

## Forecasting the Potential Impact of the COVID-19 Pandemic on Employment Opportunities in the North Carolina Textile Industry

Sneha Rani, Lori F. Rothenberg, Helmut Hergeth, Lisa Chapman,  
Department of Textile and Apparel, Technology and Management,  
NC State University Wilson College of Textiles,  
Raleigh, NC, USA

### ABSTRACT

*Employment opportunities in any industry are largely driven by several macroenvironmental factors. The global outbreak of COVID-19 slowed operations and transactions due to the extended lockdowns and changed consumer behaviors. The purpose of this study was to forecast the 2020 employment trends in the North Carolina textile industry from pre-pandemic data and to explore the potential impact of COVID-19 on employment in the industry. Data were obtained from the NC Department of Commerce Labor & Economic Analyses on employment, number of establishments, and wages for each of four textile businesses: textile mills, textile retail, textile wholesale, and textile services. Time series forecast models were built for data from 2014-2019 which were used to forecast data for 2020. In general, the number of establishments, employment and wages could be forecasted accurately for the first quarter of 2020. However, virtually none of the forecasts for the second quarter of 2020 were accurate. Interestingly, a few of the third and fourth quarter forecasts were accurate. Some of the inconsistencies could be unique to textiles because of its existing slow decline.*

*Keywords: ARIMA, Time Series, Employment, textile industry*

---

### Introduction

The textile industry in North Carolina has historically provided a large number of employment opportunities for the eligible labor force. Over time, macro environmental factors such as changes in global and regional trade policies (Pickles et. al., 2015; Lu, 2013), technological advancements (Bessen, 2019), recession (Barker, 2011), and pandemics (Bodenhorn, 2020) affected employment (Kunz et al., 2016). The recent global outbreak of COVID-19 in 2020 slowed the entire textile industry global supply chain. Due to extended lockdowns

and changed consumer behavior, several major businesses were adversely affected which led to closures of company divisions, furloughs, layoffs, wage reductions, and company shutdowns (Women's Wear Daily, 2020; Wall Street Journal 2020). However, new textile employment opportunities requiring different skillsets emerged during this period. For instance, medical textiles demand increased because of increased healthcare operations and increased purchasing of masks and PPE through ecommerce websites (Wall Street Journal, 2020).

Most extant literature largely focuses on the impact of historic macro environmental factors on labor force opportunities. As an extension of these previous studies, this study explored the possible impact of the recent pandemic, COVID-19, in 2020 on the textile industry. This study characterized labour growth opportunities for 2014-2019, when there was no pandemic. Using this as a benchmark, the 2020 scenario of labour growth employment opportunities in the textile industry was explored and compared, using the most recent validated employment data from the U.S. federal government. This study extended previously published studies that lacked analyses at a four-digit industry level particular to the textile industry (Rumberger et al, 1985; Duarte et al 2018; Acemoglu et al, 2016; Farooq & Kugler, 2015; Montgomery et al, 1998; Zhao et al, 2021). Though there have been studies which discuss the evolution and growth of the textile manufacturing sector or textile retail sector (Textile Heritage Museum, 2021; Acemoglu et al, 2016), all the four major business components (mills, retail, wholesale, and retailer) need exploration.

The purpose of this study was to forecast the 2020 employment trends in the North Carolina textiles industry from pre-pandemic data.

## 2. Background and Previous Research

As the U.S. economy expanded in the past, textile companies evolved and created employment opportunities for the eligible labour force at different wage rates depending on their skills and type of labour. Total employment has always depended on the supply of and demand for labour (Cyert & Mowery, 1987; Mankiw, 2018). The labour supply is determined by demographic factors, which influence the number of entrants to the labour force each year, and by changes in the proportion of different groups of the population seeking employment (Cyert & Mowery, 1987; Mankiw, 2018). The demand for labour depends on the rate of growth in total output and real wages. Numerous

factors affect supply and demand (Cyert & Mowery, 1987; Mankiw, 2018) and can even create persistent unemployment despite economic expansion (Cyert & Mowery, 1987; Mankiw, 2018). The job market has always been impacted and driven by several macro environment factors such as global and regional trade policies (Lu, 2013; Kunz et al., 2016), technological advancements (Bessen, 2019), recession (Barker, 2011), and pandemics (Bodenhorn, 2020). The effectiveness of the entire economic system causes the creation or elimination of employment (Leonard, 1986).

Historically, there have been a series of changes in the international and regional trade policies (Murray, 1995; Chan, 2019; Pipkin, 2018; Noland, 2018), technology (Murray, 1995; Bessen, 2019; Kincade et al., 2017; Hodge et al., 2011), globalization (Sharp, 1980; Anderson et al., 2001), production shifts (Bals et al., 2016; Moore et al., 2018; Anderson et al., 2001), recession (Barker, 2011) and labour laws (Clark, 2018; Kaplan, 2017). These changes influenced the upstream and downstream trade for both manufacturing and non-manufacturing sectors. Removal of quotas and tariffs from textile and apparel imports in the U.S. increased the imports from Asian countries (Fugazza & Conway, 2010). The U.S. advancement in technology reduced the need for labour intensive work and hence the employment rates in the manufacturing facilities fell in the U.S. (Rotman, 2013; Hodge et al., 2011). Globalization facilitated the exchange of services and goods from cost-effective regions which led to the shift of production and manufacturing to developing countries (Cyert & Mowery, 1987). U.S. manufacturing employment had already started to face a contraction before the Great Recession of 2008 and continued to drop during the Recession (Harris, 2020; Atkinson et al., 2012).

In the following sections, individual macro environment factors and their impacts on employment are explored.

## 2.1 Impact of Trade Policies & Globalization

Global and regional policies have played a significant role in influencing the business dynamics of the textile industry. They have influenced sourcing and manufacturing networks at the state as well as at the international level. In the 1950s, the U.S. applied the first nontariff trade barrier, the voluntary export restraint (VER), to limit the apparel imports from Japan. In the 1960s, import quotas on cotton apparel were imposed under the Short- and Long-Term Arrangements. The agreements ultimately were not sufficient in curtailing imports enough. In 1974, the Multi Fiber Agreement (MFA) was enacted which created a quota system that would protect domestic manufacturing. In 1976, the U.S. had the highest number of apparel workers in the world. (Karlovac et al, 2021). In 1994, the U.S. signed the North American Free Trade Agreement (NAFTA) that dealt a blow to U.S. manufacturing. In 1995, the Agreement on Textile and Clothing (ATC) was initiated to phase out the MFA quotas over the next ten years. Roughly one million U.S. textile mill workers lost their jobs as a result, where 193,000 losses were solely in North Carolina (Sutton, 2007; Lu, 2018).

After the removal of the MFA quota system in 2005, trade patterns were diversified with liberalized trade flow. U.S. exports declined, with an accompanying increase in imports (Fugazza & Conway, 2010). The entry of China and Vietnam in the World Trade Organization in the 2000s also had a negative impact on the textile industry in the U.S. (Knappe, 2004) and impacted North Carolina. A large number of textile and apparel products were sourced from Asian countries such as India and China (Fugazza & Conway, 2010). Imports from China provided increased competition. Between 1990 and 2011, the share of world manufacturing exports originating in China increased from 2% to 16% (Hanson, 2012). The surge in China's exports came from the deep economic reforms in the 1980s and

1990s and the country's accession to the World Trade Organization in 2001 (Naughton, 2007). Among U.S. manufacturing imports, China's share rose from 4.5% in 1991 to 10.9% in 2001, and to 23.1% in 2011. Simultaneously, after staying relatively constant during the 1990s, U.S. manufacturing employment declined by 18.7% between 2000 and 2007 and further declined in 2011 (Acemoglu et al., 2016).

