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A Note on Unemployment Persistence and Quantile Parameter Heterogeneity

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ABSTRACT

A Note on Unemployment Persistence and Quantile Parameter Heterogeneity*

The standard approach to the estimation of unemployment persistence assumes that quantile parameter heterogeneity does not matter. Using panel quantile autoregression techniques on state-level data for the United States (1980-2010), we suggest that it does.

JEL Classification: C23, J64

Keywords: quantile regression, unemployment, dynamic models

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1 Introduction

There is a vast literature, both theoretical and empirical, on unemployment persistence. The works by Blanchard and Summers (1986), Lindbeck and Snower (1987), Barro (1988), Alogoskoufis and Manning (1988), Mortensen (1989), Blanchard (1991), Elmeskov and MacFarlan (1993), Mitchell (1993), Greenwald and Stiglitz (1995), Jimeno and Bentolila (1998), León-Ledesma (2002), Ortigueira (2006), Romero-Ávila and Usabiaga (2007), Sephton (2009), Dromel et al. (2010) and Cheng et al. (2012) are just few examples.

Most of the debate has focused on the "natural rate" vs. "hysteresis" controversy regarding the dynamic behaviour of unemployment. Under the "natural rate" hypothesis, the unemployment rate tends to a long-run equilibrium and the speed of convergence depends on the degree of unemployment persistence. Under the "hysteresis" hypothesis, a long-run equilibrium cannot be defined and unemployment follows a purely random walk. In the first case, macroeconomic shocks do not have permanent effects on the level of unemployment, even though it may take time before their effects disappear. In the second case, they do have permanent effects. Despite the start of the debate dates several decades back, the current "state of the art" is characterized by the absence of a theoretical consensus and mixed empirical evidence. However, many authors tend to see European labour markets as more "sclerotic", meaning that the effects of macroeconomic shocks tend to last longer than in the United States.

One distinctive feature of the existing empirical literature is its initial focus on the estimation of the conditional mean unemployment persistence (Blanchard and Summers, 1986). Afterwards, the interest has moved towards the implementation of more and more sophisticated unit-root tests. Yet, the general setting has not changed: conditional mean regression.

In this paper, we will go back to the origins, tackling the issue of unemployment persistence from a completely new perspective. Indeed, we will argue that the existing empirical literature, by focusing on the conditional mean, has disregarded an important empirical issue: there may be a lot of heterogeneity behind a mean result (see Koenker and Hallock, 2001, p. 151). In particular, we will study whether unemployment persistence is subject to "quantile parameter heterogeneity", i.e. to what extent a particular result for the conditional mean is driven by something happening at specific quantiles of the conditional unemployment distribution.

As we shall see, our analysis suggests that unemployment persistence is, in fact, larger at the upper tail of the conditional unemployment distribution, and lower at the lower tail. Our evidence is based on a novel model of unemployment persistence and on a set of recently developed techniques for panel quantile autoregression due to Galvão (2011), Galvão and Montes-Rojas (2010) and Lin and Chu (2013).

The paper is structured as follows. Section 2 introduces a model for unemployment persistence where quantile parameter heterogeneity plays a role. Section 3 discusses the literature on panel quantile regression, from both static and dynamic perspectives. Section 4 presents the estimation results. Section 5 concludes.

2 Model

In a famous contribution to the *American Economic Review*, mainly inspired by an earlier article due to Hall (1979), Barro (1988) has argued that the unemployment dynamics of a country can be modelled as follows:

$$u_t = s + (1 - s - f)\, u_{t-1} + \xi_t \tag{1}$$

where u is the unemployment rate, $s \in [0, 1]$ represents the job-separation rate, $f \in [0, 1]$ is the job-finding rate and ξ is viewed as a country-level macroeconomic shock. Unemployment persistence is seen as equal to $1 - (s + f)$ where $(s + f)$ is the gross turnover rate. The "natural" unemployment rate is thus given by $s/(s + f)$.

