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EMPLOYMENT REALLOCATION AND UNEMPLOYMENT REVISITED: A QUANTILE REGRESSION APPROACH

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Employment Reallocation and Unemployment Revisited: A Quantile Regression Approach

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ABSTRACT

This study revisits the sectoral shifts hypothesis for the US for the period 1948 to 2011. A quantile regression approach is employed in order to investigate the asymmetric nature of the relationship between sectoral employment and unemployment. Significant asymmetries emerge. Lilien's dispersion index is significant only for relatively high levels of unemployment and becomes insignificant for low levels suggesting that reallocation affects unemployment only when the latter is relative high. More job reallocation is associated with higher unemployment.

Keywords: unemployment, employment reallocation, sectoral shifts, aggregate shocks, conditional quantile regression model, bootstrapping

JEL Classification: C22, C50, E24

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1. Introduction

The relevance of intersectoral labor reallocation as a triggering force of aggregate (un) employment fluctuations is at the centre of an ongoing controversy. This debate persists because of the "observational equivalence" problem which is endemic in the sectoral shifts analysis (Lilien 1982b; Abraham and Katz, 1986). Both aggregate and allocative shocks can explain the observed positive correlation between unemployment and intersectoral employment dispersion signals.

Discriminating between the impact of these two sources of shocks on unemployment has become one of the major challenges of empirical macroeconomics, and the massive effort aimed at overcoming this identification problem has led to important analytical extensions (e.g. job creation and job destruction analysis) and a vast and growing literature (for a survey c.f. Gallipoli and Pelloni, 2008).

Originally the observational equivalence problem emerged in linear regression models which can only identify the conditional mean response of unemployment to changes in the covariates. The linear regression model (LRM) restricts the analysis to responses of the conditional mean and would be misleading as reallocation shocks are asymmetric and non-directional by nature. In the present paper, we adopt a different line of analysis which has novel features. We estimate a reduced form equation for unemployment of the Lilien (1982a) type and draw inferences by implementing a quantile regression (QR) approach to exploit the intrinsic asymmetries of allocative shocks. Quantile regression modelling allows us to quantify the response of each unemployment quantile to covariates. We can analyze not only the conditional central location but also the off-central location responses. In section 2 we put the sectoral shifts issue into the perspective of QR. In section 3 we introduce our QRM (Quantile Regression Model) for sectoral shifts and discuss briefly estimation and inference issues leaving details to an appendix. In section 4 we present results and finally in section 5 we draw conclusions and briefly outline possible developments.

2. Quantile Regression and Employment Reallocation

Lilien (1982a) claims that intersectoral shifts in demand composition could operate as the driving force of unemployment fluctuations. Idiosyncratic shocks can bring about a process of workers reallocation (from declining to expanding sectors) which could be slow enough to require prolonged unemployment spells. Periods of relatively higher aggregate unemployment would be then associated with periods of relatively higher dispersion in employment demand.

Lilien's reduced form specification can be written as:

$$u_t = \beta_0 + \beta_1\sigma_t + \beta_2 m_t + \beta_3 d_t + \beta_4 e_t + v_t \qquad (1)$$

where u_t is the unemployment rate, m_t is the growth rate of M2, d_t is the natural logarithm of the US public deficit and e_t the growth rate of energy prices. The covariate σ_t, often called the Lilien dispersion proxy, is the weighted standard deviation of cross-sectoral employment growth rates:

$$\sigma_t = \left[\sum_j (N_{j,t} / N_t)(\Delta \ln N_{j,t} - \Delta \ln N_t)^2 \right]^{1/2} \qquad (2)$$

where N_{jt} is employment in sector j at time t for j= 1,2…, K, N_t is aggregate employment at time t, and (N_{jt}/N_t) are weights defined by the relative size of each sector.

Lilien's empirical evidence suggests that σ_t is significantly and positively correlated with u_t over the period 1948-1980 and that much of US unemployment in the 1970's, contrary to that of the early 1960's, can be explained by sectoral shifts. Figure 1 shows that over time in the US, there has been a large amount of workers reallocation, as characterized by σ_t, and that peaks in σ_t often coincide with peaks in unemployment.

Figure 1 Here

Earlier analysis of these phenomena (Lilien 1982b; Abraham and Katz 1986, 1987; Weiss 1986) showed that the positive unemployment-sectoral dispersion (u-σ) correlation (as measured by using Lilien's proxy) could instead capture the effects of aggregate shocks if cyclical responsiveness varies across sectors. Thus two alternative theories of unemployment fluctuations could yield observationally equivalent predictions (aggregate shocks vs sectorals shocks). Subsequent research has been moving in disparate directions and has seen a flourishing of empirical studies but at the same time no unifying analytical framework has obtained a widespread consensus[1].

Explorations of the (u - σ) correlation have in most cases borne out Abraham and Katz's (1986) skeptical views about sectoral shifts[2]. These results, rooted in the LRM, reflect the response of the conditional mean function to a change in the covariates. They ignore the asymmetric and non-directional nature of allocative shocks. Aggregate shocks are directional (positive/negative), and, through the relevant propagation mechanism, could bring about large unemployment oscillations even when they are small. In principle these effects are reflected in each quantile of the unemployment distribution and would imply essentially a change in the central location. Reallocation shocks are disturbances *unfavourable* to the existing allocation of resources: a sectoral shock should bring about a reallocation process which is followed by an oscillation in aggregate unemployment. Some sectors will expand and others will contract. At the macro level, this change in demand composition is reflected in the ensuing reallocation of workers which, for given search technology, would bring about an increase in unemployment consistent with the size of the required job reallocation. It is the magnitude of the engendered reallocations which determines the aggregate response in terms of higher unemployment. As reallocation shocks affect unemployment to the extent they are unfavorable to the current allocation of resources, small shocks generate a small unemployment increase while large shocks generate a large rise in unemployment. In analytical terms, it is the size of the shock and its asymmetric structure that count. Thus, the conditional unemployment distribution would be skewed to the left and the effects of employment reallocations on the lower quantiles will be small and insignificant.

Asymmetry together with the non-directional nature of idiosyncratic shocks have received a relatively small and restricted attention in testing the "job reallocation hypothesis" (e.g. Davis and Haltiwanger, 1999; Pelloni and Polasek, 1999; Pelloni and Polasek, 2003; Panagiotidis et al 2003 and for nonlinearity Panagiotidis and Pelloni, 2007). In the context of Lilien-type approach, equations (1) and (2) above, asymmetry has played no role and most of the focus has been on the mean response and / or the volatility[3]. In this paper, we take a different view and suggest that modelling the conditional mean of unemployment is not an appropriate strategy as it fails to take into account the fundamental intrinsic asymmetries of allocative shocks. As a measure of central location the conditional mean would be distorting if the distribution is skewed. Furthermore, given the intrinsic skewness of the conditional unemployment distribution under the employment reallocation assumption, researchers would be interested in measuring and testing off-central location responses and changes in the shape of the conditional unemployment distribution in response to changes in the covariates. Clearly, the LRM would not be able to provide the necessary information. Preceding analyses were all based on the LRM and so all of them suffered of the shortcomings just illustrated.

In summary in this paper we argue that two main features characterize unemployment fluctuations brought about by allocative shocks: (i) the size of the shock; nand (ii) the asymmetric response of unemployment.

The first of these traits could be handled within the LRM through a polynomial representation of the dispersion proxy which would capture the non-linearity of the allocative shocks[4]. However such a framework would capture only the shock size effect on the conditional mean. The second feature could hardly be captured within a LRM. We suggest handling the analysis of equations like (1) and (2) by using quantile regression. In fact the QRM would provide an approach capable of overcoming some of these shortcomings. It would identify variations in the conditional quantile in response to changes in the covariates and gives us the possibility to focus on different segments of the distribution[5]. Our approach is not embedded within a tight theoretical framework. However, no fully developed theoretical model of sectoral shifts has been developed up to now. Thus our approach, similar to others in the past, is based on fundamental features of sectoral shifts. Though it may not provide a final assessment on sectoral shifts (this would have to wait for the missing theory), we maintain that it can provide important and useful clues and leads.