By the end of 2010, new free trade agreements (FTAs) such as the Central American Free Trade Agreement (CAFTA) and trade preference programs, such the African Growth Opportunity Act (AGOA) were established. Due to increased competition, U.S. textile manufacturers saw a drastic decline in the demand of their yarns and fabrics. Simultaneously, there was a huge rise in global sourcing and marketing in the retailing industry. Sales in the U.S. apparel retail market rose during this period. By 2014, the number of FTAs had increased again (Karlovac et al, 2021). At the end of the decade, with the popularity of "Made in USA" among a segment of U.S. consumers, some apparel and textile manufacturers have started to bring domestic production back (Karlovac et al, 2021).

## 2.2 Technological Change

Technological change transforms the production of goods and services while improving the efficiency of production processes. Technological change in manufacturing processes reduces the amount of labor and other resources to produce a unit of output, resulting in lower costs of production and lower labor requirements for the same output level. Technological changes often involve difficult adjustments for industries and individuals. Such change poses significant challenges at different levels of the economy: government policymakers, business, manager, labor, and individual workers (Cyert & Mowery, 1987).

The rates of development and adoption of technology by U.S. companies are different from the rates of companies located in other countries. Therefore, the impact on the labor force rate is relatively different leading to differences in labor costs, assuming other factors are constant. The quicker the adoption of technology, the quicker the fall in the production costs. To remain competitive, companies with less technological advancement in foreign countries, have lower labor costs. However, if technology is adopted at a fast rate by U.S. or foreign companies, a different scenario occurs.

Technology could create a need for more skilled workers which might produce higher-wage jobs. The changing nature of global competition has made it important for the U.S. workforce to have advanced skillsets (Cyert & Mowery, 1987; Rotman, 2013). A phenomenon called skill biased technological changes (SBTC), describes the relationship between technological change and employment. When a company implements or adopts innovative technology, many jobs requiring unskilled labor disappear. However, there is a positive employment effect for jobs requiring higher qualifications. Generally speaking, technological advancement leads to temporary unemployment which may disappear in the long term (Lenger, 2016) because unskilled

laborers either find employment in other industries, other suitable positions or acquire new skills. The impact of technology is an important macro environment consideration in the analysis of the labor force job market, however, it is out of scope in our current study.

### 2.3 Recession

The U.S. economy went through a deep recession in December 2007. Similar to the other recessions, the 2007 Great Recession led to the contraction in overall demand in the consumer market. Consumer spending decreased to a great extent. The fourth quarter of 2008 was the lowest point for GDP contraction for the U.S. economy. Sharp contraction in demand led to large layoffs, which increased the unemployment in the U.S. Job losses during the Great Recession were huge. However, from February 2010 to 2014, total employment and private sector employment grew consistently by 178,000 jobs per month and 188,000 jobs per month on average, respectively. By May 2014, the U.S. economy had finally recovered the 8.7 million jobs it had lost in the Great Recession (Farooq & Kugler, 2015). Figure 2.3 shows the unemployment rate in the U.S. from 1965 to 2013. The increase in unemployment during the recession followed by the fall of unemployment can be seen.



**Figure 2.3. U.S. Unemployment rate, 1965-2013 (Dec) (Bureau of Labor Statistics-Current Population Survey, 2015)**

To stimulate the economy and employment growth, several programs came into being when the U.S. economy began to slow down in 2006. Under President Bush, Congress passed the Economic Stimulus Act of 2008, which provided approximately \$100 billion in tax rebates to qualified households and other tax incentives for businesses. Then in 2008, the Emergency Economic Stabilization Act (EESA) was passed which then authorized the U.S. Treasury to invest up to \$700 billion as part of the Troubled Asset Relief Program (TARP). Promoting job and economic growth was among the goals of TARP. TARP's auto industry financing program was explicitly designed to protect jobs in the auto industry (Congressional Oversight Panel [COP], 2011). TARP was followed in early 2009 by the \$800 billion American Recovery and Reinvestment Act (ARRA). In December 2010, Congress enacted a tax cut package that temporarily reduced Social Security taxes for individuals and extended the 2001 and 2003 tax cuts. Moreover, this tax cut package extended unemployment insurance benefits, at an estimated cost of \$700 billion. Initial analysis suggested that these stimulus efforts done by the government had a limited impact on job creation and unemployment. There are contrasting views on the impact of TARP and other financial rescue efforts in the 2008 financial crisis. While there is agreement that these efforts helped in getting through the crisis, most economists have been skeptical about TARP's success in its other goals of increasing business lending, stemming the rising tide of foreclosures, and promoting job growth. While auto industry employment declined, the Congressional Budget Office (CBO) estimated that through the second quarter of fiscal year 2010, total ARRA stimulus expenditures were \$570 billion and that the effect on employment ranged from 1.4 to 3.6 million jobs. These figures imply costs per job created of \$158,000 to \$407,000 (Neumark & Troske, 2011).

In 2020, it was predicted that the global output, including from the U.S., would be far

worse than during the 2008 recession. As per an article by the New York Times published on April 14, 2020, the International Monetary Fund reported that the global economy was expected to contract by 3 percent in 2020 because of the shuttered factories, quarantines, and national lockdowns. This downturn was expected to be the worst in history. The IMF projected that the U.S. economy would contract by 6 percent in 2020. Tracking by S&P Global Panjiva showed that global shipments of goods into the US had dropped by 10.1 percent in March. This was the smallest number of monthly shipments since 2016. Consumer goods faced the most impact. Shipments of furniture, apparel, steel, and electronics fell by more than 15 percent in February 2020 compared with one year ago. According to IMF's chief economist Gita Gopinath, the loss of global output would be much worse than the 2008 financial crisis. Moreover, she said the traditional stimulus measures seemed to be little match for a pandemic fraught with shutdowns and quarantines (The New York Times, 2020). The GDP growth of the U.S. economy fell during Q2 2020 by 31.40%, which was the highest since the Great Recession in 2008. The unemployment rate went up to 14.7% in early 2020, which was the highest since World War II (Forbes, 2020).

It is predicted there will be a recession due to the 2020 pandemic which is expected to impact the labor force. In the current study, we explored the impact of the pandemic on the labor force, specifically in the different businesses of the textile industry. In addition to this, we determined the projected unemployment figures along with the number of projected establishments, which is contingent on the current situation.

## 2.4 Pandemic/Outbreak

The scale and scope of the COVID-19 pandemic has been compared to a previous pandemic in the U.S. in 1918-1919, known as the Influenza pandemic (or Spanish Flu).

