Macroeconomic Dynamics, **22**, 2018, 1298–1320. Printed in the United States of America.
doi:10.1017/S1365100516000602

UNEMPLOYMENT PERSISTENCE AND QUANTILE PARAMETER HETEROGENEITY

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We argue that a random-coefficients representation of the classical Barro's model of unemployment dynamics can be used as a theoretical basis for a panel quantile autoregressive model of the unemployment rate. Estimating the latter with State-level data for the United States (1980–2010), we find that (i) unemployment persistence increases along quantiles of the conditional unemployment distribution; (ii) disregarding State-fixed effects implies an overestimation of unemployment persistence along unemployment quantiles; (iii) a macroeconomic shock changes not only the location but also the dispersion of the distribution of the State unemployment rates; (iv) a federal policy equally applied in each State can reduce unemployment inequality among States; (v) "hysteresis" and "natural rate" hypotheses can co-exist along quantiles of the unemployment distribution, with the former being not rejected at upper quantiles. In sum, while the standard approach to the estimation of unemployment persistence implicitly assumes that quantile parameter heterogeneity does not matter, we suggest that it does.

Keywords: Quantile Regression, Unemployment, Dynamic Models

1. INTRODUCTION

The evolution over time of the average unemployment rate in the United States has been extensively studied. Less known is how the dispersion of unemployment rates across U.S. States changes during booms and busts. Figure 1 suggests that

We are grateful to an associate editor and two anonymous referees for valuable comments and suggestions, which have greatly improved the paper. We would like to thank Ivan Canay for extremely useful comments on an earlier version of this article. In addition, we are grateful to Gabriel Montes-Rojas for sharing a code in R used in his own work, which has helped us to understand some technical issues with the estimations performed in this paper. Finally, we are indebted to Steve Fleetwood, who has helped us to present our ideas more clearly. The views expressed in this paper do not necessarily reflect those of the institutions with which we are affiliated. The usual disclaimer applies. Address correspondence to: Corrado Andini, University of Madeira, 9000-390 Funchal, Portugal; e-mail: andini@uma.pt.

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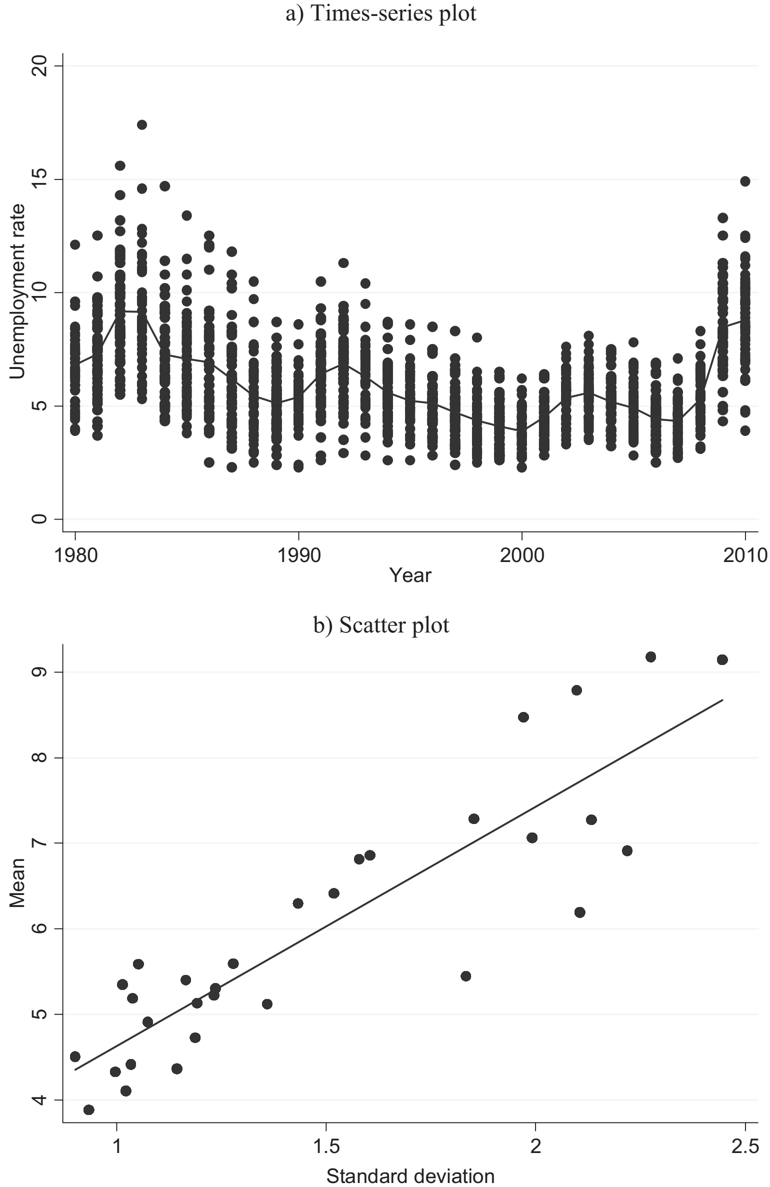

FIGURE 1. Positive association between mean unemployment and dispersion. The vertical axis reports the mean of the distribution of the unemployment rates of U.S. States in a given year. The horizontal axis reports the standard deviation of the distribution.

https://doi.org/10.1017/S1365100516000602 Published online by Cambridge University Press

there is a positive association between mean unemployment and dispersion. In periods of declining mean unemployment, the dispersion seems to decrease. The converse happens when the average unemployment rate rises.

This paper studies how the dispersion of the unemployment distribution across U.S. States changes when the economy is hit by a shock changing the mean of the unemployment distribution. We will argue that, if unemployment persistence is subject to quantile parameter heterogeneity, such a shock changes not only the location—the mean—but also the dispersion of the unemployment distribution.[1]

In a simple model of unemployment dynamics where unemployment follows a first-order autoregressive process, a shock generates its effects depending on the degree of unemployment persistence[2] (the autoregressive coefficient). For instance, higher persistence means that the effect of a shock takes more time to disappear. As a result, the accumulated effect of a shock after some time is stronger if persistence is higher.[3]

The standard approach to the estimation of unemployment persistence has focused on the mean [see Blanchard and Summers (1986), among others], implicitly assuming that the persistence of unemployment does not change along quantiles of the unemployment distribution. The implication is that, when an economy is hit by a shock, all the quantiles react in the same way as the mean does: The location of the unemployment distribution changes, but its dispersion does not.

