understand the past in order to forecast the future. While most research focuses, on TAP products that lost comparative advantage due to globalization, this enquiry

focuses on U.S. TAP products that maintained export comparative advantage in recent years (e.g., at least three consecutive years between 2010-2016).

Existing academic research into U.S. TAP competitiveness that uses RCA or its variants rely on factor endowment analysis and graphical illustration of indices values over time (Chi & Kilduff, 2006; Chi et al., 2005; Kilduff & Chi, 2006a, 2006b). Outdated research and the past tendency to rely on qualitative approaches to times series analysis suggest the necessity for an updated investigation into competitiveness of U.S. TAP products using quantitative time series analysis. Therefore, the purpose of this study is to utilize univariate time series analysis based on *Autoregressive Integrated Moving Average* (ARIMA) to forecast short-term performance of *Revealed* U.S. TAP categories with export advantage (i.e., six categories). The corresponding ARIMA outlier analysis correlates past shifts in trends to identify possible drivers and random events. The research examines *Normalized Revealed Comparative Advantage* (NRCA) for 169 TAP categories at the four-digit HS code level (1996-2016). The following objectives address the research purpose:

Research Objective 1 (RO1): To determine NRCA (four-digit harmonized code) among U.S. TAP categories from 1996-2016 (21 years) and identify categories that indicate comparative advantage over a minimum of three consecutive years between 2010 and 2016.

Research Objective 2 (RO2): To identify appropriate time series models to forecast short-term (2-years) comparative advantage among categories identified in RO1.

Research Objective 3 (RO3): To identify significant changes in trends among categories by interpreting additive outliers and permanent level shifts generated by the time-series models.

Forecasting the competitive position of TAP categories identified as competitive in recent years (at least three consecutive years between 2010 and 2016) is necessary for practitioners to assess opportunities and invest resources. The categories that forecast competitive decline can signal calls to action for practitioners and policymakers alike. Additionally, insight from outlier analysis identifies potentially important level shifts in TAP categories' competitiveness.

Data Description

The United Nations Commodity Trade database (UN COMTRADE) provides data for the study. The database contains annual bilateral merchandise trade metrics (i.e., imports and exports) at the country level for different versions of standardized coding systems. The metrics for Harmonized Commodity Description and Coding System (HS) use two, four and six digit product classifications, which provide increasingly specific product information, respectively. Product-level trade data on the 1996 revision at four-digit HS code levels from 1996 to 2016 constitutes the data for this study[4]. The dataset includes Chapters 50-67 (i.e., textiles, textile articles, footwear, etc.).

After compiling the data, NRCA is calculated to identify products with comparative advantage. NRCA values for *Revealed* categories from 1996 to 2015 comprise the ARIMA training models and NRCA values for 2016 test these models.

[4] World Integrated Trade Solution (2016)

Measures and Methodologies

NRCA. To predict the trade pattern among countries, the classical theory of comparative advantage assumes production cost as the sole indicator of a given country's specialization, which does not account for non-price factors (e.g., consumer preference, product quality) that impact trade flows. To address these limitations, Balassa introduced the concept of *Revealed Comparative Advantage* (RCA) (1965) which predicts trade patterns using historical trade data. RCA values vary from zero to infinity, which makes the index asymmetric. Therefore, empirical and theoretical research identifies inherent shortcomings of the index (Benedictis & Tamberi, 2001; Hoen & Oosterhaven, 2006; e.g., Proudman & Redding, 2000). Yu et al. (2009) derived a recent variant of RCA known as *Normalized Revealed Comparative Advantage* (NRCA). The NRCA is defined as:

$$NRCA = (E_j^i/E) - (E_j * E^i/E * E) \tag{3.1}$$

Where E_j^i stands for the country i export of commodity j,

E_j refers to the export of commodity j by all countries in the world,

E^i is the country i export of all commodities,

and E is the export of all commodities by all countries.

The neutral point of NRCA is zero, therefore deviations from zero indicate a country's comparative advantage or disadvantage in a given commodity. An additional feature of NRCA is its ability to generate stable distributions over time, which allows application of time-series analysis to comparative advantage.

The NRCA at the four-digit level generates the metrics to identify specific textile categories (i.e., 169 categories) with export comparative advantage over the full 21-year period. Further analysis of the indices in a focused timeframe identifies products that indicate a

minimum of three consecutive years of comparative advantage in the recent past (2010-2016) (RO1).

ARIMA. Box and Jenkins (1976) developed a method, ARIMA, for analysing stationary time series data. The ARIMA method differences the series to stationary and combines autoregressive parameters to moving average. An autoregressive parameter, AR, indicates that the value of the series during the current period is a function of its immediate previous values and some error, while the moving average parameter, MA, involves a finite memory of past time lags. The order of MA indicates the number of time lags. The ARIMA model is capable of greater flexibility and power compared to both extrapolative and decomposition models. The Box and Jenkins model requires discrete, equally spaced data with no missing values. The series should be or made to be stationary for a time-invariant model. A stationary series presents stable but rapidly decreasing autocorrelation whereas a non-stationary series diminishes auto-correlation gradually.

Prior to fitting the time series models, the Augmented Dickey Fuller Unit Root (ADF) test is used to identify differencing orders and build a stationary series. Using the stationary series three different methods, Extended Sample Autocorrelation Function (ESACF), Minimum Information Criterion (MINIC), and The Smallest Canonical (SCAN), which tentatively identify the order of ARMA process, suggest different options for the lag order of AR and/or MA terms, p and q respectively. Suggested p and q orders generate several ARIMA models. Akaike's Information Criterion (AIC) evaluates model fit and identifies the best p and q order. Additionally, the $\chi 2$ statistic examines residuals to assure adequate model fit. Finally, fitted models generate two-year forecasts for NRCA (2017 and 2018).

Additive Outlier and Permanent Level Shift. Outlier analysis is typically used to detect and remove anomalous observations. Researchers address the importance of outliers and debate whether they should be kept or removed (Osborne & Overbay, 2004). For the purpose of this study, outlier analysis identifies possible indicators of losing or gaining comparative advantage. Therefore, outlier analysis is performed along with time series analysis to detect the shifts in level or additive outliers to the response series that are not accounted for by the previously estimated model. Specifically, the model considers permanent level shifts because they can convey important information about policy changes or other influential drivers and random events.

Results and Discussion

NRCA at the four-digit level identifies specific textile categories (i.e., 169 categories) with export comparative advantage over the full 21-year period. Interpretation of the indices suggests six categories that meet the requirement of three sustained years of appreciable comparative advantage. The categories that indicate adequate advantage include; *HS 5201* (Cotton; not carded or combed), *HS 5502* (Artificial filament tow), *HS 5603* (Nonwovens; whether or not impregnated, coated, covered or laminated), *HS 5205* (Cotton yarn (other than sewing thread), containing 85% or more by weight of cotton, not put up for retail sale), *HS 5703* (Carpets and other textile floor coverings; tufted, whether or not made up), and *HS 6309* (Textiles; worn clothing and other worn articles). See **Error! Reference source not found.**3.1 f or NRCA values of revealed categories 1996-2016 (RO1).

Table 3.1

NRCA for TAP at Four-Digit Level, Indicated a Minimum of Three Consecutive Years of Comparative Advantage (2010-2016)

	Cotton fiber	Artificial filament tow	Nonwovens	Cotton yarn > 85%	Carpet	Worn Clothing
Year	5201	5502	5603	5205	5703	6309
1996	474.32	73.14	3.91	-102.75	-8.37	23.11
1997	420.97	53.29	18.69	-90.44	7.80	22.84
1998	392.00	53.07	15.41	-75.10	11.50	17.54
1999	92.27	47.23	9.92	-61.45	11.22	13.01
2000	217.65	35.92	26.78	-44.77	22.18	15.24
2001	273.19	45.73	32.63	-42.71	21.61	12.79
2002	255.00	40.32	39.27	-32.39	19.10	13.69
2003	366.25	34.13	50.53	-32.45	18.00	15.00
2004	406.10	37.40	50.64	-14.37	22.47	15.49
2005	334.84	39.64	61.20	1.69	25.70	13.20
2006	332.55	37.25	60.09	5.98	26.17	10.89
2007	293.19	40.76	39.51	11.12	17.13	12.44
2008	269.48	45.10	39.46	17.85	24.97	13.81
2009	237.20	61.84	41.84	20.24	22.68	14.16
2010	326.33	50.86	45.75	15.74	24.73	15.51
2011	400.89	44.47	39.32	50.69	22.07	18.34
2012	277.48	50.92	42.85	18.85	23.23	18.59
2013	241.65	52.98	44.10	7.87	20.43	19.26
2014	189.75	51.94	40.45	12.02	19.05	18.47
2015	198.94	47.55	36.44	13.06	16.50	16.17
2016	239.33	50.07	33.56	20.09	17.20	17.82

Extreme advantage Extreme Disadvantage

*Note: NRCA values are multiplied by 10^6

Table 3.2

Augmented-Dickey-Fuller Unit Root (ADF) Single Mean Test Results
(The null hypothesis is the non-stationary series ($\alpha \leq 0.05$).

Categories	Tau	Pr < Tau	Stationary
5201	-2.93	0.0600	No
5502	-3.75	0.0119	Yes
5603	-2.44	0.1456	No
5205	-2.35	0.1667	No
5703	-5.29	0.0005	Yes
6309	-2.53	0.1247	No

Table 3.2 presents the Augmented Dickey Fuller Unit Root (ADF) tests for revealed products from which cotton fiber (HS 5201), nonwovens (HS 5603), cotton yarn (HS 5205) and worn clothing (HS 6309) requires differentiation to make stationary series. The ADF test is repeated to ensure that first order differentiation effectively made the series stationary and no additional differentiation is needed (Table 3.3).

Table 3.4 presents the tentative models with the order of p + d and q using the SCAN and ESACF methods and p, q order using the MINIC method. The suggested orders of p and q are applied to the training dataset. At this point the model indicating the minimum AIC, is selected to fit the data (RO2) (Table 3.5). Based on the minimum AIC criterion in four out of six categories one order of differentiation was the only required element in the time series (I(1)). That is, the suggested order of p and q relevant to autoregressive and moving average is equal to zero. I (1) series represents white noise after differencing and is formulated as $NRCA_t = NRCA_{t-1} + e_t$. Artificial filament tow, HS 5502, involves an autoregressive parameter with the order of two and carpet and other floor covering, HS 5703, requires one autoregressive parameter.

Table 3.3

Augmented Dickey Fuller Unit Root (ADF) Single Mean Test Results After First Order Differentiation (The Null Hypothesis is he Non-Stationary Series ($\alpha \leq 0.05$).

Categories	Tau	Pr < Tau	Stationary	Period of Differencing
HS 5502	-4.63	0.0021	Yes	1
HS 5603	-4.10	0.0061	Yes	1
HS 5205	-4.70	0.0018	Yes	1
HS 6309	-3.19	0.0375	Yes	1

Table 3.4

Tentative Model Order Selection Using SCAN, ESACF and MINIC

	SCAN			ESACF			MINIC		
Categories	p+d	q	BIC	p+d	q	BIC	p	q	BIC
HS 5201	0	0	7.06	0	0	7.06	M0	3	-30.36
	-	-	-	1	0	7.20	-	-	-
HS 5502	0	1	3.02	0	0	3.03	3	1	-36.49
	-	-	-	2	0	1.85	-	-	-
	-	-	-	3	0	-31.36	-	-	-
HS 5603	0	0	3.57	0	0	3.57	1	3	-35.79
HS 5205	0	0	2.77	0	0	2.77	4	2	-36.06
	-	-	-	1	0	2.86	-	-	-
	-	-	-	2	0	2.84	-	-	-
HS 5703	1	0	0.78	1	0	0.78	1	2	-33.87
	0	1	1.06	0	1	1.06	-	-	-
HS 6309	0	0	- 0.24	0	0	-0.24	3	2	-37.99
	-	-	-	1	0	-0.15	-	-	-
	-	-	-	2	0	-2.68	-	-	-

Table 3.5.

Choosing the Order of p, d, and q with Minimum AIC (* did not converge)

Categories	p	d	q	AIC
HS 5201	0	1	0	228.08
HS 5502	2	0	0	145.50
HS 5603	0	1	0	136.72
HS 5205	0	1	0	154.09
HS 5703*	1	0	0	129.14
HS 6309	0	1	0	85.71

The $\chi 2$ test statistics fail to reject the no-autocorrelation hypothesis at an alpha of 0.05 indicating that the residuals are white noise, therefore the applied models are adequate for all series (Table 3.6). To evaluate model accuracy, forecast error is calculated by comparing actual and forecasted NRCA values for 2016 (Table 3.7). The largest forecast error equal to 22.93 percent belongs to cotton fiber followed by nonwovens and worn clothing. The forecast error for artificial filament tow, cotton yarn and carpet is less than five percent. Assuming observed errors as reasonable, NRCA values are forecasted for 2017 and 2018 (see Table 3.8). Overall, the two-year forecast for cotton fiber, and worn clothing (HS 5201, HS 5603) decreases compared to the actual NRCA value of 2016. Nonwovens and cotton yarn (HS 5603, HS 5205) shows an increase in NRCA value. The NRCA changes for artificial filament tow (HS 5502) are not considerable, however this value decreases for 2017 and increases for 2018. Carpet (HS 5703) shows a slight decrease for 2017 and remains the same for 2018 compared to 2017.