Influenza infected approximately 500 million people worldwide, one-third of the population. This virus killed between 50 and 100 million people. The pandemic also coincided with the end of World War I. The war began in 1914, the U.S. entered in April 1917, outbreaks in the second much deadlier phase of the pandemic occurred in August 1918, and the Armistice occurred in November 1918. Workers were severely affected as they had to continue working unless they were physically unable. As per newspapers, retail-oriented sectors experienced dramatic declines in their business. Since the pandemic coincided with World War I, it was hard to identify the sole impact of the pandemic on the U.S. economy in 1918-19 (Clay, 2020). There is not extensive research on the impacts of the virus on the economy. However, the World Economic Forum estimated that the outbreak decreased real GDP per capita by 6-8%. According to the Forum, it was the fourth most negative macroeconomic shock in U.S. history following World War II, the Great Depression, and World War I, respectively. A study led by University of Florida biologists concluded that transmission of the disease had a significant correlation with unemployment. In particular, the scientists concluded that mortality rates in Chicago increased by 32% for every 10% increase in illiteracy rate. Many businesses including entertainment and service industries suffered huge losses, whereas healthcare businesses' revenues rose. The size of the labor force decreased because of a significant loss of prime working-age people, which led to an increase in wages. However, according to the St. Louis Federal Reserve, the economic effects of the 1918 Influenza Pandemic were short-term. Many businesses were able to restart their operations. A boost in the wages also declined eventually (Mintzer, 2020).

Comparing the current pandemic situation to the Influenza pandemic, the former has greater cushions such as private savings and government policies (Clay, 2020). There are several apparent effects on the labor market in the U.S. due to the current COVID-19

pandemic. The unemployment rate increased rapidly in the early months of the COVID-19 crisis. In the U.S. payroll employment numbers show that more than 20 million jobs were lost in April, which is a record amount for one month. However, employment has been increasing every month since then, while unemployment declined to 7.9% in September after a 14.7% April peak. (Engemann, 2020).

In an Economic Synopsis essay published in July 2020, Economist Serdar Birinci and Research Associate Aaron Amburgey found that workers in occupations with lower average earnings were disproportionately displaced by the pandemic, whereas workers in occupations with higher average earnings were less affected (Engemann, 2020).

J  
T  
A  
T  
M

The findings of the current study will help in understanding the impact of the pandemic on the labor force employed in different businesses/sectors of the textile industry. By comparing the patterns of a regular employment scenario with the current scenario, we were able to describe the potential level of impact to the North Carolina textile industry.

## 2.5 Forecasting the US Unemployment Rate

Actual estimates of GDP growth reported by forecasters have been falling after the month of March, when COVID-19 entered the U.S. For a regular 2020, OECD's forecast of global GDP for this period was to rise 2.4 percent. Now, in the Economic Outlook forecasts done in late May 2020, the global GDP forecasts were for a decline of 6.0% in 2020 in the scenario of a single wave. In the case of a second wave, a decline of 7.6% in 2020 was projected. Since the economic activities have declined rapidly, monthly, or even quarterly data do not highlight the current position of the economy. Weekly labor market data or unemployment claims are being utilized to evaluate the situation and direction of the volatile economy (Bowne, 2020). At present, certain adjustments are

continuously being made to forecasting methods to evaluate the market situation, and to track it on a frequent basis.

Many econometric models and time series models have been utilized in the past for forecasting various measures. There have been previous studies that focused on measuring forecasting performance during the rise and decline of unemployment using ARIMA models (Montgomery et al., 1998; Adenomon, 2017). The current study will add to that literature.

### 3. Data and Methodology

The North Carolina Department of Commerce, Labor and Economic Analysis Division (LEAD) and the U.S. Department of Labor's Bureau of Labor Statistics (BLS) have a federal-state cooperative program called The Quarterly Census of Employment and Wages (QECW) program. This program provides quarterly employment and wage data for the state of North Carolina and the United States. The QECW classifies business establishments using the North American Industry Classification System (NAICS) ([www.nccommerce.com](http://www.nccommerce.com)). We were interested in the data for the textile industry in North Carolina. We consulted the LEAD as to which NAICS codes would provide us with the most relevant and precise data. As suggested by LEAD, we used four-digit NAICS codes in the identification of companies. Data for the most recent years starting from the first quarter 2014 through the fourth quarter of 2020 came from <https://d4.nccommerce.com/QCEWSelection.aspx>.

This study divided textile companies based on the business types: Mills (all kinds of fiber, yarn, thread, fabric, apparel, and textile manufacturing, knitting, and finishing units), Retail (all kinds of apparel, textile, and home furnishing retail units), Services (dry cleaning and laundry services), and Wholesale (all kinds of apparel and textile related wholesalers) in North Carolina. Mills consisted of NAICS codes 3131, 3132, 3133,

3141, 3149, 3151, 3152, 3159. Retail consisted of NAICS codes 4422 and 4481. Services consisted of NAICS code 8123. Wholesale consisted of NAICS code 4243. For these four businesses, we chose three variables from the database: quarterly number of establishments (qtrly\_estabs\_count), quarterly employment (sum of month1\_emplvl, month2\_emplvl, and month3\_emplvl), and quarterly wages (total\_qtrly\_wages). These are all quarterly measures over all of the years studied. Data for the textile businesses encompass data for textile and apparel businesses, hereafter referred to as the textile industry.

As in previous analyses of the textile industry (Saki, 2020; Lu, 2015), this study used Autoregressive Integrated Moving Average (ARIMA) time series models to predict establishment, employment, and wages for textile companies in North Carolina.

## 4. Analysis & Results

### 4.1 The North Carolina Textile Industry (Q1 2014 – Q4 2018)

Data from Q1 2014 – Q4 2018 were analyzed to determine the suitability of using ARIMA models. ARIMA models fit satisfactorily. The predicted values of 2019 were then compared with the actual values of 2019. With very few exceptions, forecast and actual values for 2019 were not statistically different using 95% prediction intervals. The prediction intervals contained the actual values: establishments, employment, and wage data for all four textile industry sectors (mills, retail, wholesale, and services), with 95% confidence (only 2 actual observations from 2019 data did not fit in the upper confidence limit of 95% prediction interval). This was true for all textile companies analyzed together as well as for the individual textile sectors/businesses. Based on this validation, these ARIMA models were used for further predictions.

## 4.2 The North Carolina textile industry (Q1 2014 – Q4 2019)

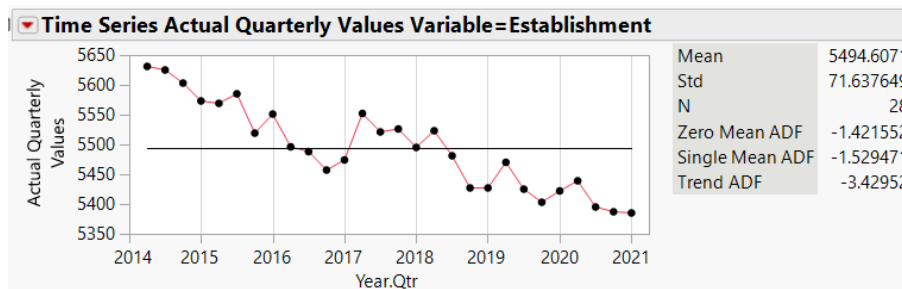
This section consists of the analyses using data up to the end of 2019. Time series analysis with ARIMA models was used to explore the trends, followed by forecasting future values. ARIMA models were used to forecast the values for the first four quarters of 2020. The predicted values for 2020 were calculated as follows. Based on ACF and PACF plots, parameters for AR (p) and MA (q) were chosen. To identify the differencing orders, d, and build a stationary series, the Augmented Dickey Fuller (ADF) test was used. Based on the suitable parameters p, d, q, ARIMA models were fit and compared to find the best model to predict the growth of establishments across the total number of textile companies in 2020. AIC was used to compare models. The residuals for the model were assessed for normality. The Ljung-Box

Q values were used to assess the models for autocorrelation. In section 4.2.1, the trends and best fitting forecast models for all textile companies combined without regard to industry sector/business are presented. This is done for establishment, employment, and wages across all the industry sectors (or business types). Section 4.2.2 covers the trends examined across all four sector/business types followed by the details on best fit forecast models for each of them.