3. A Benchmark QRM of Unemployment.

We estimate linear versions of equation (1), which provide representations of how each conditional quantile of unemployment depends on a (purged) Lilien's dispersion measure and a vector of aggregate covariates.

We start by providing a brief overview of the econometric methodology adopted here. Let u represent a random variable, in our case the unemployment rate, the conditional quantile function (CQF) at quantile τ given a vector of regressors, X_i: can be defined as

$$Q_\tau(u_i | X_i) = F_U^{-1}(\tau | X_i)$$

where $F_U(\tau | X_i)$ is the distribution function for u_i at u, conditional on X_i. When τ=0.5, $Q_\tau(u_i | X_i)$ would give us the conditional median, while τ=0.9 provides the upper decile of u given X_i. The following minimisation problem is solved by the CQF:

$$Q_i(u_i | X_i) = \arg\min E\left[\rho_\tau(u_i - q(X_i))\right]$$

where $\rho_\tau(w) = (\tau - 1(w \leq 0))$ is the absolute value check function. When τ=0.5, we have the least absolute deviations (LAD) estimator, so that when $Q_i(u_i | X_i)$ is the conditional median. The check function puts negative and positive weights in an asymmetric way:

$$\rho_\tau(w) = 1(w > 0)\tau|w| + (w \leq 0)(1 - \tau)|w|$$

Within the quantile regression framework, we set:

$$\beta_\tau \equiv \arg\min E\left[\rho_\tau(u_i - X'b)\right]$$

and $\hat{\beta}_\tau$ is the quantile regression estimator. This minimisation can be considered as a linear programming problem.

We would like to keep our approach as close as possible to Lilien (1982a). However, we cannot ignore lessons which have been emerging since the publication of Lilien's article. Thus our specification of the unemployment equation is closer to the specification in Mills et al (1995).

As dependent variable, following Wallis (1987), we employ the logistic transformation of unemployment rate. Although the discussion on the stationarity properties of the unemployment rate is extensive, we treat it here as a mean reverting process. We have employed a number of unit root tests such as the ADF, Phillips-Perron, the Zivot-Andrews (1992) with a break and the nonlinear one proposed by Kapetanios et al (2003). All of them reject the unit root either at the 5% or at the 1% significance level (results available upon request). The summary statistics of the unemployment and its logistic transformation are presented in Table 1. It emerges that the mean is greater than the median and there is some positive skewness. Figure 2 presents the kernel density together with the histogram for the two series. It is worth mentioning that the right tail of the distribution of the unemployment seems longer than its left tail and the one of its logistic transformation. We interpret it as a potential signal of asymmetry.

Table 1 Here

Figure 2 Here

The unemployment rate is modelled as a linear function of money growth (m), the dispersion index (s), the natural logarithm of the US public deficit (d), the growth rate of energy prices (e) and so for the τth quantile vector $\mathbf{x} = (s, m, d, e)$.

Our covariate, s, is Lilien's dispersion measure purged of aggregate effects (Lilien's sigma was constructed using data from the Bureau of Labor Statistics using four sectors: Construction, Finance, Manufacturing and Trade). Because of potential aggregate influences on the weighted cross-sectoral variance of employment growth rates, we have purged the Lilien's proxy in (2) by regressing it on the current value of the aggregate variables appearing on the right hand side of (1).

As the state of the art dictated in 1982, Lilien's monetary policy covariate was a measure of unanticipated monetary growth. Since in the interim period empirical evidence has not borne out the importance of unperceived money changes as a potential triggering force of cycles, we can cast aside the separation between perceived and unperceived money growth. In our model we use the growth rate of M2 as a measure of monetary policy.

The natural logarithm of the US public deficit is introduced to capture the effects of fiscal policy while the growth rate of energy prices, *e*, enters as another potential source of aggregate real shocks. The inclusion of energy prices as an aggregate source of fluctuations might be controversial. Early important work on energy costs, Loungani (1986), Hamilton (1988), Keane (1991), Keane (1993) and Keane and Prasad (1996) suggest that relative productivity changes associated with oil price changes could lead to significant variations in frictional unemployment as labour is reallocated across sectors. We prefer to interpret oil price changes as aggregate shocks, because we wish to present a lower bound estimation for the hypothesis of sectoral shifts (c.f. Mills et al., 1995).

The gist of our experiment is linked to the different nature of allocative and aggregate shocks. Allocative shocks being compositional and not directional induce only movements of the unemployment rate above its long run steady state value (LRSSV). For instance, if the LRSSV is 5% when an allocative shock hits the economy, unemployment will increase temporarily above its 5% LRSSV, to converge back to it in due course when reallocations have been completed. This characteristic entails that a Lilien's proxy, if properly designed to capture sectoral shocks, would only affect significantly values of the unemployment rate above the LRSSV of unemployment. Furthermore the compositional nature of allocative shocks implies that only size matters. Directional shock could affect the economy even when they are small through the magnifying effect of a propagation mechanism while allocative shock effects depend on the size of change in demand composition. Thus we postulate that the effect of our Lilien proxy will be non-significant for the lower quantiles of a skewed conditional distribution of the unemployment rate. On the other end, aggregate shock, though not necessarily strictly symmetric, must capture variations above and below the unemployment LRSSV and would moderately affect the shape of the distribution and would tend to look like central location shifts (conditional means effects). Our experiment claims that a unit change of one of the aggregate covariates should cause every quantile to change (approximately) by the same amount because aggregate shocks would represent a central-location shift. Aggregate shocks might bring about scale shifts but not changes in the shape of the unemployment distribution. This property should strictly hold for nominal shocks, while the aggregate real shocks may present minor variations across quantiles because of associated distributional effects. Sectoral reallocations, operating through a one sided dimensional effect (*unfavorable* to the current allocation of resources) linked to the magnitude of the shock, entail a left skewed unemployment distribution. An increase of the dispersion proxy from a lower to a higher value has a greater effect on high unemployment rates and would affect the shape of the unemployment distribution by increasing its left-skewness.

4. Empirical Results

We start our analysis with the linear benchmark model. Our experiment is carried out for the United States using monthly data for the period 1958:01-2011:03 (Data were retrieved from the Bureau of Labor Statistics). We have employed 10 quantiles to reveal the behavior of the entire distribution.

Given the complexities and unsolved intricacies of a dynamic analysis (identification of lags structure) in the QR context [6], we suggest a simple but still informative procedure. We apply this procedure to both the LRM and the QRM. We run three regressions and each of these regressions would relate the unemployment rate measured at time *t* to a specific lag (*t-j*) of the set of the covariates. The first regression would capture the effect on U_t of the contemporaneous set of covariates (j = 0). The other two independent regressions should catch the impact on U_t of the set of regressors lagged six months (j=6) and twelve months (j=12). In such a way, without entering the not yet fully explored territory of QR dynamics, we can draw useful comparative inferences about the potential role of the covariates within a one year horizon.

The OLS results are presented in Table 2. The statistical significance of σ_t emerges for model 1 (contemporaneous relationship), for model 2 with 6 lags and model 3 with 12 lags. The coefficient of the federal deficit is also statistically significant but its significance decreases as we move from model 1 (contemporaneous) to model 3 (12 months lags). The money growth coefficient is insignificant for model 1 but becomes significant in the case of model 2 and 3. Energy price inflation also becomes significant in the case of model 3. However, strong evidence of autocorrelation emerges (see Table 2).

Table 2 Here

The next step would be to re-examine the linear relation by relaxing the assumption of symmetry. The QRM results are presented in Table 3 (tests for asymmetries are also available upon request, see Tables 7 and 8).