Table 3.6

Autocorrelation Check for Residuals, Significance Level α=0.05
(Hypothesis: Residuals are White Noise)

Categories	ARIMA model	To lag	Chi-Square	DF	Pr > ChiSq
HS 5201	(0,1,0)	6	3.07	6	0.7997
HS 5502	(2,0,0)	6	2.34	4	0.6731
HS 5603	(0,1,0)	6	2.36	6	0.8836
HS 5205	(0,1,0)	6	1.61	6	0.9519
HS 5703	(1,0,0)	6	1.69	5	0.8896
HS 6309	(0,1,0)	6	2.55	6	0.8632

Table 3.7

NRCA Forecast for 2016 and Forecast Error

Categories	Actual 2016	Forecast 2016	Std. Error	95% Confidence Limits		Percent Forecast Error
HS 5201	239.327	184.445	95.356	-2.449	371.340	22.93
HS 5502	50.073	48.808	8.583	31.986	65.631	2.53
HS 5603	33.561	38.153	8.613	21.273	55.033	13.68
HS 5205	20.087	19.151	13.604	-7.513	45.815	4.66
HS 5703	17.195	16.504	5.826	5.085	27.922	4.02
HS 6309	17.815	15.802	2.250	11.391	20.212	11.30

The additive outlier and permanent level shift analysis performed along with the time series indicates one outlier for all categories with the exception of worn clothing (HS 6309) (**Error! Reference source not found.**). Both permanent level shifts and additive outliers are i llustrated on forecast graphs (Figure 3.1). Permanent level shifts for artificial filament tow and carpet after 1997 might be associated with the WTO phase I quota restriction elimination or implementation of the North American Free Trade Agreement (NAFTA) in 1994. Specifically, for carpet, which is mostly traded regionally due to its bulkiness (extensive shipping cost per square meter) the implementation of NAFTA in 1994 may have caused an increase in favor of

U.S. carpet export competitiveness. A permanent level shift for nonwovens occurred in 2007 which, clearly shows a stop point to its consistent growth from 1998. Nonwovens NRCA dropped by more than 30 percent in 2007. Further investigation into gross U.S. nonwovens exports shows that the category is not actually declining in terms of export value. This suggests that emerging technologies in other countries (increased nonwoven export competition) contribute to the observed NRCA decrease in 2007. Specifically, increasing gross exports of nonwovens from China explains this observation. Chinese exports of HS 5603 increased 30 percent in 2007 and quintupled in 2016 compared to 2006. Outlier analysis of cotton fiber (HS 5201) only suggests one additive outlier in 1999. Additive outliers are associated with random events and do not relate to structural changes in series. The abrupt drop of cotton fiber competitiveness in 1999 is commonly explained by the 1998 drought (Outlook for U.S. Agricultural Exports, 1998) which led to less yield and exports. An additional additive outlier is identified in 2011 for cotton yarn. Further investigation into this finding does not yield a viable explanation.

Table 3.8

NRCA Forecast for 2017 and 2018

	2017 Forecast				2018 Forecast			
HS Code	Forecast	Std Error	95% Confidence Limits		Forecast	Std Error	95% Confidence Limits	
5201	169.95 ▼	134.85	-94.36	434.26	155.46 ▼	165.16	-168.25	479.16
5502	49.17 ▼	11.10	27.41	70.92	49.66 ▲	13.17	23.85	75.46
5603	39.87 ▲	12.18	15.99	63.74	41.58 ▲	14.92	12.34	70.81
5205	25.25 ▲	19.24	-12.46	62.95	31.34 ▲	23.56	-14.84	77.52
5703	16.50 ▼	8.24	0.36	32.65	16.50 ▬	10.09	-3.27	36.28
6309	15.44 ▼	3.18	9.20	21.67	15.07 ▼	3.90	7.43	22.71

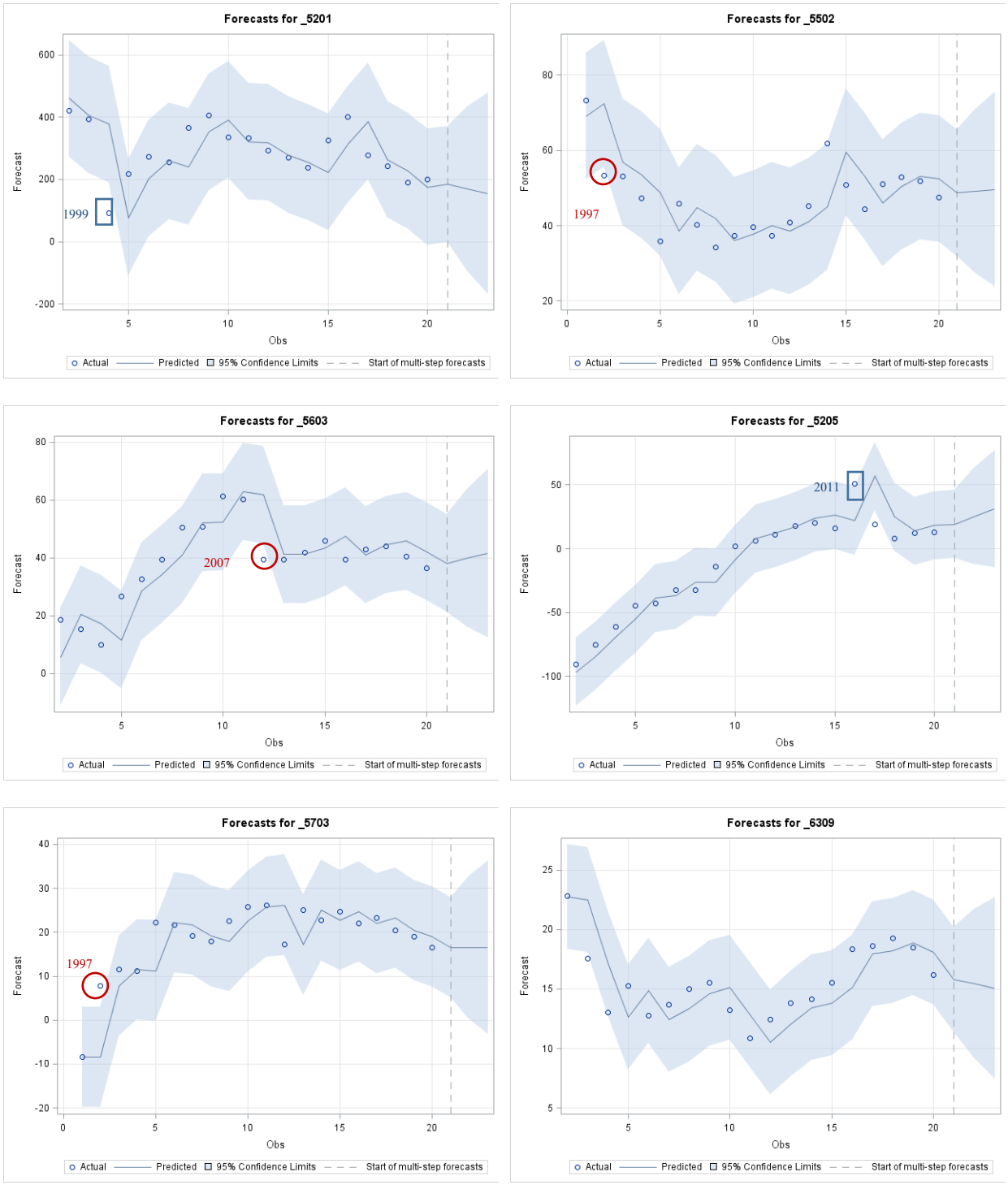


Figure 3.1. Forecast graph indicating outliers for *Revealed* categories
(Observations indicated by circles are level shifts and by rectangles are additive outliers).

Table 3.9

Additive Outlier and Permanent Level Shifts

Categories	Additive Outlier	Permanent Level Shift
HS 5201	1999	-
HS 5502	-	1997
HS 5603	-	2007
HS 5205	2011	
HS 5703	-	1997
HS 6309	-	-

Conclusion, Limitations and Future Research

This research demonstrates a first-time application of the ARIMA procedure to forecast U.S. TAP export competitiveness using NRCA. NRCA at a four-digit level reveals six categories (i.e., cotton fiber, artificial filament tow, nonwovens, cotton yarn, carpet, and worn clothing) with recent sustained export advantage that creates the basis for further time series analysis to forecast short-term future and identify outliers. Cotton fiber, the most important source of U.S. TAP advantage, is forecasted to lose advantage in 2017 and 2018 compared to 2016. However, high forecast error (i.e., more than 22 percent) suggests examination of additional times-series method such as cyclical approaches. Export advantage projection of artificial filament tow which is driven by the availability of resources (mainly cellulose from wood) suggests a slight decline in 2017 and an increase in 2018. However, the magnitude of the change is negligible.

An increasing trend of nonwovens export advantage stopped in 2007 after which NRCA value oscillates at a reduced NRCA value. This observation signals increasing competition from emerging economies in technical and knowledge intensive products. Cotton yarn is projected to continue to increase advantage for 2017 and 2018. Export advantage of carpet and other floor covering is expected to experience a slight decline in 2017 and maintain a similar level in 2018.

Export advantage of worn clothing, more of a challenge than a source of advantage, is expected to decline in the next two years. Further, application of outlier analysis to identify permanent level shifts and additive outliers, and correlate those to influential drivers and random events, provides an innovative method that not only improves the accuracy of models but also conveys valuable information about the sources of losing or gaining export advantage. The most important insight from the outlier analysis is the permanent level shift of Nonwovens in 2007. Although, this observation does not necessarily relate to changes in policy and suggest further investigation. Due to the relative nature of NRCA (if a country loses advantage other countries gain advantage) and further analysis of trade data for the nonwoven industry indicate that Chinese export growth of nonwovens contributes to U.S. declining advantage.

A limitation of this research is the sole analysis of products with comparative advantage. In addition to this enquiry, further analysis of U.S. TAP products that lost advantage using the NRCA approach is insightful. The results suggest high forecast error percent for the cotton fiber, nonwovens and worn clothing which requires further investigation and application of other time series methods (i.e., cyclical). Another limitation relevant to *revealed comparative* advantage is its sole reliance on exports as an indicator of competitiveness.

In terms of measurement, the small number of data points, 21, can affect the accuracy and reliability of the ARIMA process. On the other hand, compiling NRCA using data before 1996 creates other sources of error such as the existence of different HS code versions (revisions) which necessitated merging of new and old categories over time. Second, trade date prior to 1996 is not inclusive of all countries' trade activity which can result in less reliable NRCA values.

CHAPTER 4

TEXTILE TRADE MAPING USING R *SHINY* APPLICATION

Introduction

In order to efficiently interpret and integrate the findings generated among the three distinct analyses (CH 1-CH3) (Saki et al., 2019), interactive visual models are designed and implemented using the Shiny application supported by the R software platform (Chang W, Cheng J, Allaire J, Xie Y, 2019). The Shiny application allows users to interactively explore complex flow scenarios through generation of customized visual tools that provide an accessible medium for interpretation. Over the past decade Shiny application to a range of dynamic phenomena is increasingly evident in the academic literature. Fields as diverse as Plant Genomics (Y. Yu, Yao, Wang, & Huang, 2020), Epidemiology (Moraga, 2017) Psychology (Ellis & Merdian, 2015), and Pharmacology (Kirouac, Cicali, & Schmidt, 2019) demonstrate use of Shiny applications to explore and interpret complex data.

The application developed for this research facilitate evaluation of originating export countries and destination import countries over time for the following TAP categories: HS 5201 (Cotton; not carded or combed), HS 5502 (artificial filament tow), HS 5603 (Nonwovens; whether or not impregnated, coated, covered or laminated), HS 5205 (Cotton yarn, other than sewing thread, containing 85% or more by weight, not for retail sale), HS 5703 (Carpets and other textile floor coverings; tufted, whether or not made up) and HS 6309 (Textiles; worn clothing and other worn articles).

In contrast to the subsequent analyses within this dissertation, the focal metric for this research is represented by export value (USD) rather than the NRCA competitiveness index. The interactive feature facilitated through Shiny R programming allows efficient, comparative

interpretation of complex trade patterns. Models are constructed to allow user manipulation of product HS- code (5201, 5502, 5603, 5205, 5703, 6309), time (1996-2018), number of export countries (10 maximum) and number of import countries (10 maximum) with real-time corresponding visual output (i.e., Sankey diagram) with an added ability to dynamically observe exact export values by hovering over the output graphic. The process for creating the application is presented in detail in the following sections.

