https://doi.org/10.20965/jaciii.2015.p0335

Paper:

The Determinants of the Textile Index: Linear or Nonlinear

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[Received December 15, 2013; accepted February 26, 2015]

This paper analyzes the Keqiao Textile Index of China, which reflects China Textile City, the leading wholesale textile market in China. China Textile City is a textile entrepot with the most extensive scale and the largest line of business in China, and it is the largest specialized market for light textile in Asia as well. Thus, it is worthwhile to analyze this index. In this paper, 10 variables that represent the factors that significantly influence the Textile Index are selected from the set of possible variables that are deemed to be valid to the index. 6 variables are identified as nonlinear and 4 as linear by the nonparametric method. Then, varying-coefficient partially linear models are established, dividing the index into five terms: one nonparametric term and four linear terms. Each of the five terms comprises approximately 20% of the index, with the linear terms accounting for nearly 80%. Among the six nonparametric variables, cotton index A plays the most important role. The empirical and simulated results consistently show that the percent of each of the five terms would not vary substantially during the sample period if cotton index A were not more than twice the sample mean. Thus, textile prices can be regulated by properly adjusting the cotton price.

Keywords: local-constant least squares, local-linear least squares, base model, path model, semiparametric time-varying coefficient model

1. Introduction

This paper analyzes the Keqiao Textile Index of China, which reflects China Textile City, China's leading professional textile wholesale market for the last 17 years. This index is comprised of a raw materials index, a grey cloth index, an apparel fabric index, a home textile index, and a fashion accessories index. Recently, fluctuations in the prices of international oil and cotton have caused the prices of upstream and downstream products in the textile industry to fluctuate substantially. This index serves as a barometer of the national textile industry, and it is thus a worthwhile subject of analysis.

In the paper, we first investigate the Keqiao Textile Index of China (henceforth, "the Textile Index") in order to identify the determinants from the numerous factors that may affect the Textile Index and then identify the mechanism by which the determinants affect the Textile Index, whether linearly or nonlinearly, by the nonparametric approaches proposed by Hall et al. [1]. Finally, we construct varying-coefficient partially linear models to analyze and simulate the fluctuation of the primary nonlinear variables and identify the responses of the linear terms and the nonlinear term.

The first step is to select and identify the variables. Conventional studies tend to assume that the relationship between the independent variable and the dependent variables is linear. To select the relevant variables that determine the independent variable, a regression equation is established, and a t-test is then needed to determine whether each of the dependent variables is significant. If a variable is not significant, it is believed not to affect the independent variable statistically, and it will be omitted from the set of possible dependent variables. However, if there are numerous multicollinear variables in the variable set, it is unnecessary for the variables that accept null hypothesis are not significant. Therefore, researchers typically try to find determinants by stepwise regression or principal component analysis.

Stepwise regression is widely applied in various areas to select the factors that affect the independent variable. Its uses have included analysis of the factors that influence commodity house prices [2], evaluation of economic growth by investment, consumption, government expenditures, export, and a four-trillion-yuan economic stimulus plan based on ridge regression [3], analysis of how corporate governance and company finance affect cash dividend distribution policies [4], research on cash dividend distribution policy in listed companies based on a multiple regression model [5], analysis of the factors that influence hepatitis B [6], analysis of the factors that influence on-line time among senior high school students [7], and research on the factors that influence rice yields [8].

Principal component analysis is also used to select dependent variables. It has been utilized in various ways, including the study of an evaluation system for real estate bubble levels [9], empirical study of the widened differences in the personal income of Chinese city dwellers [10], regional disparities in production efficiency and the decomposition of productivity growth [11], and analysis of factors that affect living standards in rural areas of Jilin Province [12]. Because principal component analysis includes a linear combination of several factors, the meaning of its coefficient is not explicit. Thus, the parametric methods are not so satisfactory.

Both stepwise regression and principal component analysis must satisfy the Gauss Markov assumptions; otherwise, any inferences and policy suggestions based on these approaches would be unreasonable. In fact, the assumptions might hold approximatively. Further, these two methods can only describe linear relationships between the independent variable and dependent variables or relationships that can be transformed into linear ones. Actually, it is true that all the relationships are not linear or all of the nonlinear can be transformed into linear ones.

[1] shows that with the local-constant least squares (LCLS) regression method, if the bandwidth on any regressor reaches its upper bound, that regressor is essentially smoothed out from the dependent variable set. Actually, when the bandwidth reaches its upper bound, the kernel function becomes a constant [13]. With local-linear least squares (LLLS) regression method, if the true functional form is linear, the LLLS estimator nests the OLS estimator when the bandwidth is very large [13]. This means that the dependent variables can be identified as linear or nonlinear according to their bandwidths. [13] employed such methods to select the relevant variables for economic growth and to determine its mechanism.