### 4.2.1 All textile companies

#### 4.2.1.1 All textile companies: Establishments.

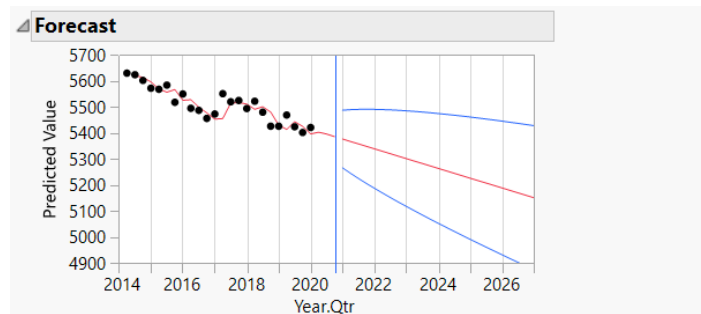
Figure 4.1 shows a time series plot of the number of establishments over time, including the actual values for the first three quarters of 2020.



**Figure 4.1. Time Series graph for establishments in the textile industry (Q1 2014 – Q4 2020)**

ARI (1,1) had the lowest AIC 230.17 when compared with other models. Figure 4.2 shows the plot with the 95% prediction

interval for the forecasts. The interval was less wide for this variable compared to employment and wages.



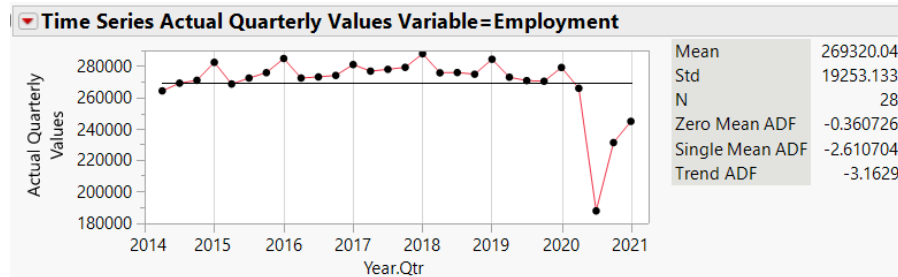
**Figure 4.2. Forecast plot for establishments in the textile industry based on the data from Q1 2014 to Q4 2019**



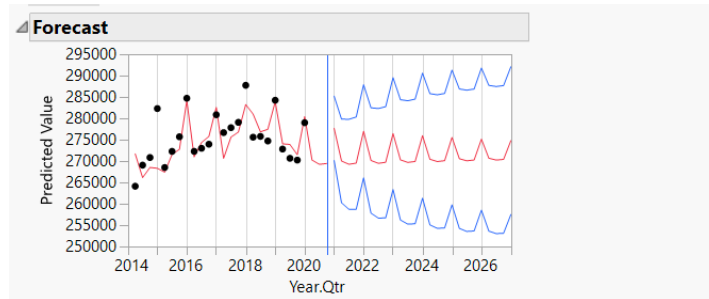
**4.2.1.2. All textile companies: Employment.**

Figure 4.3 shows a time series plot of employment over time, including the actual values for the first three quarters of 2020. The

seasonal ARIMA (1,0,0) (1,0,0) 4 fit the best with the lowest AIC of 463.465. As shown in Figure 4.4, the 95% prediction intervals are wide for this variable, compared to establishments and wages.



**Figure 4.3. Time Series graph for employment in the textile industry (Q1 2014 – Q4 2020)**

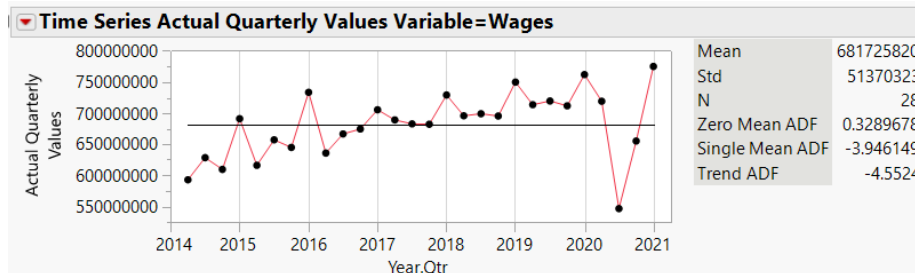


**Figure 4.4. Forecast plot for employment in the textile industry based on the data from Q1 2014 to Q4 2019**

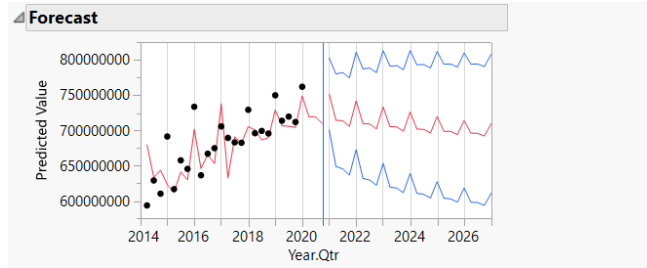
**4.2.1.3. All textile companies: Wages.**

Figure 4.5 shows a time series plot of wages over time, including the actual values for the first three quarters of 2020. The seasonal ARIMA (1,0,0) (1,0,0) 4 fit the best with an

AIC 890.453. Other models did not have adequate model fit indicated by the significant Q statistic. As shown in Figure 4.6, the 95% prediction interval is wide for this variable.



**Figure 4.5. Time Series graph for wages in the textile industry (Q1 2014 – Q4 2020)**



**Figure 4.6. Forecast plot for wages in the textile industry based on the data from Q1 2014 to Q4 2019**

**4.2.2 Trends across textile industry sectors in North Carolina (Q1 2014 – Q4 2019)**

**4.2.2.1. Establishment time series models**

The best fitting models' forecast graphs based on the lowest AIC are shown in table

4.1. Mills and services had narrower 95% prediction intervals as compared to those of retail and wholesale. In addition, mills and retail showed a downward trend for establishments whereas wholesale showed an upward trend for establishments.