Methodology

Multiple software sources and versions provide the means for creating the interactive applications (Table 4.1). R is an open source programing language that is commonly used for statistical computing and graphics (https://www.r-project.org/). Because R is open source there are numerous public resources for guidance regarding software installation and implementation. After installing R software, RStudio which provides an integrated development environment (IDE) for R is downloaded (https://rstudio.com/). Using R and RStudio facilitates flexible data manipulation, statistical modeling and graphics creation, while Shiny facilitates interactivity. The installation method used to develop visuals is accessed by the Tools/Install Packages in RStudio.

Table 4.1
Software Applications and Versions Used to Develop Interactive Visual Model

Software/R Package Library	Version
R	3.6.1
RStudio	1.2.1335
Shiny	1.3.2
Shinythemes	1.1.2
Htmlwidgets	1.3
Tidyverse	1.2.1
Viridis	0.5.1
Hrbrthemes	0.6.0
networkD3	0.4

Data. The data are downloaded from the UN COMTRADE database in a CSV format. Data includes the export value and year for the reporter (export country) and the partner (import country) for each HS code. Original data can be accessed at https://github.com/Zahra-Saki/Textile-and-Apparel-Global-Trade. Data is read into RStudio using the *read.csv()* statement, including the path to the downloaded file. Several alterations were carried out to clean the data by developing a function (data_prep) using the R *tidyverse* package. The label for Belgium varied between 1996-1998 during which time the country was labeled Belgium-Luxembourg. For consistency, the variable label was edited to reflect Belgium across all years. Additionally, to reveal internal trade between EU member countries, corresponding reporter and partner names reflecting the *European Union* label were excluded from the data.

Sankey diagram. Tufte (2001) refers to perhaps the earliest form of a Sankey diagram as a depiction of Napoleon's Russian war campaign, rendered by Minard in 1861.The map illustrates multiple dimensions of data, including but not limited to the size of Napoleon's troops, demonstrated by line thicknesses at different time and geographical points. Today, Sankey diagrams are commonly used to illustrate traffic, energy or material flows. For this analysis, the Sankey diagram is used to visualize the trade flows from origin countries to respective country destinations. Specifically, the networkD3 package in R is used to generate the Sankey diagram. Countries and groups of countries are denoted by green rectangles, referred to as nodes in Sankey diagrams. Gray shaded arcs represent export flows and vary proportionately in width according to volume (Figure 4.1)

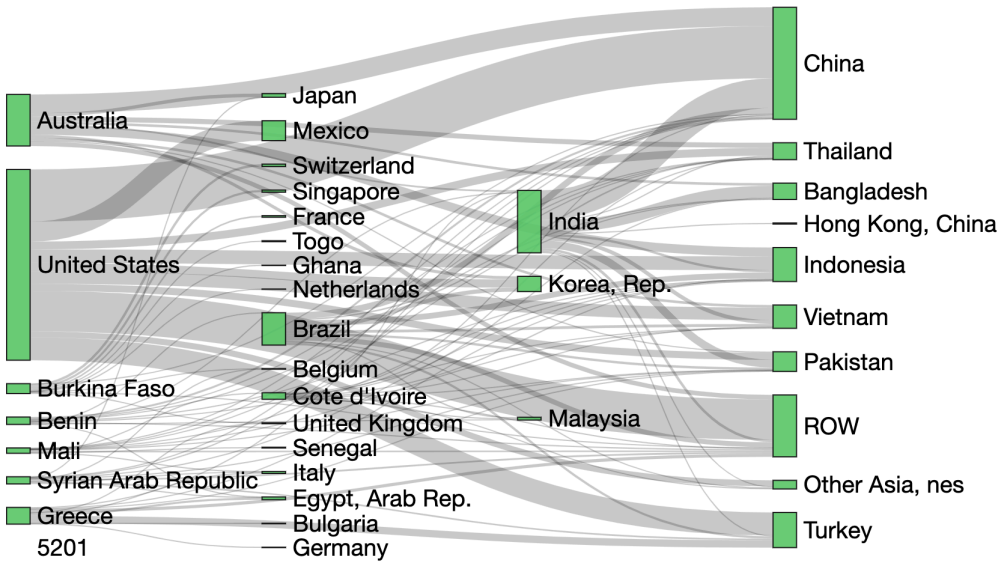


Figure 4.1. Sankey diagram example*.
*Note: Width of shaded arcs is proportionate to volume export flows

The example above (Figure 4.1) depicts a snapshot of export flows in time which can vary between a single year or the full 23-year period, dependent on user specifications. The ability of flexibly view historical data and change the context (i.e., export and import countries and product HS code) facilitates efficient interpretation for researchers. Therefore, this application is particularly useful for examining and interpreting trade patterns over different temporal scenarios and countries.

Structure of shiny applications. Shiny applications are built using two R scripts that communicate with each other: a user-interface script (ui.R) which controls layout and appearance and a server script (server.R) which establishes instructions for user-input , and data processing using R language and appropriate functions from different packages. To run an application locally in RStudio, ui.R and server.R scripts should be saved in the same directory. To launch the application the user must open ui.R and server.R script in RStudio and select *RunApp*, in the top right hand corner of the source pane. Shiny will open a Web-browser window for subsequent application.

User-interface (ui.R) development. The ui.R script directs the application's layout, user-input mechanisms, popularly referred to as *widgets* (i.e., interactive web elements such as sliders) and the output display format. The ui.R script directs the application layout which includes two panes: the side panel (user input widgets) and the main panel (Sankey diagram). The user-input widget designed for the analysis is presented in Figure 4.2. Note that the interface includes four dimensions for interaction related to product code, time, number of export countries and number of import countries. The interface in Figure 4.2 is constrained to return a Sankey Diagram that visualizes export flows for an eleven-year period (2008- 2018) reflecting the top five exporting countries and top four import countries for cotton fiber.

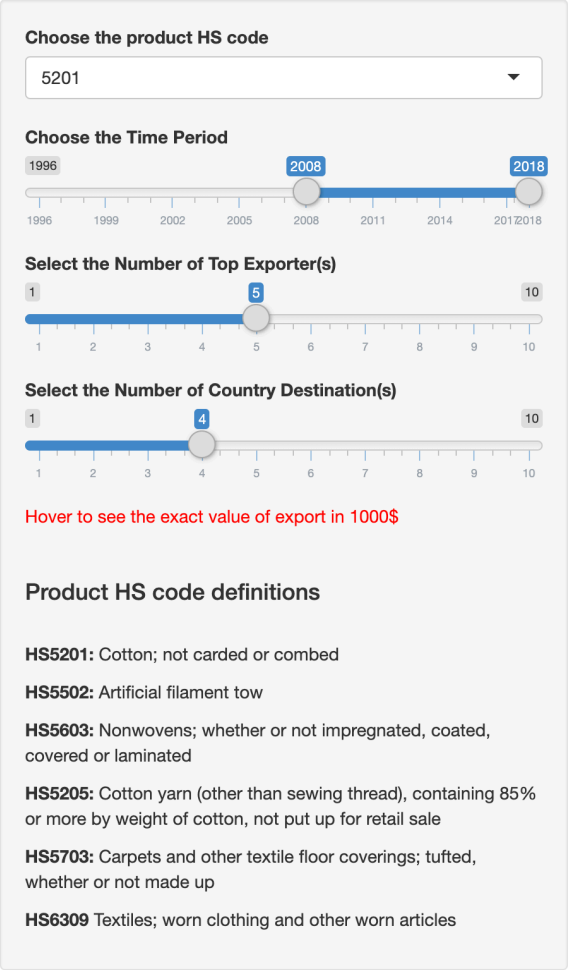


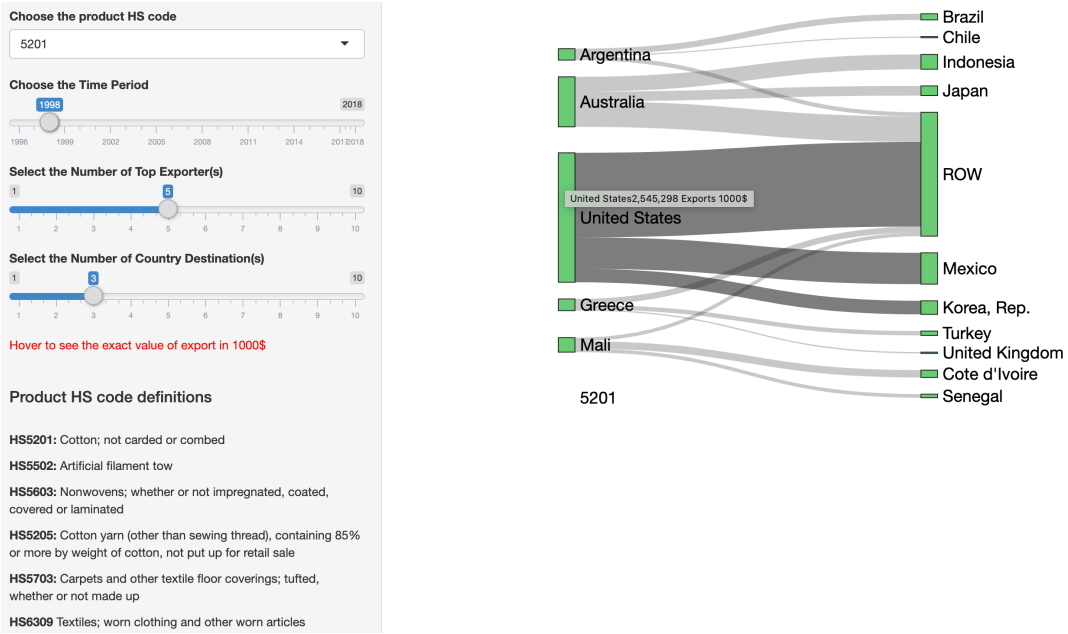
Figure 4.2. User-input widgets for year, number of export and import countries.

Defining application instructions (server.R). The server.R file includes two sections: the reactive objects and the output render function from shinyServer. The reactive objects connect user generated widget inputs to the output mechanism. The reactive expression and the render function are re-executed with each user interaction that directs changes via widget inputs. Shiny provides a number of render functions in this case, *renderSankeyNetwork* is adopted. The shinyapps.io server is used to make the application available online for users (https://zahra-saki.shinyapps.io/SelectTextilesGlobalTrade/).

Results and Discussion

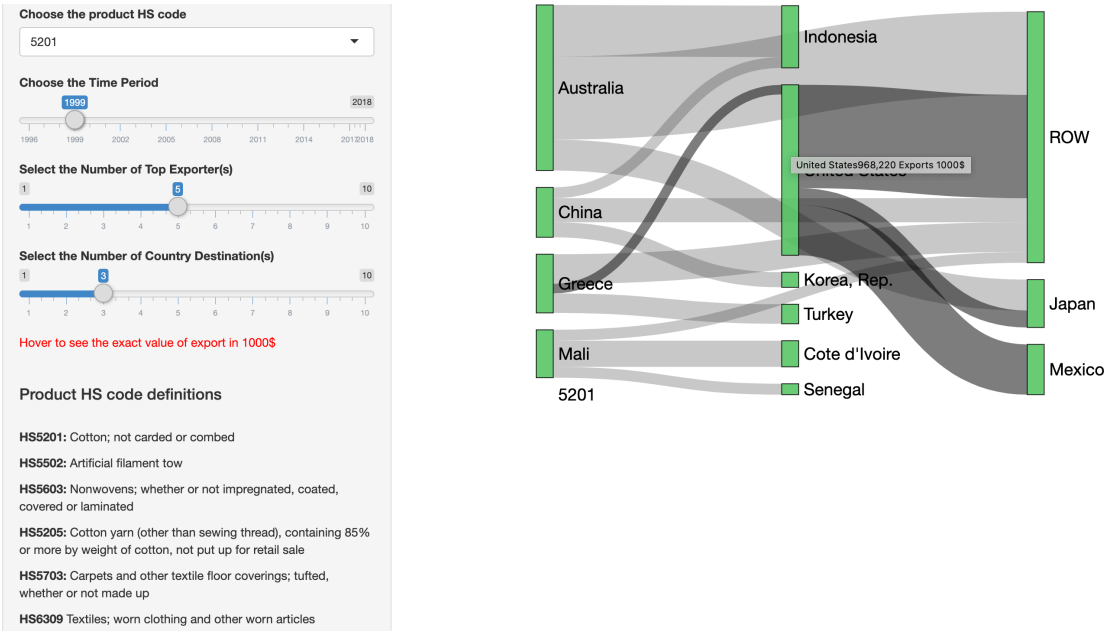
Findings reported in previous chapters of this document are further explored using the application. Interactive models for each of the focal HS codes are directed to examine earlier findings by focusing on specific time frames and in some cases import and export countries. Visualizations for all interactive models are statically demonstrated (Figures 4.3 – 4.14) featuring before and after scenarios.