We apply nonparametric methods to determine the factors that affect the Textile Index and then identify them as linear or nonlinear. Our goal is to determine how these linear and nonlinear variables affect the Textile Index and to provide a basis for controlling textile prices by adjusting these variables.

The rest of this paper is organized as follows. In Section 2, we determine an initial set of variables that may affect the Textile Index and then select significant ones from it and do identification to the significant variables as linear or nonlinear: there are four linear variables and seven nonlinear ones. In Section 3, we establish partial linear models and use them to estimate the coefficients. In Section 4, we find cotton index A is the most important of the seven nonlinear variables. In Section 5, we simulate cotton index A to find out how it affects on the Textile Index. Section 6 concludes.

2. Selection and Identification of the Dependent Variables

2.1. The Initial Dependent Variable Set

In this paper, we study the Textile Index, which has been received relatively little study. However, numerous studies have been conducted on stock indexes, such as S&P 500 stock index, Shanghai composite index, and Shenzhen component index, and the theories and models are mature. In theory, the macroeconomic environment, the market itself, and the mentality of investors are among the factors that affect market conditions. Many factors may influence the Textile Index. As the textile market is a part of the economy, factors that affect the stock market may affect the textile market as well, but the substantial difference between the exchange objects in the two markets may mean that there is a substantial difference in the factors. Insiders believe that textile prices are affected by raw material price, labor costs, and the printing and dyeing industry in addition to the macroeconomic environment.

We use an economic boom consistent index to stand for the demand for textiles; the cotton price, crude oil price and labor cost for the costs of the textile industry, and labor productivity and investment in research and development for technological innovation. The macroeconomic environment is characterized by the supply of money, inflation, interest rates, loans from financial enterprises, the level of the exchange rate, and other factors. The availability of observations must also be take into consideration. We choose 14 variables for the initial dependent variable set to be nested for whether they are relevant or irrelevant for and linear or nonlinear to the Textile Index. The nonlinear variables are possible paths by which the index can change. The variables and their notations are listed below.

- y : the Textile Index (the dependent variable);
- t : time;
- z_1 : economic boom consistent index (1996 = 100);
- z_2 : monthly average crude oil price (dollars per barrel);
- z_3 : cotton index A (cents per kg);
- z_4 : supply of money (M1);
- z_5 : consumer price index (a year earlier = 100);
- z_6 : retail price index (a year earlier = 100);
- z_7 : producer price index (a year earlier = 100);
- z_8 : benchmark one-year deposit rate (annual percentage rate);
- z_9 : enterprise deposits in financial institutions (one hundred million yuan);
- z_{10} : saving deposits in financial institutions (one hundred million yuan);
- z_{11} : short-term loan from financial institutions (one hundred million yuan);
- z_{12} : medium- and long-term loans from financial institutions (one hundred million yuan);
- z_{13} : level of exchange rate, yuan/U.S. dollars);
- z_{14} : ending state foreign exchange reserves (one hundred million US dollars).

Because there are many other factors, we add the first-order lag term (y_{-1}) and the second-order lag term (y_{-2}) of the Textile Index to the initial dependent variable set, for a total of 16 variables.

2.2. The Sample

The sample period is from January 2008 to December 2012, and the number of observations is 60. The Textile Index data, which are published every Monday, were downloaded from the website of the Keqiao Textile Index of China. We obtain the average of the numbers for each month as the monthly data. The supply of money and the benchmark one-year deposit rate were obtained from the People's Bank of China, and the other data were obtained from DRCNet Statistical Database System. Several missing data were supplemented by the cubic spline interpolation function method.

2.3. Selection and Identification

In this subsection, we apply the results of Hall, Li, and Racine [1] to select and identify the initial variables by nonparametric regression.

Suppose

$$y_i = g_1(t_i, y_{i-1}, y_{i-2}, \mathbf{Z}_i) + \varepsilon_i,\ (i = 1,2,\ldots,n)\ . \quad (1)$$

where $\mathbf{Z}_i = (z_{i1}, z_{i2}, \ldots, z_{i,14})$, $g_1(\cdot)$ is an unknown function, and ε_i is a random disturbance with zero expectation. It is unnecessary to assume that the dependent variables are linear and uncorrelated with each other. We estimate the unknown function $g_1(\cdot)$ by two nonparametric regression methods, which are local-constant least squares (LCLS) and local-linear least squares (LLLS). The bandwidth of each dependent variable for the sample is specified by least-square cross-validation (LSCV). In the asymptotic sense, the corresponding dependent variable is independent of or linear to the independent variable when its bandwidth is equal to the upper bound. If the sample size is infinite, the upper bound of the bandwidth is infinite. Empirically, the upper bound of the bandwidth is set as twice the sample standard deviation.

