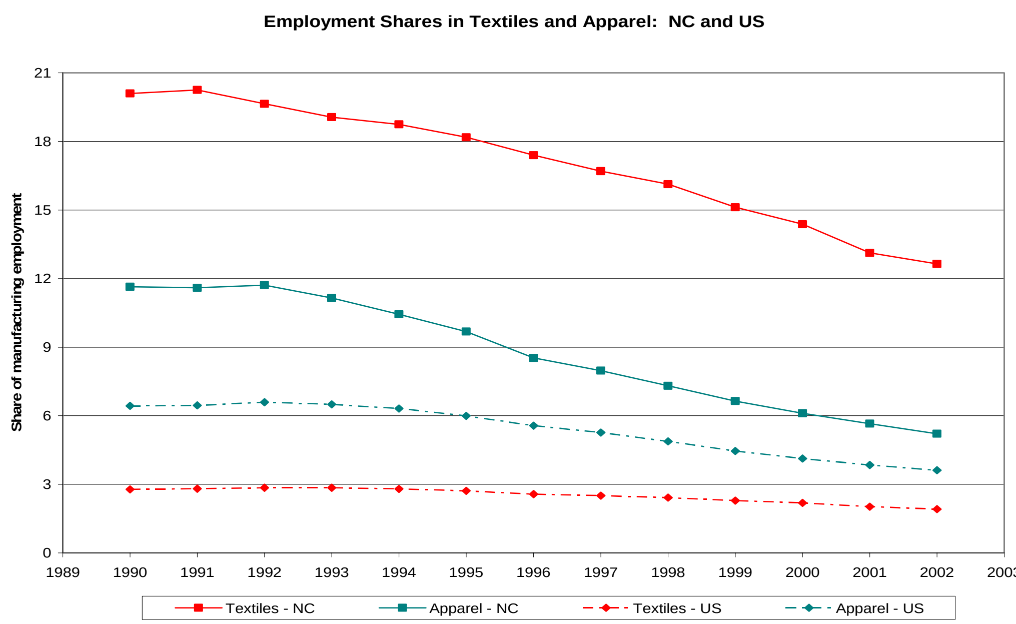
P. Conway
14 January 2004

Charting Employment Loss in North Carolina Textiles[1]

The job losses in North Carolina manufacturing, and the textiles industry in particular, are most often attributed to the effect of competition from foreign textiles producers.[2] However, between 1977 and 1997, nearly 82000 jobs were eliminated in North Carolina textiles, whether through mill closings or substitution of labor-saving machinery.[3] This occurred even as production was rising. The following figure illustrates the trends in employment in North Carolina and the US from 1989 to the present.



This was, however, only the beginning: since 1997 the rate of job elimination has accelerated. From 1997 to 2002 over 100,000 jobs were eliminated in the textile industry in North Carolina.[4] Nearly 70,000 jobs were eliminated during the same period in the apparel industry in North Carolina. While the industries remain a substantial part of the North Carolina economy, their contributions are greatly reduced relative to the 1970s.

In this note I decompose the evolution of employment in North Carolina since 1990 into three components. The first component is the technology-induced reduction in employment that had its beginnings in the 1950s in the US. The second component is the

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[1] Thanks to Bidisha Lahiri for excellent research assistance.
[2] As Senator Elizabeth Dole put it, succinctly, "Many of North Carolina's woes in manufacturing can be summed up in one word. One word, and you know what it is: China." As reported in the Raleigh News and Observer, 14 October 2003.
[3] Bureau of Economic Analysis, US Department of Commerce.
[4] US Bureau of Labor Statistics, State and Area Employment figures.

cyclical movement in employment that can be attributed to textiles- and apparel-demand fluctuations along the business cycle. The third component is the effect attributable to increased competitive pressure from foreign products.

The model.

It is beyond the scope of this note to derive a complete structural model of the employment decision. In its place, I consider a reduced-form model of the evolution of the number of individuals employed in a given industrial sector. There are three parts to this model:

- The long-run evolution of employment in the sector is modeled as an error-correction process in industry-specific employment and overall manufacturing employment.
- The business-cycle component is represented through inclusion of an indicator of state GDP, instrumented by its one-period lag value to reduce the potential for simultaneity bias. Also included are monthly dummy variables to correct for the seasonal influences of demand on employment.
- The international competition component is represented by inclusion of indicators for a number of "events": implementation of NAFTA, the Asian crisis, lifting of textile quotas. The contribution of these events to the evolution of textiles and manufacturing employment will indicate the independent effect of international competition.