HS 5201 Cotton fiber not carded or combed. Study one suggests that cotton exports were impacted significantly by U.S. drought in 1998. Sankey diagrams for U.S. cotton exports for 1998 and 1999, support this finding through indication of a drastic decline in U.S. export values during the following year (1999) (Figures 4.3 and 4.4). An additional Sankey diagram for the most recent year (2018) suggests major changes in the top exporters and import destinations over the preceding decade (Figure 4.5) likely due to global shifts in supply chain activities. For example, Vietnam, Bangladesh and Pakistan emerge as the top three import destinations globally. Further, compared to the earlier models China's position as a major exporter shifted to an import role.



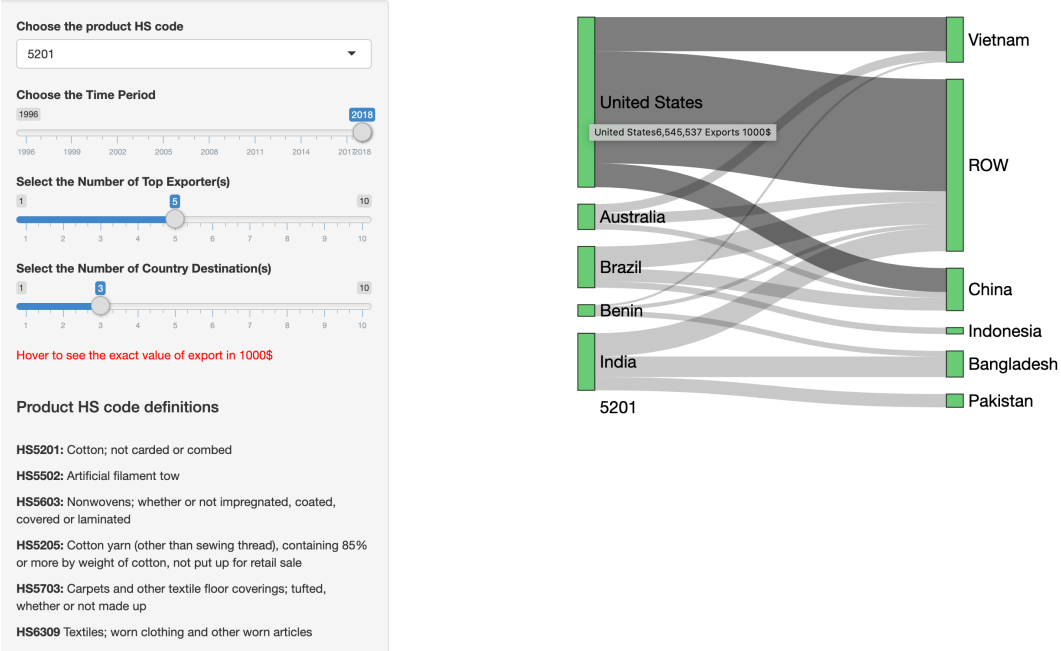
KEY. Time period: 1998, Export countries: 5 largest, Import destinations: 3 largest

Figure 4.3. Cotton fiber exports, 1998.



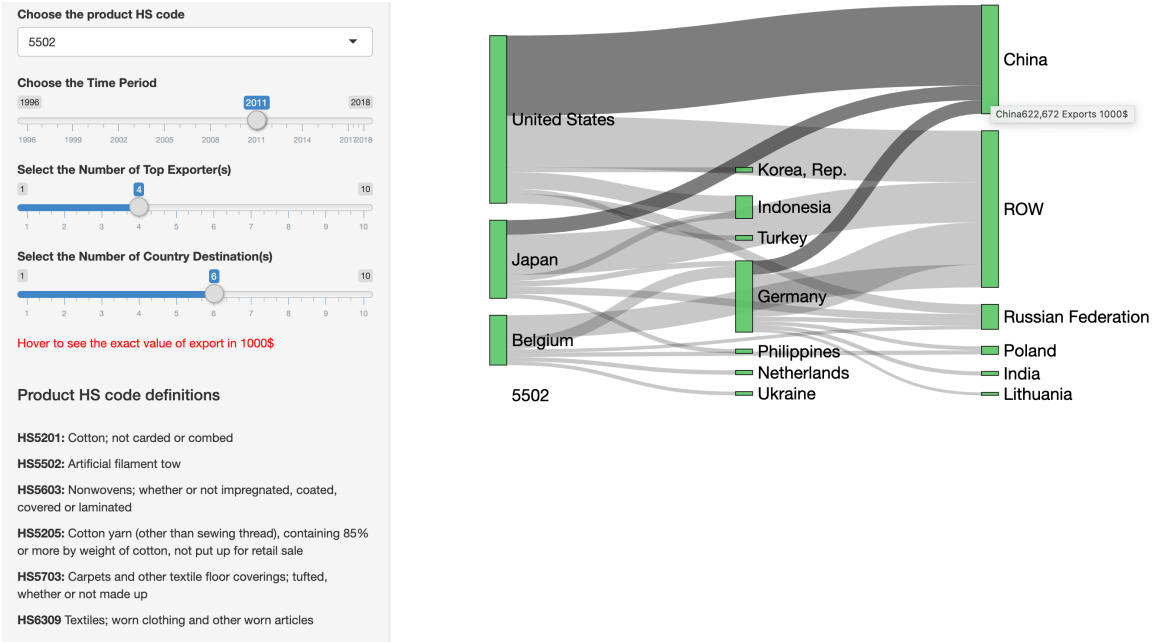
KEY. Time period: 1999, Export countries: 5 largest, Import destinations: 3 largest

Figure 4.4. Cotton fiber exports, 1999.

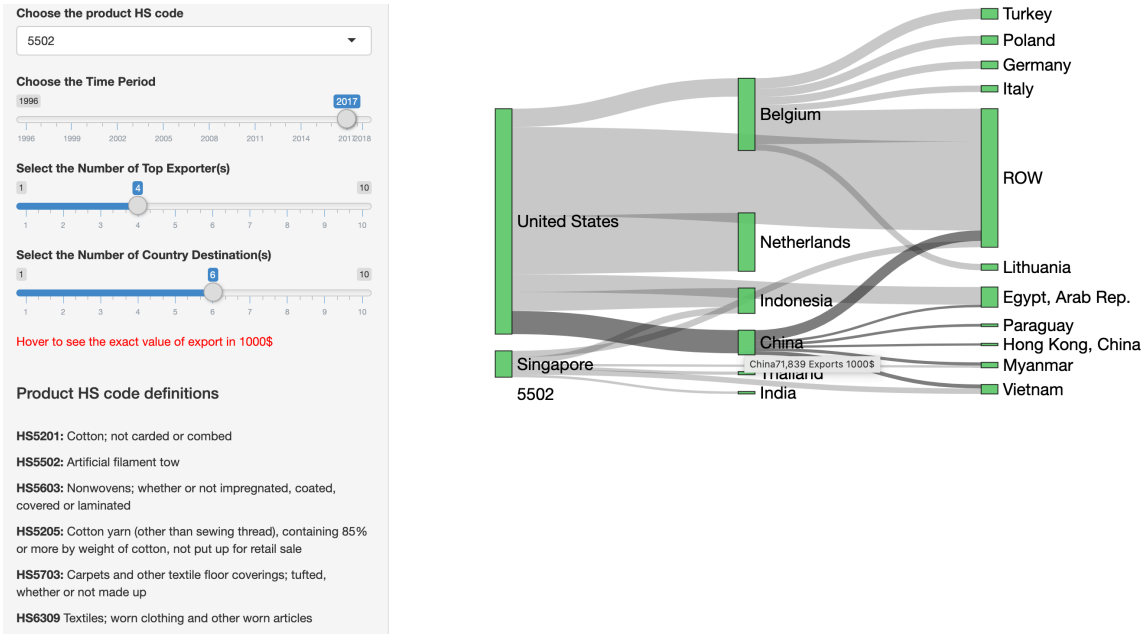


KEY. Time period: 2018, Export countries: 5 largest, Import destinations: 3 largest
Figure 4.5. Cotton fiber exports, 2018.

HS 5502 Artificial filament tow. Findings from study one suggests that China was a primary destination for U.S. artificial filament tow exports until 2011. The related Sankey diagram indicates that China imported in excess of 600 million USD of this commodity globally, of which a sizable proportion originated in the U.S. (Figure 4.6). In striking contrast, a second diagram reveals China as the fourth largest global exporter of Artificial Filament Tow only six years later (Figure 4.7) Further demonstrating China's economic self-sufficiency and economic diversity.



KEY: Time period: 2011, Export countries: 4 largest, Import destinations: 6 largest
Figure 4.6. Artificial filament tow exports, 2011.

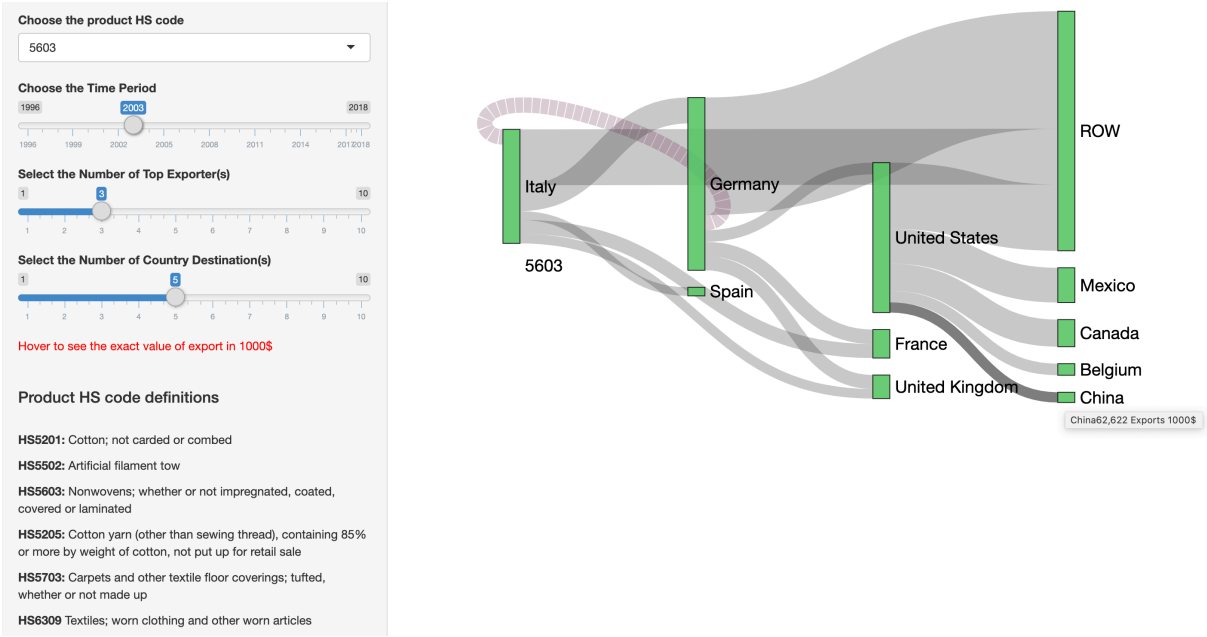


KEY: Time period: 2017, Export countries: 4 largest, Import destinations: 6 largest
Figure 4.7. Artificial filament tow exports, 2017.

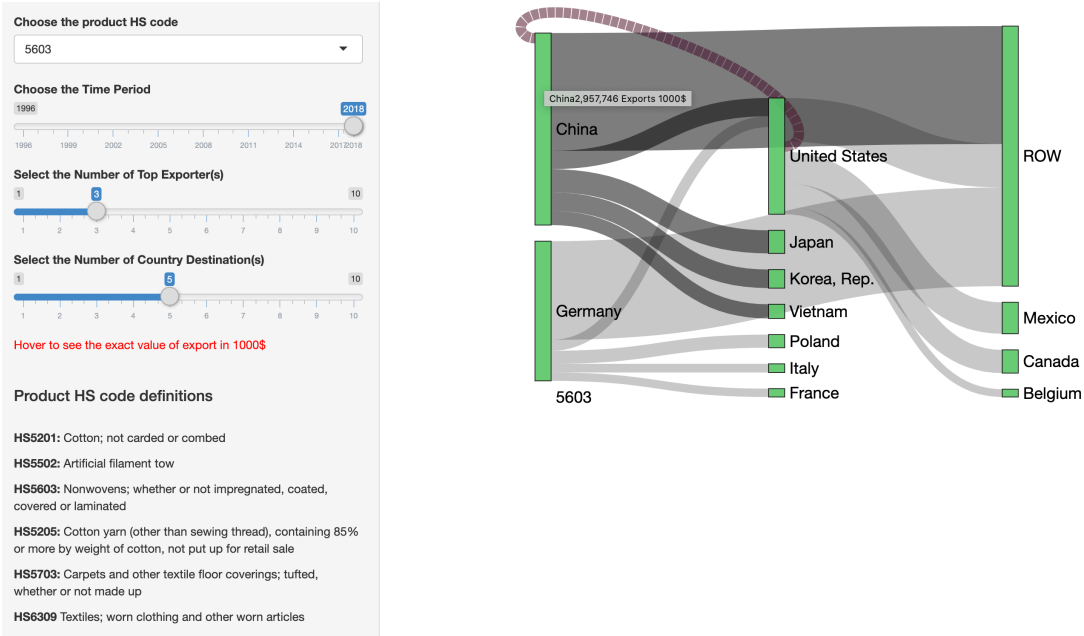
HS 5603 Nonwovens; whether or not impregnated, coated, covered or laminated.