Despite it dates several decades back, model (1) is the basis for the Beveridge curve in the standard matching model by Mortensen and Pissarides (1994) and it has been used by many authors, even recently. An example is an interesting article by Barnichon (2012). Versions of model (1) with additional unemployment lags or a set of relevant covariates or a flexible error specification may fit the data better. For instance, Barro (1988) has elaborated on model (1), using an ARMA(1,1) specification with time-series data. Yet, model (1) is clearly not satisfactory when state-level panel data for the United States are used because state heterogeneity is not taken into account.

Our key argument is as follows. Suppose an economy is hit by a country-level macroeconomic shock and this shock is "well-behaved", i.e. it affects the unemployment rate in all states equally at the time it arrives. This shock may have different consequences in the years following the shock, depending on the specific characteristics of the local labour market. For instance, in response to the same adverse shock, unemployment may increase more in some states (or regions) than in other states of the same country. However, the standard approach assumes homogeneity of responses. There is a shift towards right in the location of the conditional unemployment distribution but its shape does not change.

In this paper, we suggest to do one step onwards with respect to the "state of the art" by showing that even a "well-behaved" country-level macroeconomic shock can affect the shape of the conditional unemployment distribution. To this end, we first need to remove some restrictive assumptions behind the Barro's model: i) constant job-flow coefficients, both across states and over time; and ii) constant labour force, both across states and over time.

Let U be the number of unemployed, E be the number of employed, and n the growth rate of the labour force. Since the variation of the number of unemployed in state i at time t is, by definition, $\Delta U_{i,t} = s_{i,t}E_{i,t-1} - f_{i,t}U_{i,t-1}$, then it is easy to show that a general model of unemployment-rate dynamics is a random-coefficient model of the following type:

$$u_{i,t} = \frac{s_{i,t}}{1 + n_{i,t}} + \frac{1 - s_{i,t} - f_{i,t}}{1 + n_{i,t}}\, u_{i,t-1} \tag{2}$$

In this case, the "natural" unemployment rate in state i is given by $s_i/(n_i+s_i+f_i)$. The fixed-coefficient case is clearly a particular case of the random-coefficient case where state and time heterogeneity of job-flow rates and labour-force growth is not allowed (the Barro's model further assumes the absence of labour-force growth). In contrast, this paper allows for heterogeneity. However, while there are already studies (Romero-Ávila and Usabiaga, 2007; Sephton, 2009) which use mean regression techniques to deal with the heterogeneity of the model coefficients across states and over time, we innovate by looking at a different type of heterogeneity, which we refer to as quantile parameter heterogeneity. The latter is in place when the model coefficients vary along quantiles of the conditional unemployment distribution. Studying it allows to say something about the impact of a "well-behaved" country-level macroeconomic shock on within-states unemployment inequality.

Model (2) is the main insight behind our estimated quantile-regression model. In particular, it can be written as $u_{i,t} = \rho_0(\Theta_{i,t}) + \rho_1(\Theta_{i,t})u_{i,t-1}$. Under the assumption that $\Theta_{i,t}|u_{i,t-1}$ is uniformly distributed between 0 and 1 and that $\theta \rightarrow \rho_{0\theta}+\rho_{1\theta}\, u_{i,t-1}$ is strictly increasing and continuous in θ, it follows, by construction, that $\rho_{0\theta}+\rho_{1\theta}\, u_{i,t-1}$ is the θ-quantile of $u_{i,t}$ conditional on $u_{i,t-1}$, i.e. $Q_\theta(u_{i,t}|u_{i,t-1}) = \rho_{0\theta} + \rho_{1\theta}\, u_{i,t-1}$ (see Chernozhukov and Hansen, 2008, p. 380).

The economic intuition behind $\Theta_{i,t}$ is very simple. We build on individual wage-schooling models where $\Theta_{i,t}$ is usually interpreted as an individual unobserved ability index (see Chernozhukov and Hansen, 2006; Chernozhukov and Hansen, 2008; and Chernozhukov et al., 2007). In particular, using a state-level unemployment persistence model, we can interpret the latent random variable $\Theta_{i,t}$ as a state unobserved labour-market matching efficiency index (i.e. ranging between 0 and 1) at a given time. For instance, if the number of matches in state i at time t is given by $M_{i,t} = \Theta_{i,t}V_{i,t}^{\phi}U_{i,t}^{1-\phi}$ where V stands for vacancies, then the job-finding rate $\frac{M_{i,t}}{U_{i,t}} = \Theta_{i,t}(\frac{V_{i,t}}{U_{i,t}})^{\phi}$ is a function of the matching efficiency index. If $\Theta_{i,t} = 0$, then the local labour market is completely inefficient and thus unable to produce job matches even in presence of vacancies and unemployed. If $\Theta_{i,t} = 1$, then the opposite case of a maximally efficient local labour market applies.