Figure 1, however, suggests that a shock may change not only the location—the mean—but also the dispersion of the unemployment distribution. The latter happens when the quantiles of the unemployment distribution react differently to the same shock (Figure 2a).[4] It follows that assuming persistence to be homogenous along quantiles of the unemployment distribution can be a rather restrictive hypothesis. This paper tests this hypothesis, finding evidence of quantile parameter heterogeneity.

From a policy point of view, studying whether unemployment persistence is subject to quantile parameter heterogeneity is important because it helps predicting how a federal policy, equally implemented in all States, may affect the dispersion of the unemployment distribution. For instance, suppose the federal government is interested in reducing the unemployment dispersion across U.S. States. One way to do this is to target the policy intervention to specific States, say those with higher unemployment. However, the government can also exploit the existing differences, to the extent that the States located at upper quantiles of the unemployment distribution react more to the same policy than those located at lower quantiles. In particular, Figure 1 suggests that a policy aimed at reducing the average unemployment rate can also reduce the unemployment dispersion among States. Intuitively, this happens because some States—those in the upper tail of the unemployment distribution—benefit more than other States—those in the lower tail—from the same policy. If this is the case, then the relative position of a State along the unemployment distribution matters.

Why should the relative position of a State along the unemployment distribution matter? An intuitive reason is that the relative position reflects the relative

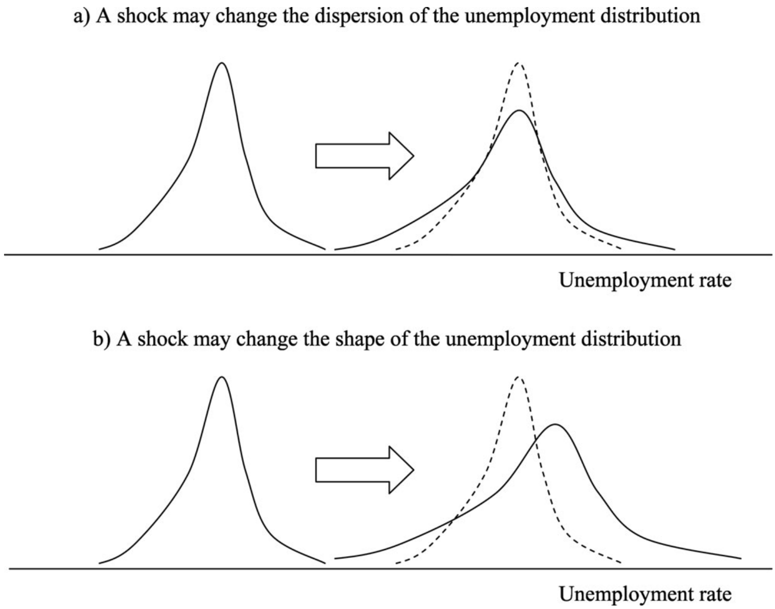

FIGURE 2. Effects of a shock on the unemployment distribution.

labor–market matching inefficiency of a State (compared to the other States in the federal labor market). Our theoretical prior is that States in the lower tail of the unemployment distribution have lower matching inefficiency, and thus lower unemployment persistence: This is why they suffer less from an initial shock increasing unemployment, and the accumulated increase in unemployment is lower for them. Thus, if all States are hit by the same (unemployment-increasing) shock, the unemployment dispersion widens. The good news, however, for the States in the upper tail, is that the converse is also true. When the initial shock reduces unemployment, the accumulated decrease in unemployment for the States with higher persistence is higher. Thus, if all States are hit by the same (unemployment-decreasing) shock, the unemployment dispersion gets smaller.

In summary, this paper attempts to shed new light on the sources of unemployment dispersion among U.S. States. What we add here is that a federal policy, even if equally implemented in each State, can have differentiated effects—affecting unemployment dispersion—because the relative position of a State along the unemployment distribution matters. In particular, we find that a lower relative position implies a lower degree of unemployment persistence.

Another reason why policy makers should care about quantile parameter heterogeneity is that the average unemployment effect of a given federal policy can be driven by something happening at specific quantiles of the unemployment distribution. For example, the policy may be effective for States located in some quantiles, but ineffective for those located in other quantiles of the unemployment distribution. Looking exclusively at the effect of a policy on the mean of the unemployment distribution would disguise the existence of such heterogeneity.

A final reason to investigate the issue of quantile parameter heterogeneity is purely academic. So far, part of the debate on unemployment persistence has focused on the "natural rate" versus "hysteresis" controversy. 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 the unemployment follows a purely random walk. In the first case, macroeconomic shocks do not have permanent effects on the mean level of unemployment, even though it may take time before their effects disappear. In the second case, shocks do have permanent effects. 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 labor markets as more "sclerotic," meaning that the effects of macroeconomic shocks tend to last longer in Europe than in the United States. This paper adds to this literature by stressing that macroeconomic shocks not only change the mean level of unemployment but also the dispersion of the unemployment distribution. A tail of the unemployment distribution may be sclerotic, another one may be not. In particular, we find evidence consistent with the "hysteresis" hypothesis at the upper quantiles and with the "natural rate" hypothesis at the remaining quantiles.

The paper is structured as follows. Section 2 introduces a model for unemployment persistence, where quantile parameter heterogeneity plays a role. Section 3 describes our empirical approach based on panel quantile autoregression. Section 4 presents the estimation results. Section 5 discusses tests, extensions, and robustness. Section 6 concludes.

2. MODEL

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

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

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 the fact that it dates back to the late 1980s, 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) himself has elaborated on model (1) by using an ARMA(1,1) specification to get estimates of the model parameters from time-series data. Yet, model (1) is clearly not satisfactory when State-level panel data for the United States are used because the cross-sectional information is not exploited.