Figures 4.8 and 4.9 illustrate that though China was among the top five import countries for U.S.

nonwovens exports in 2003, the nation emerged as the largest global exporter of nonwovens in 2018. This observation strengthens the earlier interpretation of NRCA related findings (Chapter 1) which suggest that Chinese export boost of HS 5603 caused U.S. NRCA decline.

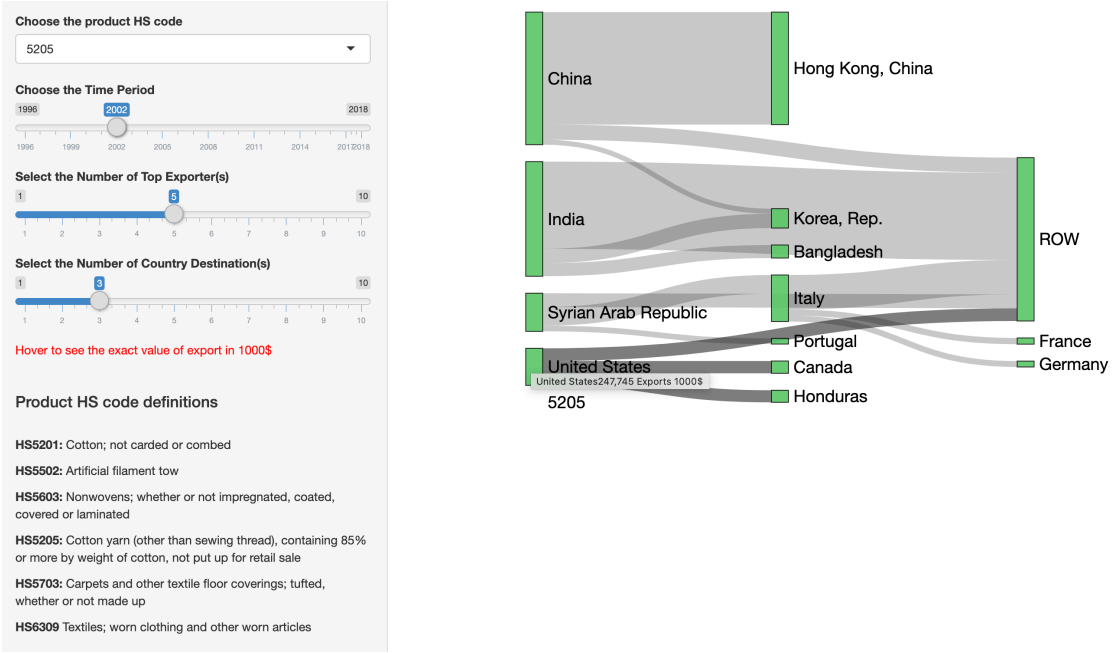


KEY: Time period: 2003, Export countries: 3 largest, Import destinations: 5 largest
Figure 4.8. Nonwovens exports, 2003.

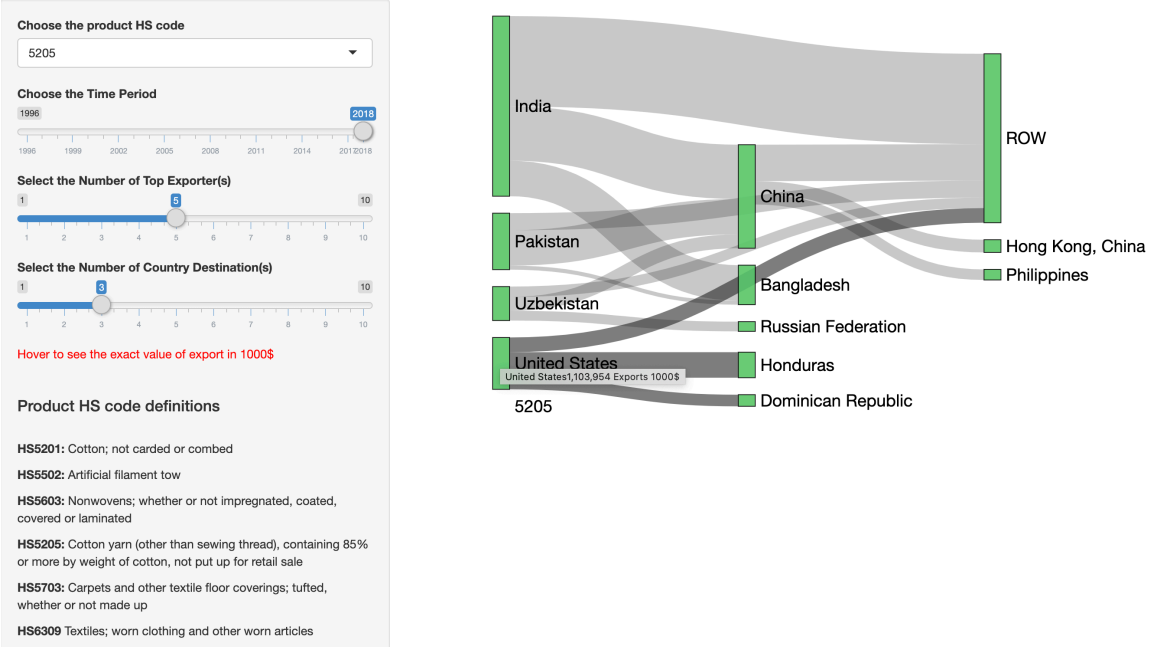


KEY: Time period: 2018, Export countries: 3largest, Import destinations: 5 largest
Figure 4.9. Nonwovens exports, 2018.

HS 5205 Cotton yarn other than sewing thread, etc. The pattern of increasing advantage for U.S. Cotton yarn (HS 5205) continued to increase over time reaching more than a billion dollars in 2018 (Figure 4.11) in contrast to less than 250 million dollars in 2002 (Figure 4.10). An additional insight revealed in this comparison is the disappearance of Italy and Syria as the third and fourth largest global cotton yarn exporters in the 2018 diagram compared to the 2002 diagram. In turn, Pakistan and Uzbekistan emerged as the third and fifth largest exporters of cotton yarn on a global scale.



KEY: Time period: 2002, Export countries: 5 largest, Import destinations: 3 largest
Figure 4.10. Cotton yarn exports, 2002.



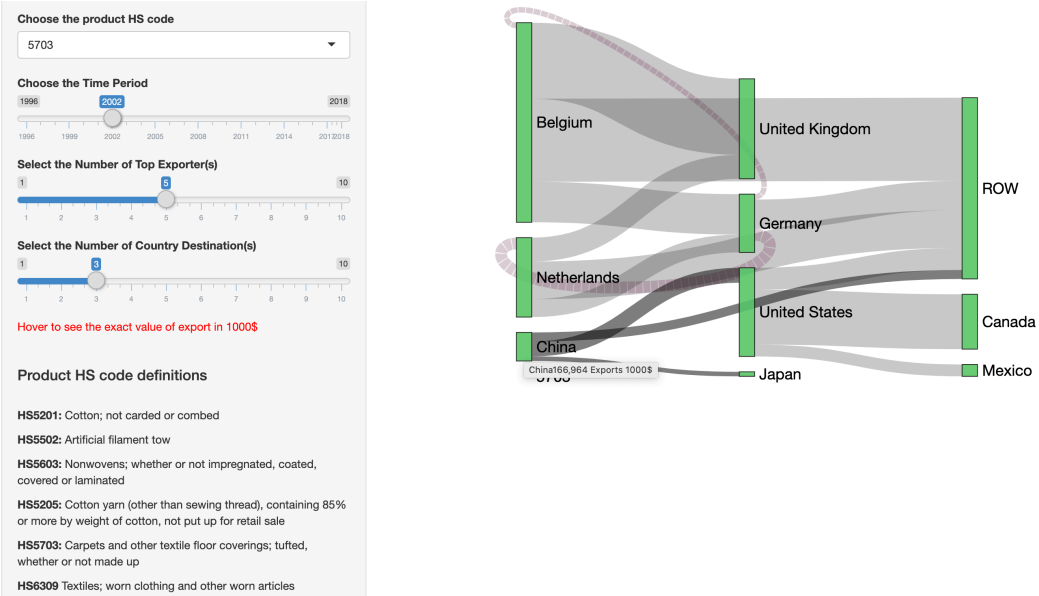
KEY: Time period: 2018, Export countries: 5 largest, Import destinations: 3 largest

Figure 4.11. Cotton yarn exports, 2018.

HS 5703 Carpet and other textile floor coverings; tufted whether or not made up. Chinese exports of HS 5703 increased more than 700 percent in value from 2002 to 2018 (Figures 4.12 and 4.13). Additionally, illustration of trade flow emphasizes the importance of regional exports. While European countries (i.e, Belgium, Netherlands, United Kingdom and Germany) continue to trade locally, the emergence of India in as the fifth largest exporter of HS 7503 and the dominant position of China as the world's largest exporter of carpet in 2016 emphasizes the influential role of Asian economies in textile production.

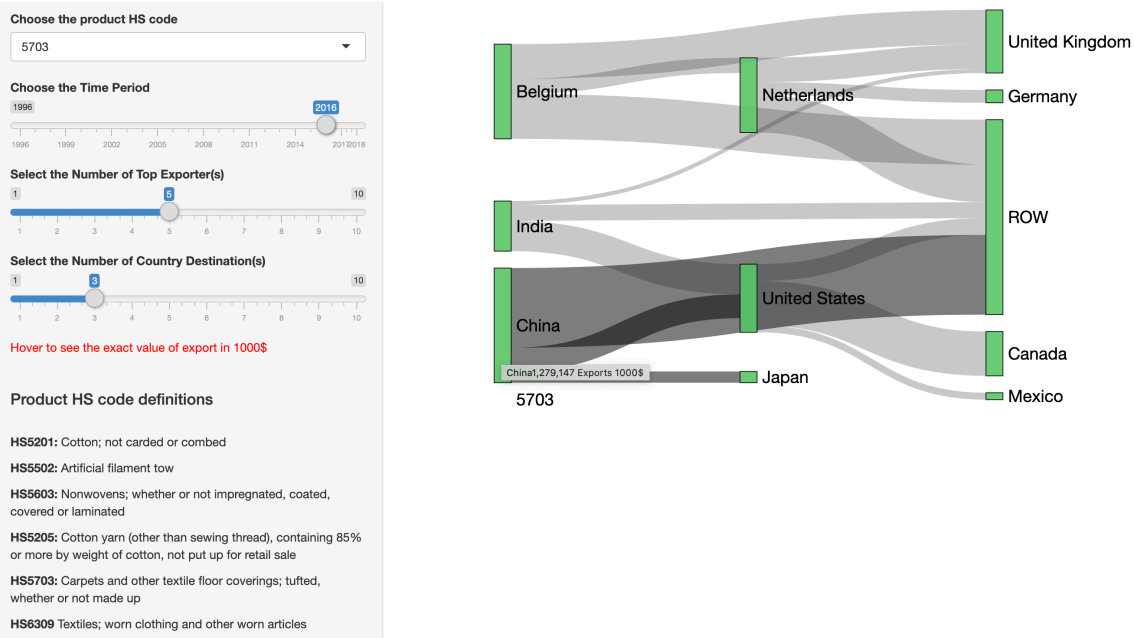
Comparison of 2002 to 2016 reveals the drastic change in rank among exporting countries, with the exception of the Netherlands which maintained its position as third during both years. Belgium as the largest country exporter in 2002 moved to second largest exporting country in 2016, ceding first place to China which occupied the fifth rank in 2002. The U.S. rank as the second largest exporter in 2002 dropped to fourth in the world during 2016. Through

observing the related plots, the disappearance of Germany as the fourth top exporting country in 2002 and emergence of India in 2012 represent two of the most surprising observations.



KEY: Time period: 2002, Export countries: 5 largest, Import destinations: 3 largest

Figure 4.12. Carpet and other textile floor coverings exports, 2002.