First, we select variables from the initial dependent variable set, estimating the unknown function $g_1(\cdot)$ by LCLS. The bandwidths and twice the standard deviations of the samples are presented in **Table 1**. If a variable's bandwidth is greater than twice the sample standard deviation, the variable is believed to have no relevance to the Textile Index and should thus be omitted from the variable set; otherwise, the variable is relevant to the Textile Index. As **Table 1** shows, the economic boom consistent index, consumer price index, benchmark one-year deposit rate, saving deposits in financial institutions, medium- and long-term loans from financial institutions, and second-order lag term of the Textile Index are omitted. Eq. (1) becomes

$$y_i = g_2(t_i, y_{i-1}, \mathbf{Z}_i) + \varepsilon_i,\ (i = 1,2,\ldots,n)\ \ldots \quad (2)$$

where $\mathbf{Z}_i = (z_{i2}, z_{i3}, z_{i4}, z_{i6}, z_{i7}, z_{i9}, z_{i,11}, \ldots, z_{i,14})$, $g_2(\cdot)$ is an unknown function, and ε_i is a random disturbance with zero expectation.

Second, we identify the remaining variables, estimating $g_2(\cdot)$ by LLLS and specifying the bandwidths by LSCV. The bandwidths are listed in **Table 1**. Comparing column 3 and column 4 in **Table 1**, if a variable's bandwidth is greater than twice the sample standard deviation, the variable is linear in the model; otherwise, it is nonlinear. As a result, the monthly average crude oil price, retail price index, producer price index, and first-order lag term of the Textile Index are linear. Thus, Eq. (2) becomes

Table 1. Bandwidths and twice the standard deviations of the sample.

var	LCLS BW	LLLS BW	2SD
z_1	2216900.00	——	5.96
z_2	5.41	46.15	43.90
z_3	18.30	118.63	179.97
z_4	5136.41	28426.31	100859.01
z_5	7778601.29	——	5.45
z_6	1.72	174233.20	5.66
z_7	0.96	85604.01	10.85
z_8	1641351.00	——	1.28
z_9	5358.84	57618.12	188280.64
z_{10}	4404973716.61	——	136311.84
z_{11}	31132.65	42958.75	106352.89
z_{12}	1066956337.72	——	148275.31
z_{13}	6.05	19.59	50.82
z_{14}	747.21	5197.43	11690.45
y_{-1}	1.81	72.87	13.85
y_{-2}	6479142.21	——	13.77

$$\begin{aligned} y_i &= a_1 y_{i-1} + a_2 z_{i2} + a_3 z_{i6} + a_4 z_{i7} \\ &\quad + g_3(t_i, \mathbf{Z}_i) + \varepsilon_i, \qquad (i = 1,2,\ldots,n) \quad . \ . \quad (3) \end{aligned}$$

where $\mathbf{Z}_i = (z_{i3}, z_{i4}, z_{i9}, z_{i,11}, z_{i,13}, z_{i,14})$, $g_3(\cdot)$ is an unknown function, ε_i is a random disturbance with zero expectation, and a_1, a_2, a_3, a_4 are coefficients to be estimated. The six nonparametric variables are z_{i3}, z_{i4}, z_{i9}, $z_{i,11}$, $z_{i,13}$, $z_{i,14}$; they are hereinafter referred to as control variables.

Finally, we estimate Eq. (3) with different control variables, which we call path models.

3. The Model and Estimations

3.1. The Model

In model (3), the coefficients a_1, a_2, a_3, a_4 are estimated with sample observations, so they are determined by the data. Moreover, each of the estimations is the average in the sample period. However, they vary over time, and are functions of time. Furthermore, we use the varying-coefficient partially linear model [14], which is given by

$$\begin{aligned} y_i &= a_1(t_i) y_{i-1} + a_2(t_i) z_{i2} + a_3(t_i) z_{i6} + a_4(t_i) z_{i7} \\ &\quad + g_3(t_i, \mathbf{Z}_i) + \varepsilon_i, \quad (i = 1,2,\ldots,n) \quad \ldots \quad (4) \end{aligned}$$