More generally, we interpret $\Theta_{i,t}|u_{i,t-1}$ as reflecting unobserved characteristics of the local labour market (such as matching efficiency, intensity of labour productivity shocks, and intensity of job search), making the job-flow rates and labour-force growth higher or lower. Indeed, as suggested by Blanchard and Portugal (2001), the level of the unemployment rate may provide a misleading picture of the labour market. The same level of unemployment can be associated to very different labour markets in terms of job flows. Even if two states have the same unemployment rate at time $t-1$, they can still be pretty different in terms of unobserved characteristics of the labour market at time t and, thus, of observed job-flow rates. In a way, we provide an economic foundation for an earlier statistical model by Koenker and Xiao (2006) who also studied to what extent the U.S. unemployment persistence is subject to quantile parameter heterogeneity, using time-series data and finding evidence of asymmetric dynamics across quantiles. To the best of our knowledge, we are the first to study unemployment persistence using state-level panel data in a dynamic quantile-regression model.

Hence, the empirical analysis in the next section will be based on a model of the following type:

$$u_{i,t} = \rho_{0\theta} + \rho_{1\theta}\, u_{i,t-1} + \xi_{\theta i,t} \tag{3}$$

In this model, the effect of $\xi_{\theta i,t}$ on $u_{i,t+j}$ is given by $\rho_{1\theta}^{j}$. The cumulative effect is given by $1/(1-\rho_{1\theta})$.Therefore, if two states located in different quantiles receive the same shock at the same time, the response of the unemployment rate after $j \geq 1$ years will be different in each state. It will be more pronounced where $\rho_{1\theta}$ is bigger. As a matter of example, Figure 1 plots the response of the unemployment rate to a unit shock for two different levels of $\rho_{1\theta}$ (0.8 and 0.4). This is one of the key points in our paper: in earlier literature, if two or more states located at different quantiles are hit by the same shock at the same time, the responses of the unemployment rate in each state after j years will be identical because persistence is assumed to be the same across quantiles. Of course, our model allows to investigate the consequences of a macroeconomic shock which is not "well-behaved". States located at different quantiles can be affected unequally at the time the shock arrives. As a consequence, the unemployment response in one state will be different from that in another state just because the initial shock was different. Clearly, the latter is not the point we want to stress here.

The focus of the estimation will be on the autoregressive coefficient $\rho_{1\theta}$. Intuitively, model (1) is a particular case of model (3) under quantile parameter homogeneity. Thus, every single assumption behind model (3) is implicitly behind model (1) too. The main difference is that model (3) allows for quantile parameter heterogeneity. Initially, we will assume that $Q_{\theta}(\xi_{\theta i,t}|u_{i,t-1}) = 0$ for each θ and, likewise model (1), that $E(\xi_{i,t}|u_{i,t-1}) = 0$. So, both the least squares estimator and the quantile-regression estimator by Koenker and Bassett (1978) are consistent. However, we will then make things more complicated by introducing fixed effects to take into account potential differences in state "natural" unemployment rates, when they exist.

One implication of a quantile-regression approach is that, if the model coefficients are functions of θ, then there are multiple possible answers to the "natural rate" vs. "hysteresis" debate, depending on the level of θ.

3 Empirical approach

The quantile-regression approach originally proposed by Koenker and Bassett (1978) is nowadays very popular in applied economics. It allows us to characterize the effect of a covariate along quantiles of the conditional distribution of the dependent variable. Despite typically used in micro-level studies, such as individual wage-schooling models, quantile regression is increasingly becoming a working tool for the macroeconomist as well. A recent example is an article by Andini and Andini (2014).