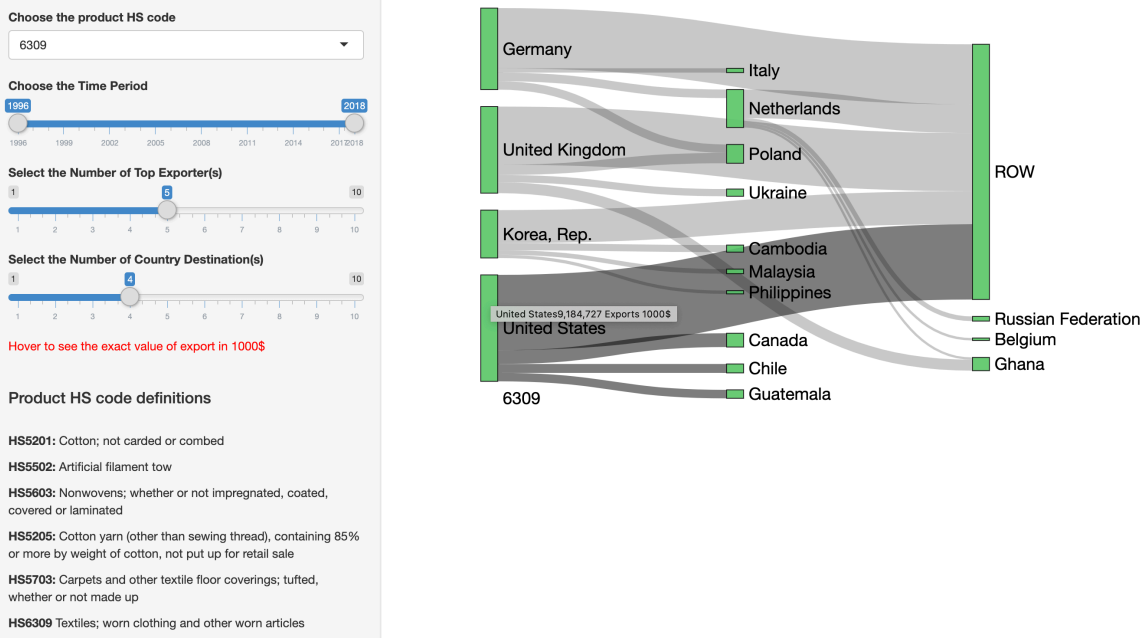
KEY: Time period: 2016, Export countries: 5 largest, Import destinations: 3 largest

Figure 4.13. Carpet and other textile floor coverings exports, 2016.

HS 6309 Worn clothing. Identification of worn clothing as the sixth largest source of U.S. TAP export comparative advantage, encourages further investigation of global exports of

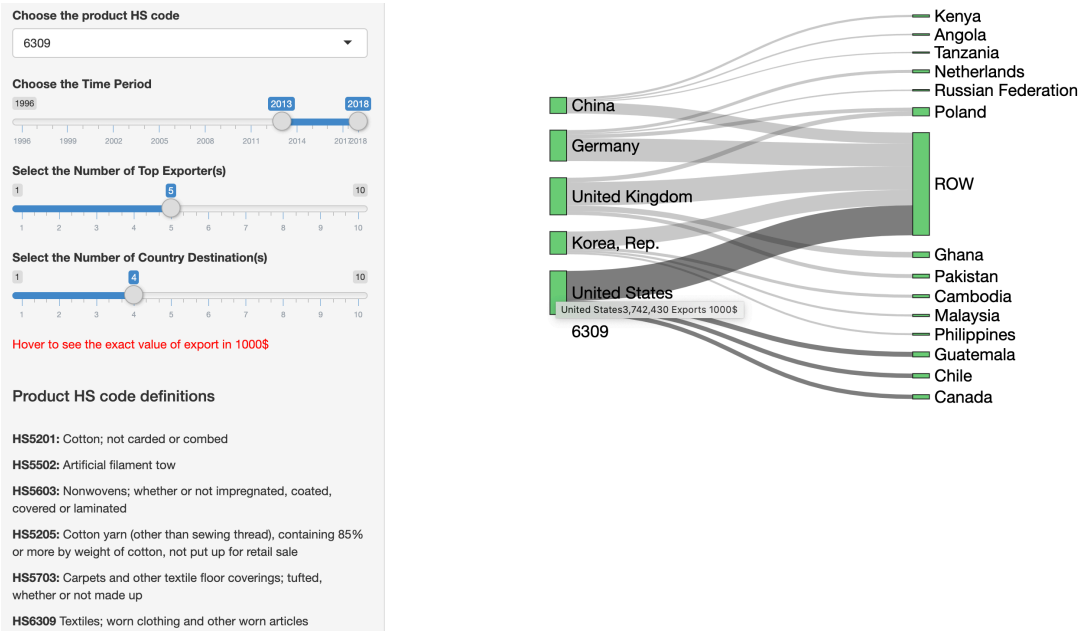
this product to disclose the major players in this field. As the world's largest exporter of worn clothing, the U.S. cumulatively exported more than nine billion dollars between 1996 and 2018. Additional analysis focusing on the recent timeframe (2013-2018) indicates continued predominance of the U.S. as the largest exporter of worn clothing. Further, among the more recent scope, the United Kingdom, Germany, and South Korea maintained their ranks from the longer term analysis as second through fourth, respectively. However, the Netherlands which occupied the fifth rank among the longer term, was supplanted by China in the more recent analysis. This finding is yet another symbol of China's global economic expansion during the study's time period.

Though, level of economic development of countries, seems to play a role in worn clothing export positioning, there exist other elements that require further investigation. For example, countries' investment in research and development to promote circular economy rather than linear approaches. Efforts to promote circular economies for apparel and textiles are beginning to surface in Europe (Fischer & Pascucci, 2017). The fact that worn clothing is the sixth largest source of U.S. TAP export advantage does not portend sustainable economic prosperity for U.S. textiles and apparel given the persistence of traditional linear approaches to textile production and consumption.



KEY: Time period: 1996-2018, Export countries: 5 largest, Import destinations: 4 largest

Figure 4.14. Worn clothing exports, 1996 to 2018.



KEY: Time period: 2013-2018, Export countries: 5 largest, Import destinations: 4 largest

Figure 4.15. Worn clothing exports, 2013 to 2018.

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APPENDICES

Appendix A.1: Aggregated U.S. TAP Export, Import and Trade Deficit

Aggregated U.S. TAP Export, Import and Trade Deficit Billion Dollar (HS 50 to HS 68- 1996-2016)

Year	export	import	deficit
1996	19.61	66.41	(46.80)
1997	21.74	76.15	(54.40)
1998	21.51	82.35	(60.84)
1999	19.53	86.68	(67.14)
2000	21.94	96.63	(74.69)
2001	19.98	95.51	(75.52)
2002	19.05	97.83	(78.79)
2003	19.93	103.95	(84.02)
2004	21.43	111.89	(90.46)
2005	21.23	119.72	(98.50)
2006	21.93	125.00	(103.07)
2007	21.27	128.13	(106.87)
2008	21.73	124.74	(103.00)
2009	17.40	108.15	(90.75)
2010	22.42	125.71	(103.28)
2011	27.21	136.20	(108.99)
2012	24.76	131.78	(107.02)
2013	24.58	136.62	(112.04)
2014	23.71	146.59	(122.88)
2015	22.16	153.58	(131.42)
2016	20.92	145.30	(124.38)

Appendix A.2: TAP Categories Defined at Two-Digit HS Code

TAP Categories Defined at Two-Digit Harmonized Code Level

HS Code	Product description
50	Silk
51	Wool, fine or coarse animal hair; horsehair yarn and woven fabric
52	Cotton
53	Vegetable textile fibres; paper yarn and woven fabrics of paper yarn
54	Man-made filaments; strip and the like of man-made textile materials
55	Man-made staple fibres
56	Wadding, felt and nonwovens, special yarns; twine, cordage, ropes and cables and articles thereof
57	Carpets and other textile floor coverings
58	Fabrics; special woven fabrics, tufted textile fabrics, lace, tapestries, trimmings, embroidery
59	Textile fabrics; impregnated, coated, covered or laminated; textile articles of a kind suitable for industrial use
60	Fabrics; knitted or crocheted
61	Apparel and clothing accessories; knitted or crocheted
62	Apparel and clothing accessories; not knitted or crocheted
63	Textiles, made up articles; sets; worn clothing and worn textile articles; rags
64	Footwear; gaiters and the like; parts of such articles
65	Headgear and parts thereof
66	Umbrellas, sun umbrellas, walking-sticks, seat sticks, whips, riding crops; and parts thereof
67	Feathers and down, prepared; and articles made of feather or of down; artificial flowers; articles of human hair

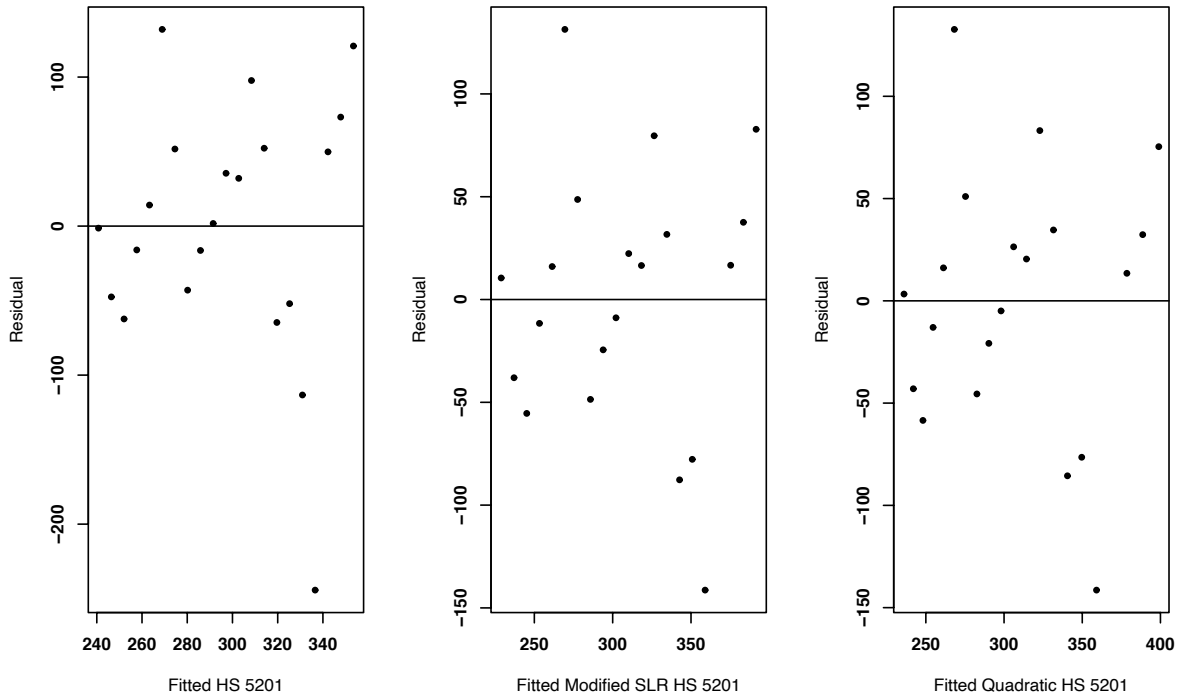
Appendix A.3: TAP Categories with Comparative Advantage at Four-Digit HS Code

TAP Categories with Comparative Advantage at Four-Digit Harmonized Code Level

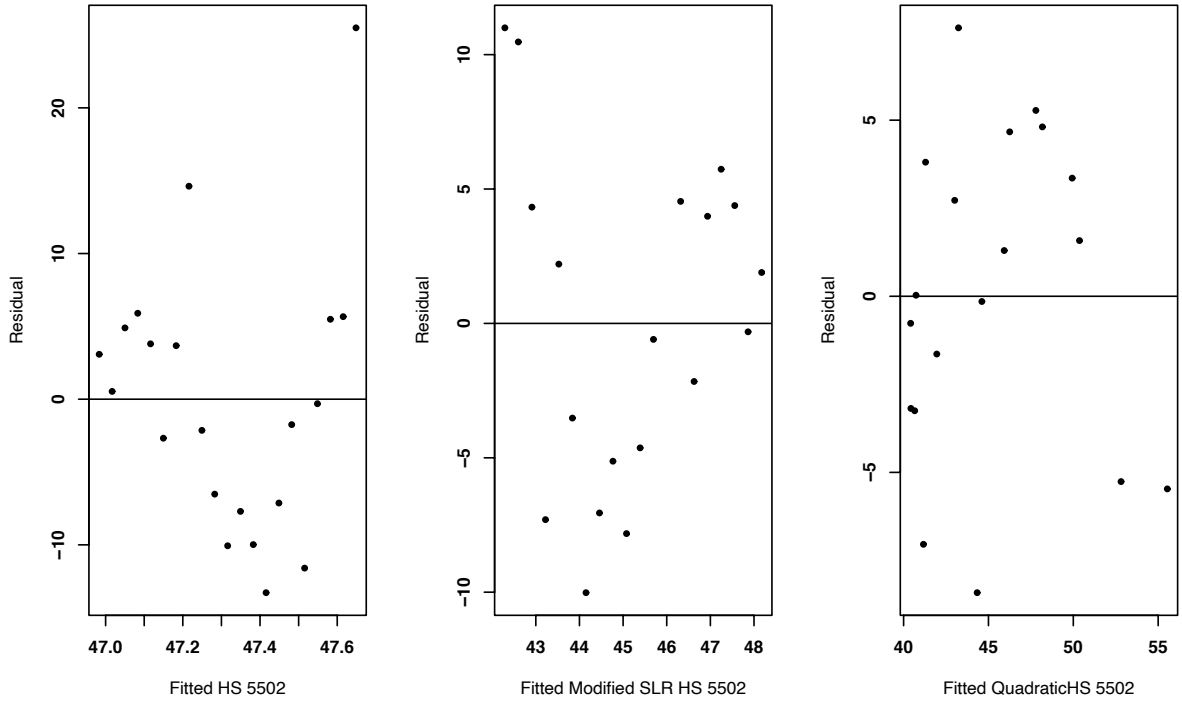
HS Code	Product description
5201	Cotton; not carded or combed
5205	Cotton yarn (other than sewing thread), containing 85% or more by weight of cotton, not put up for retail sale
5502	Artificial filament tow
5603	Nonwovens; whether or not impregnated, coated, covered or laminated
5703	Carpets and other textile floor coverings; tufted, whether or not made up
6309	Textiles; worn clothing and other worn articles