Table 3 Here

In a standard fashion we have obtained estimates of the CQF via the solution of the linear programming minimization problem min $\sum[\rho_\tau (u_i - q(X_i, \beta)]$, where ρ_τ is the absolute value check function. A crucial estimation and inference issue concerns the estimates of the asymptotic covariance matrix. In this study we apply bootstrapping techniques for the estimation of the covariance matrix. We use *XY*-pair (design) out of the various potential bootstrapping methods. The latter is valid in cases where U and *X* are not independent. The methodology works as follows: after generating *B* randomly drawn subsamples of size *m* from the original data, we compute estimates of $\beta(\tau)$ using (U^*, X^*) replacements for each subsample. The estimated asymptotic covariance matrix is then derived from the sample variance of the bootstrap results (for a detail discussion (see Kocherginsky et al., 2005). In this case we have used 100 repetitions.Table 4 shows goodness of fit statistics and diagnostic tests which bear out that the equation is sufficiently general to be viewed as an adequate benchmark model.

In Figures 3, 4 and 5 we present the results for the simultaneous effects, the six and twelve months horizons respectively. In all three graphs the slopes of the estimated curve for the fitted constant could look flatter below the median than above the median. However, the coefficient values are negative thus suggesting a left skewed distribution.

Figures 3, 4 and 5 Here

The contemporaneous sectoral shift variable displays a moderately positively sloped graph which is insignificant only at the first three quantiles. The positive slope indicates an increase in the scale of the response of the conditional distribution. A unit increase in the dispersion index has a greater effect on unemployment for higher quantiles than for lower quantiles other things equal. In other words, the higher the unemployment, the higher is the effect of reallocation.

When we introduce lags, we can see that the sectoral shifts scale effect increases after six months and becomes flatter with twelve months horizon. Thus as the time horizon becomes longer, the scale effect associated with the dispersion proxy first increases, then falls leaving only a location effect. This may seem to suggest that the effect on unemployment of employment dispersion after a one year horizon does not reflect the expected stylized characteristic of an allocative shock.

In figure 3 federal deficit has a significant impact on unemployment. The graph somehow resembles a straight line between the 30th quantile and the 60th quantile (i.e. suggesting a location effect) while presenting a positive slope for lower quantiles and a negative slope for higher quantiles. Since the associated coefficients are negative, this concave shape of the plot may indicate deficits would affect unemployment negatively at higher quantiles and positively at lower quantiles. The Federal deficit is positively sloped with associated negative coefficients both at the six and twelve months horizons. The effect of an extra unit of deficit is significant, positive and increasing for all unemployment quantiles.

The contemporaneous money covariate is insignificant for all values of τ, while it is significant for $0.4 \leq \tau \geq 0.7$ and for $0.6 \leq \tau$ at six-month and twelve-month horizons respectively. Both significant portions of the curves are horizontal reflecting location shifts. Overall money has little impact on unemployment within a one year horizon.

The energy price variable is insignificant whatever the considered time horizon. This outcome may reflect the ambiguous nature of oil shocks which may have strong re-distributional effects captured by the *s*-proxy.

Given the autocorrelation issue, we have also added a lagged value of the logistic transformation of unemployment. These are models 4 and 5 (presented in Tables 5 and 6 and in Figures 6 and 7). Two important conclusions emerge. On the one hand autocorrelation is corrected in this case (see Table 9). On the other hand upward sloping coefficient of sigma remains, providing further support for our results.

Tables 5 and 6 here

Figures 6 and 7 here

5 Conclusions and further outlook

We revisit the sectoral shifts hypothesis 30 years after the seminal paper of Lilien (1982a). Employing US data from the period 1948 to 2011, we examine the case of asymmetry within a quantile regression framework. A purged version of Lilien's dispersion proxy was used as a measure of turbulence in the labour market. Significant asymmetries consistent with the sectoral shifts hypothesis are revealed. This is found to be significant only when unemployment takes relative high values (relative to its median) whereas becomes insignificant when unemployment is low. That is, as predicted by the sectoral shifts hypothesis, the effects of labour reallocation are significant at higher level of unemployment.

Notes

1) See Gallipoli and Pelloni (2008) for references and details of the different approaches to the macroeconomic impact of employment reallocation.
2) A notable exception is Mills et al. (1995). This article, to the best of our knowledge, uses the most updated time series methodology applied to this specific framework (i.e. a reduced form equation with a Lilien dispersion proxy).
3) An exception is Byun and Hwang (2009). They emphasize that the skewness of the distribution of reallocation shocks can have a significant role in a Lilien-type model. Their empirical results show a significant effect of the skewness measure on the aggregate unemployment rate. However, they set their analysis in a LRM context and unfortunately fail to take into account recent advances in time series analysis.
4) The second order polynomial in Davis (1986) and Loungani (1986) could fall in this line of reasoning.
5) Koenker and Bassett (1978) proposed the QRM that provides estimates of the linear relationship between the covariates and a specified quantile of the dependent variable. For a detailed analysis of quantile regression see Koenker (2005). For a more concise and less technical exposition see Koenker and Hallock (2001);
6) Koenker (2005) inserts quantile autoregression in the "twilight zone of quantile regression".

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Figure 1: Unemployment rate and Lilien's σ_t for the USA

