

The Geographic Mobility of Labor and the Rigidity of European Labor Markets

Preliminary.

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Abstract

Regional unemployment and non-participation rates are higher, more disperse, and more stable in Europe than in the U.S. This paper helps understand what may cause this phenomenon. Specifically, it looks at the role of migration in regional differences. I analyze the adjustment mechanisms of regional labor markets in seven countries of continental Europe (Belgium, Germany, Spain, France, Italy, The Netherlands, and Portugal), and the United States. I develop a simple model to understand the role of migration in the adjustment mechanism and estimate comparative static parameters. Under demand shocks, migration elasticities are identified relative to other supply elasticities. I argue that comparative statics give more reliable results than the usual Vector Autoregression approach. I exclude part of the possible supply-induced variation in my analysis. According to the results, aggregate migration elasticities relative to other supply responses are significantly weaker in Europe than in the U.S. The differences are small for the economically most active cohorts, and the aggregate differences are driven primarily by the less active cohorts, both young and old. This suggests that the Europe-US differences in regional inequality are driven at least as much by stronger unemployment and non-participation responses than weaker migration.

Key words: regional labor markets, migration, labor supply adjustment.

Regional unemployment and non-participation rates are not only higher in continental Europe than in the U.S., but they are also more disperse and more stable over time. Maurice Obstfeld and Giovanni Peri (1998) found that, in the late 1980's and early 1990's, the coefficient of variation of regional unemployment rates was around 0.38 in the European Union. The corresponding U.S. figures were about 0.23. They have also shown that differences were a lot more persistent in Europe. The correlation of regional unemployment rates of 1985 and 1995 are moderate in the U.S. (with a coefficient of 0.38) but strong in the U.K. (0.89), Germany (0.76), and Italy (0.83). They argue that higher persistence is due to a less adequate adjustment to exogenous changes. The same patterns are true if we do not distinguish between unemployment and non-participation (see section 2.2 below).

That European labor markets are less flexible than those in the United States is a commonplace among economists. Olivier Blanchard and Pedro Portugal (2001) find that flows of workers into and out of unemployment are about three times lower in Portugal than in the U.S. At the same time, however, while job creation and job destruction ("job flows") are lower in Portugal at high frequencies, but they are actually very similar at the annual level. They also find evidence that worker mobility across firms in addition to job creation are significantly lower in Portugal. This latter fact suggests that an important part of the inflexibility of the Portuguese labor market is due to lower worker mobility.

Another commonplace is that people in Europe are less mobile than people in the U.S. Blanchflower and Oswald (1999) report that the fraction of people moving between American states is almost three times larger than the fraction of people moving between German regions (3 per cent versus 1.1 per cent in 1986). Although realized mobility may reflect lower incentives to move as well as less propensity to move given the incentives (a point made by Obstfeld and Peri), casual empiricism and most of the previous literature

support that propensity to migrate among Europeans is indeed lower (see, for example, Krueger, 2000).

The question I try to answer in this paper is whether there is a causal connection between these phenomena. That is, I try to assess the extent to which the more diverse unemployment rates in Europe (often considered an indicator of less flexible labor markets) is due to lower geographic mobility of people. Note that I aim at uncovering supply side differences between European job markets and the U.S.: I do not focus on labor demand rigidities. I believe however that the question itself may be of interest in itself. A significant part of the lower mobility of workers documented by Blanchard and Portugal (2001) might be a result of lower propensity to migrate. This is an important factor if different industries are clustered at different places in order to enjoy the benefits of agglomeration, and at the same time changes in industry-specific labor demand are different. Although European countries are known to be less diverse in industrial composition than the U.S., that difference is not very large (see section 3.2 below).

Andrew Oswald (1999) presents evidence that correlation between home-ownership and unemployment rate is positive and surprisingly large. The relationship holds across countries and across regions within the countries he considers, both in cross-section and in long-term changes. Moreover, Oswald presents results that suggest that unemployment benefits, taxes on labor income, or unionism have a lot weaker (if any) impact on the spatial distribution of unemployment rates. He notes that "conventional wisdom [on the source of labor market rigidities] is more of a result of theoretical preconception than a weighing of hard evidence." The causal mechanism between home-ownership and unemployment rates is through the geographic mobility of people. He argues that widespread home-ownership makes markets for housing less liquid and therefore increases migration costs, which makes regional adjustments less complete. Oswald lists different mechanisms for candidate explanations, all of which rest on the primary role of migration

responses.

In order to answer my question I examine aggregate adjustment mechanisms of European and U.S. regional labor markets. The topic has been extensively researched: Bartik (1991), Blanchard and Katz (1992), and Bound and Holzer (2000) analyze U.S. regional labor markets, while Decressin and Fatás (1994), Obstfeld and Peri (1998), and Mauro and Spilimergo (1999) look at European regions (the first one looks at all Europe, the second one at Germany, Italy, and the U.K., and the third one at Spain).

The European literature follows the structural VAR methodology developed by Blanchard and Katz (1992). It offers quite conflicting conclusions for the role of inter-regional migration in adjustment to exogenous changes in Europe. Decressin and Fatás' (1994) results suggest that there is a relatively weak migration response in the first year after an exogenous shock in labor demand in Europe. In five years, they find no remaining unemployment or participation, which indicates that changes in employment completely translate to migration. This finding is at odds with the prior of low mobility being an important factor in Europe. On the other hand, Mauro and Spilimergo's results for Spain suggest a migration response less than 50 per cent. Obstfeld and Peri (1998) also conclude that people's propensity to migrate is a lot smaller than Decressin and Fatás' results would suggest. For all three European countries they examine (Germany, Italy, and the U.K.), the migration response after five years is about 30 per cent (compared to 80% in the U.S. and 70% in Canada).

In this paper I argue that the VAR approach requires assumptions that are implausible. I show however that, even if some of those assumptions do not hold, there is an intuitive interpretation of the results it gives. In particular, I show that the migration elasticity is identified only relative to other supply elasticities. Even that is true only if regions experienced only demand shifts. Except for the Blanchard and Katz paper, the VAR literature did not pay much attention to this identification problem.

In this paper, I try to identify and estimate the same parameter by simpler means. Instead of making use of the year-to-year dynamics, I look at simple differences covering five-year spans. (I also repeat the results to one to ten years). If most of the dynamics happens within a year, some of my results are comparable to the VAR estimates. I follow a comparative static approach. At the same time, I try to think harder about what drives variation in the data and what identifies the coefficients I estimate. In particular, I try to restrict variation to the result of demand shocks. This approach is close to Bartik's (1991) and Bound and Holzer's (2000) analysis. The results indicate that although supply factors do not play a major role in the US, they confound the European results considerably. Using an alternative measurement strategy, I decrease the problem and get substantively different results.

I examine seven countries in continental Europe: Belgium, Germany, Spain, France, Italy, The Netherlands, and Portugal. I develop a simple supply and demand framework that helps understanding the identification problems. OLS estimates might be biased by supply shocks, in either direction. The IV used for the US of the 1980's by Bartik (1991) and Bound and Holzer (2000) does not work in our context. I exclude parts of the supply shifts by looking at within birth-cohort changes, which has no effect on US estimates but changes European results considerably.

I find evidence that aggregate migration responses are indeed smaller in Europe. The role of migration within total supply adjustment in Europe is about half as large as in the US. However, these are a result of relatively small differences in the most active cohorts and large differences in older and very young cohorts. Since the migration elasticity is identified only relative to other supply responses, the results suggest that it is probably those other mechanisms (adjustment at the unemployment and non-participation margin) that are responsible for most of the difference. The same interpretation holds up when one compares the results by gender and by schooling.

The rest of the paper is organized the following way. The first section develops a simple theoretical model and connects it to a simple measurement strategy. The model is useful to interpret the empirical results and sheds light on the main problem of identification. It also helps understanding the difference in my empirical strategy from the previous literature, which is the subject of Section 2. Section 3 introduces the data, and Section 4 discusses the alternative measurement strategies. The fifth section describes the main results, and the last part concludes.

1 Adjustment mechanisms of regional labor markets

1.1 A simple model

The goal of the paper is to understand how a regional labor markets adjust to exogenous changes in labor demand or supply, and what is the role of migration in the adjustment. This section introduces a simple model of aggregate adjustment of regional labor markets. The model very simple, but I believe that it incorporates the basic elements of most economists' intuition. There is no emphasis on dynamics; the analysis focuses on long-run issues. As the data will confirm, the long run may be quite short in our case: one-year differences are not that different from longer ones.

All important parameters (demand and supply elasticities) are assumed to be the same for all regions in a given country, but different regions are assumed to experience different exogenous shocks. This is a "small economy" (small regions) partial equilibrium model: whatever happens in one region does not directly affect the others. Quantities and wages should be understood as differentials from the national average. This makes sense if countries are closed for factor mobility, and it is probably a good approximation if mobility within countries is a lot larger than mobility between countries.