Appendix B.1: Residual Versus Fitted Value Graphs for Linear Models

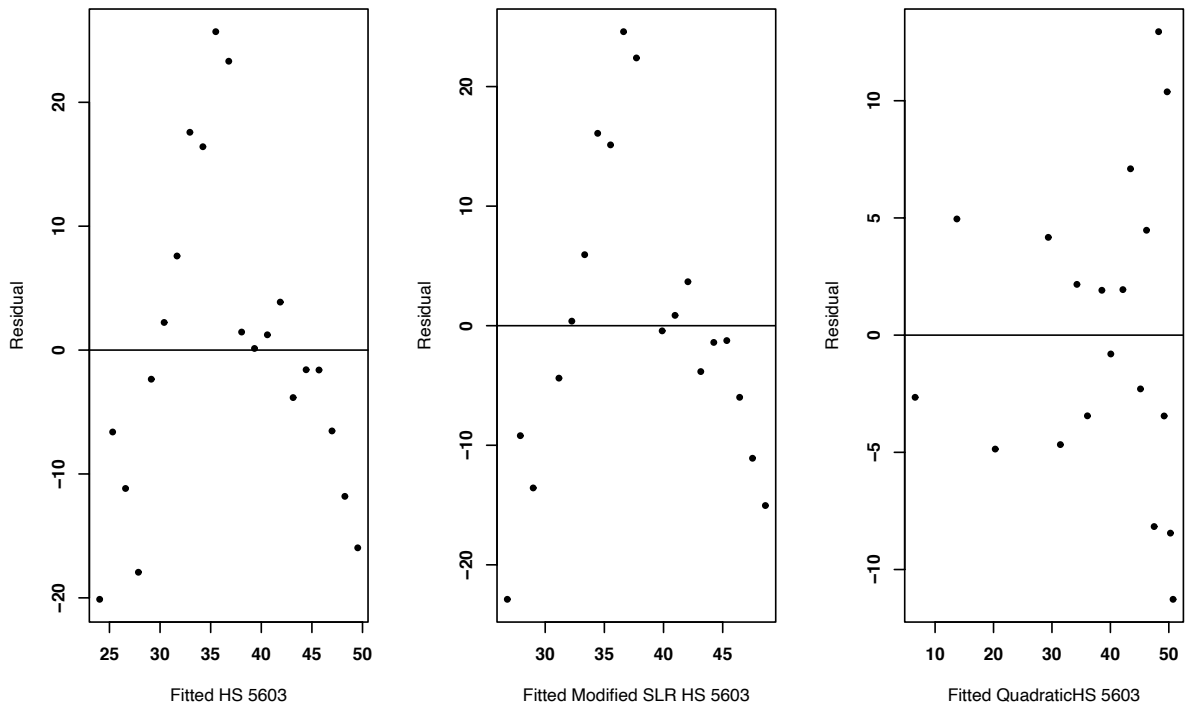
Residual Versus Fitted Value Graphs for Linear Models



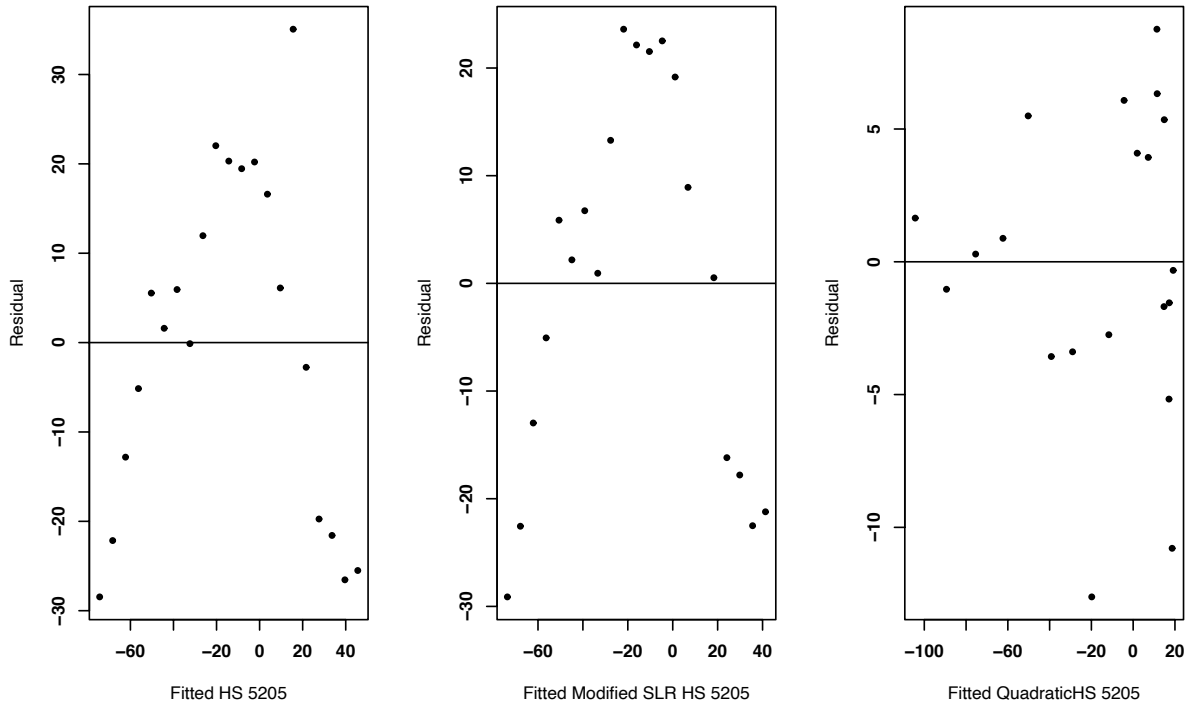
a) Cotton fiber (HS 5201)



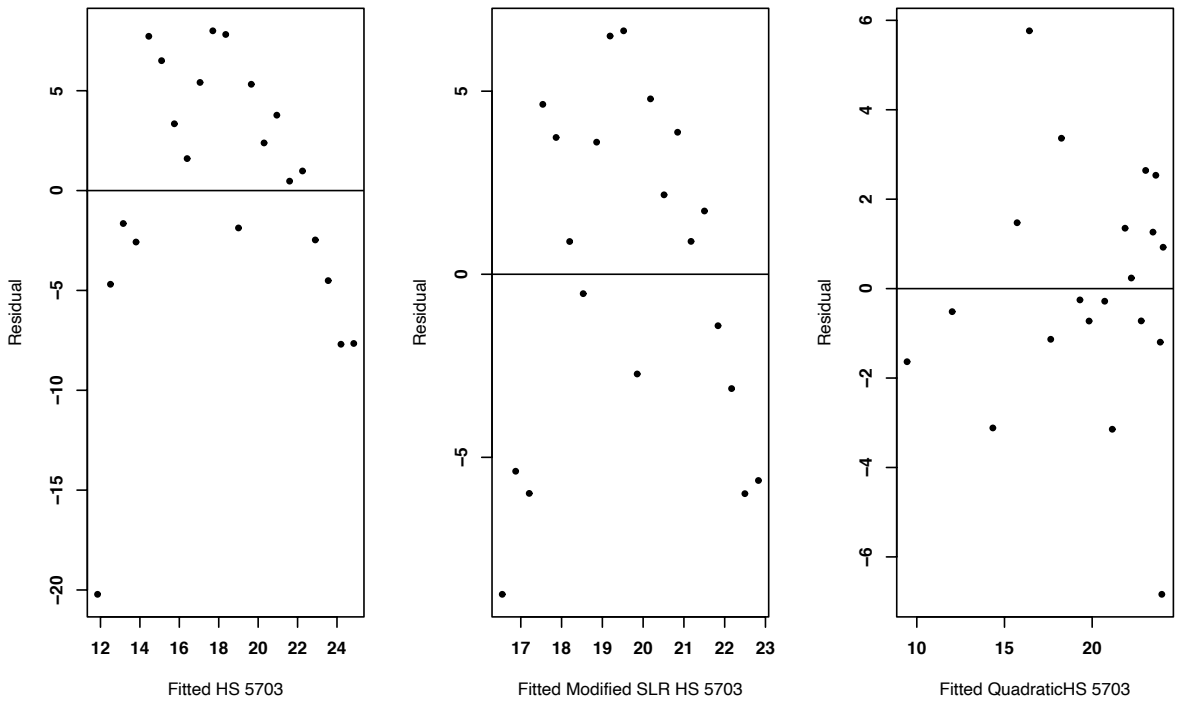
b) Artificial filament tow (HS 5502)



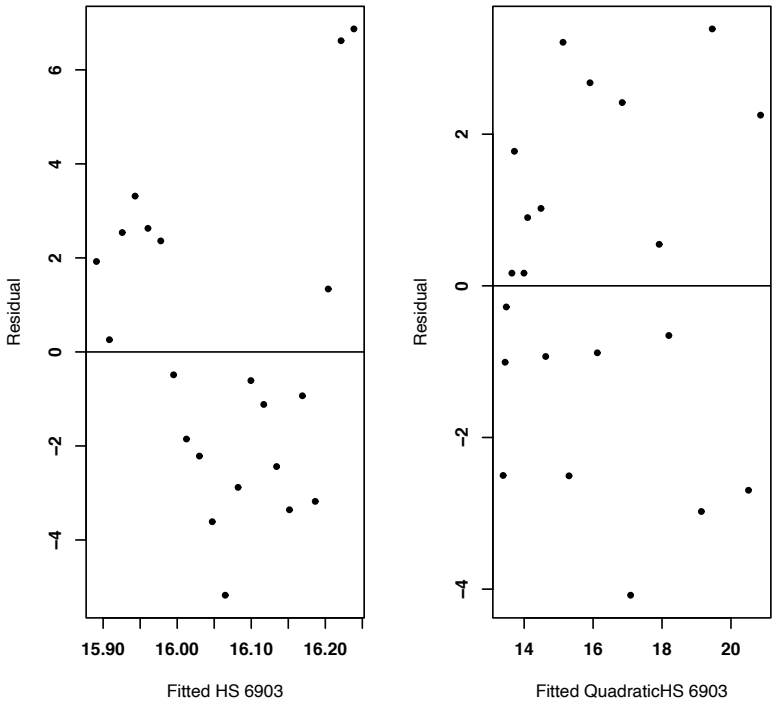
c) Nonwovens (HS 5603)



d) Cotton yarn (HS5205)



e) Carpet (HS 5703)



f) Worn clothing (HS 6903)