Over the last ten years, the advantages of quantile regression have been combined with those of time-series and panel data. Indeed, Koenker and Xiao (2006) have investigated the properties of a time-series quantile autoregressive model, while Koenker (2004) has introduced an estimator for static quantile-regression models with fixed effects conceived as pure location shifters. His approach involves the exogenous choice of a penalty parameter. However, building on Koenker's (2004) original article, Lamarche (2010) has proposed a method to endogenously choose the penalty parameter under the additional assumption that fixed effects and covariates are independent.

More recently, Canay (2011) has suggested a different approach to static panel-data quantile regression which does not rely on the independence assumption used by Lamarche (2010). In addition, Canay's method does not imply the choice of a penalty parameter. Finally, the estimator proposed by Canay (2011) is consistent when both T and N tend to infinity, while the estimators proposed by Koenker (2004) and Lamarche (2010) rely on the additional assumption that N^a/T goes to zero for some $a > 0$. In a recent article, Rosen (2012) has proposed an estimator which is consistent for fixed T.

A further step onwards in the literature has occurred with the treatment of endogeneity in quantile-regression models. In this specific field, pioneering articles by Arias et al. (2001), Lee (2007) and Chernozhukov and Hansen (2006; 2008) have been followed by other important contributions. In particular, Harding and Lamarche (2009) have extended the approach by Chernozhukov and Hansen (2006; 2008), suggesting a quantile-regression estimator for a static panel-data model with endogenous covariates where fixed effects are indexed by quantiles. In addition, Galvão and Montes-Rojas (2009) have proposed an alternative to Harding and Lamarche (2009) for a model where the fixed effects are pure location shifters.

Further exploiting the ideas of Chernozhukov and Hansen (2006; 2008) and Koenker and Xiao (2006), Galvão (2011) has proposed an estimator for the case of a quantile autoregression with quantile-independent fixed effects. In particular, Galvão (2011) has shown two things. First, we should not use the estimator by Koenker (2004) in a dynamic quantile-regression model with non-penalized location-shifting fixed effects because this estimator suffers from the same type of small-T sample bias as the within-estimator in a mean regression framework. Second, we can use instrumental variables, in the same fashion as Anderson and Hsiao (1981), and the Chernozhukov-Hansen's estimator to obtain better estimates in small-T samples.

An alternative to Galvão (2011) has been suggested by Lin and Chu (2013) who have developed a fitted-value approach. This is a classical two-step estimator. In the first step, the lagged variable is regressed against instruments using the least squares estimator, and the predicted value is obtained. In the second step, the lagged variable is replaced by the predicted value, and the estimator of Koenker (2004) is used. The authors do not provide indications about the choice of the penalty parameter. However, using Monte Carlo simulation and focusing on the median autoregressive coefficient, Lin (2012) has shown that the fitted-value approach is less finite-sample biased than the approach by Galvão (2011) when the penalty parameter is set equal to unity.

A further alternative to Galvão (2011) has been proposed by Galvão and Montes-Rojas (2010) who have shown that a penalized approach reduces the dynamic bias of the estimator by Koenker (2004) and increases efficiency. The implication is that there is no need to use instrumental variables in quantile autoregressive models with location-shifting fixed effects when a penalized approach is used. In short, the appropriate choice of the penalty parameter, based on a Bayesian information criterion, allows us to use the static-model estimator by Koenker (2004) even in dynamic models. This approach is particularly useful when the autoregressive coefficient is close to unity because, in this case, instruments based on lags tend to perform poorly in dynamic quantile regression models with fixed effects (Galvão and Montes-Rojas, 2010), likewise the mean regression case.

Next section will use all the existing approaches to the estimation of a quantile autoregressive model with location-shifting fixed effects. All the estimators considered are consistent in large-T samples.

4 Estimation results

The evidence proposed in this section is based on unemployment data taken from the U.S. Bureau of Labor Statistics. The dataset contains annual observations on 51 U.S. states for the period of 1980-2010. Since our dataset covers 30 years, potential biases arising from short-T panels are likely to be small.