**Table 4.1. Forecast plots for establishments in all four businesses in the textile industry based on the data from Q1 2014 to Q4 2019**

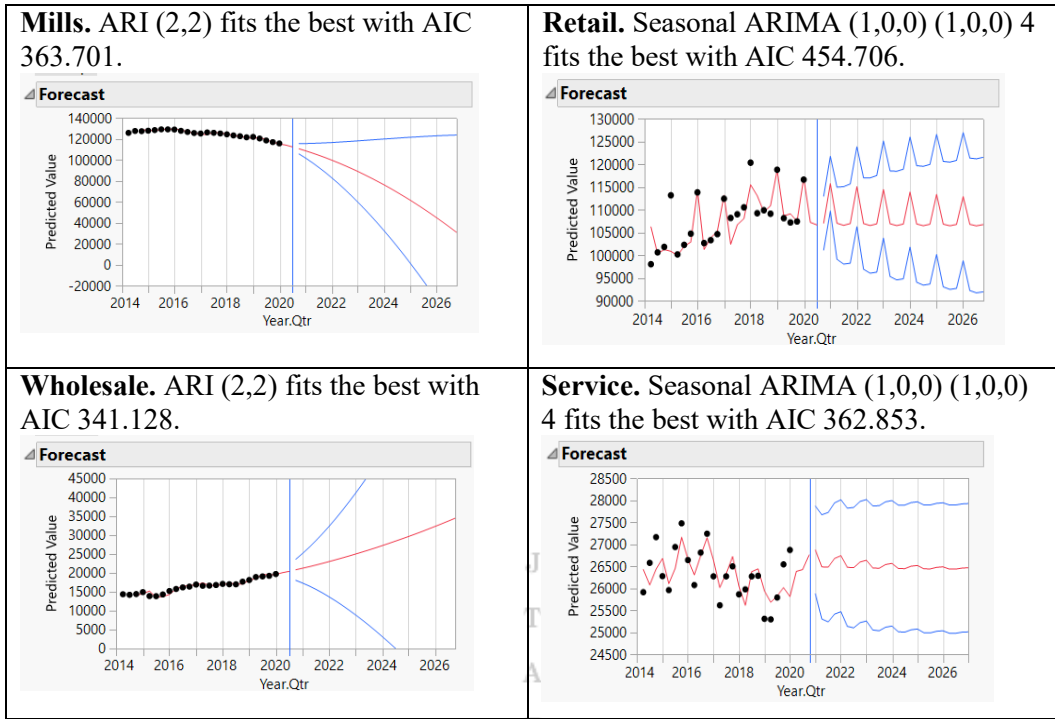
<p><b>Mills.</b> ARI (2,1) fits the best with AIC 150.206.</p>	<p><b>Retail.</b> ARI (1,1) fits the best with AIC 224.187.</p>
<p><b>Wholesale.</b> ARI (1,1) fits the best with AIC 175.245.</p>	<p><b>Service.</b> ARI (2,1) fits the best with AIC 162.260.</p>

**4.2.2.2. Employment time series models.**

The best fitting models' forecast graphs based on the lowest AIC are shown in Table 4.2. Services and retail had wide 95%

prediction intervals. Wholesale had an expanding upward trending 95% prediction interval and mill had an expanding downward trending 95% prediction interval for employment.

**Table 4.2. Forecast plots for employment in all four businesses in the textile industry based on the data from Q1 2014 to Q4 2019**

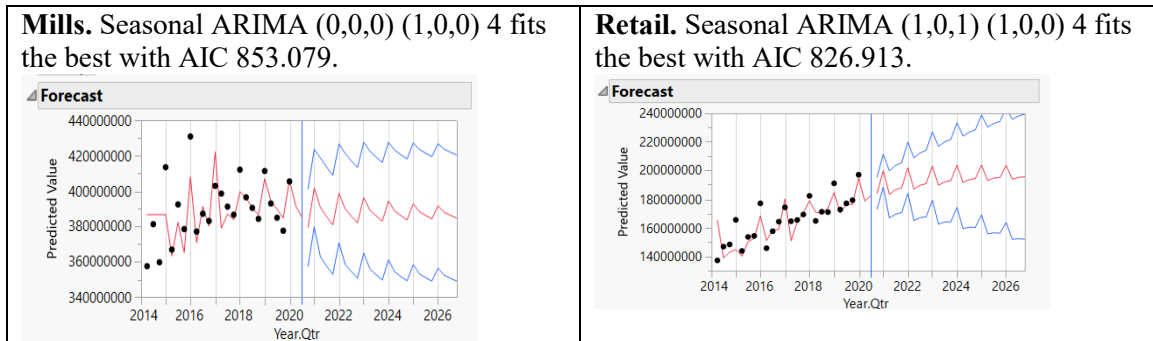


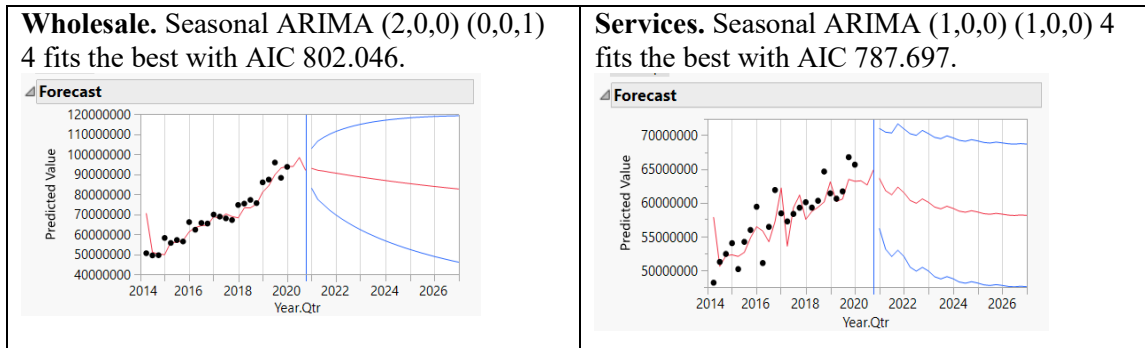
**4.2.2.3. Wage time series models.**

The best fitting modes' forecast graphs based on the lowest AIC are shown in table 4.3. All

four businesses had wide 95% prediction intervals.

**Table 4.3. Forecast plots for wages in all four businesses in the textile industry based on the data from Q1 2014 to Q4 2019**





### 4.3 Forecasts for Q1 – Q4 2020

#### 4.3.1 The North Carolina textile industry: All textile companies

Table 4.4 shows the actual quarterly values, predicted quarterly values, upper 95% confidence limit, and lower 95% confidence

limit based on Q1 2014 – Q4 2019 data for employment, establishments, and wages for all the textile companies. The difference column shows the difference between the actual and predicted values. This difference indicates whether the time series models built on pre-pandemic data (Q1 2014- Q4 2019) were able to predict pandemic conditions.

**Table 4.4. Comparison of the predicted data of 2020 with the actual data of 2020 for the textile industry**

Variable	Year	Qtr	Actual Quarterly values	Predicted Quarterly values	Upper CL (0.95)	Lower CL (0.95)	Difference	% difference
Employment	2020	1	265732	270227	276214	264240	(4,495)	-1.66%
Employment	2020	2	187767	269221	276260	262183	(81,454)	-30.26%
Employment	2020	3	231229	269424	276825	262024	(38,195)	-14.18%
Employment	2020	4	244710	277660	285194	270127	(32,950)	-11.87%
Establishments	2020	1	5439	5404	5472	5336	35	0.65%
Establishments	2020	2	5395	5397	5480	5315	(2)	-0.04%
Establishments	2020	3	5387	5387	5485	5289	0	0.00%
Establishments	2020	4	5385	5378	5489	5267	7	0.13%
Wages	2020	1	\$719,219,695	\$719,198,147	\$764,361,305	\$674,034,988	21,548	0.00%
Wages	2020	2	\$547,288,601	\$718,881,774	\$768,771,268	\$668,992,280	(171,593,173)	-23.87%
Wages	2020	3	\$655,527,548	\$709,667,282	\$760,538,788	\$658,795,777	(54,139,734)	-7.63%
Wages	2020	4	\$774,976,115	\$751,708,953	\$802,794,212	\$700,623,694	23,267,162	3.10%

Red colored values with negative sign in the table show that the actual data of 2020 did not fit in the prediction interval with the value less than the lower confidence limit

### 4.3.2 The North Carolina textile industry: Textile industry sectors/businesses

Table 4.5 has the following columns: the actual quarterly values, predicted quarterly values, upper 95% confidence limit, and lower 95% confidence limit based on Q1 2014 – Q4 2019 data for employment, establishments, and wages for all the textile industry sectors. The difference column

shows the difference between the actual and predicted values. This difference indicates whether the time series models built on pre-pandemic data (Q1 2014 - Q4 2019) were able to predict pandemic conditions. The largest decrease is in the second quarter of 2020. The third quarter numbers are better than the second quarter. Fourth quarter numbers are better than the third quarter.