Let l denote log employment in a region, and let dl denote changes in log employment (approximate percentage changes). Similarly, let w denote the log (real) wage and dw the change in log wage. Labor demand is described by the following log-linear relationship:

$$dl^D = -\eta dw + d\xi. \quad (1)$$

η is the elasticity of demand and $d\xi$ is an exogenous shock. Labor supply is assumed to follow a similar log-linear relationship. However, here I distinguish two elements of shocks and adjustments. In the "short run", people don't migrate and all adjustment takes place on the employment - non-employment margin (unemployment and participation).¹ In the "long run", however, people can move and therefore leave or enter the region. The short-run versus long-run distinction should be thought of more as theoretical concepts than real timing differences. The short-run elasticity is meant to be counterfactual: it describes what would happen if there were no migration at all.

$$dl^{SS} = \psi dw + d\zeta \quad (2)$$

$$dl^{SL} = (\psi + \lambda) dw + (d\zeta + d\kappa). \quad (3)$$

Short-run supply is denoted by superscript SS , and SL means long-run supply. ψ is the short-run elasticity of labor supply. It is the counterfactual elasticity of adjustment on the employment - non-employment margin without migration. λ is the migration elasticity in response to changes in real wages. $d\zeta$ is non-migration shocks to labor

¹This broad interpretation of labor supply is very similar to Olivier Blanchard's use of the term (see, for example, Blanchard, 1997). A more elastic short-run labor supply means a stronger relationship between real wages and participation or unemployment. A more generous welfare system with wide disability pensions coverage, early retirement possibilities, or longer unemployment assistance may result in a more elastic supply. Countries in continental Europe may therefore be characterized by more elastic supply curves than the U.S.

supply while $d\kappa$ is migration shocks.

Figure 1 illustrates the setup. D is demand for labor. S_S is labor supply "in the short run", and S_L is labor supply "in the long run". S_L is more elastic than S_S because the latter incorporates responses through migration (λ). At each wage level, the difference between the short-run and the long-run supply curve corresponds to migration. In the absence of labor mobility, the short-run and the long-run curves coincide. Under perfect mobility, the long-run curve is horizontal.

Figure 1 shows a situation where there is some labor supply response without migration (S_S is not vertical). There is migration response in addition, but is not infinitely elastic (S_L is different from S_S but it's not horizontal). Initially, the labor market is in equilibrium at point E_0 , where demand equals supply and employment is at l_0 . Figure 1 illustrates the case where all curves intersect at E_0 in the initial equilibrium. That is, there is no migration at the going real wage. This corresponds to a world where there are no changing region-specific "consumption amenities" that would result in inter-regional migration at equilibrium wages.

In the long run, equilibrium changes are the following:

$$dw^* = \frac{d\xi - d\zeta - d\kappa}{\eta + \psi + \lambda} \quad (4)$$

$$dl^* = \frac{\psi + \lambda}{\eta + \psi + \lambda} d\xi + \frac{\eta}{\eta + \psi + \lambda} (d\zeta + d\kappa). \quad (5)$$

Long-run wage effects are larger the smaller the elasticities (η, ψ, λ) . The long-run change in employment is a function of the relative size of the demand and supply elasticities, and it depends on the source of the shock. It is always less than or equal to the size of the shock for it is dampened by wage effects. For a given demand shock, the long-run employment response is larger the larger the supply elasticities relative to the

elasticity of demand. For a given supply shock, the opposite is true.

By definition, equilibrium migration is exogenous migration plus the migration response to the equilibrium changes in the real wage:

$$dp^* = \lambda dw^* + d\kappa = \frac{\lambda}{\eta + \psi + \lambda} (d\xi - d\zeta) + \frac{\eta + \psi}{\eta + \psi + \lambda} d\kappa. \quad (6)$$

Similarly to the employment effects, the long-run migration response depends on where the shock comes from. Following a non-migration shock, the larger the migration elasticity relative to the other elasticities the larger the long-run effect. For an exogenous migration shock the opposite is true.

If there are only demand shocks, long-run equilibrium changes simplify to $dw^* = \frac{1}{\eta + \psi + \lambda} d\xi$, $dl^* = \frac{\psi + \lambda}{\eta + \psi + \lambda} d\xi$, and $dp^* = \frac{\lambda}{\eta + \psi + \lambda} d\xi$. Figure 1 illustrates a negative demand shock. The demand curve shifts by $d\xi$, from D to D' (the shift is represented by the dashed arrow). In the absence of labor mobility, the new equilibrium would be at point E_S. The full effect is represented by point E_L with employment l_L and wage w_L . The long-run change in employment is $dl \equiv l_L - l_0$, illustrated by the bottom thick arrow on Figure 1. With mobility, the decrease in employment is larger and the decrease in wages is smaller in equilibrium. Equilibrium migration is equal to the distance between the long-run and the short-run supply curve at the equilibrium wage w_L . After the negative demand shift, there is net outmigration of dp from the region, illustrated by the upper thick arrow on Figure 1.

1.2 The role of migration

One can assess the role of migration in accommodating exogenous changes by measuring the share of migration in total adjustments,

$$\begin{aligned}\beta &\equiv \frac{dp^*}{dl^*} \\ &= \frac{\lambda (d\xi - d\zeta) + (\eta + \psi) d\kappa}{(\psi + \lambda) d\xi + \eta (d\zeta + d\kappa)}.\end{aligned}\tag{7}$$

β describes the role of migration in total adjustment of employment. It is a function of the demand and supply elasticities, and those parameters interact with the source of the exogenous changes. In what follows I focus on demand shocks.

In response to a demand shift only, we have that

$$\beta^D \equiv \beta_{d\zeta=0, d\kappa=0} = \frac{\lambda}{\psi + \lambda}.\tag{8}$$

β^D depends on two parameters: migration elasticity and the elasticity of short-run labor supply (unemployment and participation responses). In this isoelastic setup, the size of the demand shift does not matter for β^D . The elasticity of demand has no effect either.

β^D is always between 0 and 1. A stronger migration response relative to other supply adjustments results in a larger β^D (unless $\psi = 0$, that is unless all adjustment falls on migration). If there is no migration response at all (S_S and S_L coincide), $\beta^D = 0$. For the same migration elasticity, a larger non-migration response (a flatter S_S) results in a smaller β^D . Naturally, in the absence of any kind of supply adjustment (S_S is vertical and is the same as S_L), there is no change in employment at all, $dp^* = dl^* = 0$, and β^D is not defined.

The parameters of the model are not identified from a single source of shock. In the case of demand shifts, it is the relative importance of migration and non-migration elasticities in the supply schedule that are identified. In principle, one could identify all

three parameters from β if the three shocks were observable separately. As we will see, however, even demand shocks are not easy to identify in the data. Therefore I do not try to isolate other sources of exogenous variation.

1.3 Migration and cross-regional variation of employment rates

The phenomenon I'd like to explain is the rigidity of European regional labor markets, illustrated by the larger and more persistent dispersion of unemployment rates. In the spirit of the simple theoretical model outlined above, I do not distinguish between unemployment and non-participation. As a result I focus on the employment rate defined as the fraction of the active age population that is employed.

Under demand shocks only, $\beta = \beta^D$ is closely related to inter-regional variation of employment rates (employment over population). In order to have a scale-independent measure of its variation, let us look at log employment rates:

$$e \equiv \log\left(\frac{L}{P}\right) = l - p, \quad (9)$$

where L is employment and P is population. Let's imagine a thought experiment, in which all regions start with the same employment rate. They experience a demand shock, each region a different one. After the shock, their (equilibrium) employment rate changes to

$$de^* = dl^* - dp^*.$$

Before the shock, inter-regional variation in log employment rates were zero. After the shock, they change to

$$\begin{aligned}
Var(de^*) &= Var(dl^*) + Var(dp^*) - 2Cov(dl^*, dp^*) \\
&= \left(\frac{\psi}{\eta + \psi + \lambda} \right)^2 Var(d\xi) \\
Sd(de^*) &= \sqrt{Var(de^*)} = \frac{\psi}{\eta + \psi + \lambda} Sd(d\xi) \\
&= \left(1 - \frac{\eta}{\eta + \psi + \lambda} \right) \times (1 - \beta^D) \times Sd(d\xi).
\end{aligned}$$

If we assume that all regions experienced demand shocks only, the standard deviation of log employment rates is a function of the elasticity of demand relative to the long-run elasticity of supply; the role of migration; and the standard deviation of the demand shocks (measured in log employment). Stronger demand elasticity (relative to supply adjustment) and larger migration response lead to smaller dispersion.

Larger European dispersion of log employment rates are therefore a result of weaker demand adjustment, weaker migration responses, stronger unemployment and non-participation responses, or larger shocks. As we will see when we look at the size of actual ("equilibrium") changes in employment, the last explanation is unlikely. If demand shocks are dominant, the relative rigidity of European labor markets is a result of weaker demand or migration responses, or stronger adjustment on the non-employment margin.

1.4 Measurement of β^D

We can identify β^D from cross-regional variation by estimating a simple two-variate regression with changes in population on the left-hand side and changes in employment on the right-hand side:

$$dp = \beta dl + u. \quad (10)$$

If we assume that changes we look at correspond to two equilibria, and all regions experienced demand shocks only, the population regression coefficient β in the above population regression (from now denoted by β_{reg}) is equal to β^D :

$$\beta_{reg} = \frac{Cov(dp, dl)}{Var(dl)} = \frac{\lambda(\psi + \lambda)Var(d\xi)}{(\psi + \lambda)^2 Var(d\xi)} = \frac{\lambda}{\psi + \lambda} = \beta^D. \quad (11)$$

On the other hand, when measuring the thought experiment β by comparing different regions, we may compare regions that experienced different kinds of exogenous changes from both supply and demand factors. In that case, the probability limit of the OLS estimate of β is not β^D .