We extend model (1) to take advantage of State-level panel data. Let U be the number of unemployed, E be the number of employed, and ℓ the growth rate of the labor force. Since the variation of the number of unemployed people 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 for the U.S. economy has a random-coefficients representation of the following type:

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

Proof. Let $L = E + U$ be the labor force. The expression for $\Delta U_{i,t}$ implies $U_{i,t} = s_{i,t}E_{i,t-1} + (1 - f_{i,t})U_{i,t-1}$, which in turn implies $U_{i,t} = s_{i,t}(L_{i,t-1} - U_{i,t-1}) + (1 - f_{i,t})U_{i,t-1}$. From the latter, we get $U_{i,t} = s_{i,t}L_{i,t-1} + (1 - s_{i,t} - f_{i,t})U_{i,t-1}$. Dividing both sides by $L_{i,t}$ gives $\frac{U_{i,t}}{L_{i,t}} = s_{i,t}\frac{L_{i,t-1}}{L_{i,t}} + (1 - s_{i,t} - f_{i,t})\frac{U_{i,t-1}}{L_{i,t}}$, which is equivalent to $\frac{U_{i,t}}{L_{i,t}} = s_{i,t}\frac{L_{i,t-1}}{L_{i,t}} + (1 - s_{i,t} - f_{i,t})\frac{L_{i,t-1}}{L_{i,t}}\frac{U_{i,t-1}}{L_{i,t-1}}$. Since $\ell_{i,t} = \frac{L_{i,t}-L_{i,t-1}}{L_{i,t-1}}$, it follows that $\frac{1}{1+\ell_{i,t}} = \frac{L_{i,t-1}}{L_{i,t}}$. Then, using the latter expression, we can write $\frac{U_{i,t}}{L_{i,t}} = s_{i,t}(\frac{1}{1+\ell_{i,t}}) + (1 - s_{i,t} - f_{i,t})(\frac{1}{1+\ell_{i,t}})\frac{U_{i,t-1}}{L_{i,t-1}}$. ■

In this case, the "natural" unemployment rate in State i is $s_i/(\ell_i + s_i + f_i)$.

For the purpose of this study, model (2) is important for three reasons. First, it suggests that understanding the variability of s, f, and ℓ, across States and over time, is crucial to understand the variability of the unemployment rate across States and over time. In particular, both Shimer (2012) and Elsby et al. (2013) have argued that at least 3/4 of the fluctuations of the unemployment rate in the United States are due to fluctuations in the job-finding rate, with separation rates playing a minor role. However, Barnichon (2012) has stressed that, once the interdependence between s and f is recognized, the separation rate plays a more important role [see also Fujita and Ramey (2009, 2012)]. Second, model (2) holds by definition: There is no place for additional unemployment lags, and no place for additional covariates. What makes it a statistical model, rather than a simple accounting identity, is the fact that its coefficients $\frac{s_{i,t}}{1+\ell_{i,t}}$ and $\frac{1-s_{i,t}-f_{i,t}}{1+\ell_{i,t}}$ can be seen as random variables. Third, the random-coefficients representation of model (2) can be used as a theoretical basis for a panel quantile autoregressive model of the unemployment rate, which is the empirical model estimated in this paper. Now, let us see why.

If $\frac{s_{i,t}}{1+\ell_{i,t}}$ and $\frac{1-s_{i,t}-f_{i,t}}{1+\ell_{i,t}}$ are random variables (as we assume), they both have a cumulative distribution function, which can be assumed to be strictly increasing and continuous in the quantile level. Being a number between 0 and 1, each quantile of a cumulative distribution function can be seen as the realization of a standard uniform latent random variable $\Theta_{i,t}$. Then, since the inverse of a strictly increasing and continuous function always exists, both coefficients $\frac{s_{i,t}}{1+\ell_{i,t}}$ and $\frac{1-s_{i,t}-f_{i,t}}{1+\ell_{i,t}}$ can be seen as unknown functions of $\Theta_{i,t}$. Formally, we have $\frac{s_{i,t}}{1+\ell_{i,t}} = \rho_0(\Theta_{i,t})$ and $\frac{1-s_{i,t}-f_{i,t}}{1+\ell_{i,t}} = \rho_1(\Theta_{i,t})$, where the $\rho_0(.)$ and $\rho_1(.)$ are unknown functions $[0, 1] \to R$. As the random coefficients in model (2) can take any value in R, the model is general and it is able to account for a variety of labor–market dynamics. For instance, it allows for every kind of labor-force dynamics due to endogenous choices of migration and mobility.

As a result, model (2) can be written as follows:

$$u_{i,t} = \rho_0(\Theta_{i,t}) + \rho_1(\Theta_{i,t})u_{i,t-1}. \tag{3}$$

Under the assumptions that $\Theta_{i,t}|u_{i,t-1}$ is uniformly distributed between 0 and 1, θ is a given quantile of $\Theta_{i,t}$ conditional on $u_{i,t-1}$, and $\theta \to \rho_{0\theta}+\rho_{1\theta}\, u_{i,t-1}$ 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)].

Proof. Let us write $u_{i,t} = \rho_0(\Theta_{i,t}) + \rho_1(\Theta_{i,t})u_{i,t-1}$ in the more compact form $u = \rho(\Theta)u_{-1}$. If we define the θ-quantile of Θ conditional on u_{-1} as $P(\Theta|u_{-1} \leq \theta)$, the latter can be written as $P(\Theta \leq \theta|u_{-1})$. If $\theta \to \rho(\theta)u_{-1}$ is strictly increasing and continuous in θ, then the inequality for the domains also holds for the co-domains, i.e., $P(\rho(\Theta)u_{-1} \leq \rho(\theta)u_{-1}|u_{-1})$. This expression, using $u = \rho(\Theta)u_{-1}$, can be written as $P(u \leq \rho(\theta)u_{-1}|u_{-1})$. It follows that $P(u|u_{-1} \leq \rho(\theta)u_{-1})$, which is the θ-quantile of u conditional on u_{-1}, i.e., $Q_\theta(u|u_{-1}) = \rho(\theta)u_{-1}$ or, more compactly, $Q_\theta(u|u_{-1}) = \rho_\theta u_{-1}$. ■

The economic intuition behind $\Theta_{i,t}$ is simple. We borrow from the 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, since we will use data that vary across States and over time, we interpret $\Theta_{i,t}$ as an index reflecting unobserved characteristics of the labor market in a given State at a given point in time, which affect the coefficients $\frac{s_{i,t}}{1+\ell_{i,t}}$ and $\frac{1-s_{i,t}-f_{i,t}}{1+\ell_{i,t}}$ through the job-flow rates and the labor-force growth.