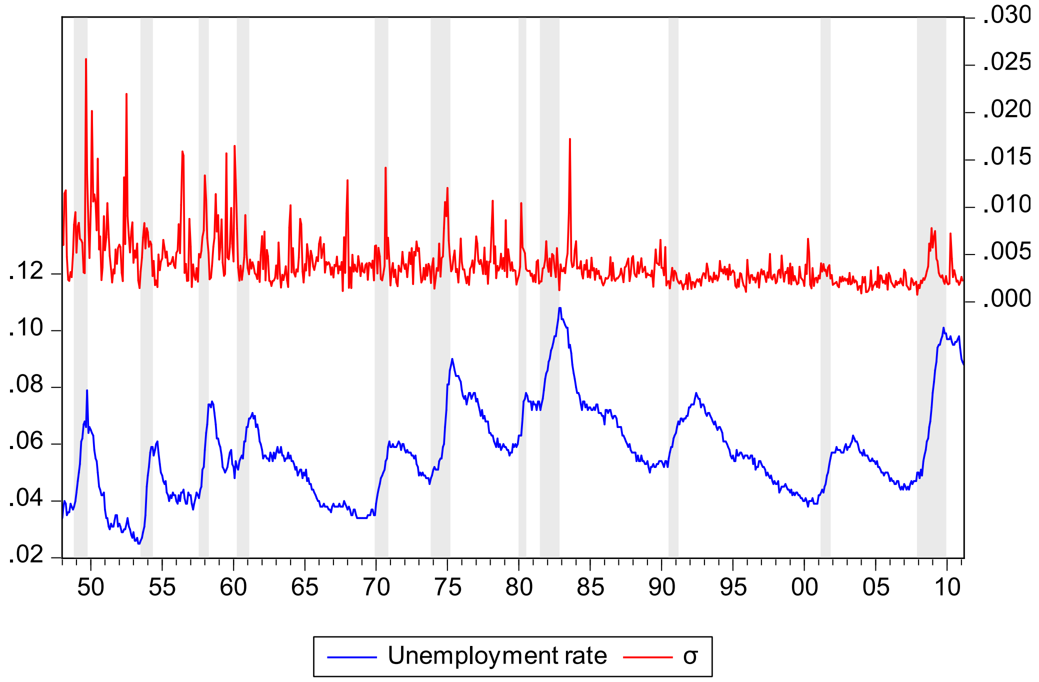


Figure 2: Kernel Density for Logistic Transformation

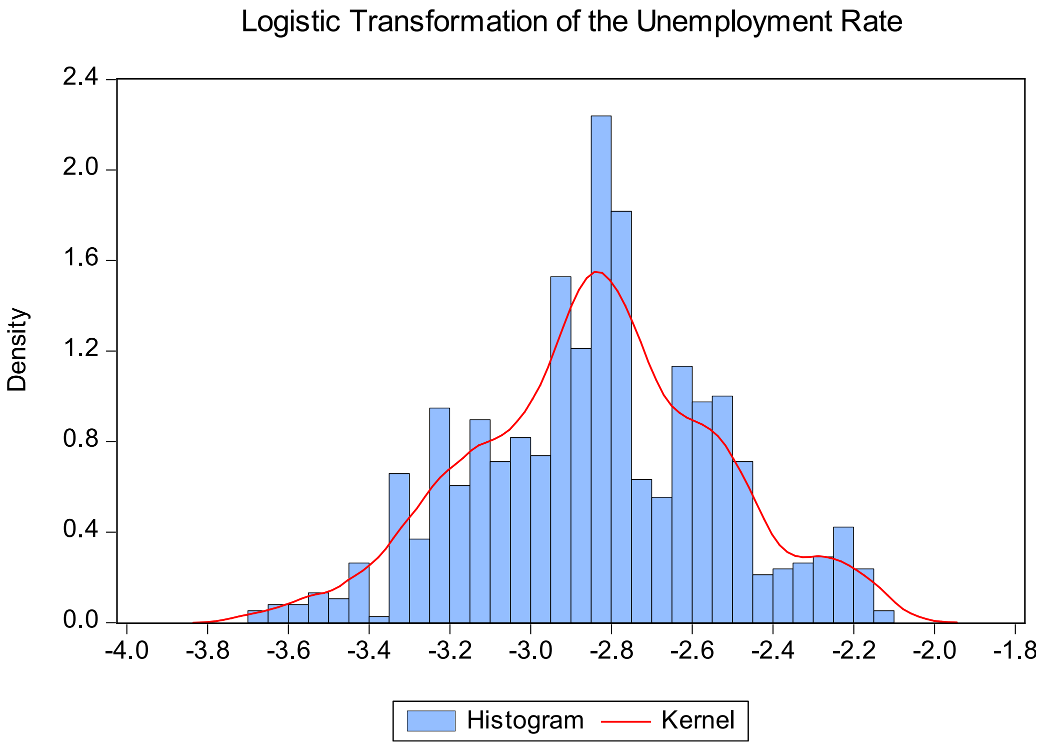


Figure 3

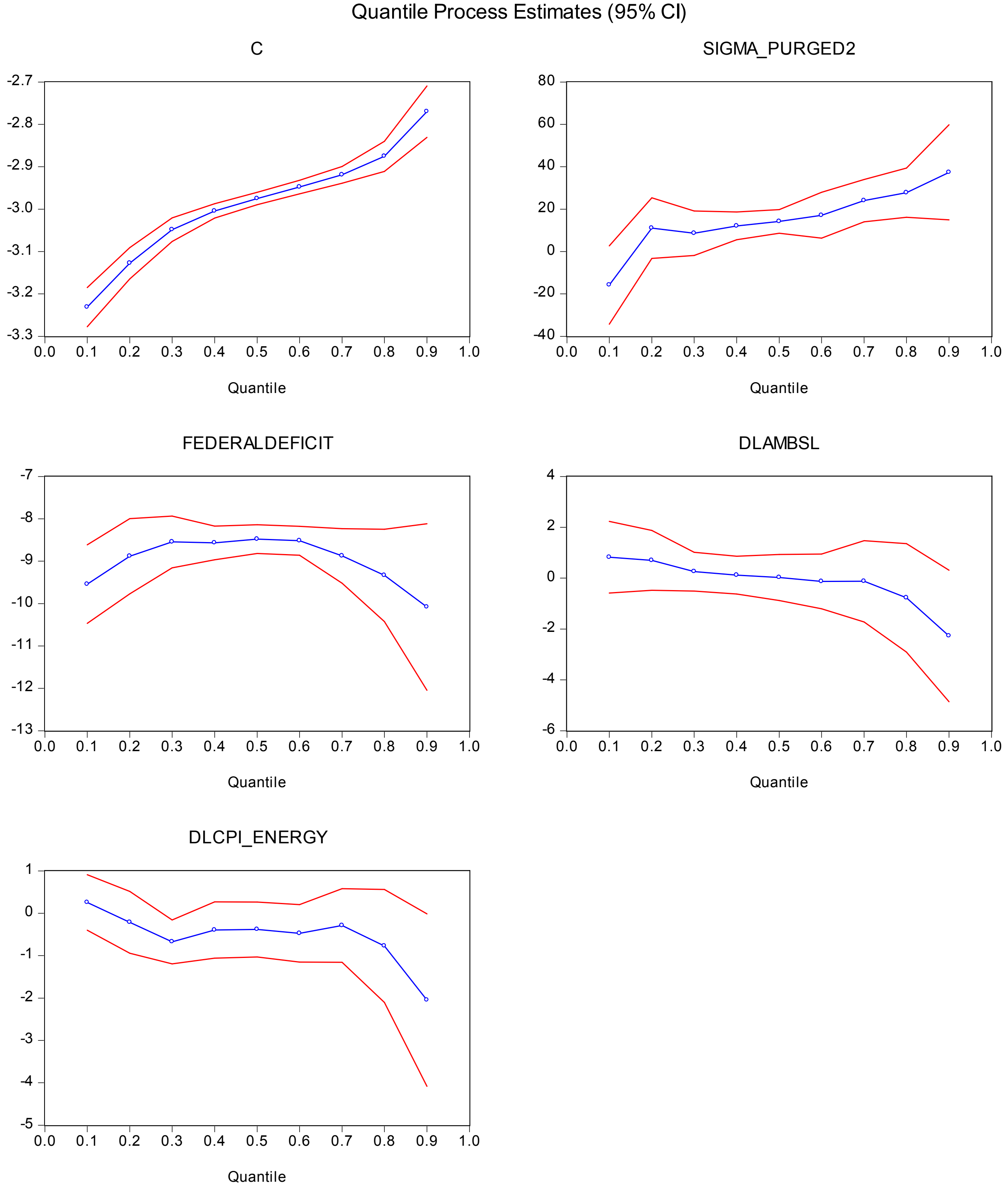
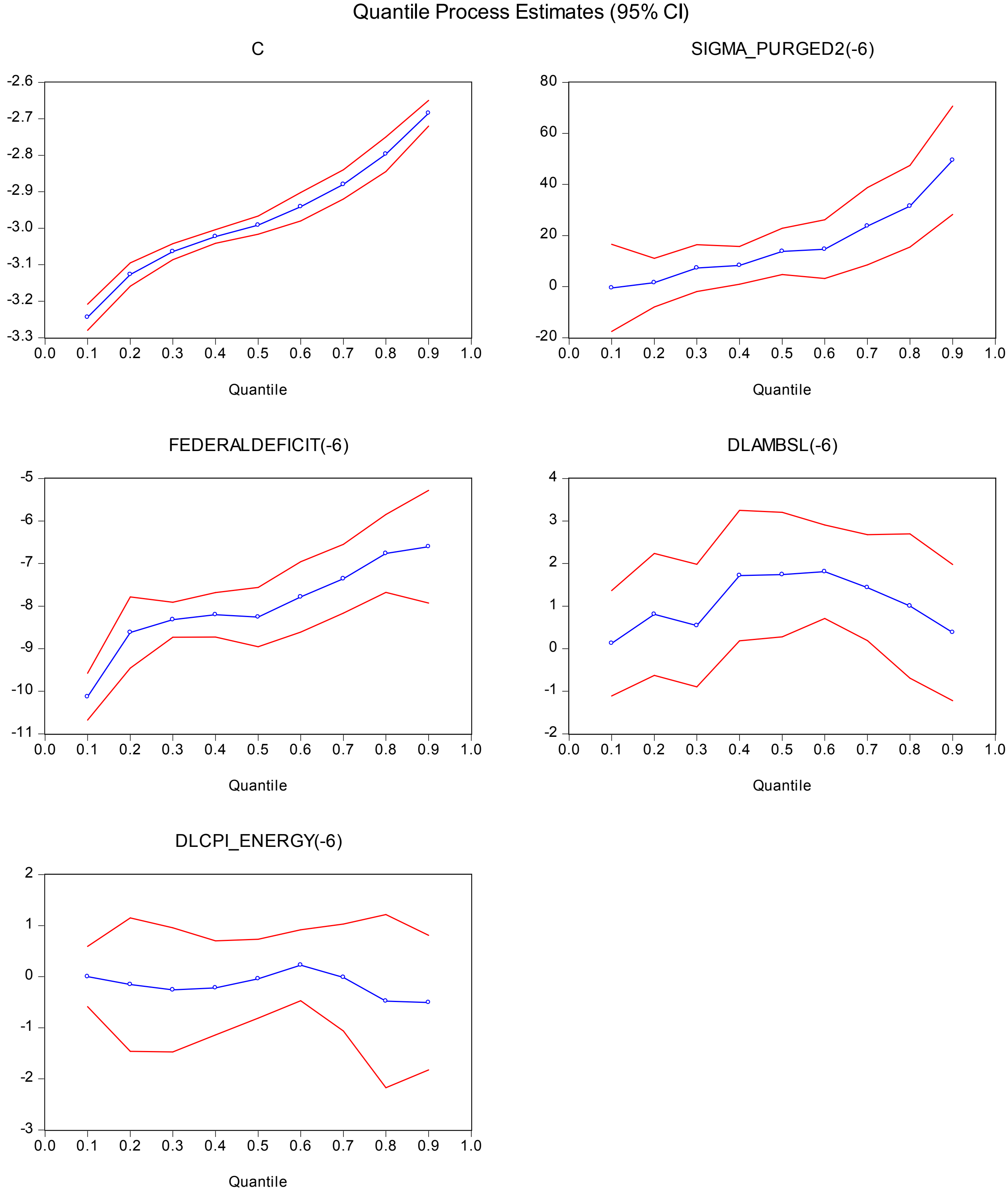