If regional labor markets experience both demand shocks and non-migration labor supply shocks, and the two shocks are uncorrelated, the probability limit of the OLS estimate is smaller than β^D :

$$\beta_{reg} = \frac{\lambda}{\psi + \lambda} \times \frac{(\psi + \lambda)Var(d\xi) - \eta Var(d\zeta)}{(\psi + \lambda)Var(d\xi) + \frac{\eta^2}{\psi + \lambda}Var(d\zeta)} < \beta^D. \quad (12)$$

If, however, the demand shocks and the non-migration labor supply shocks are negatively correlated, one cannot sign the direction of the bias:

$$\beta_{reg} = \frac{\lambda}{\psi + \lambda} \times \frac{(\psi + \lambda)Var(d\xi) - \eta Var(d\zeta) + (\eta - \psi - \lambda)Cov(d\xi, d\zeta)}{(\psi + \lambda)Var(d\xi) + \frac{\eta^2}{\psi + \lambda}Var(d\zeta) + 2\eta Cov(d\xi, d\zeta)} \begin{matrix} \leq \\ \geq \end{matrix} \beta^D. \quad (13)$$

If the elasticity of demand is large enough and the negative correlation is strong enough, the identified regression coefficient is larger than the parameter we are after.

1.5 Supply adjustment of different groups

Two groups: A and B, with labor force weights w_A and w_B . Aggregate elasticities are averages of group-elasticities: $\lambda = w_A\lambda_A + w_B\lambda_B$ and $\psi = w_A\psi_A + w_B\psi_B$. Then,

$$\begin{aligned}\beta^D &= \frac{\lambda}{\lambda + \psi} = \frac{w_A\lambda_A + w_B\lambda_B}{w_A(\lambda_A + \psi_A) + w_B(\lambda_B + \psi_B)} \\ &= w_A \frac{\lambda_A}{\lambda_A + \psi_A} \frac{\lambda_A + \psi_A}{\lambda + \psi} + w_B \frac{\lambda_B}{\lambda_B + \psi_B} \frac{\lambda_B + \psi_B}{\lambda + \psi} \\ &= \beta_A^D w_A \frac{\lambda_A + \psi_A}{\lambda + \psi} + \beta_B^D w_B \frac{\lambda_B + \psi_B}{\lambda + \psi}.\end{aligned}$$

The aggregate β^D is a weighted average of the two disaggregated parameters since $w_A \frac{\lambda_A + \psi_A}{\lambda + \psi} + w_B \frac{\lambda_B + \psi_B}{\lambda + \psi} = 1$.

2 A note on the structural VAR approach

The structural VAR approach makes use of the yearly dynamics of employment and other variables, and is typically based on a balanced panel of regions through time. In the background is the following identity:

$$\begin{aligned}P &= L \frac{P}{L}, \text{ and therefore} \\ \Delta \log P &= \Delta \log L - \Delta \log \frac{L}{P},\end{aligned}$$

or in a notation closer to ours,

$$\Delta p = \Delta l - \Delta e.$$

L is employment, P is population, L/P is employment rate, and their logs are denoted by p , l , and e , respectively. The VAR literature further decomposes L/P into L/L^* and L^*/P , one minus the unemployment rate and participation rate.² To keep things simple, I do not make that distinction here.

Of the three linearly dependent variables two can be used in a system such as a VAR. In order to stay as close to my model as possible, I retain population and employment and treat employment rate as part of unobserved heterogeneity. The identifying assumption of demand shocks to employment imply that one has to keep L among the observed variables but the two others are interchangeable. In the population and employment space, the VAR system is the following:

$$\begin{aligned}\Delta p_t &= \alpha_0 \Delta l_t + \alpha_{11p} \Delta p_{t-1} + \alpha_{11l} \Delta l_{t-1} + \alpha_{12p} \Delta p_{t-2} + \alpha_{12l} \Delta l_{t-2} + u_{1t} \\ \Delta l_t &= \alpha_{21p} \Delta p_{t-1} + \alpha_{21l} \Delta l_{t-1} + \alpha_{22p} \Delta p_{t-2} + \alpha_{22l} \Delta l_{t-2} + u_{2t}.\end{aligned}$$

The VAR approach focuses on dynamics at yearly frequencies. Under its assumptions, it follows the effects of a unity shock to labor demand on population, unemployment rate, and non-participation rate. The two main identifying assumption it uses are that (1) all variation in employment is caused by shocks to labor demand, and (2) year-to-year changes in employment identify the magnitude of labor demand shocks ($d\xi$ in our notation). The exclusion of contemporary effect of changes in population on employment reflect the exogeneity of labor demand shocks.

If we neglect the lagged terms, the first equation is identical to the comparative static exercise outlined above. Under the assumption of demand shocks only, α_0 then would

²Blanchard and Katz (1992) make use of the $\log(1 - L/L^*) \approx -\log(L/L^*)$ approximation and write the system in terms of log changes of employment, participation rate, and unemployment rate.

identify identify $\beta^D = \lambda / (\lambda + \psi)$, at the time-horizon defined by Δ . That means that the instantaneous impulse response is

$$IR_0 = E(\Delta p_t | u_{2t}) = \alpha_0 E(\Delta l_t | u_{2t}) + E(u_{1t} | u_{2t}) = \alpha_0 u_{2t},$$

provided the two innovations are mean-independent (which is obviously true if no autonomous innovation drives Δp_t).

The question is what additional information the dynamics gives us and under what assumptions. The lagged terms in the first equation allow for some migration to take place with a lag. The lagged employment terms in the second equation are there to pick up serial correlation in the shocks to employment. Under the identifying assumption of no supply shocks occurring, lagged population does not belong to that equation ($\alpha_{21p} = \alpha_{22p} = 0$) for they would correspond to effects of migration shocks on employment. One test for the assumption is therefore to see whether their estimated coefficients are indeed zero. The system describes the dynamics correctly if the second-order autoregressive specification is correct and the lagged terms pick up all serial correlation in demand shocks. This means that its implications at longer horizon are also correct.

A unity shock to log employment ($u_{2t} = 1$) increases expected log population by α_0 in the same time period. In the next period, expected log population continues to increase by α_{11p} times its first period change, plus α_{11l} times the previous log employment shock (unity), plus α_0 times whatever inertia remained from the original shock (α_{21l}). Here we ruled out lagged effects of autonomous population changes on employment (α_{21p}). Or, in short, the impulse response function at $t + 1$ can be written as

$$IR_1 = E(\Delta p_{t+1} | u_{2t}) = \alpha_0 E(\Delta l_{t+1} | u_{2t}) + \alpha_{11p} E(\Delta p_t | u_{2t}) + \alpha_{11l} E(\Delta l_t | u_{2t}) + E(u_{1t+1} | u_{2t})$$

$$\begin{aligned}
&= \alpha_0 E(\alpha_{21p} \Delta p_t + \alpha_{21l} \Delta l_t + u_{2t+1} | u_{2t}) + \alpha_{11p} E(\alpha_0 \Delta l_t + u_{1t} | u_{2t}) \\
&\quad + \alpha_{11l} E(\Delta l_t | u_{2t}) + E(u_{1t+1} | u_{2t}) \\
&= \alpha_0 E[\alpha_{21p}(\alpha_0 u_{2t} + u_{1t}) + \alpha_{21l} u_{2t} + u_{2t+1} | u_{2t}] + \alpha_{11p} E(\alpha_0 u_{2t} + u_{1t} | u_{2t}) \\
&\quad + \alpha_{11l} u_{2t} + E(u_{1t+1} | u_{2t}) \\
&= (\alpha_0^2 \alpha_{21p} + \alpha_0 \alpha_{21l} + \alpha_0 \alpha_{11p} + \alpha_{11l}) u_{2t} + \alpha_0 E(u_{2t+1} | u_{2t}) \\
&\quad + \alpha_{11p} E(u_{1t} | u_{2t}) + E(u_{1t+1} | u_{2t}) \\
&= (\alpha_0 \alpha_{21l} + \alpha_0 \alpha_{11p} + \alpha_{11l}) u_{2t} + \alpha_0 E(u_{2t+1} | u_{2t}),
\end{aligned}$$

where the last equation follows from the assumption of mean-independence of the two types of innovations and that population changes do not contribute directly to changes in employment.

Note two things in the impulse response function. Firstly, it depends on the time-series properties of the innovation in employment after two lags had been taken out. Serial mean-independence of the structural shocks (the u) is granted if the AR(2) specification is correct, but it fails if there is remaining dynamics. Note that this is a testable hypothesis. Second, even if the dynamics is correctly specified, the impulse response depends on the serial correlation of demand shocks. Therefore, the impulse response beyond period one is going to depend on demand features of the labor market in question and also the specific demand shocks it experienced. The more persistent the shocks are the larger the impulse response and thus the larger the implied role of migration. Recall that the same is not true for the comparative static exercise outlined above, for it identifies the same β^D in a given time period regardless of the size and dynamic properties of the demand shocks.

Under the main identifying assumption of demand shocks driving the system, the difference of impulse responses to a unity shock to employment between Europe and the

U.S. are the following:

$$\begin{aligned}
IR_0^{EU} - IR_0^{US} &= \alpha_0^{EU} - \alpha_0^{US} \\
IR_1^{EU} - IR_1^{US} &= [(\alpha_0^{EU} \alpha_{11p}^{EU} + \alpha_{11l}^{EU}) - (\alpha_0^{US} \alpha_{11p}^{US} + \alpha_{11l}^{US})] \\
&\quad + [\alpha_0^{EU} \alpha_{21l}^{EU} - \alpha_0^{US} \alpha_{21l}^{US}] \\
&\quad + [\alpha_0^{EU} E^{EU}(u_{2t+1}|u_{2t}) - \alpha_0^{US} E^{US}(u_{2t+1}|u_{2t})].
\end{aligned}$$

Impulse responses between the labor markets may differ because of different 1-period migration elasticities relative to total supply adjustment (α_0), different delayed migration responses (α_{11p} and α_{11l}), and different shock dynamics (α_{21l} and $E(u_{2t+1}|u_{2t})$). Note that it also depends on the dynamics itself even if it is the same in the two markets.