The estimating equation for industry i can be represented as:

$$\Delta L_{it} = \Sigma_{s=1} \alpha_{is} \Delta L_{i,t-s} + \Sigma_{s=1} \beta_{is} \Delta L_{m,t-s} + \gamma_i L_{i,t-1} + \delta_i L_{m,t-1} +$$

$$\Sigma_{s=1} \theta_{is} \Delta Y_{t-1} + \Sigma_{j=1} \eta_{ij} M_j + \varepsilon_{it} . \qquad (1)$$

L_{it} is employment in industry i, a part of the manufacturing sector in North Carolina. L_{mt} is aggregate employment in manufacturing, Y_{t-1} is gross state product. M_j are monthly dummy variables. ε_{it} is a random, normally distributed error.

Given the concerns that international competition has intensified in the late 1990s and has in effect caused a structural break, I choose to decompose the evolution of employment in a two-step application of (1). In the first step, I set aside the first m periods to initialize the model. I then create a time series of one-step-ahead forecasts of ΔL_{it}. I estimate (1) over the first m periods, and then create the forecast of $\Delta L_{i,m+1}$. I then increase the sample size to the first m+1 periods, and create the forecast of $\Delta L_{i,m+2}$. Through successive enlargement of the sample, I derive a complete time series of these forecasts and associated standard errors. I denote this time series of forecasts as f_{it}, and the associated standard errors as σ_{it}.

In the second step, I derive the one-step-ahead forecast error $\lambda_{it} = f_{it} - \Delta L_{it}$. I then create four event windows:

- NAFTA implemented: January-March 1994.

- Asian crisis (Thai baht depreciates): July-September 1997.
- Phase II quota removal: January-March 1998
- Phase III quota removal: January-March 2002.

For each event window e, there is a dummy variable D_e that is equal to one in the event window and zero otherwise.

The test of the impact of international events on the evolution of employment is found in the second-stage regression:

$$\lambda_{it} = \Sigma_e \varphi_e D_e + \upsilon_{it} \qquad (2)$$

Each coefficient φ_e measures the percentage-point difference between predicted and actual growth in employment in that month. The error υ_{it} is assumed random and normally distributed.

Data.

The data on employment are monthly from May 1990 to May 2003 and are provided by the North Carolina Employment Security Commission. They are converted to logarithms prior to the analysis of equation (1). Data on gross state product is reported on a quarterly basis by the Bureau of Economic Analysis, US Department of Commerce. I use a linear transformation to interpolate values of this variable for use in the regressions and convert the value to its logarithm. The monthly dummy variables and event dummies are created as described above.

The industries i used in this analysis are

tx:	Textile Mills
tp:	Textile Product Mills
tf:	Textile Furnishings Mills
ak:	Apparel Knitting Mills
cs:	Cut and Sew Apparel Manufacturing

The initializing period is defined to be May 1990 to May 1993, and one-step-ahead forecasts begin in June 1993. Specification tests (not reported) indicate that two lags of the right-hand side first differences are optimal.

Results.

As an illustration of the underlying error-correction process, Table 1 reports the results from the regression on textile mills from May 1990 to May 2003.[5] The values of α_{tx1} (-0.175) and α_{tx2} (-0.021) are negative, as expected, and are declining with the length of the lag. The values of β_{tx1} (0.076) and β_{tx2} (0.352) are positive, as anticipated: positive shocks to manufacturing employment have a significant positive effect on textile-mill employment with a two-month lag.[6] θ_{tx1} (1.408)and θ_{tx2} (0.090) are positive, as expected: positive shocks

[5] The results for shorter time periods and for the other industries in the sample are available on demand.
[6] In this and in what follows, the significance is defined at the 95 percent level of confidence.

to real gross state product have a positive impact on textile-mill employment with a lag. The one-period lag effect θ_{tx1} is significantly different from zero. There is clear evidence of seasonality in textile-mill employment: η_{txj} are significantly different from zero (defined as the January effect) for March, June, July, September and October. All but July, October and November are positive, indicating that the January effect of employment growth is among the smallest monthly effects.