Quantile Process Estimates (95% CI)
C
SIGMA_PURGED2
FEDERALDEFICIT
DLAMBSL
DLCPI_ENERGY
Quantile

Figure 4


Quantile Process Estimates (95% CI)
C
SIGMA_PURGED2(-6)
FEDERALDEFICIT(-6)
DLAMBSL(-6)
DLCPI_ENERGY(-6)
Quantile
Quantile
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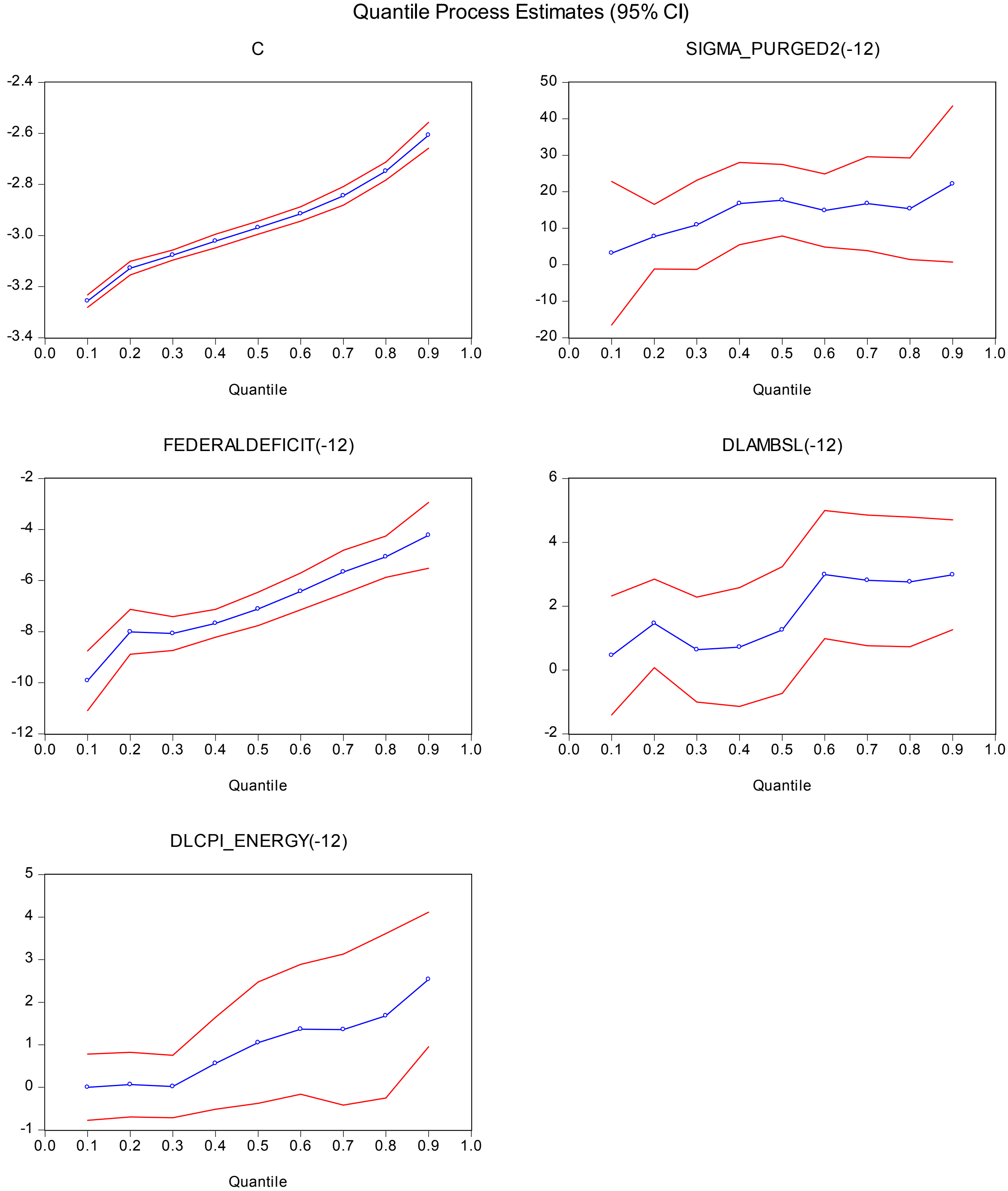
Quantile

Figure 5



Quantile Process Estimates (95% CI)
C
-2.4
-2.6
-2.8
-3.0
-3.2
-3.4
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Quantile
SIGMA_PURGED2(-12)
50
40
30
20
10
0
-10
-20
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Quantile
FEDERALDEFICIT(-12)
-2
-4
-6
-8
-10
-12
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Quantile
DLAMBSL(-12)
6
4
2
0
-2
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Quantile
DLCPI_ENERGY(-12)
5
4
3
2
1
0
-1
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Quantile