To begin with, we present an estimate of the conditional average unemployment persistence in the United States, based on pooled state-level panel data. To be precise, we estimate model (1) using the ordinary least squares estimator. A similar exercise has been performed in a seminal article by Blanchard and Summer (1986) using time-series data from 1892 to 1985. In particular, we find that the least squares estimate of the conditional mean unemployment persistence in model (1) is 0.905 (with a 0.015 robust standard error). This perfectly matches the one proposed by Blanchard and Summers (1986).

Is the above mean result driven by something happening at specific quantiles? Table 1 provides estimates for model (3) which answer this question. The standard Koenker-Bassett's estimator is applied. A similar exercise has been performed by Koenker and Xiao (2006) using time-series data. Yet, their results are not comparable to ours because they use a higher order autoregressive model, which is more flexible from a statistical point of view but less appealing from en economic-theory perspective (note that model (2) holds exactly). With pooled panel data, the estimates show that the Blanchard-Summers's result for the conditional average persistence is basically driven by the upper tail of the conditional unemployment distribution, where the autoregressive coefficient is close to unity.

To go one step further, Table 2 provides the estimation results for model (3) using the estimator by Koenker (2004) which takes fixed effects into account. In particular, it is assumed that fixed effects are location shifters, i.e. $\xi_{\theta i,t} = \alpha_i + \zeta_{\theta i,t}$ where α_i is a vector of state-specific unemployment rates (independent of θ). In order to provide a complete picture, we use a wide range of values for the penalty parameter λ, from 0.1 to 13.[1] As the penalty parameter increases, the fixed effects are forced to converge towards a common value. Hence, the autoregressive coefficient estimates are biased towards pooled estimates, not controlling for fixed effects. In contrast, when the penalty parameter decreases, the role played by the fixed effects increases.

One key finding in Table 2 is that unemployment persistence increases along quantiles of the conditional unemployment distribution, regardless of the penalty

[1]Note that Galvão and Montes-Rojas (2010) apply the estimator by Koenker (2004) to a dynamic model with $\lambda > 0$ chosen by means of a Bayesian information criterion. Here, rather than choosing a single penalty, we find more informative to explore a wide range of values for the penalty parameter.

used. As expected, the Koenker's estimates in Table 2 are biased towards the pooled Koenker-Bassett's estimates in Table 1 when the penalty parameter increases.

Another key result is that disregarding fixed effects, as in Table 1, seems to imply an overestimation of the autoregressive coefficient along quantiles of the conditional unemployment distribution. The amount of the upward bias of Table 1's estimates relative to Table 2's estimates with $\lambda = 0.1$ is measured by the "bias relative to K" in Table 1.

For comparison, Table 3 provides the estimation results for model (3) with $\xi_{\theta i,t} = \alpha_i + \zeta_{\theta i,t}$ using the fitted-value approach by Lin and Chu (2013). As instrument for $u_{i,t-1}$ in the first stage, we use $\Delta u_{i,t-2}$. We basically follow the practice of using lagged first-differences as instruments for variables in levels (Blundell and Bond, 1998). The model is just-identified, and the least squares regression of $u_{i,t-1}$ on $\Delta u_{i,t-2}$ (and constant term) provides a coefficient equal to 0.904 with standard error of 0.056 and p-value equal to 0.000. In the second stage, we use the estimator of Koenker (2004) with a penalty parameter set equal to unity.

As usual with an instrumental-variable approach, the results in Table 3 show that the estimates are more imprecise. For instance, the autoregressive coefficient at the 75th quantile is estimated from a minimum of 0.604 to a maximum of 1.029. However, the key finding is that, again, unemployment persistence is heterogeneous along quantiles of the conditional unemployment distribution. And, again, disregarding the fixed effects, as in Table 1, seems to imply an overestimation of the autoregressive coefficient along quantiles of the conditional unemployment distribution. The exact amount of the upward bias is indicated as the "bias relative to LC" in Table 1.

For further comparison, Table 4 applies Galvão's (2011) estimator to model (3) with $\xi_{\theta i,t} = \alpha_i + \zeta_{\theta i,t}$. Again, we use $\Delta u_{i,t-2}$ as instrument for $u_{i,t-1}$. The estimates are less imprecise than those based on the Lin-Chu's estimator. The key finding of quantile parameter heterogeneity is confirmed. In addition, the estimation bias due to disregarding fixed effects is also found. The latter is reported as the "bias relative to G" in Table 1. Galvão's estimates are our preferred estimates because they do not impose any shrinkage on fixed effects.