$a_k(t_i)(k = 1,2,3,4)$ are unknown functions. According to Taylor's theorem, they can be approximated by linear functions such that

$$a_k(t_i) \approx a_{0k} + a_{1k}(t_i - t_0) \quad \ldots \ldots \ldots \quad (5)$$

$k = 1,2,3,4;\ i = 1,2,\ldots,n$. In Eq. (5), t_0 is the middle of the sample period, which is convenient to use. However,

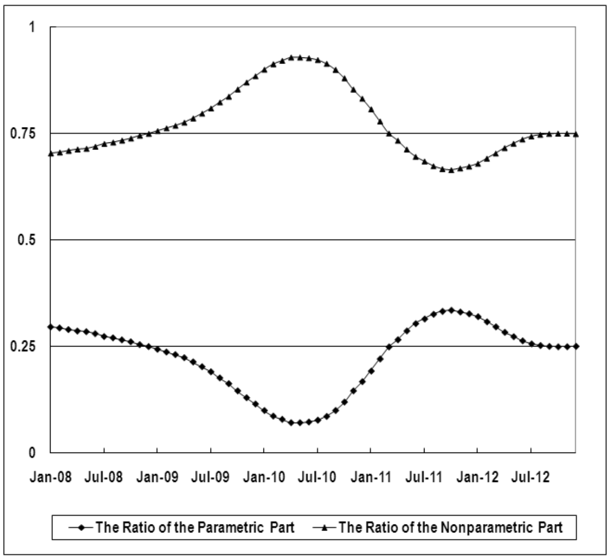

Fig. 1. The ratios of the parametric and nonparametric parts in the Textile Index of the base model.

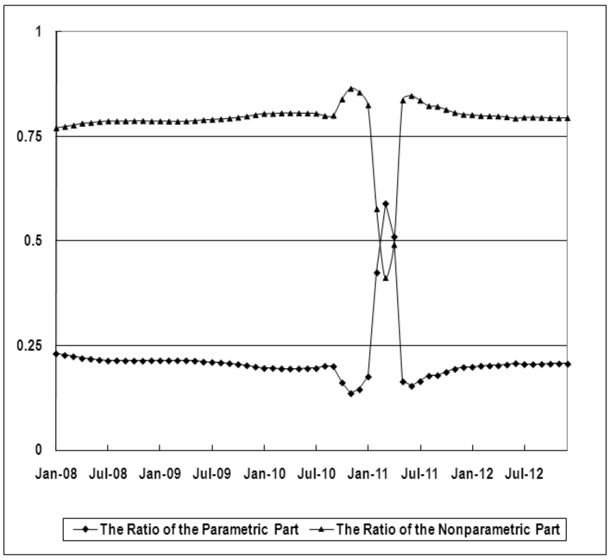

Fig. 2. The ratios of the parametric and nonparametric parts in the Textile Index of the path model.

if the sample point is far away from the middle, the error is large. Therefore, the time of the current sample point is assigned to t_0. a_{0k} and a_{1k} $(k = 1,2,3,4)$ are estimated at each point. Obviously, the terms of the first degree in Eq. (5) are identically equal to zero so that Eq. (4) can be written as

$$\begin{aligned} y_i = {} & a_{01}(t_i)y_{i-1} + a_{02}(t_i)z_{i2} \\ & + a_{03}(t_i)z_{i6} + a_{04}(t_i)z_{i7} \\ & + g_3(t_i, \boldsymbol{Z}_i) + \varepsilon_i, \qquad (i = 1,2,\ldots,n) \quad . \quad . \quad (6) \end{aligned}$$

where t_i is the point of the Taylor expansion.

Given Eq. (6), the Textile Index is composed of two parts: a parametric part $a_{01}(t_i)y_{i-1} + a_{02}(t_i)z_{i2} + a_{03}(t_i)z_{i6} + a_{04}(t_i)z_{i7}$ and a nonparametric part $g_3(t_i, \boldsymbol{Z}_i)$. The control variables affect the Textile Index directly through the nonparametric part and indirectly through the parametric part.

3.2. The Estimations

In order to compare the models with and without the control variables, we estimate Eq. (6) with only one control variable t (called the base model) as well as with all the control variables (called the path model). Their respective estimation errors described by root-mean-square error are 0.000001586542 and 0.084938. The ratios of the parametric and nonparametric parts of the two models are illustrated in **Figs. 1** and **2**, respectively.

Comparing the two curves in each of the figures, we see that the control variables make the parametric ratio small and the nonparametric ratio correspondingly large in February, March, and April 2011, and they reach their respective minimum and maximum in March. At other times, the control variables make the parametric part more stable over time comparing with that in the base model. Symmetrically, the nonparametric ratio also becomes more stable over time because of the control variables.