**Table 4.6. Comparison of the predicted data of 2020 with the actual data of 2020 for the four textile businesses (mills, retail, wholesale, and service)**

	Business	Year	Qtr	Actual Quarterly Values	Predicted Quarterly Values	Upper CL (0.95)	Lower CL (0.95)	Difference	% change
Establishment	Mills	2020	1	811	815	826	803	(4)	-0.43%
	Mills	2020	2	804	810	825	794	(6)	-0.69%
	Mills	2020	3	802	806	823	789	(4)	-0.51%
	Mills	2020	4	806	802	821	783	4	0.50%
	Retail	2020	1	3,326	3,329	3,388	3,270	(3)	-0.09%
	Retail	2020	2	3,302	3,329	3,403	3,256	(27)	-0.82%
	Retail	2020	3	3,303	3,329	3,417	3,241	(26)	-0.78%
	Retail	2020	4	3,294	3,329	3,428	3,229	(35)	-1.04%
	Services	2020	1	851	825	840	810	26	3.15%
	Services	2020	2	839	819	838	800	20	2.42%
	Services	2020	3	826	813	835	791	13	1.58%
	Services	2020	4	826	807	832	782	19	2.35%
	Wholesale	2020	1	451	436	456	415	15	3.45%
Wholesale	2020	2	450	437	465	409	13	2.95%	
Wholesale	2020	3	456	438	472	405	18	4.06%	
Wholesale	2020	4	459	439	478	401	20	4.48%	
Employment	Mills	2020	1	113,824	114,142	115,866	112,418	(318)	-0.28%
	Mills	2020	2	93,049	112,434	115,663	109,205	(19,385)	-17.24%
	Mills	2020	3	102,168	110,637	115,578	105,695	(8,469)	-7.65%
	Mills	2020	4	104,151	108,700	115,639	101,761	(4,549)	-4.19%
Retail	2020	1	106,129	107,224	112,066	102,383	(1,095)	-1.02%	

	Retail	2020	2	56,224	106,662	112,315	101,008	(50,438)	-47.29%
	Retail	2020	3	88,932	107,063	112,983	101,142	(18,131)	-16.93%
	Retail	2020	4	99,088	115,740	121,756	109,725	(16,652)	-14.39%
	Services	2020	1	26,805	26,389	27,197	25,581	416	1.58%
	Services	2020	2	21,892	26,433	27,373	25,493	(4,541)	-17.18%
	Services	2020	3	22,881	26,762	27,745	25,779	(3,881)	-14.50%
	Services	2020	4	22,721	26,877	27,875	25,879	(4,156)	-15.46%
	Wholesale	2020	1	18,974	20,068	21,098	19,038	(1,094)	-5.45%
	Wholesale	2020	2	16,602	20,419	22,298	18,540	(3,817)	-18.69%
	Wholesale	2020	3	17,248	20,829	23,622	18,037	(3,581)	-17.19%
	Wholesale	2020	4	18,750	21,237	25,132	17,342	(2,487)	-11.71%
Wages	Mills	2020	1	\$383,428,300	\$391,724,689	\$413,613,384	\$369,835,994	(8,296,389)	-2.12%
	Mills	2020	2	\$290,914,209	\$385,284,966	\$407,173,661	\$363,396,271	(94,370,757)	-24.49%
	Mills	2020	3	\$334,901,823	\$379,394,567	\$401,283,263	\$357,505,872	(44,492,744)	-11.73%
	Mills	2020	4	\$406,365,674	\$401,700,251	\$423,588,946	\$379,811,556	4,665,423	1.16%
	Retail	2020	1	\$177,689,414	\$178,683,638	\$189,467,774	\$167,899,501	(994,224)	-0.56%
	Retail	2020	2	\$122,536,066	\$182,407,725	\$193,443,315	\$171,372,135	(59,871,659)	-32.82%
	Retail	2020	3	\$166,855,049	\$184,217,930	\$195,488,113	\$172,947,747	(17,362,881)	-9.43%
	Retail	2020	4	\$197,624,219	\$199,948,213	\$211,437,674	\$188,458,753	(2,323,994)	-1.16%
	Services	2020	1	\$63,423,944	\$63,293,922	\$68,972,577	\$57,615,267	130,022	0.21%
	Services	2020	2	\$52,281,574	\$62,664,810	\$69,476,215	\$55,853,405	(10,383,236)	-16.57%
	Services	2020	3	\$59,848,428	\$64,854,087	\$72,106,852	\$57,601,323	(5,005,659)	-7.72%
	Services	2020	4	\$62,201,940	\$63,634,739	\$71,072,884	\$56,196,593	(1,432,799)	-2.25%
	Wholesale	2020	1	\$94,678,037	\$93,969,857	\$100,213,799	\$87,725,915	708,180	0.75%
Wholesale	2020	2	\$81,556,752	\$98,381,753	\$105,964,564	\$90,798,943	(16,825,001)	-17.10%	
Wholesale	2020	3	\$93,922,248	\$92,037,241	\$100,963,157	\$83,111,324	1,885,007	2.05%	
Wholesale	2020	4	\$108,784,282	\$92,956,312	\$102,928,445	\$82,984,180	15,827,970	17.03%	

Red colored values with negative sign in the table show that the actual data of 2020 did not fit in the prediction interval with the value less than the lower confidence limit. Blue colored values in the table show the actual data from 2020 did not fit in the prediction interval with the value higher than the upper confidence limit.

## 5. Discussion & Conclusion

The purpose of this study was to assess whether ARIMA models could be

constructed to predict the 2020 employment trends in the North Carolina textile industry from pre-pandemic data. The findings were mixed.

Some of the ARIMA models from 2014-2019 data forecast employment trends in 2020, however some did not. When looking at all textile businesses combined, the forecasts for Q1 2020 were accurate for establishments, employment, and wages. When examining the businesses separately, the results were mixed. The forecasts for the number of establishments were accurate for mills, retail, and wholesale for the entire 2020. For services, the forecast was accurate for only Q3 & Q4. The forecasts for employment were accurate for mills, retail, and services in Q1, but not for wholesale. No other employment forecasts were accurate besides those of mills & wholesale in Q4. The models forecast wages accurately for mills, retail, services, and wholesale in Q1 & Q4. In addition, the forecasts were accurate for services and wholesale in Q3.