For example, we can interpret the latent random variable $\Theta_{i,t}$ as a State unobserved labor–market matching inefficiency index (i.e., ranging between 0 and 1) at a given time.[5] This interpretation is consistent with a generalization of the standard matching function[6] and it is useful to understand the variability of the job finding rate [see Barnichon and Figura (2015)], which is quantitatively important [see Shimer (2012); and Elsby et al. (2013)]. Indeed, if the number of matches in State i at time t is given by $M_{i,t} = (1 - \Theta_{i,t})V_{i,t}^{\phi}U_{i,t}^{1-\phi}$, where V stands for vacancies, then the job-finding rate $f_{i,t} = \frac{M_{i,t}}{U_{i,t}} = (1-\Theta_{i,t})(\frac{V_{i,t}}{U_{i,t}})^{\phi}$ can be seen a function of the matching inefficiency index. If $\Theta_{i,t} = 0$, then the State labor market is maximally efficient and thus able to produce the highest possible number of job matches, given the number of vacancies and unemployed. If $\Theta_{i,t} = 1$, then the opposite case of a totally inefficient State labor market applies. In sum, higher inefficiency means lower job-finding rate and, thus, higher unemployment persistence. Another theoretical mechanism could be that higher matching inefficiency induces more people to abandon the State labor market, reducing the State labor-force growth $\ell_{i,t}$ and, thus, increasing persistence. Finally, our model is compatible with separation rates either endogenously determined[7] (independently of matching inefficiency) or endogenous. In the latter case, the effect of matching inefficiency on the separation rate is nontrivial. On the one hand, higher matching inefficiency makes more costly for firms to replace workers, reducing the incentive to layoff and thus the separation rate $s_{i,t}$. On the other hand, higher matching inefficiency can imply matches of lower quality or productivity, increasing the separation probability.[8]

Since $\Theta_{i,t}$ is a random variable, it is—by definition—a function linking the "space of events" (everything that can happen in a State labor market at a given time) to a real number. This number is between 0 and 1 in the specific case, and it affects the coefficients of model (3) through the functions $\rho_0(.)$ and $\rho_1(.)$. This is the conceptual structure of our model.

Exploiting the fact that $Q_\theta(u_{i,t}|u_{i,t-1}) = \rho_{0\theta} + \rho_{1\theta}\, u_{i,t-1}$ [see the proof following equation (3)], the empirical analysis in the next section will be based on a panel quantile autoregressive model of the following type:

$$u_{i,t} = \rho_{0\theta} + \rho_{1\theta}\, u_{i,t-1} + \xi_{\theta i,t}, \tag{4}$$

where, by construction, $Q_\theta(\xi_{\theta i,t}|u_{i,t-1}) = 0$ for each θ. The mean-regression model is clearly a particular case of model (4), where $\rho_{0\theta} = \rho_0$, $\rho_{1\theta} = \rho_1$, $\xi_{\theta i,t} = \xi_{i,t}$ for each θ, and $E(\xi_{i,t}|u_{i,t-1}) = 0$. The Barro's model is a particular case of the mean-regression version of model (4), where the dimension i does not exist.

In model (4), the effect of $\xi_{\theta i,t}$ on $u_{i,t+j}$ is given by $\rho_{1\theta}^{j}$. The total accumulated 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 differentiated. It will be more pronounced, where $\rho_{1\theta}$ is bigger. Since $\rho_{1\theta}$ plays a key role, the focus of the estimation will be on the autoregressive coefficient $\rho_{1\theta}$.

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" versus "hysteresis" debate, depending on the level of θ.

To fully exploit the potential of panel data, we will extend model (4) by introducing State-fixed effects, which allow us to take into account potential differences in "natural" unemployment rates across States.

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 being typically used in microlevel 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 past 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.

Though initially thought for static models, Koenker's (2004) estimator can also be used in a dynamic setting. Formally, Koenker (2004) assumes that $\xi_{\theta i,t} = \alpha_i + \zeta_{\theta i,t}$, where, in our application, α_i is a vector of State-specific fixed effects (independent of θ) and $\zeta_{\theta i,t}$ is i.i.d at each θ. Then, his estimator $(\hat{\rho}, \hat{\alpha})$ solves

$$\min_{\rho,\alpha} \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{t=1}^{T} w_k \Gamma_{\theta_k}(u_{i,t} - \rho_{0\theta_k} - \rho_{1\theta_k} u_{i,t-1} - \alpha_i) + \lambda \sum_{i=1}^{N} |\alpha_i|, \tag{5}$$

where $\rho = (\rho_{0\theta_k}, \rho_{1\theta_k})$, $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_N)$, w_k is a subjectively chosen weight for the θ_k quantile,[9] and $\Gamma_\theta(\zeta) = \zeta(\theta - I(\zeta < 0))$ is the piecewise linear quantile loss function of Koenker and Bassett (1978).

Koenker's (2004) approach involves the exogenous choice of a penalty parameter $\lambda \geq 0$, which regulates the degree at which the fixed effects are forced to be all equal to zero (in a pure fixed-effects model, the penalty is equal to zero).[10]

The reason why Koenker's estimator can be used in a dynamic setting has to do with the presence of the penalty parameter. In particular, Galvao and Montes-Rojas (2010) have shown that an appropriate choice of λ, based on a Bayesian information criterion, allows us to use Koenker's estimator (2004) not only in static but also in dynamic models. Indeed, a penalized approach reduces the dynamic bias of Koenker's (2004) estimator and increases its efficiency. The implication is that there is no need to use instrumental variables when a penalized approach is adopted. And, the latter approach is particularly useful when the autoregressive coefficient is close to unity because, in such a case, instruments based on lags tend to perform poorly in dynamic quantile-regression models with fixed effects [Galvao and Montes-Rojas (2010)], likewise the mean-regression case.

Yet, Koenker's (2004) estimator is not the only estimator that can be used in a quantile autoregression with quantile-independent fixed effects. Exploiting the ideas of Chernozhukov and Hansen (2006, 2008),[11] Galvao (2011) has proposed a different estimator, based on instrumental variables, and provided two theoretical results. First, we should not use the estimator by Koenker (2004) in a dynamic

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quantile-regression model with *nonpenalized* location-shifting fixed effects because it 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), to obtain better estimates in small-T samples.