From a statistical perspective, the six control variables affect the Textile Index significantly, but we still want to determine which play primary roles in the system and to adjust them to try to regulate textile prices.

4. Further Empirical Results

4.1. Cotton Index A

We estimate the path models using various combinations of the six control variables and find that cotton index A plays the most important role. Because of space limitation, the nonparametric ratios of only several combinations are illustrated in **Fig. 3**.

The four curves in **Fig. 3** are the nonparametric percentages in the Textile Index of the base model and the three path models with all control variables, with all control variables except cotton index A, and with only cotton index A. The ratio with all the control variables reaches its maximum of 58.95% in March 2011. The Textile Index and cotton index A reach their maximums at the same time. Excluding February, March, and April 2011, the ratio curves with cotton index A and with cotton index A only almost overlap. Thus, it appears that cotton index A plays the most important role in the Textile Index. However, in February, March, and April 2011, cotton index A and the other control variables together raised the parametric ratio.

4.2. Cotton Index A's Indirect Influence on the Textile Index

Cotton Index A affects the Textile Index indirectly by way of four linear variables: the first-order lag term of the Textile Index (y_{-1}), the monthly average crude oil

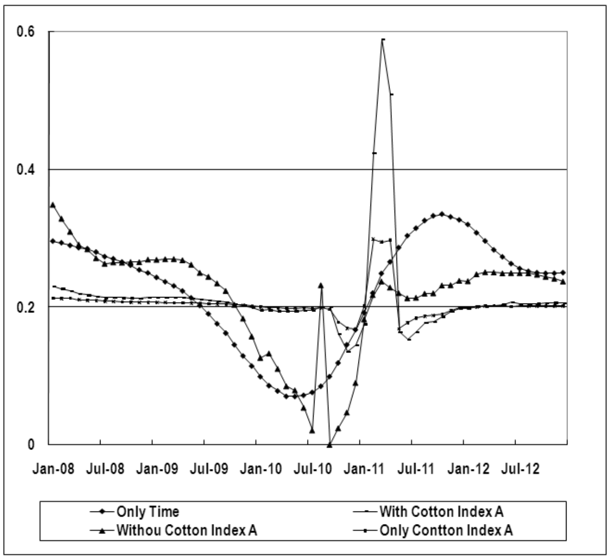

Fig. 3. The influence of cotton index A.

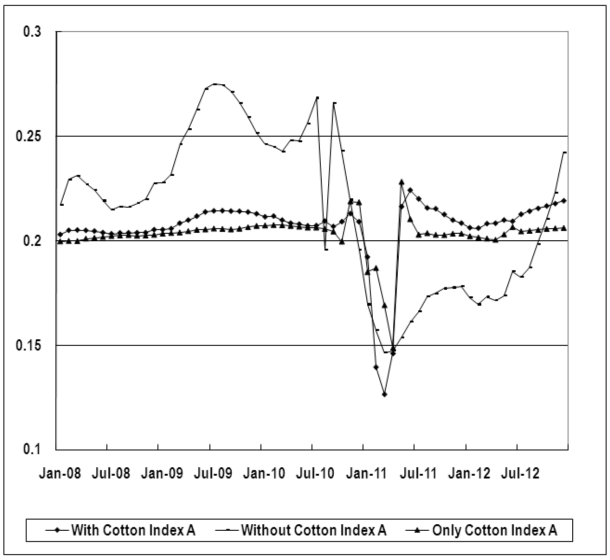

Fig. 4. The ratios of the first-order lag of the Textile Index under different conditions.

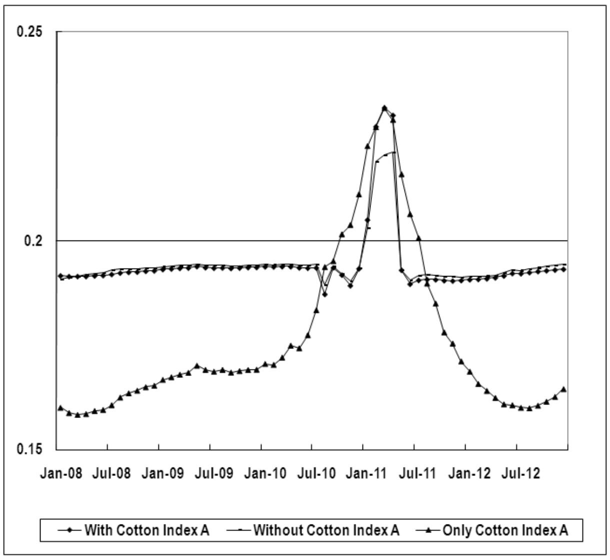

Fig. 5. The ratios of the monthly average crude oil price under different conditions.