Figure 6

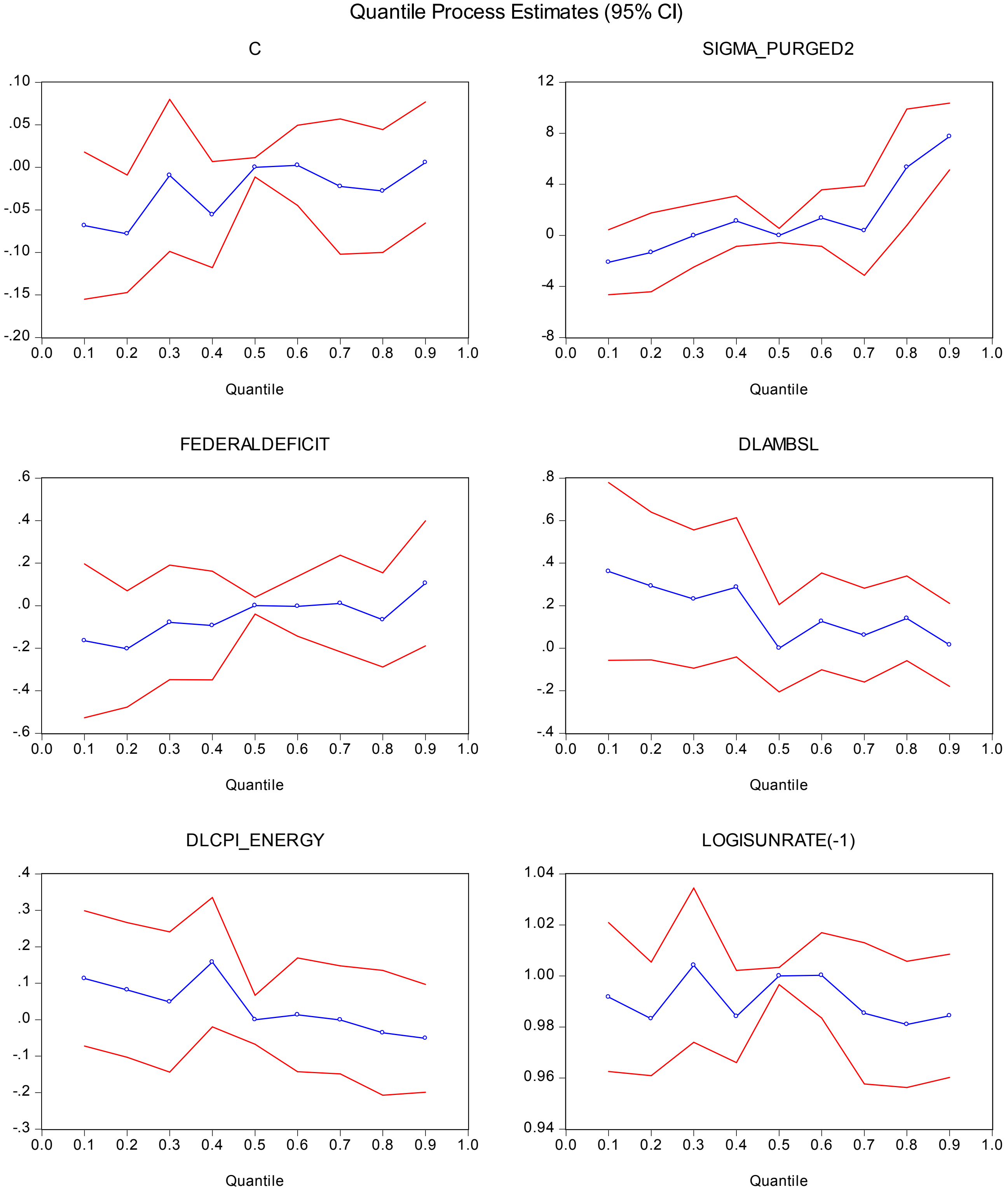

Quantile Process Estimates (95% CI)
C
SIGMA_PURGED2
FEDERALDEFICIT
DLAMBSL
DLCPI_ENERGY
LOGISUNRATE(-1)
Quantile

Figure 7

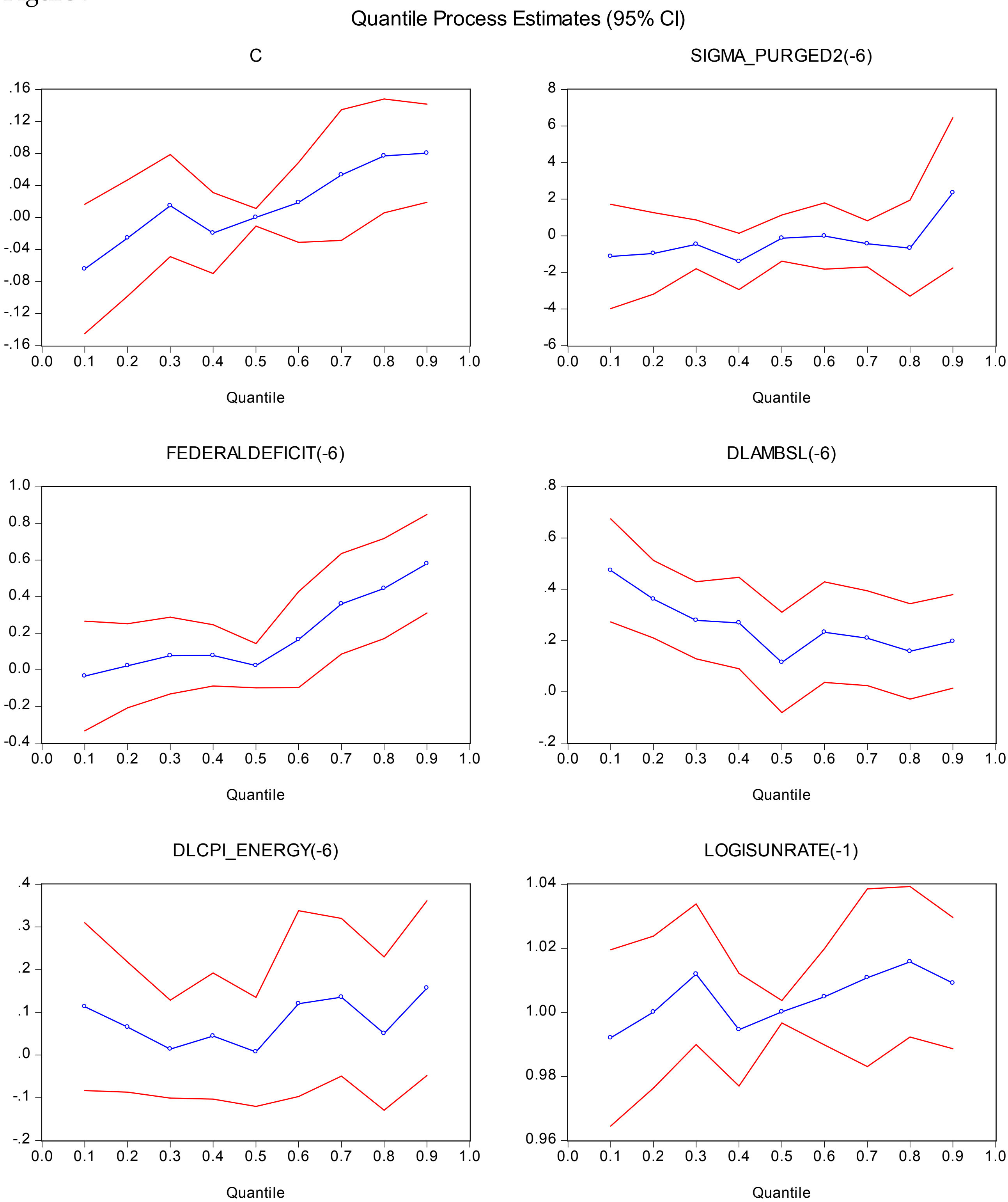

Quantile Process Estimates (95% CI)
C
.16
.12
.08
.04
.00
-.04
-.08
-.12
-.16
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Quantile
SIGMA_PURGED2(-6)
8
6
4
2
0
-2
-4
-6
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Quantile
FEDERALDEFICIT(-6)
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Quantile
DLAMBSL(-6)
.8
.6
.4
.2
.0
-.2
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Quantile
DLCPI_ENERGY(-6)
.4
.3
.2
.1
.0
-.1
-.2
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Quantile
LOGISUNRATE(-1)
1.04
1.02
1.00
0.98
0.96
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Quantile