Table 1: **Evolution of employment in the NC textiles sector**

Source	SS	df	MS			
				Number of obs	=	156
				F(19, 136)	=	7.31
Model	.007030101	19	.000370005	Prob > F	=	0.0000
Residual	.006883197	136	.000050612	R-squared	=	0.5053
				Adj R-squared	=	0.4362
Total	.013913298	155	.000089763	Root MSE	=	.00711

ΔL_{txt}	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
L_{txt-1}	.0361069	.0081252	4.44	0.000	.0200389	.052175
ΔL_{txt-1}	-.1749238	.0921002	-1.90	0.060	-.3570575	.00721
ΔL_{txt-2}	-.0207618	.0918955	-0.23	0.822	-.2024908	.1609672
L_{mt-1}	-.0836534	.022342	-3.74	0.000	-.1278361	-.0394708
ΔL_{mt-1}	.0758501	.1705128	0.44	0.657	-.2613493	.4130494
ΔL_{mt-2}	.3523925	.1665307	2.12	0.036	.023068	.6817171
ΔY_{t-1}	1.408523	.5257996	2.68	0.008	.3687224	2.448324
ΔY_{t-2}	.0898806	.585294	0.15	0.878	-1.067574	1.247335
M_2	.0055198	.003111	1.77	0.078	-.0006323	.0116719
M_3	.0080803	.0031824	2.54	0.012	.0017868	.0143737
M_4	.0026146	.0029187	0.90	0.372	-.0031574	.0083865
M_5	.0024897	.0028645	0.87	0.386	-.0031749	.0081544
M_6	.0093609	.0029052	3.22	0.002	.0036158	.0151061
M_7	-.0108154	.0029896	-3.62	0.000	-.0167275	-.0049033
M_8	.0038482	.003282	1.17	0.243	-.0026422	.0103385
M_9	.0068484	.0033091	2.07	0.040	.0003044	.0133923
M_{10}	-.0061194	.0030942	-1.98	0.050	-.0122383	-5.10e-07
M_{11}	-.000081	.0029087	-0.03	0.978	-.0058332	.0056712
M_{12}	.0026806	.0028947	0.93	0.356	-.0030439	.008405
Constant	.3703045	.1132683	3.27	0.001	.1463096	.5942994

The error-correction effects indicate a significant tendency for industry employment to converge to a constant ratio of manufacturing employment (δ_{tx} = -0.084) but no such evidence of convergence to a constant long-run employment level specific to the industry

(γ_{tx} = 0.036). In fact, this is evidence of a significant snowballing effect of employment losses over time.

This specification thus has reasonable characteristics. It also explains a significant percentage of the variation in the textile-mill employment growth over time, as the F(19,136) statistic indicates and the R^2 confirms.

Hypothesis testing.

Our null hypothesis for this exercise is that (1) and the coefficients estimated from it are a complete characterization of the employment growth evolution in North Carolina. The alternative hypothesis is that this set of models fails to predict the impact on textile employment due to a series of trade "events" beginning with NAFTA in 1994, including the Asian crisis exchange-rate meltdown in 1997, and various phases of the ATC quota removal between 1995 and 2003. To test the null against the alternative, I create a one-step-ahead forecast for each month in the sample, using the estimation of (1) for those observations prior to that month. This one-step-ahead forecast f_{it} is used to create the one-step-ahead forecast error (predicted minus actual) defined as λ_{it} above. The λ_{it} for the five textile industries are then stacked, forming a sample of 600 observations of forecast error. Regression (2) is undertaken for the stacked sample and for the event windows defined above. The results of this regression are reported in Table 2.

The alternative hypothesis predicts that λ_{it} will be significantly larger in the trade event windows: in terms of equation (2), $\varphi_e > 0$ for all events e. In fact, there are no significant coefficients larger than zero on the event windows. There is one significant coefficient, but it is the negative effect attached to the quota-removal Phase 2 window. Thus, the alternative hypothesis must be rejected in favor of the null hypothesis of no effects of these international-trade "events".