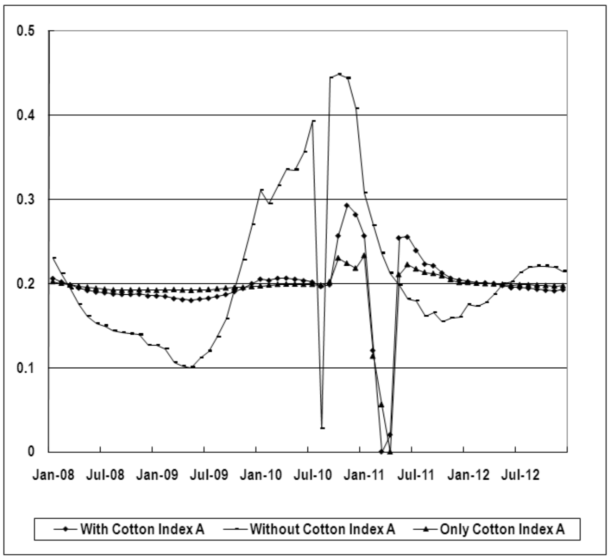

Fig. 6. The ratios of the retail price index under different conditions.

price (z_2), the retail price index (z_6), and the producer price index (z_7). The ratios of the four linear terms with and without cotton index A are shown in **Figs. 4–7**.

As **Figs. 4–7** show, each of the four parametric terms' ratios is around 20%; that of the first-order lag item $(a_{01}(t_i)y_{i-1})$ is somewhat large, while that of the monthly average crude oil price $(a_{02}(t_i)z_{i2})$ is somewhat small. The nonparametric remainder of the ratio, about 20%, is $(g_3(t_i, Z_i))$. Except for February, March, and April 2011, cotton index A smoothes the fluctuations of the four parametric ratios. In other words, cotton index A partly absorbs the effect of the four parametric variables. However, in February, March, and April 2011, it aggravated their fluctuation. We note that cotton index A was larger than its sample average during September 2010–April 2012 and that in February, March, and April 2011, it was three times the sample average. Therefore, adjusting cotton prices' fluctuation by not more than twice the average in a period can stabilize textile prices.

4.3. Cotton Index A's Direct Influence on the Textile Index

The three curves in **Fig. 8** are the ratios of the nonparametric part under different conditions: which are with cotton index A in the control variable, without cotton index A, and with only cotton index A. The sum of the five ratios is 1 under the same condition. The parametric and nonparametric ratios move in opposite directions: the parametric ratio goes up while the nonparametric one goes down. Thus, the change in the nonparametric ratio is symmetric with the total ratio of the four parametric

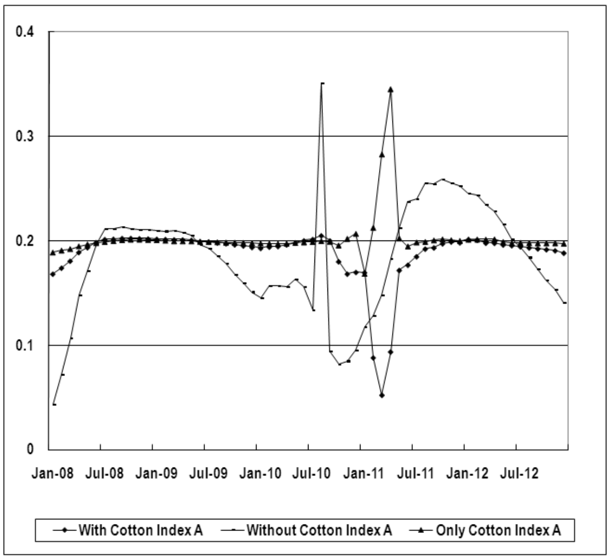

Fig. 7. The ratios of the producer price index under different conditions.