It is perhaps not surprising that the forecasts were the best for Q1 2020. The pandemic was just beginning. The economy would not feel the effects immediately. The fact that the number of establishments were accurately predicted for the entire 2020 may be due to the fact that the businesses adjusted to stay in business.

The actual and predicted values from the 2020 data were compared to get a snapshot of the textile industry in North Carolina. The data showed a downward trend in the number of establishments from 5650 in 2014 to 5400 by the third quarter of 2020. Forecasts based on pre-pandemic data through 2019 showed a downward and narrow prediction interval, as compared to prediction intervals for other variables, for 2020. Establishments for mills and services were already decreasing before 2020. Retail establishment numbers were fluctuating before 2020. The number of wholesale establishments, however, increased in 2018 and 2019. When comparing actual and predicted values for 2020, there was a very small impact on the total establishments. The actual number of retail establishments was smaller than the projected values by approximately 0.8% in Q2 and Q3, followed by textile mills with an

overestimate in establishments by approximately 0.5-0.7% by the projected values. However, the number of textile service and wholesale establishments were overestimated by approximately 2-4% in 2020.

All textile companies together in North Carolina employed 0.27 million people on average with a seasonal rise in the fourth quarter every year. As expected, the employment numbers dropped down to approximately 0.19 million people in Q2 2020. Since the employment trend was uniform by the end of 2019, the prediction intervals were moving along the mean with wide intervals for 2020 and later years. The ARIMA model overestimated employment in the textile retail companies by approximately 47% in the second quarter of 2020. However, in the third quarter, there was an increase with 32,000 people employed which showed potential recovery in the textile retail industry. Employment by mills was overestimated by approximately 17% in Q2 2020. Similarly, employment by wholesale companies was overestimated by approximately 19% in Q2 2020. The overestimate improved by just 1% from the projected values in the third quarter of 2020. Laundry and dry-cleaning services were overestimated by approximately 17% by the projections in Q2 2020, which recovered in Q3 2020 adding approximately 1000 jobs in this quarter. This is still 14.5% less than the projected jobs.

There had been a gradual increase every year until the end of 2019 in the wages earned by the population employed by all the textile companies. In addition to the gradual increase in wages, there was a higher rise in the fourth quarter every year because of a seasonality factor. However, similar to the employment case, wages also had a huge downward spike by the end of Q2 2020. Forecasts show wide prediction intervals for the wages of the textile companies. Mills had a uniform trend along the mean line for wages mixed with year-end seasonality. Retail, wholesale, and services had a gradual

J  
T  
A  
T  
M

increase through the period from 2014 to 2019. However, by the end of Q2 2020, wages were down across all the four business types. For mills, the actual reduction was as large as 24.5% from the projected wages, which improved in the third quarter. For retail, wages were overestimated by 33% from the projected values. Wages did improve in the third quarter. Similarly, for both wholesale and services the wages were overestimated by 16-17% from the projected values, and the situation for both improved in the third & fourth quarter of 2020.

There were some limitations. First, we did not conduct outlier analysis. There were clearly outliers and if those were taken into account when modeling, we would have achieved better models in some cases. Second, we utilized the public data available on the LEAD website which is limited to quarterly data. Using a greater number of data points from monthly, weekly, or daily data might help with better forecasts. Third, this study is limited to the textile industry located in North Carolina. Fourth, it is possible that there can be other possible reasons behind the changes in numbers, such as changing government regulations, subsidies, and technology disruption. Analyzing those reasons are out of the scope of the study and recommended for future research.

## References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., & Price, B. (2016). Import competition and the Great US Employment SAG of the 2000s. *Journal of Labor Economics*, 34(S1). doi:10.1086/682384

Adenomon, M. (2017, April). Modelling and forecasting unemployment rates in Nigeria using ARIMA model. *RUW Trends in Science & Technology Journal*, 2, 525-531.

Anderson, C. D., Schulman, M. D., & Wood, P. J. (2001). Globalization and uncertainty: The restructuring of southern textiles. *Social Problems*, 48(4), 478-498. doi:10.1525/sp.2001.48.4.478

Atkinson, R. D., Stewart, L. E., Andes, S. M., & Ezell, S. J. (2012, March). Worse Than the Great Depression: What Experts Are Missing About American Manufacturing Decline (Rep.). Retrieved [http://www2.itif.org/2012-american-manufacturing-decline.pdf?\\_ga=2.238659456.1063962372.1617901994-943341213.1617901994](http://www2.itif.org/2012-american-manufacturing-decline.pdf?_ga=2.238659456.1063962372.1617901994-943341213.1617901994)

Bals, L., Kirchoff, J. F., & Foerstl, K. (2016). Exploring the reshoring and insourcing decision-making process: Toward an agenda for future research. *Operations Management Research*, 9(3-4), 102-116. doi:10.1007/s12063-016-0113-0

Barker, M. (2011, April). Manufacturing employment hard hit during the 2007-09 recession. *Monthly Labor Review*. [Washington, DC]: U.S. Dept. of Labor, Bureau of Labor Statistics. <https://www.bls.gov/opub/mlr/2011/04/art5full.pdf>

Bessen, J. (2019). Automation and jobs: When technology boosts employment\*. *Economic Policy*, 34(100), 589-626. doi:10.1093/epolic/eiaa001

Bodenhorn, H. (2020.) Business in a time of Spanish Influenza. *National Bureau of Economic Research*. <http://www.nber.org/papers/w27495>

Bowne, T. (2020). Forecasting in a Time of Crisis: How COVID-19 is Affecting Economic Forecasting [Interview]. Retrieved October 25, 2020, from <https://www.freedoniagroup.com/Content/Macroeconomics-Trends-Talk-with-Freedomia-Chief-Economist>

Chan, J. (2019). Tariffs and the composition of Employment: Evidence from the Canada-US free trade agreement. *Canadian Public Policy*, 45(3), 342-365. doi:10.3138/cpp.2018-080

Clark, G. E. (2018). Coercion and contract at the Margins: Deportable labor and the laws of employment termination Under US capitalism (1942-2015). *Law & Social Inquiry*, 43(03), 618-646. doi:10.1111/lsi.12255