The longer impulse responses are more complicated but the qualitative implications are the same.

I estimate the model on the European and American data described below. The results are available upon request. In short, they do not reject the hypothesis that demand shocks govern the observed changes in employment and population but strongly reject the hypothesis of serially uncorrelated shocks even after two lags had been taken out. As a result, the VAR impulse response functions (except the immediate ones) identify a mixture of supply adjustment and demand persistence. In the remainder of the paper, I will focus on the comparative static analysis outlined earlier for it identifies a parameter that does not depend on the particular demand shocks and is easier to interpret.

3 Data

I estimate β^D for seven countries of continental Europe and the U.S., using yearly balanced panel data from 1987 to 1998. The raw data are yearly aggregates of employment and population by gender and year of birth, compiled from individual labor force surveys.

3.1 Regions

The seven European countries analyzed here are Belgium (BE), Germany (DE for Deutschland), Spain (ES for Espana), Italy (IT), France (FR), the Netherlands (NL) and Portugal (PT).³ In the U.S. regions are the States. In the European countries, the regions are NUTS-1 and NUTS-2 level units (NUTS stands for Nomenclature of Territorial Units). Table 1 provides summary statistics for the regions, for the 16-74 years old population. For more details, see Eurostat (1999).

There are 43 NUTS1 regions in the seven countries altogether (not counting East Germany, Berlin, and the overseas territories)⁴. These regions are in size comparable to states in the U.S., but they are a lot more similar to each other. Inter-regional variation in the U.S. is therefore probably overstated relative to Europe, and so will be migration responses. At any rate, using the NUTS1 regions when comparing European and U.S. regions is better than using the NUTS2 regions.

The U.S. data come from the annual March CPS files. Sample size is around 50,000 households altogether. The sample is based on a stratified design with the strata are based on States since 1985. The European data are from national labor force surveys harmonized and aggregated by Eurostat, the statistical agency of the European Commu-

³Regional classification changed during the period in the U.K. Other countries were either extremely small or had no data for most years.

⁴Overseas territories of the European countries, regions in former Eastern Germany (and all Berlin), Corse (FR), Sardegna (IT) the Balears Islands (ES) and Ceuta y Melilla (ES, the tiny part of Africa opposite to Gibraltar) were excluded from the analysis. Alaska and Hawaii were excluded from the U.S. dataset but D.C. was retained.

nity.⁵ The samples are very large: in terms of households, they are 35,000 in Belgium; 350,000 in Germany; 65,000 in Spain; 75,000 in France; 75,000 in Italy; 60,000 in the Netherlands; and 20,000 in Portugal. All samples are stratified with strata at or below the level of NUTS2 regions. Table 2 shows the most important sample statistics.⁶

In addition to the data based on labor force surveys, establishment-based series by 17 industries are going to be used for IV estimation. The data is based on Eurostat series and were cleaned by Cambridge Econometrics.⁷

3.2 Regional employment rate differentials

Between 1987 and 1998, the standard deviation of the log employment rates for age 16 to 64 was 0.14 in the seven European countries, on average (nuts1 regions). The corresponding figure for the U.S. was 0.06. This is a significant difference, both in statistical and economic terms. Figure 2 shows the joint distribution of the 1988 and 1998 log employment rates for the EU7 and the US. It is evident just by looking at them that the European rates are not only smaller and more disperse but also more persistent over time. Indeed, the correlation coefficient is 0.87 for Europe and 0.75 for the U.S.

Figure 3 shows the same log rates for each European country, for the smaller nuts2 regions. Germany, the Netherlands, and Portugal show relatively high, less disperse, and less persistent rates; Belgium and France show more persistence; and regional employment in Spain and Italy is the lowest, most disperse, and most persistent.

⁵The data I use in this analysis are yearly NUTS2 aggregates of population, employment, and unemployment, by sex and single years of age. Following my specifications, all data I use were created by Eurostat.

⁶There are two reasons why samples of the European labor force surveys are so much larger compared to the population, and therefore, within comparable regional units. The first one is to help detailed national analyses. The second one is an explicit policy of Eurostat to facilitate NUTS2-level regional analysis. In particular, one major goal when determining the optimal size of the survey samples is to get unemployment rates with less than 10 percent of standard error (in terms of the coefficient of variation) at the NUTS2 regional level (Eurostat, 1998).

⁷The source of the data is Cambridge Econometrics and ERECO, European Regional Data (www.camecon.com). I thank Cambridge Economics for granting access to this rich database.

Summarizing the results, the data at hand show the same phenomenon the literature has established: non-employment in continental Europe is not only higher than in the U.S. but it shows larger and more stable regional differences, both within and across individual countries.

4 Measurement strategy

Just as in the theoretical section, let l denote log employment and p log population. Index c corresponds to countries and i to regions. Let changes from t to $t + 5$ (or any other span) be denoted by Δ . Changes in variables can be decomposed into two factors: changes shared by all regions in the economy and other factors that are specific to the region. Let $\tilde{\Delta}l$ and $\tilde{\Delta}p$ denote changes that are cleaned of changes shared by all regions. Then, for a country c , we have that

$$\Delta l_{cit} = \gamma_{(l)c} + \tilde{\Delta}l_{cit} \text{ and} \tag{14}$$

$$\Delta p_{cit} = \gamma_{(p)c} + \tilde{\Delta}p_{cit}, \tag{15}$$

where i is region in country c , and t is year of observation. Standard deviation of the two variables ($\tilde{\Delta}l_{cit}$ and $\tilde{\Delta}p_{cit}$) are presented in Table 3. The standard deviations inform us about the typical size of (equilibrium) employment changes, measured as deviations from the national trends.

An alternative approach (used in most of the literature) assumes that there are fixed patterns of migration between the regions that are (or may be) independent of the adjustment mechanisms we want to analyze. These long-term patterns can be "differenced out" by replacing the country-specific constants by region-specific ones into the above

equations:

$$\Delta l_{cit} = \gamma_{(l)ci} + \Delta \ddot{l}_{cit} \text{ and} \quad (16)$$

$$\Delta p_{cit} = \gamma_{(p)ci} + \Delta \ddot{p}_{cit}, \quad (17)$$

All samples cover the years from 1987 to 1998, and therefore for a given time horizon s (5 years for most of the analysis), the number of observations is equal to $s + 1$ times the number of the regions. For example, the U.S. sample for the five-year time horizon consists of 6×49 regions. Region-level observations are not weighted throughout the entire analysis.

4.1 The baseline model

Region-specific deviations of employment change from the national average changes are regressed on similar measures of changes in population, in each country and together in Europe, without a constant term (results are very robust to inclusion of constants). The following equations are estimated for different age-groups:

$$\Delta \tilde{l}_{cit} = \beta^{OLS} \Delta \tilde{p}_{cit} + u_{cit} \quad (18)$$

$$\Delta \ddot{l}_{cit} = \beta^{FE} \Delta \ddot{p}_{cit} + v_{cit} \quad (19)$$

where i is region in country c , and t is year of observation. In what follows, I will call β^{OLS} as the "OLS" parameter while β^{FE} as the "FE" or "fixed-effects" parameter.

Standard errors in each estimation allow for arbitrary heteroskedasticity and within-region clustering, acknowledging the fact that overlapping 5-year changes are obviously

not independent observations.⁸

4.2 Instrumenting for exogenous changes in demand

The instrument I planned to use is regional employment growth predicted from national (or all-European) employment growth by industry and the industrial composition of the regions' employment. This "mixing variable" was introduced by Bartik (1991) and used subsequently by Blanchard and Katz (1992) and Bound and Holzer (2000). Let $j = 1 \dots J$ denote different industries. Then the instrument is defined as

$$\Delta \hat{l}_{it} \equiv \sum_{j=1}^J s_{ijt} \Delta \log(L_{.jt}) = \sum_{j=1}^J \frac{L_{ijt}}{L_{.jt}} \Delta \log(L_{.jt}),$$

where $L_{.jt} = \sum_{i=1}^I L_{ijt}$ is total employment in industry j in Europe or the U.S. For the analysis, $J = 17$ industry categories were used, following the available European data.

$\Delta \hat{l}_{it}$ can be interpreted as the hypothetical change in employment in region i if it simply followed the overall industrial changes. If regional labor demand shocks originate from industry-specific changes in technology or product demand, this variable is probably a good predictor of that. The instrument is valid for $\Delta \tilde{l}_{it}$ if no supply factors in region i can affect overall employment growth in any industry. The smaller regions are in overall employment the more likely that this condition holds. In what follows, I use two different instruments for Europe. One is constructed from all-European trends (including countries left out from the main analysis: the data come from another source). The other one is constructed from national trends. The latter captures country-specific changes in industrial labor demand (resulting for example from the large exchange-rate movements in the late 1980s), but its validity is more questionable in small countries.

We expect the instrument to explain more of the variation in employment changes in

⁸See Arellano (1985) and Kézdi (2002) for robust standard estimation in Fixed-Effects models.

the U.S. than in Europe because regional differences in industrial structure are smaller in the EU than in the US. Table 4 presents the country-wide means of the Herfindahl-Hirschman index of industrial concentration of employment within regions. Here it is defined as $\sum_{j=1}^J \left(\frac{L_{ijt}}{L_{.it}} \right)^2$, for each region i .⁹ The results indicate that U.S. states are more specialized than comparable European regions. This difference is significant although not enormously large. To understand magnitudes, compare this 300 points difference to the changes within the U.S. From 1977 to 1998 this amounted roughly to 100 points.