A further alternative to Galvao (2011) and Koenker (2004) 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 ordinary 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 Galvao (2011) when the penalty parameter is set equal to unity.

The next section will use all the existing approaches to the estimation of a quantile autoregressive model with location-shifting fixed effects. Yet, our preferred estimator is the one by Galvao (2011) in that no shrinkage on State-fixed effects is imposed. 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 data set contains annual observations on 51 U.S. States for the period of 1980–2010. Since our data set covers 31 years, potential biases arising from short-T panels are likely to be small.[12]

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 the mean-regression version of model (4) 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 ordinary least-squares estimate of the conditional mean unemployment persistence is 0.905 (with a 0.015 bootstrapped 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 (4), which answer this question. The standard Koenker–Bassett's estimator is applied. 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. This conclusion is supported by Figure 3, which plots the function $\theta \rightarrow \rho_{1\theta}$. The existence of a positive association is what the data tell us about the function $\rho_1(.)$ linking the realization of the matching inefficiency index $\Theta_{i,t}$ (on the horizontal axis) and the realization of the coefficient $\frac{1-s_{i,t}-f_{i,t}}{1+\ell_{i,t}}$ (on the vertical axis).[13]

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)
Bias relative to K(0.1)	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. K(0.1), LC, and G stand for Koenker (2004) with lambda = 0.1, Lin and Chu (2013), and Galvao (2011), respectively.

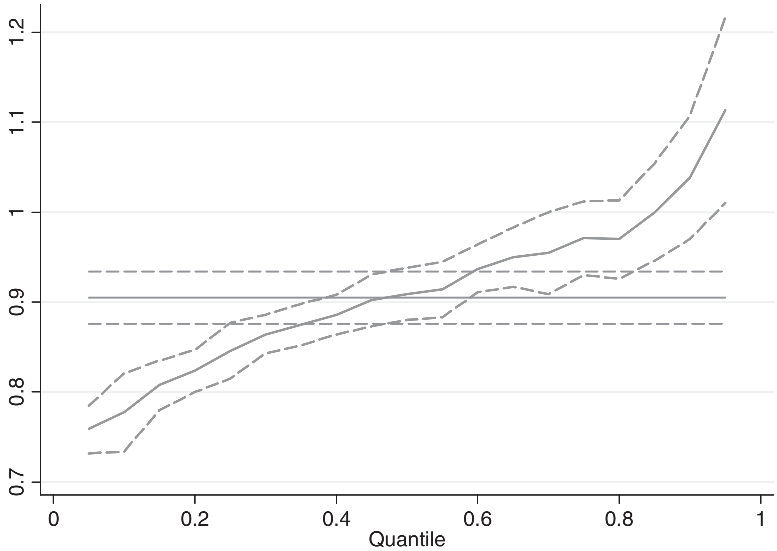

FIGURE 3. Unemployment persistence by quantiles: Koenker and Bassett's (1978) estimator. The ordinary least-squares estimate and its confidence interval are in gray. Confidence intervals are based on bootstrapped standard errors (100 repetitions).

The theoretical interpretation that we give to this increasing pattern is as follows. Matching inefficiency affects the coefficient $\frac{1-s_{i,t}-f_{i,t}}{1+\ell_{i,t}}$ in three ways. First, higher matching inefficiency reduces the job-finding rate $f_{i,t}$. Second, it induces more people to abandon the State labor market, lowering the growth rate of the labor force $\ell_{i,t}$. Third, it makes worker replacement more costly for firms, thus reducing $s_{i,t}$ (though it may also increase $s_{i,t}$, as we have seen).[14]

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

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

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

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

order autoregressive model, which is more flexible from a statistical point of view but less appealing from a theoretical perspective [note that model (2) allows for only one unemployment lag].

To go one step further, Table 2 provides the estimation results for model (4) using the estimator by Koenker (2004), which takes fixed effects into account. In order to provide a complete picture, we use a wide range of values for the penalty parameter λ, from 0.1 to 13.[15] As the penalty parameter increases, the fixed effects are forced to be all equal to zero. Hence, the autoregressive coefficient estimates are biased toward 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 used. As expected, the Koenker's estimates in Table 2 are biased toward 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 estimates relative to Table 2 estimates with $\lambda = 0.1$ is measured by the "bias relative to K(0.1)" in Table 1.

For comparison, Table 3 provides the estimation results for model (4) 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

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

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

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

TABLE 4. Quantile instrumental-variable autoregression with nonpenalized fixed effects: Galvao'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.

practice of using lagged first-differences as instruments for variables in levels [Blundell and Bond (1998)]. The model is just-identified, and the ordinary 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 amount of the upward bias is indicated as the "bias relative to LC" in Table 1.

For further comparison, Table 4 applies Galvao's (2011) estimator to model (4) 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. Galvao's estimates are our preferred estimates because they do not impose any shrinkage on fixed effects. Figure 4 plots the function $\theta \to \rho_{1\theta}$.

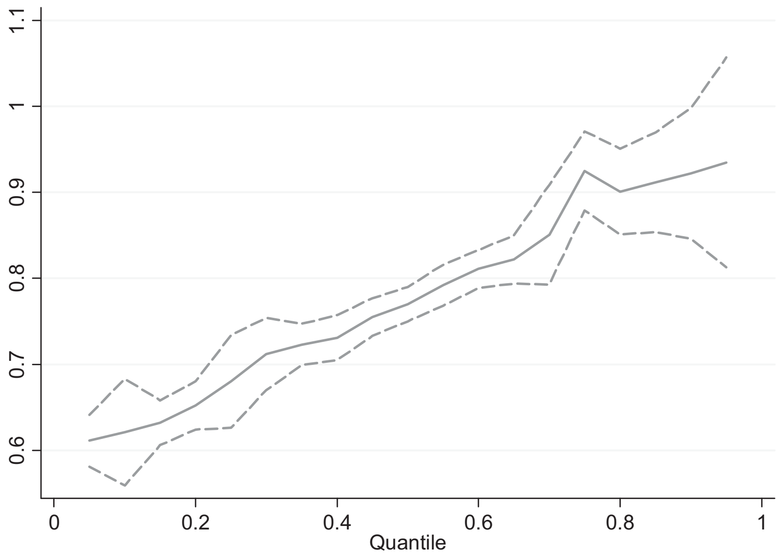

FIGURE 4. Unemployment persistence by quantiles: Galvao's (2011) estimator. Confidence intervals are based on bootstrapped standard errors (100 repetitions).