Appendix B.2: R Software Output for Linear Models

R Software Output for SLR, Modified SLR and Quadratic Models fit to NRCA Values

```
library(readxl)
# read in data
df <- read_excel("/Users/saaki/Desktop/ecconomic competitiveness/Research/Pap
er 2/NRCA.xlsx")

# fit a linear regressiopn model and plot the diagnisis plots
lm.cotton.fit <- lm(NRCA_cotton_fiber ~ Year, data = df)
summary(lm.cotton.fit)

##
## Call:
## lm(formula = NRCA_cotton_fiber ~ Year, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -244.298  -47.449    1.715   51.761  131.962
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11603.198   6319.804   1.836   0.0821 .
## Year           -5.636      3.150  -1.789   0.0896 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 87.42 on 19 degrees of freedom
## Multiple R-squared:  0.1442, Adjusted R-squared:  0.09912
## F-statistic: 3.201 on 1 and 19 DF,  p-value: 0.08957

lm.artificial.fit <- lm(NRCA_artificial_filament_tow ~ Year, data = df)
summary(lm.artificial.fit)

##
## Call:
## lm(formula = NRCA_artificial_filament_tow ~ Year, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -13.286  -7.131  -0.315   4.892  25.492
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 114.03199  684.23298   0.167    0.869
## Year         -0.03326    0.34109  -0.098    0.923
##
## Residual standard error: 9.465 on 19 degrees of freedom
## Multiple R-squared:  0.0005001,  Adjusted R-squared:  -0.05211
## F-statistic: 0.009507 on 1 and 19 DF,  p-value: 0.9233
```

```r
lm.nonwovens.fit <- lm(NRCA_nonwovens ~ Year, data = df)
summary(lm.nonwovens.fit)

##
## Call:
## lm(formula = NRCA_nonwovens ~ Year, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -20.122  -6.617  -1.580   3.874  25.698
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2520.1113   941.2629  -2.677   0.0149 *
## Year            1.2746     0.4692   2.716   0.0137 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.02 on 19 degrees of freedom
## Multiple R-squared:  0.2797, Adjusted R-squared:  0.2418
## F-statistic: 7.379 on 1 and 19 DF,  p-value: 0.01369

lm.cotton.yarn.fit <- lm(NRCA_cotton_yarn ~ Year, data = df)
summary(lm.cotton.yarn.fit)

##
## Call:
## lm(formula = NRCA_cotton_yarn ~ Year, data = df)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -28.46 -19.74   1.60  16.60  35.06
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.204e+04  1.402e+03  -8.584 5.79e-08 ***
## Year         5.994e+00  6.991e-01   8.574 5.90e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 19.4 on 19 degrees of freedom
## Multiple R-squared:  0.7946, Adjusted R-squared:  0.7838
## F-statistic: 73.52 on 1 and 19 DF,  p-value: 5.897e-08

lm.carpet.fit <- lm(NRCA_carpet ~ Year, data = df)
summary(lm.carpet.fit)

##
## Call:
## lm(formula = NRCA_carpet ~ Year, data = df)
##
```

```
## Residuals:
##      Min       1Q   Median       3Q      Max
## -20.2191  -2.5771   0.9824   5.3206   7.9975
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1285.3616   499.6334  -2.573   0.0186 *
## Year            0.6499     0.2491   2.609   0.0172 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.911 on 19 degrees of freedom
## Multiple R-squared:  0.2638, Adjusted R-squared:  0.2251
## F-statistic: 6.809 on 1 and 19 DF,  p-value: 0.01724
```

```r
lm.worn.fit <- lm(NRCA_worn_clothing ~ Year, data = df)
summary(lm.worn.fit)
```

```
##
## Call:
## lm(formula = NRCA_worn_clothing ~ Year, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.1759 -2.4402 -0.6101  2.3601  6.8703
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  50.93066  242.09528   0.210    0.836
## Year         -0.01738    0.12069  -0.144    0.887
##
## Residual standard error: 3.349 on 19 degrees of freedom
## Multiple R-squared:  0.00109,    Adjusted R-squared:  -0.05148
## F-statistic: 0.02074 on 1 and 19 DF,  p-value: 0.887
```

```r
# remove outlier year and fit a linear regressiopn model and plot the diagnis
is plots
#1999 for cotton fiber
lm.cotton.revised <- lm(NRCA_cotton_fiber ~ Year, data = df[-4,])
summary(lm.cotton.revised)
```

```
##
## Call:
## lm(formula = NRCA_cotton_fiber ~ Year, data = df[-4, ])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -141.36  -40.69   13.28   33.12  131.37
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept) 16629.099   4928.795   3.374  0.00338 **
## Year           -8.135      2.457  -3.312  0.00388 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 65.85 on 18 degrees of freedom
## Multiple R-squared:  0.3786, Adjusted R-squared:  0.3441
## F-statistic: 10.97 on 1 and 18 DF,  p-value: 0.003881
```

```
#1996, 2009 for artificial tow
lm.artificial.revised <- lm(NRCA_artificial_filament_tow ~ Year, data = df[c(
-1,-14),])
summary(lm.artificial.revised)
```

```
##
## Call:
## lm(formula = NRCA_artificial_filament_tow ~ Year, data = df[c(-1,
##     -14), ])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10.0196  -4.8768  -0.3146   4.3546  10.9959
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -576.2285   493.1721  -1.168    0.259
## Year           0.3097     0.2458   1.260    0.225
##
## Residual standard error: 6.307 on 17 degrees of freedom
## Multiple R-squared:  0.08542,    Adjusted R-squared:  0.03162
## F-statistic: 1.588 on 1 and 17 DF,  p-value: 0.2247
```

```
#1999, 2007 for nonwovens
lm.nonwovens.revised <- lm(NRCA_nonwovens ~ Year, data = df[c(-4,-12),])
summary(lm.nonwovens.revised)
```

```
##
## Call:
## lm(formula = NRCA_nonwovens ~ Year, data = df[c(-4, -12), ])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -22.889  -7.591  -1.240   4.808  24.589
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2149.8127   970.8543  -2.214   0.0408 *
## Year            1.0905     0.4839   2.254   0.0377 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 12.97 on 17 degrees of freedom
## Multiple R-squared:   0.23,  Adjusted R-squared:  0.1847
## F-statistic: 5.079 on 1 and 17 DF,  p-value: 0.03772

#2011 for cotton yarn
lm.cotton.yarn.revised <- lm(NRCA_cotton_yarn ~ Year, data = df[-16,])
summary(lm.cotton.yarn.revised)

##
## Call:
## lm(formula = NRCA_cotton_yarn ~ Year, data = df[-16, ])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -29.122 -16.590   1.562  14.751  23.600
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.154e+04  1.322e+03  -8.734 6.87e-08 ***
## Year         5.746e+00  6.589e-01   8.721 7.03e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 17.97 on 18 degrees of freedom
## Multiple R-squared:  0.8086, Adjusted R-squared:  0.798
## F-statistic: 76.05 on 1 and 18 DF,  p-value: 7.025e-08

#1996 for carpet
lm.carpet.revised <- lm(NRCA_carpet ~ Year, data = df[-1,])
summary(lm.carpet.revised)

##
## Call:
## lm(formula = NRCA_carpet ~ Year, data = df[-1, ])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.7419 -3.6848  0.8978  3.7746  6.6477
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -643.7789   371.5988  -1.732    0.100
## Year           0.3307     0.1852   1.785    0.091 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.776 on 18 degrees of freedom
## Multiple R-squared:  0.1505, Adjusted R-squared:  0.1033
## F-statistic: 3.188 on 1 and 18 DF,  p-value: 0.09105
```

```r
# # fit a quadratic regression
#1999 for cotton fiber
qm.cotton.revised <- lm(NRCA_cotton_fiber ~ Year + I(Year^2) , data = df[-4,]
)
summary(qm.cotton.revised)

##
## Call:
## lm(formula = NRCA_cotton_fiber ~ Year + I(Year^2), data = df[-4,
##     ])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -141.445  -43.638    8.397   32.906  132.686
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.729e+05  1.824e+06   0.259    0.799
## Year        -4.630e+02  1.819e+03  -0.255    0.802
## I(Year^2)    1.134e-01  4.533e-01   0.250    0.805
##
## Residual standard error: 67.64 on 17 degrees of freedom
## Multiple R-squared:  0.3809, Adjusted R-squared:  0.308
## F-statistic: 5.229 on 2 and 17 DF,  p-value: 0.01699

#1996, 2009 for artificial tow
qm.artificial.revised <- lm(NRCA_artificial_filament_tow ~ Year + I(Year^2),
data = df[c(-1,-14),])
summary(qm.artificial.revised)

##
## Call:
## lm(formula = NRCA_artificial_filament_tow ~ Year + I(Year^2),
##     data = df[c(-1, -14), ])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.4169 -3.2161  0.0308  3.5813  7.6202
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  5.432e+05  1.495e+05   3.633  0.00224 **
## Year        -5.417e+02  1.490e+02  -3.635  0.00223 **
## I(Year^2)    1.351e-01  3.713e-02   3.637  0.00222 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.81 on 16 degrees of freedom
## Multiple R-squared:  0.4994, Adjusted R-squared:  0.4368
## F-statistic:  7.98 on 2 and 16 DF,  p-value: 0.003945
```

```r
#1999, 2007 for nonwovens
qm.nonwovens.revised <- lm(NRCA_nonwovens ~ Year + I(Year^2), data = df[c(-4,
-12),])
summary(qm.nonwovens.revised)

##
## Call:
## lm(formula = NRCA_nonwovens ~ Year + I(Year^2), data = df[c(-4,
##     -12), ])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.2722  -4.0592  -0.7993   4.3252  12.9449
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.279e+06  1.899e+05  -6.737 4.77e-06 ***
## Year         1.275e+03  1.893e+02   6.732 4.82e-06 ***
## I(Year^2)   -3.174e-01  4.719e-02  -6.726 4.87e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.832 on 16 degrees of freedom
## Multiple R-squared:  0.7988, Adjusted R-squared:  0.7737
## F-statistic: 31.77 on 2 and 16 DF,  p-value: 2.682e-06

#2011 for cotton yarn
qm.cotton.yarn.revised <- lm(NRCA_cotton_yarn ~ Year + I(Year^2), data = df[-
16,])
summary(qm.cotton.yarn.revised)

##
## Call:
## lm(formula = NRCA_cotton_yarn ~ Year + I(Year^2), data = df[-16,
##     ])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.6207  -2.9066  -0.0166   4.4061   8.7566
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.960e+06  1.587e+05  -12.35 6.45e-10 ***
## Year         1.948e+03  1.582e+02   12.32 6.75e-10 ***
## I(Year^2)   -4.842e-01  3.943e-02  -12.28 7.06e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.885 on 17 degrees of freedom
```

```
## Multiple R-squared:  0.9806, Adjusted R-squared:  0.9783
## F-statistic: 429.9 on 2 and 17 DF,  p-value: 2.78e-15
```

```r
#1996, 2007 for carpet
qm.carpet.revised <- lm(NRCA_carpet ~ Year + I(Year^2), data = df[-1,])
summary(qm.carpet.revised)
```

```
##
## Call:
## lm(formula = NRCA_carpet ~ Year + I(Year^2), data = df[-1, ])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.8376 -1.1481 -0.2668  1.3835  5.7646
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -5.026e+05  8.647e+04  -5.812 2.08e-05 ***
## Year         5.006e+02  8.619e+01   5.809 2.09e-05 ***
## I(Year^2)   -1.247e-01  2.148e-02  -5.805 2.11e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.846 on 17 degrees of freedom
## Multiple R-squared:  0.7151, Adjusted R-squared:  0.6816
## F-statistic: 21.34 on 2 and 17 DF,  p-value: 2.314e-05
```

```r
# no outlier
qm.worn.fit <- lm(NRCA_worn_clothing ~ Year + I(Year^2), data = df)
summary(qm.worn.fit)
```

```
##
## Call:
## lm(formula = NRCA_worn_clothing ~ Year + I(Year^2), data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.0806 -1.0090  0.1664  1.7729  3.3876
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.936e+05  6.130e+04   4.790 0.000147 ***
## Year        -2.927e+02  6.112e+01  -4.789 0.000147 ***
## I(Year^2)    7.295e-02  1.523e-02   4.789 0.000147 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.282 on 18 degrees of freedom
## Multiple R-squared:  0.5607, Adjusted R-squared:  0.5119
## F-statistic: 11.49 on 2 and 18 DF,  p-value: 0.0006087
```

```r
################# moedls with price and GDP as indipendent variables
# without year 1999
ml.cotton.fit <- lm(NRCA_cotton_fiber ~ Year + Price + GDP , data = df[-4,])
summary(ml.cotton.fit)

##
## Call:
## lm(formula = NRCA_cotton_fiber ~ Year + Price + GDP, data = df[-4,
##     ])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -148.112  -21.646   -1.721   36.901   92.982
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.101e+04  2.553e+04   1.607  0.12770
## Year        -2.061e+01  1.304e+01  -1.581  0.13346
## Price        2.384e-01  7.681e-02   3.104  0.00682 **
## GDP          3.293e+01  4.095e+01   0.804  0.43308
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 53.47 on 16 degrees of freedom
## Multiple R-squared:  0.6358, Adjusted R-squared:  0.5676
## F-statistic: 9.312 on 3 and 16 DF,  p-value: 0.0008487

ml.cotton.fit2 <- lm(NRCA_cotton_fiber ~ Year + Price , data = df[-4,])
summary(ml.cotton.fit2)

##
## Call:
## lm(formula = NRCA_cotton_fiber ~ Year + Price, data = df[-4,
##     ])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -139.490  -23.072    4.017   37.000  100.328
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.076e+04  4.154e+03   4.999 0.000110 ***
## Year        -1.026e+01  2.077e+00  -4.943 0.000124 ***
## Price        2.018e-01  6.116e-02   3.299 0.004240 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 52.91 on 17 degrees of freedom
## Multiple R-squared:  0.6211, Adjusted R-squared:  0.5766
## F-statistic: 13.93 on 2 and 17 DF,  p-value: 0.0002614
```

Appendix B.3: Number of Reporter for Cotton Export in UN COMTRADE Database

Number of Reporter for Cotton Exports Over Years in UN COMTRADE Database

Year	Number of reporting countries
1988	23
1989	50
1990	52
1991	67
1992	95
1993	116
1994	159
1995	201
1996	203
1997	214
1998	221
1999	233
2000	266
2001	259
2002	267
2003	276
2004	274
2005	286
2006	290
2007	280
2008	265
2009	276
2010	270
2011	277
2012	292
2013	287
2014	283
2015	265
2016	264