Table 5 shows the results of the first-stage regressions

$$\Delta \tilde{l}_{cit} = \delta_{0c} + \delta_c \Delta \hat{l}_{cit} + \nu_{cit}.$$

To be more precise, Table 5 shows the t-values $\hat{\delta}_c / SE(\hat{\delta}_c)$ for the 16-74 and the 25-54 years old. Nothing is significant: this IV is very weak in our context. Note that the IV works somewhat better for the U.S. if additional years from 1977 are added. That indicates that demand shifts were more important in late 1970s and early 1980s in the U.S. Besides more variation because of higher spacial disaggregation, this fact helps understanding why Bartik (1991) and Bound and Holzer (2000) could use the mixing variable as a working instrument.

4.3 Identification from within-cohort changes

In this section I presented another method to exclude at least part of the possible variation from exogenous supply changes. Although it cannot accomplish what the IV could have (excluding all supply variation and controlling for the size of the demand shifts at the same time), this method can help understanding what drives the OLS

⁹It is defined for each region and not for a whole country so that we always have 17 shares to sum. The index is different if summed over different number of points, by construction. This way, however the index always varies between 588 (equal employment shares) and 10,000 (only one industry).

results.

Exogenous changes in labor supply in a region can have many different sources. One of them is cohort-size differences: larger than usual entering cohorts, for example, shift labor supply outwards. Since throughout all estimations we restrict all variables to differences from the country average, it is region-specific cohort size differences that would matter. Unfortunately, it is not possible to tell directly how much of the population differences we dealt with so far is due to region-specific net migration and how much is from region-specific cohort size differences.

On the other hand, we can exclude the variation that comes from cohort size differences by focusing only on within birth-cohort changes. As we will see, this way we magnify the role of region-specific mortality, which is also determined by exogenous supply factors and is also impossible to identify. On the other hand, we can safely assume that mortality differences don't play a significant role for the younger cohorts. It is a clear advantage over simple population differences, because there unidentifiable cohort size differences may introduce exogenous supply variation for any age-group.

Let $\Delta_s P_{tg}$ denote change in the number of people who were born in year g , between years t and $t + s$, in the region. $\Delta_s P_{tg}$ is a result of inter-regional migration ($\Delta_s P_{tg}^{(m)}$) and mortality ($\Delta_s P_{tg}^{(d)}$):

$$\Delta_s P_{tg} \equiv P_{(t+s)g} - P_{tg} \equiv \Delta_s P_{tg}^{(m)} + \Delta_s P_{tg}^{(d)}$$

Total population is the sum of people born in different years g . Therefore we have that

$$\begin{aligned}
\Delta_s P_t &= P_{t+s} - P_t = \sum_{g=g_0}^G (P_{(t+s)(g+s)} - P_{tg}) \\
&= \sum_{g=g_0+s}^{G-s} (P_{(t+s)g} - P_{tg}) + \sum_{g=G-s-1}^G P_{(t+s)g} - \sum_{g=g_0}^{g_0+s-1} P_{tg} \\
&= \sum_{g=g_0+s}^{G-s} (\Delta P_{tg}^{(m)} + \Delta P_{tg}^{(d)}) + \left(\sum_{g=G-s-1}^G P_{(t+s)g} - \sum_{g=g_0}^{g_0+s-1} P_{tg} \right)
\end{aligned}$$

The first term is within-cohort population change, while the second term is the difference between the entering and the exiting cohorts. Cohort size differences enter to changes in total population through the second term. For year-to-year differences in total (16 to 74 years old) population, $\Delta_1 P$ will be dominated by the first term, that is by migration and mortality differences. However, same is not true for long differences in subpopulations defined by age. If we compare ten-year age groups (e.g. the 45 to 54 years old) over a ten-year period ($s = 10$), the first term disappears and cohort size differences can have a significant role.

The proposed modification is to leave out the second term and keep the first one that is not affected by cohort size differences. For year-to-year changes, that will preserve most of the changes in population. In fact, the new measure will be very close to the simple population change. For long differences in small age groups this procedure would leave us with very little or no changes at all. It seems therefore as if the new measure would be either very similar to the old one or meaningless altogether. On the other hand, long differences are a sum of sort differences. For any variable X , the long difference (in levels) is

$$\begin{aligned}
\Delta_s X_t &= X_{t+s} - X_t = X_{t+s} - X_{t+s-1} + X_{t+s-1} - \dots - X_{t+1} + X_{t+1} - X_t \\
&= \sum_{h=1}^s (X_{t+h} - X_{t+h-1}) = \sum_{h=1}^s \Delta_1 X_{t+h}
\end{aligned}$$

Therefore, we can approximate the within-cohort term by the sum of yearly within-cohort changes. Define

$$\Delta_s P_t^{(g)} \equiv \sum_{h=1}^s \Delta_1 P_{t+h}^{(g)}$$

So far relative changes were defined as log differences. They are approximations to relative differences defined in a more natural way: $\Delta_s p_t \approx \frac{\Delta_s P_t}{(P_{(t+s)} + P_t)/2}$. By analogy, define

$$\Delta_s p_t^{(g)} \equiv \frac{\Delta_s P_t^{(g)}}{(P_{(t+s)} + P_t)/2} = \frac{\sum_{h=1}^s \Delta_1 P_{t+h}^{(g)}}{(P_{(t+s)} + P_t)/2}$$

By transforming the changes in employment variable the same way we as before, we can restrict our analysis to deviations from country trends:

$$\Delta_s l_{cit}^{(g)} = \gamma_{(l)sc}^{(g)} + \Delta_s \tilde{l}_{cit}^{(g)} \text{ and} \quad (20)$$

$$\Delta_s p_{cit}^{(g)} = \gamma_{(p)sc}^{(g)} + \Delta_s \tilde{p}_{cit}^{(g)}, \quad (21)$$

and similarly for $\Delta_s \ddot{l}_{cit}^{(g)}$ and $\Delta_s \ddot{p}_{cit}^{(g)}$. Using these variables we can estimate the fraction of migration to total changes in employment in the corresponding "OLS" and "FE" models:

$$\Delta_s \tilde{l}_{cit}^{(g)} = \beta_{sc}^{(g)OLS} \Delta_s \tilde{p}_{cit}^{(g)} + u_{cit}^{(g)}, \text{ and} \quad (22)$$

$$\Delta_s \ddot{j}_{cit}^{(g)} = \beta_{sci}^{(g)FE} \Delta_s \ddot{p}_{cit}^{(g)} + v_{cit}^{(g)} \quad (23)$$

The $\beta^{(g)}$ are identified from within-cohort changes.

5 Results

5.1 Summary statistics

Comparing the NUTS2 and NUTS1 European averages confirms that spatial aggregation reduces regional differences, though this effect is modest except for the oldest age groups. A typical difference of year-to-year total employment changes from the national average is about 4 per cent in the U.S., about 2 per cent in the comparable regions of the seven European countries, and varies between 2% and 4% (France) among the more disaggregated European regions. Although realized employment changes correspond to equilibria, these figures suggest that it is unlikely for European regions to experience significantly larger shocks than US states. Therefore, the larger variation in European non-employment rates suggest rigidity and not simply larger shocks.

The size of the typical change increases by a factor of two to three as we look at ten-year differences instead of year-to-year changes. Typically, the increase in the standard deviations are slightly smaller than what a random walk would produce (which, from 1 to 10 is a factor of $\sqrt{10} \approx 3.2$). This might indicate small negative serial correlation in the exogenous changes.

The second panel of Table 3 presents the standard deviation of changes in population relative to national changes ($\Delta \tilde{p}_{cit}$). In the U.S. these show a very similar pattern to the

employment change differentials. In the European regions they are further away from employment standard deviations. This reflects lower mobility in equilibrium. To address this question more directly, the next section presents estimates of β^D , the measure of the role of migration in employment changes.

5.2 The role of migration in supply adjustment

Table 6 presents the main results for 5-year time horizon. The table summarizes aggregate relative migration responses from all specifications, for the US states and the nuts1 regions of the EU7 countries, for the 1987-2000 period. For each specification, the first column shows estimated migration elasticities relative to total supply elasticity within European countries, while second column estimates it as if the seven countries were one single economy. Operationally, changes in employment and population are taken relative to country means in the first case, and relative to all-EU7 means in the second case. Since there is significant variation in shocks to relative labor demand across countries but cross-country migration is significantly lower compared to within-country migration, the coefficients in the second should be significantly smaller. Table 6 confirms that this is indeed the case.

Note that the point estimates are tight. Standard errors allow for heteroskedasticity and arbitrary serial correlation; they take into account that overlapping time-spans are obviously not independent observations.

The OLS and the FE results show a dramatically different picture in the EU-US comparison. Typically, FE gives higher migration responses for the European countries while lower for the US states. Recall that OLS makes use of all cross-regional changes in employment and population, while FE takes out region-specific trends from the identification. The reason behind the latter is that regions may experience long-run migration

trends that are of different nature from the adjustment mechanisms we would like to focus on. If that is indeed the case, the results suggest that long-run trends and short-run fluctuations work in opposite directions for Europe, while the same direction in the US.

The simple and within-cohort estimates are very close in all cases. This implies that in the relevant time period, the regions did not experience dramatically different supply shocks from changes in cohort size, at least not to the extent that would affect aggregate results. However, this is not true for more disaggregated age groups, especially in Europe. This holds for the younger cohorts, too, which implies that it is not the artifact of regional differences in mortality rates. Therefore, I will focus on within-cohort results.