In sum, the evidence presented in this section is consistent with the hypothesis of "hysteresis" at the upper quantiles of the conditional unemployment distribution, and with the "natural rate" hypothesis at the remaining quantiles. Future research using specific unit-root tests for the upper quantiles may shed new light on this point.

5. TESTS, EXTENSIONS, AND ROBUSTNESS

Table 5 presents the tests of equality, at different quantiles, for pairs or groups of autoregressive coefficients reported in previous tables. In practice, the hypothesis of parameter homogeneity across quantiles is tested. All tests are based on bootstrapped standard errors (100 repetitions). We find strong evidence of quantile parameter heterogeneity, regardless of the estimator used.

Figure 5 plots the accumulated responses of the unemployment rate to a unit shock at both the 25th and the 75th quantile of the unemployment distribution (Figure 5a) and difference between the two responses (Figure 5b). Using the estimates based on Galvao (2011), we can see that the accumulated responses are different (Figure 5a), with the response at 75th quantile being more pronounced than the one at the 25th quantile. The plot of the difference between the two accumulated responses suggests that a shock equally affecting the 25th and the 75th quantile (a unit shock in both cases) implies an increase in unemployment dispersion over time (Figure 5b). In the case of quantile parameter homogeneity

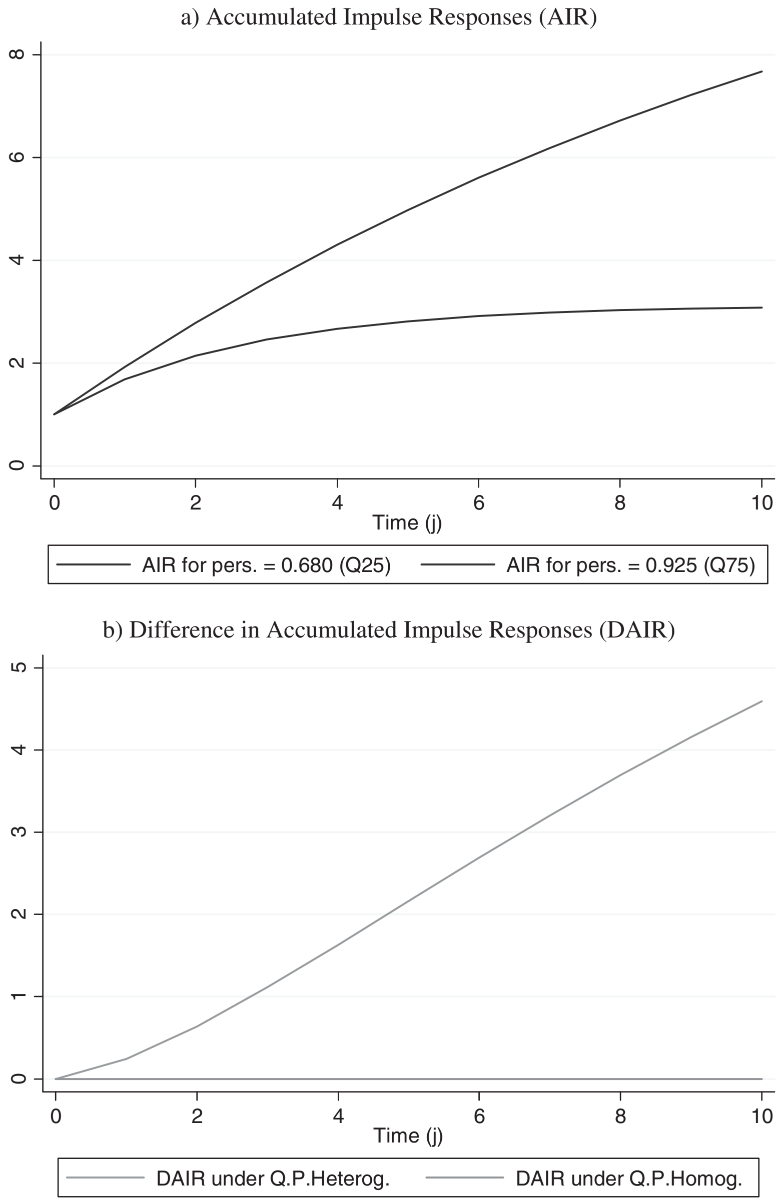

FIGURE 5. Unemployment-rate responses to a unit shock for persistence at Q75 $\neq$ Q25: Galvao's (2011) estimator.

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TABLE 5. Tests of quantile parameter heterogeneity for unemployment persistence (p-values)

	KB (Table 1)	K(0.1) (Table 2)	LC (Table 3)	G (Table 4)
H0: Q25=Q50=Q75	0.000	0.000	0.000	0.000
H0: Q25=Q50	0.000	0.009	0.012	0.000
H0: Q50=Q75	0.000	0.007	0.006	0.000
H0: Q25=Q75	0.000	0.000	0.000	0.000

Notes: All tests are based on bootstrapped standard errors (100 repetitions). Wald test statistics are computed using the bootstrapped variance–covariance matrix of the coefficients. KB, K(0.1), LC, and G stand for Koenker and Bassett (1978), Koenker (2004) with lambda = 0.1, Lin and Chu (2013), and Galvao (2011), respectively.

(not considered in Figure 5a), the responses would be identical to each other and the plot of the difference between them would be a straight line at zero level (Figure 5b), i.e., the unemployment dispersion would neither increase nor decrease.

Every empirical paper is based on assumptions that can be questioned, and this paper is not an exception. Here, the innovation $\zeta_{\theta i,t}$ is assumed to be i.i.d at each θ, which may not be the case. In principle, the innovations can be correlated across States and over time. Cross-sectional and time dependence may affect both standard errors and estimates. In the specific application discussed here, to be problematic, the innovations must be correlated at quantile level, which is less likely to happen than at mean level. This makes our empirical model more robust to this criticism than a standard mean-regression model.