J  
T  
A  
T  
M



- Clay, K. (2020, March 25). Pandemics and the Labor Market-Then and Now. IZA World of Labor. <https://wol.iza.org/opinions/pandemics-and-the-labor-market-then-and-now>
- Cyert, R. M., & Mowery, D. C. (Eds.). (1987). Technology and employment innovation and growth in the U.S. economy. Washington, D.C.: National Academy Press. Retrieved from <https://www.nap.edu/read/1004/>.
- Duarte, A., Sanches, R., & Dedini, F. (2018, December). Assessment and technological forecasting in the textile industry: From first industrial revolution to the Industry 4.0. *Strategic Design Research Journal*, 11(3), 193-202. doi:10.4013/sdrj.2018.113.03
- Engemann, K. M. (2020, October 14). How the COVID-19 Pandemic Has Affected the U.S. Labor Market: St. Louis Fed. Retrieved October 25, 2020, from <https://www.stlouisfed.org/open-vault/2020/october/how-covid19-pandemic-has-affected-labor-market>
- Farooq, A., & Kugler, A.D. (2015, February 28) What factors contributed to changes in employment during and after the Great Recession? *IZA Journal of Labor Policy* 4, 3. <https://doi.org/10.1186/s40173-014-0029-y>
- Fugazza, M., & Conway, P. J. (2010). The impact of removal of ATC quotas on international trade in textiles and apparel. New York, NY: United Nations. Retrieved October 25, 2020, from [https://unctad.org/system/files/official-document/itcctab45\\_en.pdf](https://unctad.org/system/files/official-document/itcctab45_en.pdf)
- Hanson, G. H. (2012). The rise of middle kingdoms: Emerging economies in global trade. *Journal of Economic Perspectives*, 26(2), 41-64. doi:10.1257/jep.26.2.41
- Harris, K. (2020). Beyond numbers: Forty years of falling manufacturing employment (Vol. 9, Ser. 16) (United States, U.S. Bureau of Labor Statistics, Employment and Unemployment Statistics). Retrieved from <https://www.bls.gov/opub/btn/volume-9/forty-years-of-falling-manufacturingemployment.htm>
- History. (2021, January 12). Retrieved 2021, from <https://textileheritagemuseum.org/history/>
- Hodge, G. L., Goforth Ross, K., Joines, J. A., & Thoney, K. (2011). Adapting lean manufacturing principles to the textile industry. *Production Planning & Control*, 22(3), 237-247. doi:10.1080/09537287.2010.498577
- JMP 14 predictive and specialized modeling. (2018). Cary, NC: SAS Institute.
- Kaplan, A. (2017). The complexities of US labor law – an evolving landscape. *Strategic HR Review*, 16(6), 285-287. doi:10.1108/shr-08-2017-0054
- Kincade, D. H., & Dull, E. H. (2017). Two hundred years of textile factories in the U.S. South. *Clothing and Textiles Research Journal*, 35(3), 172-186. doi:10.1177/0887302x17697840
- Knappe, M. (n.d.). Textiles and Clothing uncertainties before and after the quota phase-out (Publication). Retrieved October 25, 2020, from International Trade Centre, Geneva 2004 website: [https://www.intracen.org/uploadedFiles/intracen.org/Content/Exporters/Sectoral\\_Information/Manufactured\\_Goods/Textiles/Textiles\\_and\\_Clothing\\_Uncertainties\\_before\\_and\\_after\\_the\\_quota\\_phase-out.pdf](https://www.intracen.org/uploadedFiles/intracen.org/Content/Exporters/Sectoral_Information/Manufactured_Goods/Textiles/Textiles_and_Clothing_Uncertainties_before_and_after_the_quota_phase-out.pdf)
- Kunz, G. I., Karpova, E., & Garner, M. B. (2016). Going global the textile and apparel industry. (3rd ed.). New York, NY: Fairchild Books, Bloomsbury Publishing.
- Lenger, A. (2016). The inter-industry employment effects of technological change. *Journal of Productivity Analysis*, 46(2-3), 235-248. doi:10.1007/s11123-016-0485-z

- Lu, J. (2015). Forecasting of U.S. total textiles and apparel export to the world in next 10 years (225-2025). *Journal of Textile and Apparel, Technology and Management*, 9(2), 1-8.
- Lu, S. (2013). Impacts of quota elimination on world textile trade: a reality check from 2000 to 2010. *The Journal of the Textile Institute*, 104(3), 239-250. doi: 10.1080/00405000.2012.717753
- Mankiw, N. G. (2018). *Principles of economics* (8th ed.). Boston, MA, USA: Cengage Learning.
- Mintzer, A. (2020, April 22). A Brief Economic History of Pandemics (1264073659 934445920 A. Yao, Ed.). *Berkeley Economic Review*. Retrieved from <https://econreview.berkeley.edu/a-brief-economic-history-of-pandemics/>
- Montgomery, A. L., Zarnowitz, V., Tsay, R. S., & Tiao, G. C. (1998). Forecasting the U.S. Unemployment Rate. *Journal of the American Statistical Association*, 93(442), 478-493. doi:10.1080/01621459.1998.10473696
- Moore, M. E., Rothenberg, L., & Moser, H. (2018). Contingency factors and reshoring drivers in the textile and apparel industry. *Journal of Manufacturing Technology Management*, 29(6), 1025-1041. doi:10.1108/jmtm-07-2017-0150
- Murray, L. A. (1995, August). Unraveling employment trends in textiles and apparel. *Monthly Labor Review*. U.S. Division of Monthly Industry Employment Statistics, Bureau of Labor Statistics.
- Naughton, B. (2007). *The Chinese economy: Transitions and growth*. (2007). Cambridge, MA: MIT Press
- Neumark, D., & Troske, K. (2011). Addressing the employment situation in the aftermath of the Great Recession. *Journal of Policy Analysis and Management*, 31(1), 160-168. doi:10.1002/pam.20622
- Noland, M. (2018). US trade policy in the Trump administration. *Asian Economic Policy Review*, 13(2), 262-278. doi:10.1111/aepr.12226
- Pickles, J., Plank, L., Staritz, C., & Glasmeier, A. (2015). Trade policy and regionalisms in global clothing production networks. *Cambridge Journal of Regions, Economy and Society*, 8 (3), 381-402.
- Pipkin, S. (2018). Managing regional impacts of trade liberalization: Informal practices and collaborative economic development on the U.S.–Mexico border. *Economic Development Quarterly*, 32(2), 146-162. doi:10.1177/0891242418770004
- Press release dated July 30, 2003. (2003, July 30). Retrieved March 15, 2021, from <https://www.sec.gov/Archives/edgar/dat a/896265/000119312503032712/dex991 .htm>
- Rotman, D. (2013, June 12). How Technology Is Destroying Jobs. *MIT Technology Review*. Retrieved October 25, 2020, from <https://www.technologyreview.com/2013/06/12/178008/how-technology-is-destroying-jobs/>
- Rumberger, R. W., & Levin, H. M. (1985, July). Forecasting the impact of new technologies on the future job market. *Technological Forecasting and Social Change*. 27(4). Retrieved from [https://doi.org/10.1016/0040-1625\(85\)90020-4](https://doi.org/10.1016/0040-1625(85)90020-4)
- Sharp, C. (1980, September 16). Bobbin Show: Globalization Seen As Key To Us Textile Trade. *Women's Wear Daily*, 141(54), 22. Retrieved from <https://proxying.lib.ncsu.edu/index.php/login?url=https://www-proquest-com.prox.lib.ncsu.edu/magazines/bobbinn-show-globalization-seen-as-key-us-textile/docview/1445492521/se-2?accountid=12725>
- Saki, Z. (2020). *An investigation of U.S. textile and apparel (TAP) industry competitiveness* (Publication No. 27949949) [Doctoral dissertation, North Carolina State University]. ProQuest Dissertations & Theses Global.
- Sutton, E. (2007, July 04). A history of layoffs. Retrieved March 15, 2021, from <https://clclt.com/charlotte/a-history-of-layoffs/Content?oid=2142894>

J  
T  
A  
T  
M

United States Congressional Oversight Panel.  
(2011, January 13) An Update on TARP  
Support for the Domestic Automotive  
Industry: Congressional Oversight Panel  
January Oversight Report.  
<https://fraser.stlouisfed.org/title/5142>

Zhao, L., & Kim, K. (2021). Responding to  
the COVID-19 Pandemic: Practices and  
strategies of the global clothing and Textile  
value chain. *Clothing and Textiles Research  
Journal*, 39(2), 157-172.  
doi:10.1177/0887302x21994207

J  
T  
A  
T  
M