Taken the OLS within-cohort results as fairly reliable and easiest-to-interpret estimates, we can finally look at the main focus of the paper, the EU-US differences. The role of migration in total supply adjustment in European countries is about two-thirds of that in the US. Taking the European countries as one economy, the role of migration is less than a half of its US share. The differences are a lot smaller for men and a lot larger for women. One may conclude that the results suggest that European women are a lot more immobile than European men. However, when we'll look at other disaggregated data we'll find that another explanation is more plausible. Since our parameter identifies migration elasticities only relative to total supply adjustment, smaller female coefficients can be a result of a similar migration elasticity but a significantly stronger adjustment at the non-employment margin.

The second explanation is strongly supported by the results for different age groups, summarized in Table 7. The most active cohorts (the 25 to 54 years old men) behave surprisingly similarly in European countries and the US. The very young and the older groups show a lot larger difference. Since the very young are among the most mobile people, their lower relative elasticity is a result of significantly stronger non-employment adjustment. High young unemployment is more a European phenomenon, and so is

wide-spread early retirement. *The main conclusion of my analysis is, therefore, that the US-EU differences in non-migration supply adjustment are probably at least as important in explaining differences in regional employment rate dispersion as migration itself.*

Table 8 shows similar estimates by schooling. For the US, these are less than high-school, high school and some college, and completed college education. For Europe, the three groups are the ones created by the Eurostat, in order to have comparable groups across countries (for more details, see Eurostat, 1995). The European data do not cover the years before 1992, and therefore I restricted the analysis to the 1992 to 2000 time period. The results do not make too much sense. True, more schooling corresponds to higher propensity to migrate or lower adjustment on the non-employment margin. The European estimates are, however, out of range: all schooling-specific parameters are larger than the aggregate ones. As a result, the EU-US comparisons change dramatically. Note that this is not a result of a different time period: the 1992 to 2000 aggregate results are very similar to the earlier ones that correspond to 1987-2000.

Preliminary inspection of the raw data suggests that it is probably changes in the classification that make the results so high. By the nature of my analysis, a change in the population shows up as a large migration response. Unfortunately, measured population can change with classification changes: if a significantly large group of people show up in a different education category from the year before, it will behave as a positive outlier and result in a large estimate for β . In principle, the same can happen in the previous analyses. Although gender and age classifications are not likely to change, regional classification might have a similar effect. However, I carefully made sure that that does not happen. On the other hand, if the population estimates suddenly change for a region (because of a census result that surprisingly off from the year-to-year estimates), it would have a similar effect, unless retrospective revisions are made for the data at hand.¹⁰ After

¹⁰I thank Gary Solon for this note.

inspection of the raw population data I find this very unlikely, but evidently I cannot rule out this possibility.

Tables 9 shows country-by-country results for Europe, for the smaller "nuts2" regions. Comparing the nuts1 result to the nuts2 ones reveals that spatial aggregation indeed decreases the point estimates most of the times. The country-by-country figures show that Belgium and the Southern countries are further away, while Germany, France, and the Netherlands are quite close to the US.¹¹

Tables 11-12 show within-cohort FE results for different time horizons. Longer horizons give larger point estimates in the U.S. but not in all European countries. Results for Portugal and Italy typically decrease with the length of the time span, Belgium and The Netherlands usually show a steep increase, while the other countries are constant or increase slightly. The NUTS1-aggregated European average β also shows a decreasing pattern in most cases. Together with the almost random-walk-like increase in the employment change standard deviations, increasing values of β are consistent with delayed migration responses. Decreasing values of β , however, are hard to reconcile, if not by the possibility of negatively serially correlated shocks. Constant coefficients suggest that for those countries, the long run arrives within a year.

The fact that the one-year coefficients are not dramatically different from the ten-year ones (except for Belgium and the Netherlands) indicate that most of the migration response takes place within a year. That would not necessarily be an implication if the exogenous shocks were positively correlated, but this is not supported by the pattern of the standard deviations documented before. This finding is not new in the U.S. context (see, for example, Blanchard and Katz, 1992) and is also consistent with Obstfeld and Peri's (1998) findings for Italy. It is at odds, however, with most other results for

¹¹Lower migration elasticities in the Mediterranean countries are not surprising. In Belgium, it may be a result of more widespread commuting between smaller regions. The French results are somewhat puzzling.

Europe.¹²

6 Conclusions

Adjustment mechanisms of regional labor markets were analyzed in seven countries of continental Europe (Belgium, Germany, Spain, France, Italy, The Netherlands, and Portugal) and the United States, for years 1987 to 1998. The results indicate that the role of migration in total labor supply adjustment is indeed weaker in Europe than in the U.S. Indirect evidence suggests, however, that this may be more the result of strong non-employment (primarily non-participation) responses than a weak migration elasticity.

This interpretation of the results weakens Oswald's (1999) arguments about the importance of home ownership through restricting migration. The results point to institutions that are not directly part of the labor market. Institutions of the welfare state such as pension system or maternity benefits may be just as important for the rigidity of European labor markets as institutions that lower migration. Recall that the paper focuses on adjustments on the supply side only. Demand rigidities are probably equally important part of the picture. A different measurement strategy is needed to uncover adjustment mechanisms on the demand side.

¹²The results by Decressin and Fatás (1994) suggest that changes in employment between two consecutive years correspond to a smaller share of the migration response than in the long run, for pooled European NUTS1 regions. The other studies on specific European countries show similar results, including Obstfeld and Peri's (1998) analysis on Germany. All of these results are based on structural VAR's with long-run effects identified from two lags. Their long-run implications are therefore indirect as opposed to the direct long-differences comparisons here.

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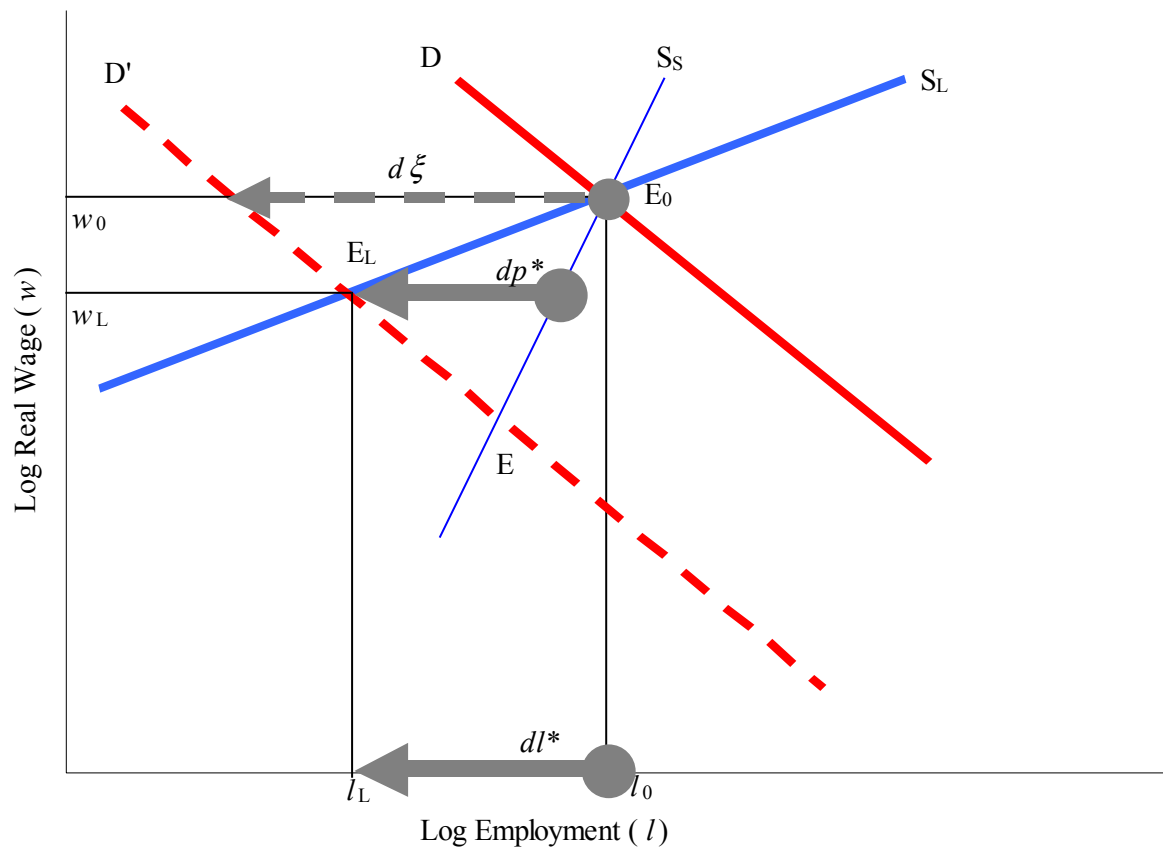


Figure 1. Simple model, negative demand shift.