Events indicated by the data.

While the test rejects the hypothesis that international events led to sharp drops in employment, it is possible to approach the data in more disaggregated fashion: which observations of the one-step-ahead forecasts are two standard deviations from zero? Figures 1 through 5 illustrate the one-step-ahead forecasts and associated 95 percent confidence bounds derived from σ_{it} for employment growth in the five sectors. Consider Figure 1, for textile mills. There are three months in which the forecast errors are significantly positive: April 1997, November 1997, and May 2001. None of these fall within the event windows, although the 1997 observations may well be associated with the Asian crisis. There are also four observations in which actual significantly exceeded predicted: July 1994, February 1998, October 2002 and January 2003. The second falls within the Phase II quota removal window.

Figure 1: One-step-ahead forecast errors for textile-mill employment

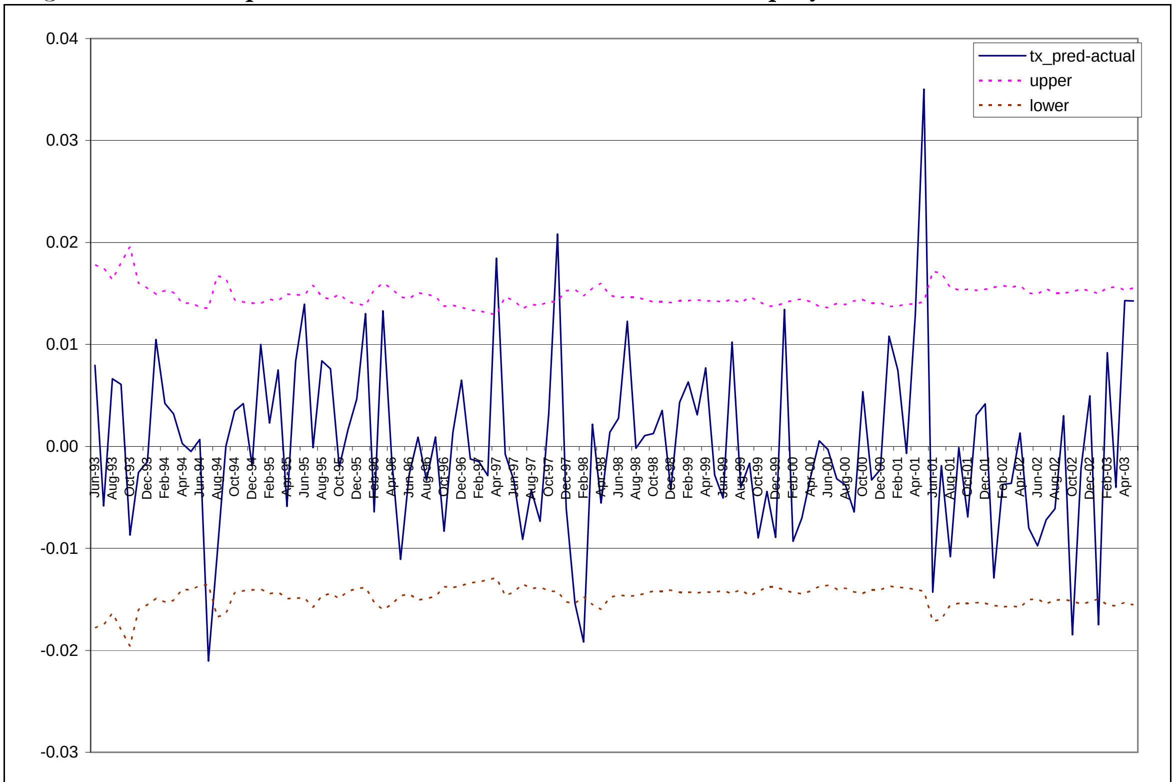

Figure 2: One-step-ahead forecast errors for textiles furnishings employment

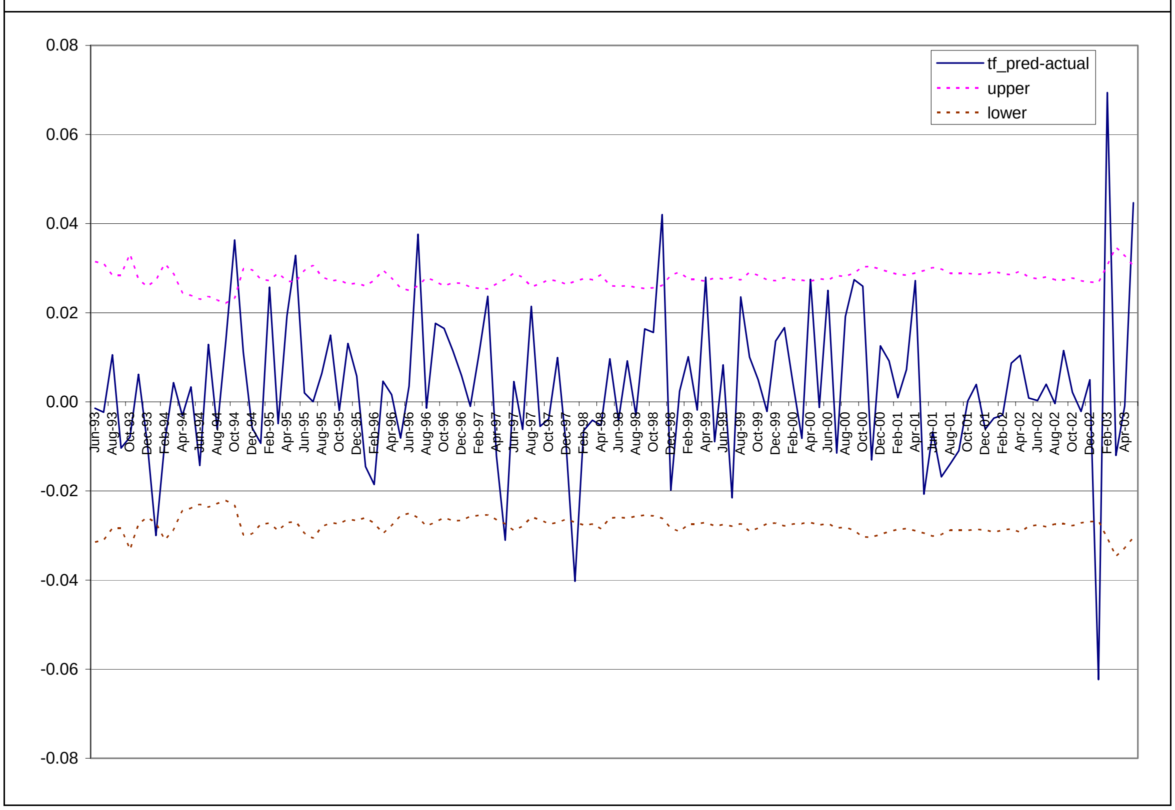

Figure 3: One-step-ahead forecasts for textile products employment

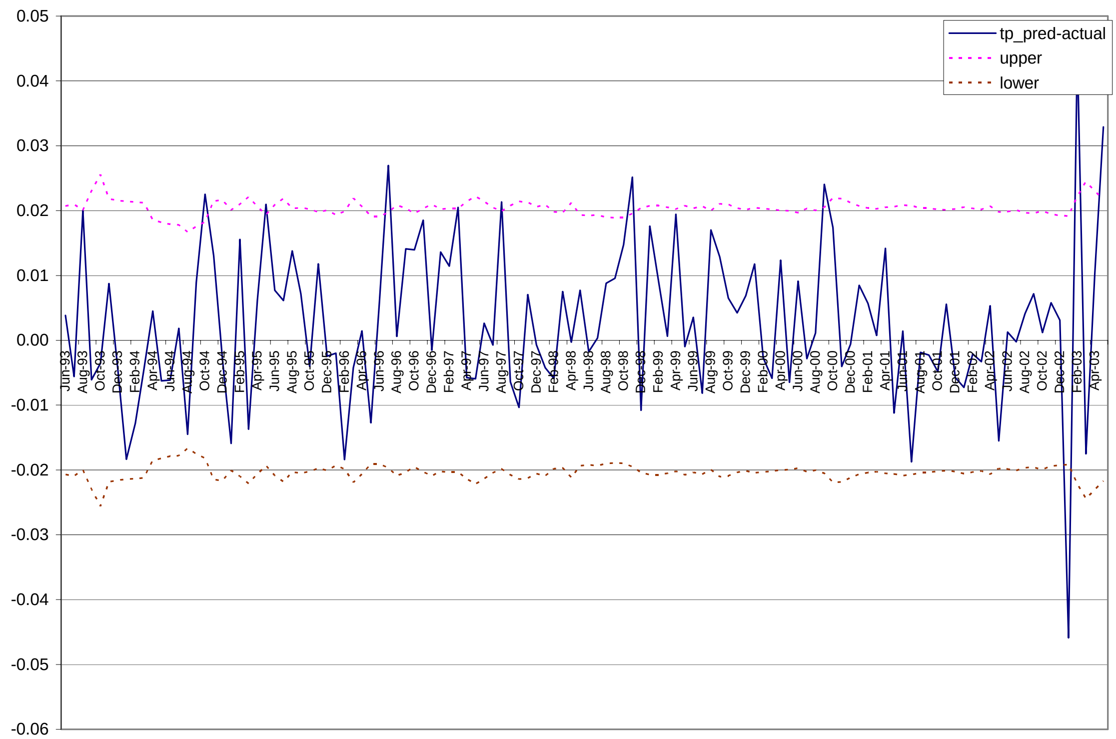

Figure 4: One-step-ahead forecast errors for apparel knitting employment

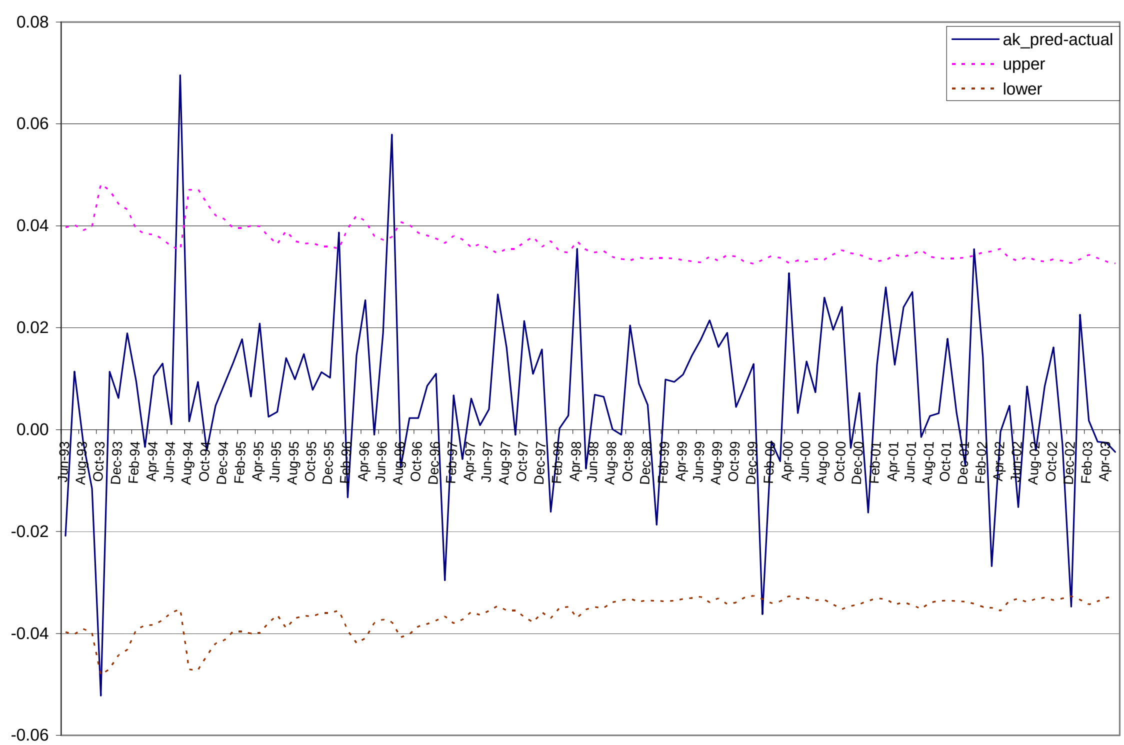

Figure 5: One-step-ahead forecast errors for cut-and-sew apparel employment

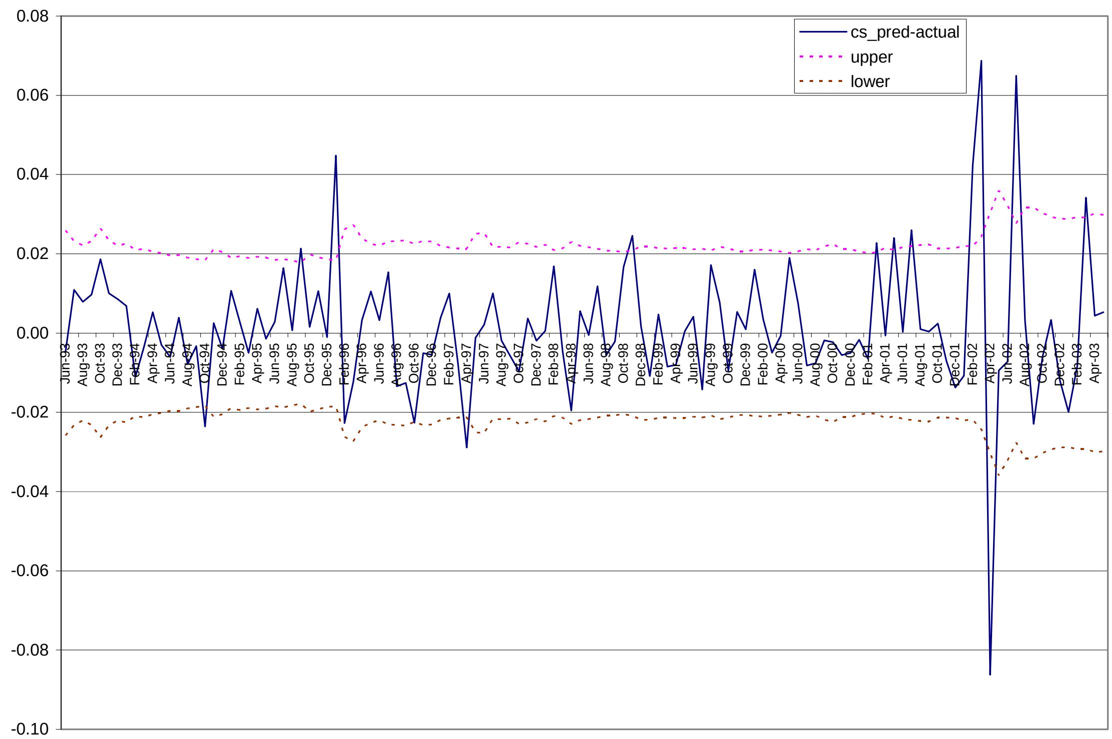

Figure 2 illustrates the one-step-ahead forecast error for textile furnishings employment for these 120 months. There are six observations with positive error outside the confidence bounds: October 1994, May 1995, July 1996, December 1998, February 2003 and May 2003. None of these falls within a trade event window as defined above. There are four observations with negative and significant forecast error (i.e., better than expected employment change): January 1994, May 1997, January 1998 and January 2003. The January 1994 and January 1998 both fall within trade event windows.

Figure 3 illustrates the one-step-ahead forecasts error for textile products employment. There are eight observations with error significantly greater than zero: October 1994, May 1995, July 1996, August 1997, November 1998, September 2000, February 2003 and May 2003. The January 2003 observation is the only one with error significantly less than zero.

Figure 4 illustrates the forecast error for apparel knitting employment. There are four observations with significantly positive forecast error: July 1994, January 1996, July 1996, and January 2002. Three observations are significantly negative: October 1993, January 2000, and December 2002.

Figure 5 illustrates the forecast error associated with apparel cut-and-sew operations. Those observations with forecast error significantly greater than zero are September 1995, January 1996, November 1998, March 2001, May 2001, July 2001, March 2002, July 2002 and March 2003. Those with forecast error significantly less than zero are October 1994, April 1997, and April 2002.

Conclusions.