It is possible to test for cross-sectional dependence in a quantile autoregression *without fixed effects* by using the approach proposed by Parente and Santos Silva (2016). The evidence that we find is mixed. On the one hand, when the standard errors are clustered at year level, the test rejects the null hypothesis of no intracluster correlation at all quantile levels in Table 6. On the other hand, however, producing standard errors that are robust to intracluster correlation provides results in line with those of Table 1. Besides the standard errors get larger, all the coefficients are still significant at 1% level.

Cross-sectional correlation may disappear when controlling for State-fixed effects. Yet, fully dealing with cross-sectional dependence is not easy in this paper because we are not aware of any estimator allowing for quantile autoregression *with fixed effects* as well as producing standard errors that are robust to cross-sectional dependence at quantile level.

In principle, time persistence in innovations at quantile level can be addressed by allowing for an additional unemployment lag in model (4), or more than one lag.[16] Yet, this approach is not taken here because this would break the link between our empirical model (4) and our structural model (2) [note that model (2) allows for only one unemployment lag].

TABLE 6. Quantile autoregression without fixed effects but with clustered standard errors: Parente and Santos Silva's (2016) estimator

	Q25	Q50	Q75
a) Year-level clusters			
Persistence	0.846	0.909	0.971
	(0.067)	(0.051)	(0.062)
H0: No intracluster correlation (p-value)	0.000	0.000	0.000
b) State-level clusters			
Persistence	0.846	0.909	0.971
	(0.008)	(0.010)	(0.015)
H0: No intracluster correlation (p-value)	0.980	0.121	0.326

Notes: The standard errors, in parentheses, are clustered at a) year level and b) State level.

In addition, when we test for time dependence by clustering the standard errors at State level, the test by Parente and Santos Silva (2016) does not reject the null hypothesis of no intracluster correlation at all quantile levels in Table 6. The fact that the empirical model controls for past unemployment can explain this result.

Our empirical model with State-fixed effects does not include year effects. These are typically used in fixed-coefficients models, additively, to take into account the effects of the business cycle. However, in random-coefficients models, such as model (2), the business cycle produces its effects through the random coefficients. Further, while in mean-regression models the year dummies estimate average effects, in quantile-regression models these dummies estimate quantile effects. This is a relevant difference with respect to State-fixed effects, which instead are typically [Koenker (2004), Galvao and Montes-Rojas (2010), Galvao (2011), Lin and Chu (2013)] not indexed by quantiles in both mean-regression and quantile-regression models. The implication is that an empirical model with year effects indexed by quantiles and State-fixed effects not indexed by quantiles would be difficult to interpret from a theoretical point of view.

Nevertheless, as a robustness check, Table 7 presents the estimates of model (4), including both State and year effects. We use our preferred estimator, i.e., Galvao (2011). To avoid the proliferation of instruments, we rely on the same identification proposed for the model without year effects. The difference between the estimates in Table 7 and those in Table 4 is not dramatic. Yet, our preferred estimates are those in Table 4 because they are closely related to the structure of model (2), where the business cycle produces its effects through the random coefficients.

The fact that the estimates based on the Galvao's (2011) estimator are our preferred estimates does not depend on the fact that this estimator performs necessarily better than others in Monte Carlo simulation. The issue here is whether, from a theoretical point of view, it makes sense to force all State "natural" unemployment

TABLE 7. Quantile instrumental-variable autoregression with nonpenalized fixed effects and year effects: Galvao's (2011) estimator

	Q25	Q50	Q75
Persistence	0.698	0.783	0.898
	(0.021)	(0.013)	(0.019)

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

rates to converge among them at some rate defined by a penalty parameter [see Koenker (2004, p. 86)]. We believe this is not realistic because we cannot a priori rule out the hypothesis that at least in one State the unemployment rate evolves over time as a random walk, and a "natural" rate for this State does not even exist. Since Galvao's (2011) estimator is the only one which does not impose any shrinkage on State-fixed effects among those used in this paper, it turns out to be our preferred estimator for this reason.

6. CONCLUSIONS

Quantile regression is nowadays widely used in microeconomic studies. One typical application is in the field of labor economics. The return to education is seen as a function of a standard uniform latent random variable—the ability index—which allocates individuals at different quantiles of the wage distribution. As a result, many authors have been interested to estimate the education returns at different points of the wage distribution in order to investigate the effect of education on the dispersion of the wage distribution. One interesting finding[17] is that, since the returns are increasing in the quantile level, a policy promoting an increase in one year of schooling for all the individuals in a given society does not necessarily reduce wage inequality.

The use of quantile regression in macroeconomics is still limited, but it seems to be increasing. In this paper, we have developed a model, where unemployment persistence is seen as a function of a standard uniform latent random variable—the matching inefficiency index—which allocates States at different quantiles of the unemployment distribution. To the best of our knowledge, we are the first to model the unemployment rate as a first-order autoregressive random-coefficients model, where the random coefficients are functions of job-flow rates and labor-force growth, which in turn depend on a matching inefficiency index. Under mild assumptions, this theoretical setup naturally leads to a quantile autoregressive empirical model. The estimation of this model allows us to elaborate on the effect of a macroeconomic shock on the dispersion of the unemployment distribution.

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

The first result is important because it shows that previous research focusing on the mean unemployment persistence in the United States [see Blanchard and Summers (1986), among others] does not capture the whole picture: Unemployment persistence is subject to quantile parameter heterogeneity. The result for the mean unemployment persistence 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. This enriches earlier evidence on unemployment persistence in the United States based on quantile autoregression for time-series data [see Koenker and Xiao (2006), among others].

From a policy perspective, our findings suggest that a macroeconomic shock does not simply shift the location of the unemployment distribution. A shock increasing the mean of the unemployment distribution also increases the dispersion of the unemployment distribution. By converse, a shock reducing the mean of the unemployment distribution is able to reduce within-States unemployment inequality. Hence, a federal policy equally applied in each State may be suitable to deal with unemployment inequality among States because some States—those in the upper tail—benefit more from it: Their higher unemployment persistence makes the accumulated positive effect of the federal policy bigger for them.

From an academic perspective, this paper stresses that "hysteresis" and "natural rate" hypotheses can co-exist along the unemployment distribution. Whether a shock has permanent effects or not, it depends on the quantile of the unemployment distribution at the time of the shock. In particular, we find the intuitive result that States located in the lower tail (i.e., in a better economic situation) absorb its effects faster than those in the upper tail.