Table 1: Summary Statistics

	Unemployment Rate	Logistic Transformation of Unemployment rate
Mean	0.057312	-2.839907
Median	0.056000	-2.824774
Maximum	0.108000	-2.111335
Minimum	0.025000	-3.663562
Std. Dev.	0.016304	0.300950
Skewness	0.666020	-0.048311
Kurtosis	3.297517	2.838616

Table 2: OLS Estimates of the model (*t*-stats below each coef)

	Model 1 Contamporaneous	Model 2: 6 lags	Model 3: 12 lags
Constant	-2.9907	-2.9703	-2.9436
	-126.98	-108.74	-94.13
σ_t purged	13.0201	14.9764	11.9904
	2.48	2.133	1.817
d_t	-8.8452	-7.8625	-6.5078
	-14.17	-13.03	-8.605
m_t	0.2692	1.6661	2.5287
	0.925	3.87	3.622
e_t	-0.3362	0.0003	1.0646
	-1.02	0.0007	1.451
Adjusted R^2	0.555	0.447	0.306
F-stat	202.271	130.841	71.246
Pr(F-stat)	0.000	0.000	0.000
Serial Correlation LM Test Pr(12 lags)	0.000	0.000	0.000

HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth 7)

Table 3: Quantile Process Estimates

Specification: $u_t = \beta_0 + \beta_1\sigma_t + \beta_2 m_t + \beta_3 d_t + \beta_4 e_t + v_t$

		Model 1 Contamporaneous		Model 2: 6 lags		Model 3: 12 lags	
	Quantile	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	0.1	-3.23	-137.42	-3.24	-178.27	-3.26	-262.38
	0.2	-3.13	-165.27	-3.13	-191.74	-3.13	-229.83
	0.3	-3.05	-215.23	-3.06	-274.23	-3.08	-302.68
	0.4	-3.00	-344.63	-3.02	-318.36	-3.02	-223.53
	0.5	-2.97	-400.81	-2.99	-235.62	-2.97	-229.21
	0.6	-2.95	-359.39	-2.94	-148.04	-2.92	-200.57
	0.7	-2.92	-288.12	-2.88	-140.53	-2.84	-153.12
	0.8	-2.88	-158.32	-2.80	-115.26	-2.75	-153.30
	0.9	-2.77	-89.62	-2.68	-148.70	-2.61	-100.60
σ_t purged	0.1	-15.81	-1.68	-0.52	-0.06	3.16	0.31
	0.2	11.00	1.51	1.55	0.32	7.70	1.71
	0.3	8.65	1.61	7.26	1.55	10.94	1.75
	0.4	12.09	3.61	8.32	2.21	16.76	2.91
	0.5	14.23	5.01	13.77	2.99	17.68	3.54
	0.6	17.09	3.09	14.67	2.51	14.87	2.91
	0.7	24.03	4.72	23.66	3.06	16.75	2.55
	0.8	27.74	4.68	31.48	3.85	15.36	2.16
	0.9	37.37	3.27	49.46	4.57	22.11	2.02
d_t	0.1	-9.54	-20.17	-10.13	-35.95	-9.92	-16.62
	0.2	-8.88	-19.64	-8.62	-20.21	-8.01	-17.92
	0.3	-8.55	-27.39	-8.32	-39.79	-8.07	-23.95
	0.4	-8.57	-42.34	-8.20	-30.82	-7.68	-27.52
	0.5	-8.48	-48.96	-8.26	-23.23	-7.11	-21.20
	0.6	-8.52	-49.13	-7.78	-18.43	-6.43	-17.45
	0.7	-8.88	-27.06	-7.35	-17.84	-5.66	-13.04
	0.8	-9.34	-16.82	-6.76	-14.48	-5.07	-12.26
	0.9	-10.08	-10.07	-6.60	-9.78	-4.23	-6.42
m_t	0.1	0.82	1.14	0.13	0.20	0.46	0.48
	0.2	0.70	1.16	0.81	1.10	1.46	2.06
	0.3	0.25	0.65	0.54	0.74	0.64	0.76
	0.4	0.12	0.31	1.72	2.20	0.72	0.76
	0.5	0.03	0.06	1.74	2.33	1.25	1.24
	0.6	-0.13	-0.23	1.81	3.23	2.99	2.92
	0.7	-0.12	-0.15	1.43	2.26	2.81	2.69
	0.8	-0.77	-0.71	1.00	1.16	2.76	2.66
	0.9	-2.27	-1.72	0.38	0.46	2.98	3.39
e_t	0.1	0.25	0.76	0.00	0.01	0.00	0.01
	0.2	-0.21	-0.58	-0.15	-0.23	0.06	0.17
	0.3	-0.68	-2.57	-0.26	-0.41	0.02	0.05
	0.4	-0.40	-1.17	-0.22	-0.47	0.56	1.02
	0.5	-0.38	-1.16	-0.04	-0.10	1.05	1.44
	0.6	-0.47	-1.37	0.22	0.63	1.36	1.75
	0.7	-0.29	-0.65	-0.02	-0.03	1.36	1.50
	0.8	-0.77	-1.13	-0.48	-0.56	1.68	1.71
	0.9	-2.05	-1.98	-0.51	-0.75	2.53	3.14

Table 4: Goodness of fit for Quantile Regressions

	Model 1	**Model 2**	**Model 3**
Pseudo R-squared	0.386	0.305	0.202
Adjusted R-squared	0.382	0.301	0.197
Quasi-LR statistic	665.011	428.219	237.933
Prob(Quasi-LR stat)	0.000	0.000	0.000

Note: Pseudo R-squared are from Koenker and Machado (1999).

Table 5: Quantile Process Estimates

	Quantile	Model 4 Contamporaneous Coefficient	t-Statistic	Model 5: 6 lags Coefficient	t-Statistic
Constant	0.1	-0.069	-1.552	-0.064	-1.562
	0.2	-0.078	-2.216	-0.026	-0.694
	0.3	-0.009	-0.207	0.015	0.456
	0.4	-0.056	-1.748	-0.019	-0.754
	0.5	0.000	0.000	0.000	0.044
	0.6	0.002	0.097	0.019	0.738
	0.7	-0.023	-0.557	0.053	1.274
	0.8	-0.028	-0.756	0.077	2.117
	0.9	0.006	0.157	0.080	2.567
σ_t purged	0.1	-2.106	-1.622	-1.128	-0.775
	0.2	-1.330	-0.845	-0.962	-0.848
	0.3	-0.018	-0.014	-0.472	-0.694
	0.4	1.118	1.112	-1.395	-1.777
	0.5	0.000	0.000	-0.129	-0.201
	0.6	1.354	1.197	-0.013	-0.014
	0.7	0.372	0.208	-0.439	-0.684
	0.8	5.341	2.295	-0.677	-0.506
	0.9	7.756	5.808	2.345	1.119
d_t	0.1	-0.165	-0.896	-0.034	-0.221
	0.2	-0.203	-1.456	0.022	0.190
	0.3	-0.078	-0.571	0.077	0.725
	0.4	-0.093	-0.715	0.079	0.920
	0.5	0.000	0.000	0.023	0.368
	0.6	-0.003	-0.039	0.165	1.233
	0.7	0.010	0.090	0.360	2.574
	0.8	-0.067	-0.589	0.444	3.183
	0.9	0.105	0.701	0.580	4.219
m_t	0.1	0.361	1.695	0.474	4.621
	0.2	0.293	1.652	0.361	4.671
	0.3	0.231	1.394	0.279	3.637
	0.4	0.286	1.716	0.268	2.952
	0.5	0.000	0.000	0.114	1.145
	0.6	0.126	1.086	0.233	2.323
	0.7	0.061	0.545	0.209	2.215
	0.8	0.140	1.380	0.158	1.662
	0.9	0.016	0.161	0.197	2.106
e_t	0.1	0.113	1.196	0.113	1.131
	0.2	0.082	0.866	0.065	0.840
	0.3	0.049	0.496	0.014	0.236
	0.4	0.158	1.743	0.044	0.589
	0.5	0.000	0.000	0.007	0.114
	0.6	0.013	0.169	0.120	1.085
	0.7	-0.001	-0.007	0.135	1.436
	0.8	-0.036	-0.411	0.050	0.551
	0.9	-0.051	-0.676	0.157	1.502
u_{t-1}	0.1	0.992	66.650	0.992	70.647
	0.2	0.983	86.602	1.000	82.590
	0.3	1.004	65.066	1.012	90.271
	0.4	0.984	106.718	0.995	110.891
	0.5	1.000	584.689	1.000	561.182
	0.6	1.000	117.149	1.005	130.977
	0.7	0.985	69.708	1.011	71.433
	0.8	0.981	77.853	1.016	84.621
	0.9	0.984	79.838	1.009	96.409