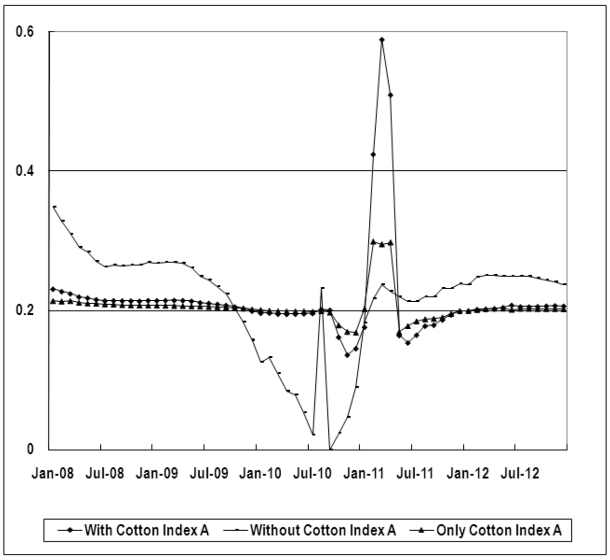

Fig. 8. The nonparametric ratio under different conditions.

terms. That is, cotton index A directly smoothes the nonparametric ratio except for in February, March, and April 2011, in which it increases its fluctuation.

5. Simulation of the Five Terms

The Textile Index was 96.317 in October 2010, after which it rose continuously, reaching a maximum of 112.705 in March 2011. After having been adjusted for more than half a year, it decreased to about 106 and later maintained a level at least 10 points higher than that in the previous year. As analyzed above, cotton index A is the major factor that makes the Textile Index fluctuate. It affects the Textile Index indirectly through every parametric term and affect the Textile Index directly through the nonparametric term.

Table 2. Simulation of cotton index A.

Date	Real Value	Simulation
2010.07	185.54	201.00
2010.08	199.18	202.95
2010.09	230.89	205.64
2010.10	279.13	208.98
2010.11	340.97	212.86
2010.12	370.34	217.16
2011.01	394.47	221.79
2011.02	469.98	226.64
2011.03	506.34	231.60
2011.04	477.60	236.56
2011.05	364.90	241.43
2011.06	317.80	246.09
2011.07	269.00	250.45
2011.08	251.50	254.38

During the sample period, cotton index A's increase precedes the Textile Index's. Cotton index A monotonically increased from 113.54 in March 2009 to 185.54 in July 2010. It increased quickly in July 2010–March 2011, reaching a maximum of 506.34, and the Textile Index reached its maximum simultaneously. After that, the cotton index decreased rapidly, reaching 251.5 in August 2011. It was 185.12 in July 2012, it maintained its level afterward. Before and after the period of fluctuation, cotton index A was nearly unchanged.

Additionally, during the sample period, while the level of the exchange rate had a decreasing trend, the supply of money, enterprise deposits in financial institutions, short-term loans from financial institutions, and ending state foreign exchange reserves mainly increased. Thus, what happens to the Textile Index without cotton index A's dramatic fluctuation?

If cotton index A had risen steadily from 113.54 in July 2011 to 251.5 in August 2011, how would the Textile Index, the four parametric terms, and the nonparametric term have changed?

We use the cubic spline interpolation method to simulate cotton index A for a 14-month from July 2010 to August 2011. The data are given in **Table 2**.

The ratios of the five terms that constitute the Textile Index are illustrated in **Fig. 9**. From the figure, we see that the ratios changed from 15% to 30% except in March, April, and May 2011. During these three months, the nonparametric ratios were 42.45%, 58.95% and 51.00%; therefore, the ratio of each linear term was less than 15%, offsetting the higher nonparametric ratio.

The results with the simulation value substituted for the real cotton index A are shown in **Fig. 10**. If cotton index A had risen steadily, the four parametric ratios and the nonparametric ratio would have been fluctuated more than in reality except for March, April, and May 2011, but would still be in the 15% to 30% interval. In those three months, the nonparametric ratio was not larger than 45%. That is, there would have been no extreme value in the ratios

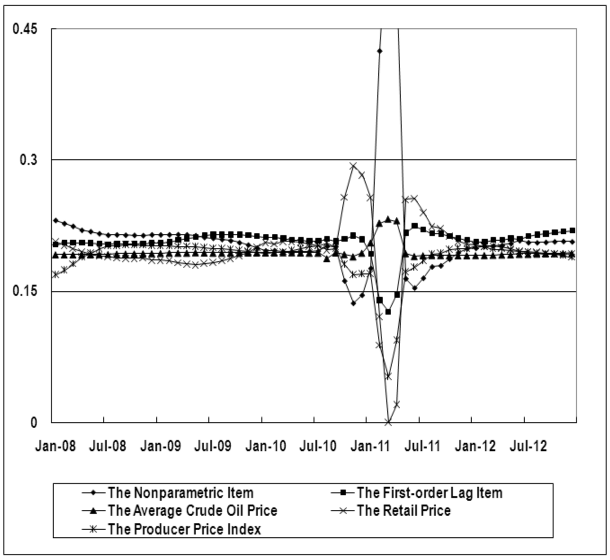

Fig. 9. The real ratios of each term.