NOTES

1. In particular, we will focus on a unit shock that hits all quantiles of the unemployment distribution in the same way as the mean. Despite such a shock is symmetric by definition, we will argue that its effects are asymmetric.

2. 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), Raurich et al. (2006), Ortigueira (2006), Romero-Ávila and Usabiaga (2007), Sephton (2009), Dromel et al. (2010), Khalifa (2012), and Cheng et al. (2012) are just few examples.

3. Since the effect of a transitory shock tends to disappear as time goes by, we will focus on the accumulated effect to proxy the effect of a permanent shock [Hamilton (1994, pp. 5–7)].

4. In general, a shock may change the shape of the unemployment distribution (Figure 2b), for instance when its median effect is different from the average one.

5. Though the standard terminology is matching efficiency, we prefer to use the term "inefficiency" to create a direct link with persistence.

6. Despite the focus on matching (in)efficiency, a search (in)efficiency index in the spirit of Barnichon and Figura (2015) can be easily incorporated in the model.

7. Heterogeneity in exogenous separation rates across States and over time is *per se* a source of heterogeneity in persistence.

8. A limitation of this paper is that we do not model the separation rate explicitly. For instance, in a more elaborated model that allows for transitions of workers from a job to another, higher matching inefficiency can be seen as a factor reducing the incentive to on-the-job search and thus endogenous separations.

9. The weights regulate the relative influence of the quantiles on the estimation of the fixed effects. More weight is typically attributed to the median quantile.

10. The article by Koenker (2004) has inspired many authors. For instance, 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 that 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 and his estimator is consistent when both T and N tend to infinity, while those proposed by Koenker (2004) and Lamarche (2010) rely on the additional assumption that N^a/T goes to zero for some $a > 0$. Finally, Rosen (2012) has proposed an estimator that is consistent for fixed T.

11. The quantile-regression literature has long dealt with the issue of endogeneity. 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 the fixed effects are indexed by quantiles. In addition, Galvao and Montes-Rojas (2009) have proposed an alternative to Harding and Lamarche (2009) for a model, where the fixed effects are pure location shifters.

12. Galvao (2011) and Galvao and Montes-Rojas (2010) have performed Monte Carlo simulations on several issues, including this specific point. Their results suggest that the bias is monotonically decreasing in T, and it is very small already at $T = 20$ for $N = 50$.

13. At the highest quantiles, we find evidence of locally explosive behaviors. Though this possibility cannot be a priori ruled out when dealing with quantiles, even when the process is mean stationary [see Koenker and Xiao (2006)], such a result does not make much sense in the context of unemployment. One reason for this strange result is that the model does not control for fixed effects. As we will see, controlling for fixed effects is enough to get more reliable estimates at the highest quantiles.

14. The estimates for the function $\rho_0(.)$ are reported in Appendix. The evidence of quantile parameter heterogeneity is confirmed. Matching inefficiency can affect the coefficient $\frac{s_{i,t}}{1+\ell_{i,t}}$ in two directions. One the one hand, higher matching inefficiency lowers the growth rate of the labor force $\ell_{i,t}$. On the other hand, higher matching inefficiency can reduce the job-separation rate $s_{i,t}$. The two effects seem to compensate each other at lower to middle quantiles, but the former seems to prevail on the latter at higher levels of matching inefficiency. Also, it is nice to see that the mean values for ρ_0 and ρ_1 (0.006 and 0.905, respectively) imply a steady-state federal unemployment rate of $\frac{0.006}{1-0.905} = 0.063$, i.e., 6.3%, which is realistic.

15. Note that Galvao 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.

16. Suppose, for instance, that $\xi_{\theta i,t} = \alpha_i + \zeta_{\theta i,t}$ and $\zeta_{\theta i,t} = \tau\zeta_{\theta i,t-1} + \upsilon_{\theta i,t}$. Then, the empirical model can be written as $u_{i,t} = (1-\tau)\rho_{0\theta} + (\tau + \rho_{1\theta})\, u_{i,t-1} - \tau\rho_{1\theta}\, u_{i,t-2} + (1-\tau)\alpha_i + \upsilon_{\theta i,t}$.

17. See, for instance, Martins and Pereira (2004) who report evidence on 16 countries.

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APPENDIX

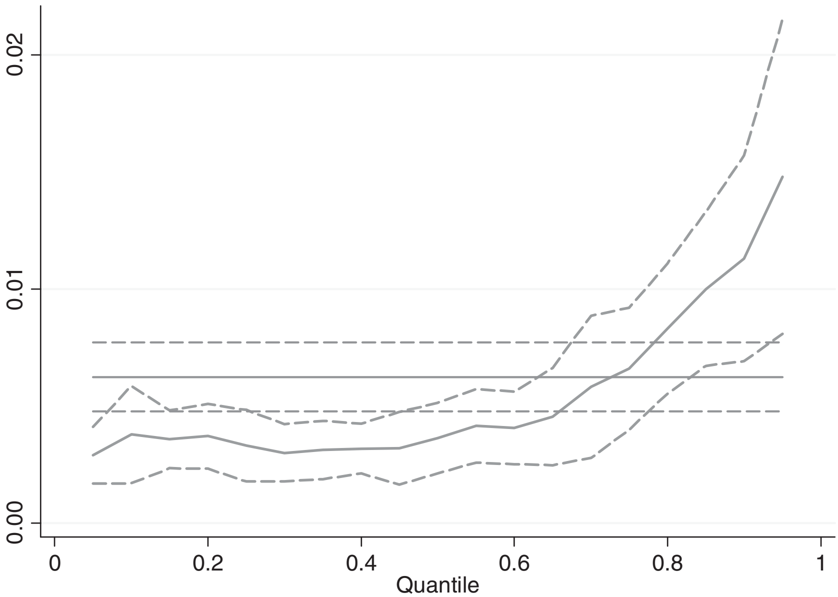

FIGURE A.1. Unemployment intercept by quantiles: Koenker and Bassett's (1978) estimator. The ordinary least-squares estimate and its confidence interval are in gray. Confidence intervals are based on bootstrapped standard errors (100 repetitions).

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