Table 6: Goodness of fit for Quantile Regressions

	Model 4	Model 5
Pseudo R-squared	0.881451	0.88268
Adjusted R-squared	0.880526	0.88176
Quasi-LR statistic	5899.5	5984.5
Prob(Quasi-LR stat)	0.000	0.000

Table 7: Quantile Slope Equality Test

		Model 1	Model 2	Model 3
Wald Test				
Chi-Sq. Statistic		106.794	144.548	152.824
Prob.		0.000	0.000	0.000
		prob value	prob value	prob value
0.1, 0.2	σ_τ purged	0.0006	0.780	0.612
	d_t	0.0785	0.000	0.001
	m_t	0.8632	0.322	0.214
	e_t	0.1869	0.768	0.857
0.2, 0.3	σ_τ purged	0.6102	0.145	0.511
	d_t	0.2998	0.347	0.849
	m_t	0.3113	0.604	0.116
	e_t	0.1133	0.7958	0.8873
0.3, 0.4	σ_τ purged	0.3666	0.7454	0.1671
	d_t	0.9191	0.6357	0.1641
	m_t	0.6404	0.0234	0.8857
	e_t	0.3374	0.9132	0.1022
0.4, 0.5	σ_τ purged	0.4574	0.0667	0.8
	d_t	0.5046	0.8069	0.0162
	m_t	0.7547	0.954	0.3847
	e_t	0.9595	0.4762	0.2244
0.5, 0.6	σ_τ purged	0.4689	0.8401	0.3463
	d_t	0.792	0.0829	0.0095
	m_t	0.6585	0.9039	0.0156
	e_t	0.6636	0.2927	0.4627
0.6, 0.7	σ_τ purged	0.0937	0.0967	0.6739
	d_t	0.1784	0.0973	0.0128
	m_t	0.9951	0.3633	0.7317
	e_t	0.5211	0.5263	0.9895
0.7, 0.8	σ_τ purged	0.4654	0.2315	0.8268
	d_t	0.2559	0.0784	0.0642
	m_t	0.4249	0.5414	0.948
	e_t	0.2929	0.389	0.5858
0.8, 0.9	σ_τ purged	0.3316	0.0465	0.4669
	d_t	0.3404	0.8027	0.1692
	m_t	0.142	0.4359	0.7667
	e_t	0.127	0.9731	0.2727

Table 8: Symmetric Quantiles Test

		Model 1	Model 2	Model 3
Wald Test				
Chi-Sq. Statistic		21.43949	21.7492	23.0275
Prob.		0.3717	0.3543	0.2874
Wald Test				
Quantiles	Variable			
0.1, 0.9	C	0.1515	0.0695	0.0267
	σ_τ purged	0.6197	0.1372	0.5052
	d_t	0.0071	0.7968	0.9458
	m_t	0.3213	0.031	0.5825
	e_t	0.3413	0.619	0.7302
0.2, 0.8	C	0.0143	0.0272	0.018
	σ_τ purged	0.216	0.5576	0.2637
	d_t	0.0486	0.1182	0.098
	m_t	0.9123	0.1915	0.2969
	e_t	0.7424	0.5118	0.7638
0.3, 0.7	C	0.2163	0.0454	0.3934
	σ_τ purged	0.5199	0.6817	0.3365
	d_t	0.2348	0.1179	0.3569
	m_t	0.9082	0.2034	0.4756
	e_t	0.666	0.7775	0.4165
0.4, 0.6	C	0.8057	0.1476	0.9294
	σ_τ purged	0.8862	0.4429	0.3958
	d_t	0.5538	0.1353	0.7476
	m_t	0.8999	0.956	0.2168
	e_t	0.767	0.8186	0.772

Table 9: Correlogram for the residuals of Models 4 and 5

	Model 4				Model 5			
	AC	PAC	Q-Stat	Prob	AC	PAC	Q-Stat	Prob
1	0.100	0.100	6.488	0.011	0.089	0.089	5.149	0.023
2	0.266	0.258	52.418	0.000	0.280	0.274	55.957	0.000
3	0.184	0.149	74.392	0.000	0.188	0.159	79.009	0.000
4	0.194	0.118	98.993	0.000	0.194	0.114	103.380	0.000
5	0.185	0.102	121.340	0.000	0.162	0.072	120.530	0.000
6	0.112	0.008	129.490	0.000	0.104	-0.003	127.600	0.000
7	0.084	-0.031	134.070	0.000	0.077	-0.031	131.470	0.000
8	0.088	0.000	139.190	0.000	0.088	0.009	136.540	0.000
9	0.065	-0.003	142.000	0.000	0.063	0.007	139.140	0.000
10	-0.038	-0.109	142.930	0.000	-0.049	-0.114	140.730	0.000
11	0.059	0.020	145.200	0.000	0.065	0.028	143.480	0.000
12	-0.130	-0.145	156.460	0.000	-0.127	-0.133	154.110	0.000
13	0.006	-0.005	156.490	0.000	0.019	0.009	154.360	0.000
14	-0.091	-0.041	162.010	0.000	-0.083	-0.028	158.910	0.000
15	0.024	0.081	162.380	0.000	0.022	0.070	159.240	0.000
16	-0.023	0.046	162.730	0.000	-0.023	0.036	159.590	0.000
17	-0.051	-0.013	164.460	0.000	-0.044	-0.022	160.860	0.000
18	-0.028	-0.001	164.980	0.000	-0.027	-0.009	161.330	0.000
19	0.018	0.053	165.210	0.000	0.020	0.046	161.590	0.000
20	-0.025	-0.015	165.640	0.000	-0.036	-0.025	162.470	0.000
21	-0.030	-0.026	166.240	0.000	-0.036	-0.031	163.340	0.000
22	-0.037	-0.054	167.160	0.000	-0.037	-0.051	164.260	0.000
23	-0.017	-0.003	167.350	0.000	-0.016	0.010	164.430	0.000
24	-0.129	-0.175	178.500	0.000	-0.133	-0.165	176.280	0.000
25	-0.074	-0.052	182.180	0.000	-0.090	-0.062	181.670	0.000
26	-0.041	0.008	183.330	0.000	-0.051	0.010	183.390	0.000
27	-0.047	0.037	184.840	0.000	-0.061	0.029	185.930	0.000
28	-0.044	0.026	186.170	0.000	-0.054	0.020	187.890	0.000
29	0.005	0.103	186.190	0.000	-0.006	0.087	187.920	0.000
30	0.002	0.063	186.190	0.000	0.011	0.072	188.000	0.000
31	-0.058	-0.041	188.450	0.000	-0.046	-0.027	189.450	0.000
32	-0.008	-0.003	188.500	0.000	0.010	0.012	189.530	0.000
33	-0.016	0.011	188.670	0.000	-0.022	0.000	189.860	0.000
34	0.021	-0.025	188.970	0.000	0.003	-0.053	189.860	0.000
35	0.011	0.001	189.050	0.000	0.003	-0.007	189.870	0.000
36	-0.080	-0.154	193.420	0.000	-0.079	-0.140	194.110	0.000