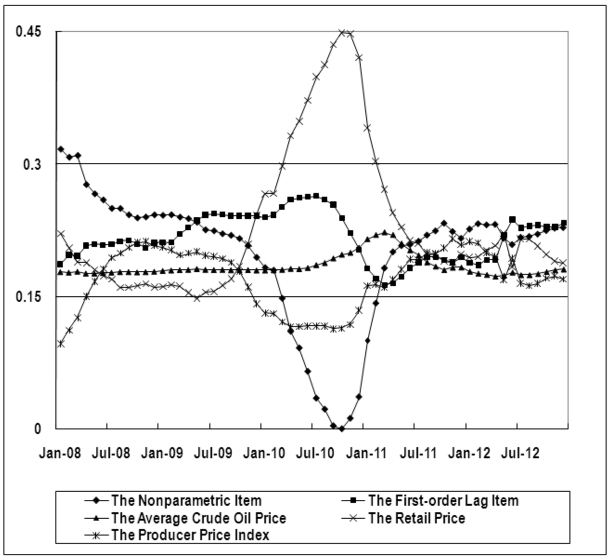

Fig. 11. The ratios of each term with simulated cotton index A and short-term loans from financial institutions.

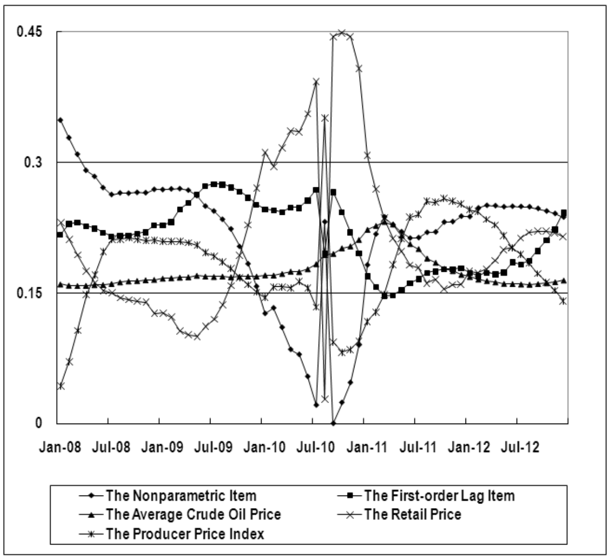

Fig. 10. The ratios of each term with simulated cotton index A.

without cotton index A's heavy fluctuation.

It is remarkable that all the ratios have a noticeable change in August 2010. The retail price index's ratio decreases suddenly, while the nonparametric ratio and producer price index's ratio increase suddenly. We find that short-term loans from financial institutions in August 2011 were three times higher than in July or in September 2011. The results for replacing the real short-term loans in August with the July and September average are shown in **Fig. 8**, which shows that the ratios of the retail price index, producer price index, and nonparametric term have no abnormal changes.

All the ratios' fluctuation intervals are larger in **Fig. 11** than in **Fig. 9**. In **Fig. 11**, the fluctuations begin eight months in advance, and the ratio of the retail price index's increase offsets the ratios of nonparametric term and the producer price index's decrease. The first-order lag item of the Textile Index's ratio and the monthly average of the crude oil price's ratio offset each other. However, in reality, the parametric ratio's rapid increase and the monthly average of the crude oil price index's gentle increase offset the others' decreases.

6. Conclusion

We choose significant variables from the variable set that possibly had effects on the Textile Index and identify them as linear explanatory variables and nonlinear control variables with the independent variable, the Textile Index. The first-order lag item of the Textile Index, monthly average crude oil price index, retail price index, and producer price index are linear. Cotton index A, money supply, saving deposits in financial institutions, short-term loan from financial institutions, level of exchange rate and ending state foreign exchange reserves are nonlinear, and are the control variables.

We establish varying-coefficient partially linear models with all the significant variables as dependent variables and the Textile Index as the independent variable, and find that each of the parametric terms accounts for 20%, while the nonparametric term is slightly higher than 20%. Cotton index A plays the most important role of the six control variables. The empirical and simulated results reveal that none of the ratios would be extreme as long as cotton index A does not exceed twice the sample mean during the sample period.

Acknowledgements

This paper is funded by The Plan of National Statistical Science Project (Grant No:2013LZ15), and the Zhejiang Provincial Key Research Base for Humanities and Social Science Research (Statistics 1020XJ3314010 & Applied Economics 1020XJ3314018G).

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