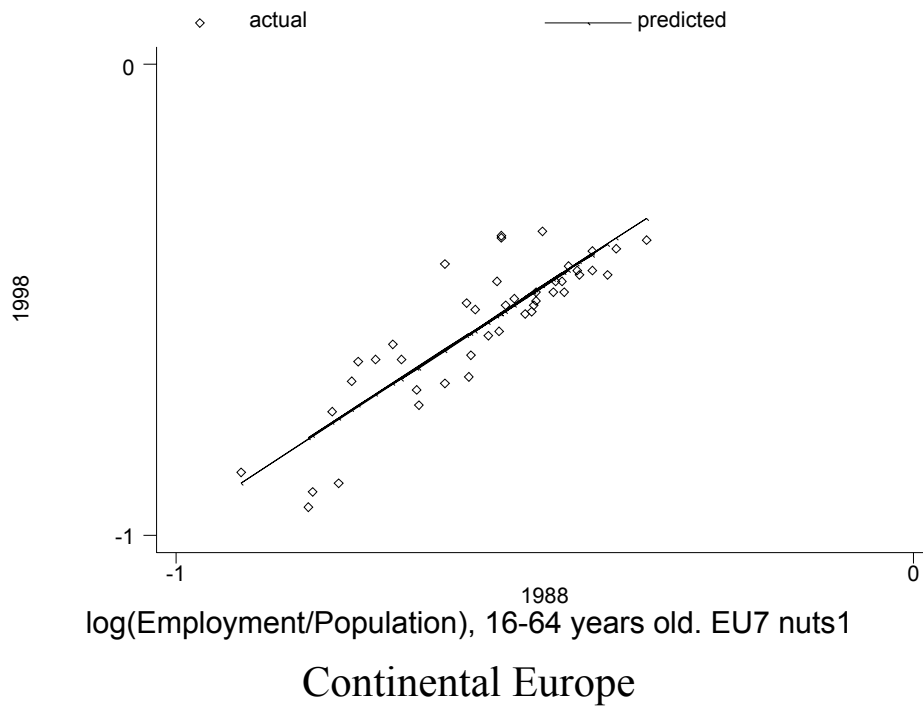
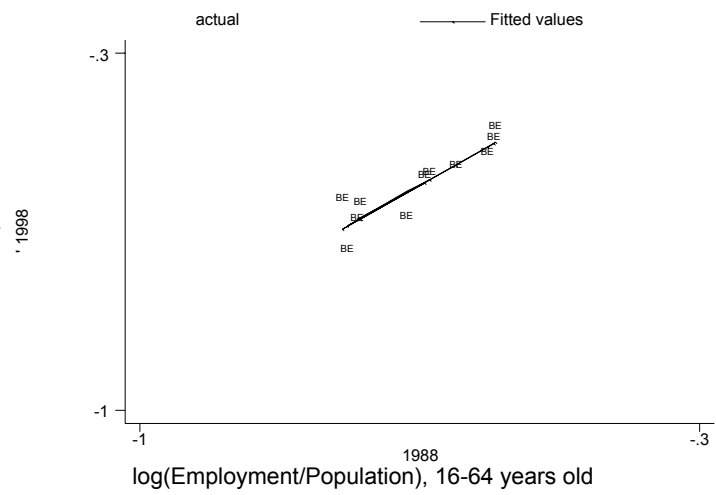
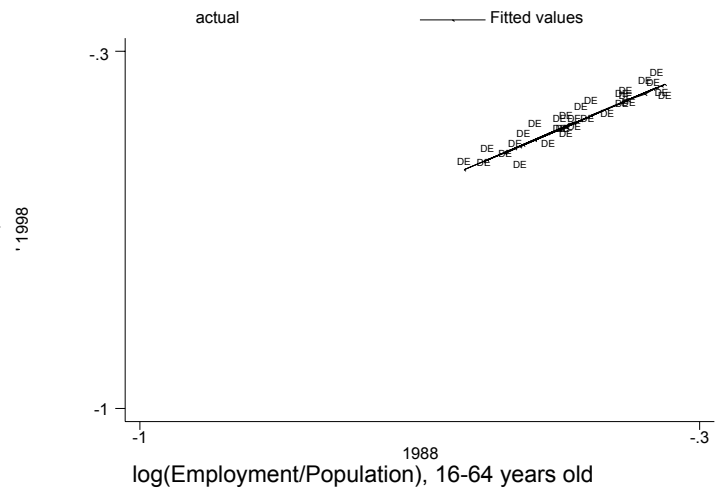


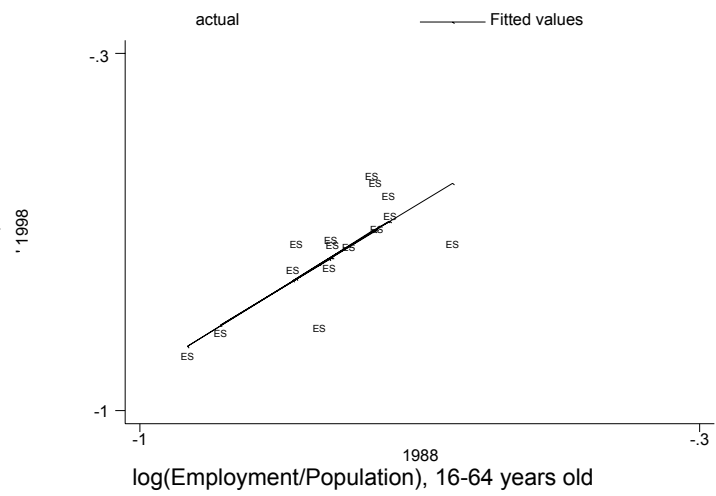
Figure 2. Log employment rates (employment over population), 1988 and 1998. EU7 and US.



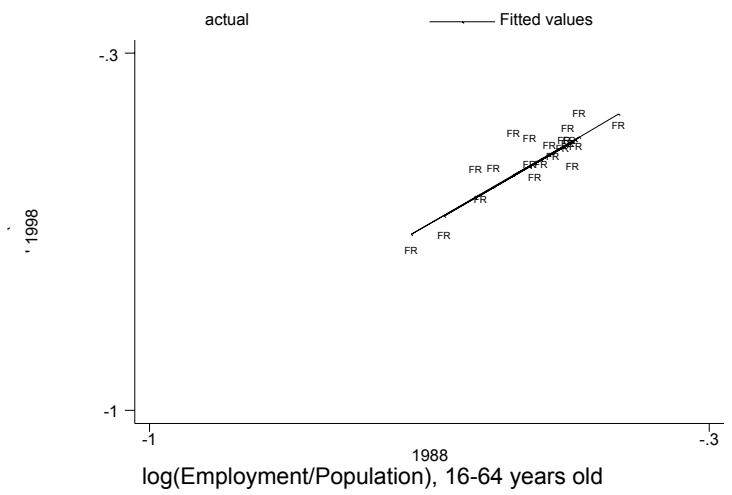
Belgium



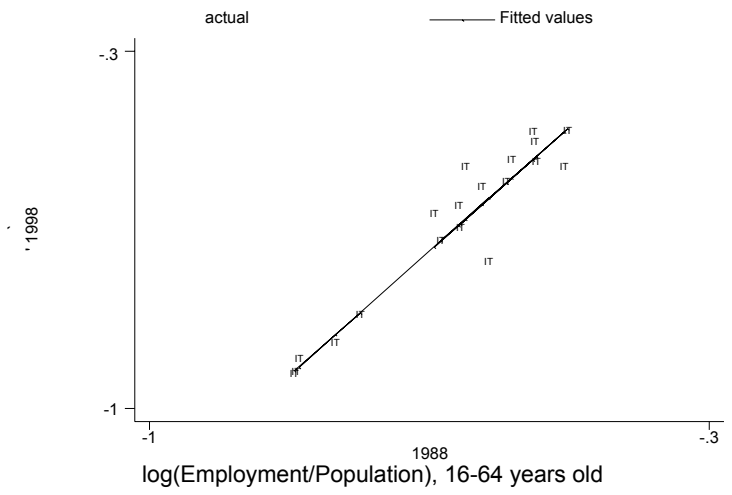
Germany



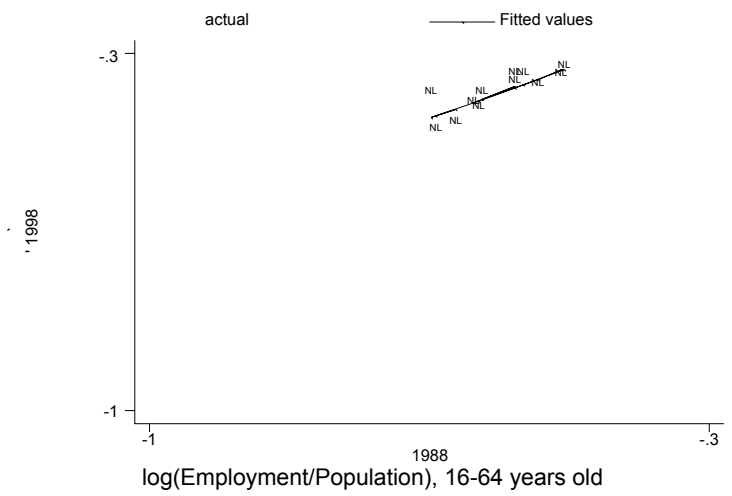
Spain



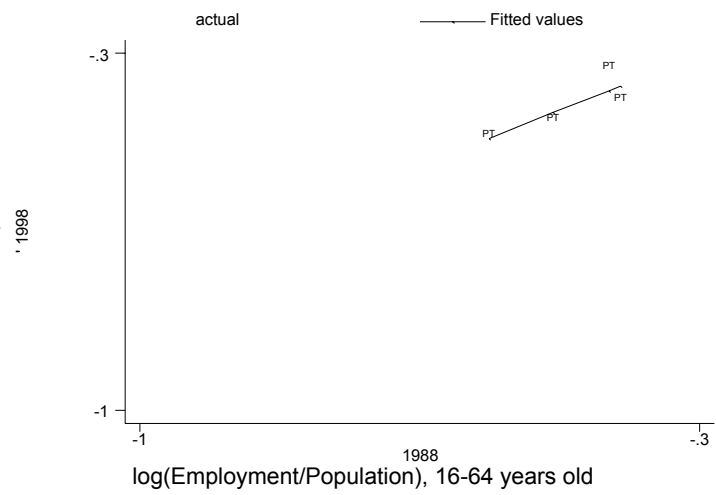
France



Italy



Holland



Portugal

Table 1. Regions in the analysis

Country	# regions		Mean population (millions)		CV of population	
	nuts2	nuts1	nuts2	nuts1	nuts2	nuts1
BE	11	3	0.7	2.5	0.5	0.7
DE	30	10	1.6	4.7	0.6	0.9
ES	15	6	1.8	4.5	0.8	0.4
FR	21	8	1.9	5	0.8	0.3
IT	19	10	2.2	4.2	0.8	0.3
NL	12	4	0.9	2.8	0.8	0.6
PT	4	2	1.8	3.5	0.5	1.1
EU-7	112	43	1.6	4.2	0.8	0.6
USA		49		3.5		1.1

Table 2. Sample sizes

	Mean	CV	min	1st dec.	median
EU-7, N2	7,647	0.74	307	2,242	5,872
EU-7, N1	19,903	0.63	2,232	4,425	23,489
USA	2,078	0.88	764	960	1,287

Table 3. Standard deviation of log changes. 16-74 years old.