In sum, the evidence presented in this section is consistent with the hypothesis of "hysteresis" at the upper tail of the conditional unemployment distribution, and with the "natural rate" hypothesis at the lower tail. Future research using specific unit-root tests for the upper quantiles may shed new light on this point. As a final note, it is worth stressing that allowing for the presence of year effects does not substantially change the evidence based on model (3) with fixed effects only.

5 Conclusions

This paper contributes to the ongoing research on unemployment dynamics with two novel empirical findings. First, we find that unemployment persistence increases along the conditional unemployment distribution. States in better economic conditions (those located at the lower tail) exhibit lower persistence rates. Second, we find that disregarding fixed effects implies an overestimation of unemployment persistence along the conditional unemployment distribution.

The first result is important because it shows that previous research focusing on the conditional mean persistence in the United States does non capture the whole picture: unemployment persistence is subject to quantile parameter heterogeneity. The result for the mean of the conditional unemployment distribution is actually driven by the upper quantiles.

The second result is important because it shows that panel quantile autoregression techniques are actually needed when dealing with unemployment persistence.

From a policy perspective, our findings suggest two things. First, “hysteresis” and “natural rate” can co-exist in the same country. Whether a shock has permanent effects or not, it depends on the position of a state (or region) along the conditional unemployment distribution at the time of the shock. In particular, we find the intuitive result that states located at the lower tail (i.e. in a better economic situation) absorb its effects faster than those at the upper tail. Second, a negative “well-behaved” country-level macroeconomic shock affects not only the mean but also the shape of the conditional unemployment distribution. It increases both the mean and the dispersion. The welcome news is that the reverse holds too. A positive “well-behaved” country-level shock reduces within-states unemployment inequality. Hence, a federal-level policy may be suitable to deal with inequality among states. State-specific policies are not necessarily needed, although they still might help.

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Table 1. Quantile autoregression without fixed effects
Koenker and Bassett's (1978) estimator

	Q25	Q50	Q75
Persistence	0.846	0.909	0.971
	(0.015)	(0.014)	(0.024)
Gross turnover	0.154	0.091	0.029
Bias relative to K	0.040	0.033	0.030
Bias relative to LC	0.094	0.127	0.124
Bias relative to G	0.166	0.139	0.046

Notes: The bootstrapped standard errors, in parentheses, are based on 100 repetitions. The bias relative to K is relative to Koenker (2004) with lambda = 0.1.

Table 2. Quantile autoregression with penalized fixed effects
Koenker's (2004) estimator

	Q25	Q50	Q75
Persistence (lambda = 0.1)	0.806 (0.009)	0.876 (0.008)	0.941 (0.014)
Persistence (lambda = 0.5)	0.807 (0.010)	0.880 (0.009)	0.949 (0.016)
Persistence (lambda = 1)	0.816 (0.010)	0.883 (0.009)	0.954 (0.016)
Persistence (lambda = 3)	0.833 (0.009)	0.896 (0.008)	0.964 (0.016)
Persistence (lambda = 7)	0.846 (0.005)	0.907 (0.008)	0.971 (0.015)
Persistence (lambda = 13)	0.846 (0.007)	0.909 (0.009)	0.971 (0.015)

Notes: The bootstrapped standard errors, in parentheses, are based on 100 repetitions.

Table 3. Quantile instrumental-variable autoregression with penalized fixed effects
Lin and Chu's (2013) estimator

	Q25	Q50	Q75
Persistence (lambda = 1)	0.752 (0.045)	0.782 (0.044)	0.847 (0.073)

Notes: The bootstrapped standard errors, in parentheses, are based on 100 repetitions.

Table 4. Quantile instrumental-variable autoregression with non-penalized fixed effects
Galvão's (2011) estimator

	Q25	Q50	Q75
Persistence	0.680	0.770	0.925
	(0.027)	(0.010)	(0.023)

Notes: The bootstrapped standard errors, in parentheses, are based on 100 repetitions.

Figure 1. Unemployment-rate responses to a unit shock for two different values of persistence