The hypothesis test undertaken here indicates that once the long-term tendency toward negative employment growth is controlled for, there is no significant independent effect of trade events such as NAFTA, the collapse of the Baht, or the later Asian crisis. While testing for robustness is certainly necessary, these initial results do not suggest the cataclysmic effects of loosening trade restrictions on employment growth that are often mentioned in the literature.

Table 2: Testing the Importance of Trade Events to Employment Evolution

Source	SS	df	MS
Model	.005015512	9	.000557279
Residual	.124098073	590	.000210336
Total	.129113585	599	.000215549

Number of obs	= 600
F(9, 590)	= 2.65
Prob > F	= 0.0051
R-squared	= 0.0388
Adj R-squared	= 0.0242
Root MSE	= .0145

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
nafta	-.0055797	.0037969	-1.47	0.142	-.0130368	.0018773
baht	-.0001094	.0037969	-0.03	0.977	-.0075665	.0073476
asian2	.0006505	.0059997	0.11	0.914	-.0111328	.0124338
phase2	-.0089934	.0037969	-2.37	0.018	-.0164505	-.0015363
phase3	.0028978	.0037969	0.76	0.446	-.0045592	.0103549
tx_dum	-.0013666	.0018723	-0.73	0.466	-.0050438	.0023107
tp_dum	.001482	.0018783	0.79	0.430	-.0022071	.005171
tf_dum	.0019654	.0018783	1.05	0.296	-.0017236	.0056545
ak_dum	.0055745	.0018783	2.97	0.003	.0018855	.0092635
_cons	.0017178	.0013477	1.27	0.203	-.000929	.0043647

Table 3: **Significant errors in one-step-ahead forecast**

Predicted exceeded actual (consistent with negative shock)

1994:	July	ak
	October	tp, tf
1995:	May	tf, tp
	September	cs
1996	January	cs, ak
	July	ak, tp, tf
1997	April	tx
	August	tp
	November	tx
1998	November	cs, tp
	December	tf
2000	September	tp
2001	March	cs
	May	cs, tx
	July	cs
2002	January	ak
	March	cs
	July	cs
2003:	February	tp, tf
	March	cs
	May	tp, tf

Predicted less than actual (consistent with positive shock)

1993	October	ak
1994	January	tf
	July	tx
	October	cs
1997:	April	cs
	May	tf
1998	January	tf
	February	tx
2000	January	ak
2002	January	cs
	April	cs
	October	tx
	December	ak
2003	January	tx, tp, tf

Data collection.
Using tx sector for example:

1) GDP figures are drawn from the Bureau of Economic Analysis. The quarterly values were divided by 3, and were taken to represent the middle month of the quarter. The monthly figures for each missing month in between, were interpolated as the linear average.

2) The labor figures for manufacturing (mnf) and for the subsection of textile/apparel (tx say) were drawn from NC ESC data, and were converted into logarithms.

3) Lagged levels of all the above 3 variables were created, as well as the first difference, the first lag of the first difference and the second lag of the first difference.

4) The start and end points of the original data were Jan90 – May03.
Due to taking the differences and lags, the final data covered the period from May90 to May03

5) 11 monthly dummies were created (Jan as base: no dummy)

Data manipulation.
1) For each sub-sector, a rolling regression exercise was done, and each regression was used to generate a one-period-ahead forecast, as well the estimated standard-deviation of the forecast.

- The first regression was based on 37 observations: May90-May93, and made the forecast for June93
- The next regression was based on 38 observations: May90-June93 and made forecast for July93
- The last regression was based on 156 observations: May90- April03 and made forecast for May03

The regression equation was:
regress dlogtx

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        (lag_logtx, lag1_dlogtx, lag2_dlogtx,
        lag1_logmnf, lag1_dlogmnf, lag2_dlogmnf,
        lag1_dloggdp, lag2_dloggdp,
        dum2 dum3 dum4 dum5 dum6 dum7 dum8 dum9 dum10 dum11 dum12)
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2) The difference between the prediction and the actual for the diff_log_tx was calculated

3) These prediction errors for the 5 sectors were stacked one on top of the other, with sector dummies to identify where each came from.

4) Event dummies were created.

5) The forecast errors were regressed on the event dummies, with sector dummies also in place to capture any sector specific deterministic effect.