16-74	std dl			std dp		
	1 y	5 y	10 y	1 y	5 y	10 y
BE	0.02	0.03	0.06	0.01	0.02	0.04
DE	0.02	0.03	0.04	0.01	0.02	0.03
ES	0.02	0.05	0.1	0.01	0.03	0.05
FR	0.04	0.07	0.07	0.03	0.06	0.06
IT	0.02	0.05	0.08	0.01	0.02	0.04
NL	0.03	0.06	0.09	0.02	0.05	0.08
PT	0.03	0.06	0.09	0.02	0.03	0.03
EU7-N2	0.03	0.05	0.07	0.02	0.04	0.05
EU7-N1	0.02	0.03	0.05	0.01	0.02	0.03
USA	0.04	0.08	0.11	0.03	0.06	0.1

Table 4: Industrial concentration of employment. Average of the Herfindahl-Hirschman index of employment in 17 industries, by country, 1987 to 1998.

	mean	std	cv
BE	1,552	250	0.16
DE	1,232	140	0.11
ES	1,303	205	0.16
FR	1,298	122	0.09
IT	1,420	197	0.14
NL	1,542	149	0.1
PT	1,633	327	0.2
EU-7 nuts2	1,367	217	0.16
EU-7 nuts1	1,361	176	0.13
USA	1,654	223	0.13

Table 5. Results of the first-stage regression of the IV model: t-statistics.

t-statistics	16-74			25-54		
	1 y	5 y	10 y	1 y	5 y	10 y
BE	-0.71	-0.74	-0.59	-1.15	-0.88	-0.99
DE	0.09	0.91	0.53	-0.20	1.03	0.53
ES	3.66	0.43	0.72	1.27	0.44	0.72
FR	0.05	-0.47	-0.09	0.05	-0.35	-0.46
IT	-0.06	-0.35	-0.01	-0.83	-0.40	0.12
NL	0.35	1.27	0.73	-0.02	1.00	0.61
PT	-0.54	2.61	3.11	-1.28	-0.60	1.44
EU7-N2	0.59	0.25	0.94	-0.42	-0.08	0.69
EU7-N1	-0.06	-0.29	0.39	-0.48	-0.48	0.08
USA	0.81	-0.18	-0.99	1.64	1.18	-0.35
USA 1977-98	0.55	1.79	0.87	1.89	2.37	0.97

Table 6. OLS and FE results, baseline and within-cohort specifications, 5-year horizon.

EU7 N1 versus US states, 1987 to 2000. 16-74 years old. By gender. Standard errors below the point estimates.

	OLS			OLS within cohort		
	within EU7 countries	within EU7	US	within EU7 countries	within EU7	US
All	0.42 <i>0.07</i>	0.23 <i>0.03</i>	0.71 <i>0.06</i>	0.42 <i>0.07</i>	0.30 <i>0.05</i>	0.65 <i>0.07</i>
Men	0.50 <i>0.08</i>	0.30 <i>0.04</i>	0.72 <i>0.04</i>	0.50 <i>0.08</i>	0.36 <i>0.07</i>	0.61 <i>0.05</i>
Women	0.20 <i>0.05</i>	0.13 <i>0.03</i>	0.56 <i>0.06</i>	0.20 <i>0.05</i>	0.14 <i>0.04</i>	0.67 <i>0.04</i>
	FE			FE within cohort		
	within EU7 countries	within EU7	US	within EU7 countries	within EU7	US
All	0.52 <i>0.08</i>	0.25 <i>0.04</i>	0.56 <i>0.05</i>	0.52 <i>0.07</i>	0.31 <i>0.05</i>	0.56 <i>0.06</i>
Men	0.49 <i>0.10</i>	0.29 <i>0.06</i>	0.61 <i>0.05</i>	0.49 <i>0.09</i>	0.34 <i>0.06</i>	0.60 <i>0.05</i>
Women	0.29 <i>0.07</i>	0.17 <i>0.05</i>	0.45 <i>0.05</i>	0.31 <i>0.07</i>	0.22 <i>0.05</i>	0.44 <i>0.06</i>

Table 7. OLS within-cohort results, 5-year horizon. EU7 N1 versus US states, 1987 to 2000. By age and gender. Standard errors below the point estimates.

	Men			Women			All		
	within EU7 countries	w/in EU7	US	within EU7 countries	w/in EU7	US	within EU7 ctries	w/in EU7	US
16-24	0.25 <i>0.06</i>	0.06 <i>0.03</i>	0.53 <i>0.04</i>	0.25 <i>0.04</i>	0.06 <i>0.03</i>	0.47 <i>0.04</i>	0.28 <i>0.05</i>	0.06 <i>0.03</i>	0.47 <i>0.05</i>
25-34	0.68 <i>0.07</i>	0.67 <i>0.06</i>	0.89 <i>0.03</i>	0.52 <i>0.05</i>	0.43 <i>0.05</i>	0.90 <i>0.02</i>	0.66 <i>0.06</i>	0.60 <i>0.06</i>	0.89 <i>0.03</i>
35-44	0.86 <i>0.03</i>	0.84 <i>0.02</i>	0.87 <i>0.03</i>	0.40 <i>0.05</i>	0.46 <i>0.03</i>	0.85 <i>0.03</i>	0.70 <i>0.05</i>	0.71 <i>0.02</i>	0.82 <i>0.02</i>
45-54	0.87 <i>0.03</i>	0.61 <i>0.07</i>	0.84 <i>0.03</i>	0.37 <i>0.06</i>	0.34 <i>0.05</i>	0.83 <i>0.03</i>	0.77 <i>0.05</i>	0.48 <i>0.07</i>	0.79 <i>0.02</i>
55-64	0.37 <i>0.05</i>	0.07 <i>0.03</i>	0.58 <i>0.03</i>	0.14 <i>0.03</i>	0.05 <i>0.02</i>	0.63 <i>0.03</i>	0.33 <i>0.05</i>	0.06 <i>0.03</i>	0.57 <i>0.04</i>
65-74	0.03 <i>0.02</i>	0.03 <i>0.01</i>	0.17 <i>0.03</i>	0.00 <i>0.01</i>	0.00 <i>0.01</i>	0.17 <i>0.03</i>	0.03 <i>0.02</i>	0.02 <i>0.01</i>	0.18 <i>0.03</i>
16-74	0.50 <i>0.08</i>	0.36 <i>0.05</i>	0.61 <i>0.05</i>	0.20 <i>0.05</i>	0.17 <i>0.04</i>	0.67 <i>0.04</i>	0.42 <i>0.07</i>	0.30 <i>0.05</i>	0.65 <i>0.07</i>

Table 8. OLS within-cohort results, 5-year horizon. EU7 N2 by country and age. Standard errors below the point estimates.

	Belgium	Germany	Spain	France	Italy	Netherlands	Portugal	EU7 all
16-24	0.06 <i>0.05</i>	0.45 <i>0.05</i>	0.13 <i>0.07</i>	0.42 <i>0.09</i>	0.21 <i>0.03</i>	0.36 <i>0.08</i>	0.32 <i>0.05</i>	0.27 <i>0.03</i>
25-34	0.63 <i>0.06</i>	0.77 <i>0.04</i>	0.69 <i>0.08</i>	0.92 <i>0.04</i>	0.58 <i>0.05</i>	0.91 <i>0.15</i>	0.80 <i>0.04</i>	0.79 <i>0.03</i>
35-44	0.59 <i>0.06</i>	0.81 <i>0.03</i>	0.56 <i>0.06</i>	0.90 <i>0.05</i>	0.83 <i>0.04</i>	0.68 <i>0.04</i>	0.74 <i>0.07</i>	0.78 <i>0.02</i>
45-54	0.43 <i>0.05</i>	0.76 <i>0.04</i>	0.58 <i>0.09</i>	0.87 <i>0.03</i>	0.46 <i>0.08</i>	0.43 <i>0.05</i>	0.52 <i>0.04</i>	0.64 <i>0.03</i>
55-64	0.07 <i>0.04</i>	0.31 <i>0.05</i>	0.22 <i>0.05</i>	0.32 <i>0.04</i>	0.22 <i>0.04</i>	0.11 <i>0.03</i>	0.28 <i>0.13</i>	0.23 <i>0.02</i>
65-74	0.01 <i>0.00</i>	0.02 <i>0.02</i>	0.04 <i>0.02</i>	0.02 <i>0.02</i>	0.03 <i>0.02</i>	0.00 <i>0.01</i>	-0.02 <i>0.04</i>	0.01 <i>0.01</i>
16-74	0.21 <i>0.07</i>	0.31 <i>0.04</i>	0.22 <i>0.04</i>	0.80 <i>0.04</i>	0.41 <i>0.06</i>	0.63 <i>0.12</i>	0.31 <i>0.12</i>	0.52 <i>0.05</i>