Online appendix

"Market Externalities of Large Unemployment Insurance Extension Programs" by Lalive, Landais & Zweimuller

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A Externalities in search and matching models and their identification

The probability that an individual finds a job in a given time period t depends on how hard that individual searches for a job and/or on how selective he is in his acceptance decisions. It also depends on the aggregate labor market conditions that determine how easy it is to locate jobs or to be matched to a potential employer for each unit of search effort. These two forces are usually represented in equilibrium search and matching models by using the stylized decomposition: $h_{it} = e_{it} \cdot f(\theta_t)$. h is the hazard rate out of unemployment (the probability to find a job in period t for individual i). e_{it} captures the search effort / selectiveness component. θ_t is the ratio of job vacancies to total search effort, and represents the tightness of the labor market. $f(\theta_t)$ therefore captures the effect of labor market conditions on the job finding probability per unit of effort. If there are no job vacancies created by employers, then $f(\theta_t) = 0$ and no amount of search effort by an unemployed worker would yield a positive probability of obtaining a job.

Changes in unemployment benefit policies affect the search intensity /selectiveness of unemployed workers. We call this effect the *micro effect* of UI. It can be identified by comparing two individuals with different levels of UI generosity in the same labor market. Changes in unemployment benefit policies also affect the aggregate job finding rate per unit of search effort through equilibrium effects. We call this second effect *market externalities.* It stems from equilibrium adjustments in labor market tightness θ_t in response to a change in UI generosity. The first aim of this appendix is to provide a simple theoretical framework explaining the mechanisms shaping the sign and magnitude of these market externalities. The second aim is to explain how to identify these market externalities empirically.

We start by presenting a one group equilibrium to explain the forces shaping equilibrium adjustments in labor market tightness in response to variations in UI. Then we extend the model to a two-group equilibrium in order to explain how to identify market externalities empirically and connect more closely the framework to the policy experiment that we analyze in the paper. In particular, we detail how to choose groups of workers to identify market externalities. We also explain how the sign and magnitude of market externalities depend on the structure of the labor market treated by the change in UI generosity and its connection to other labor markets.

The representation of the labor market that we use was developed by Michaillat [2012]. It is also strongly related to Landais, Michaillat and Saez [2010], where search effort is endogeneized and unemployment insurance is introduced in the model of Michaillat [2012].

Readers are referred to these two papers for further details on the set-up and equilibrium analysis.

A.1 One group equilibrium

The labor market is characterized by the presence of matching frictions. We normalize the size of labor force to unity. We present a simplified, static equilibrium analysis of search and matching models and characterize the comparative static for steady state equilibria. To keep things simple, we assume throughout that all workers within a group get the same wage. We start by looking at a one group equilibrium, as in Landais, Michaillat and Saez [2010], where all workers are eligible to the same unemployment benefits B, and explain the two main mechanisms that shape the equilibrium response in labor market tightness to a variation in unemployment benefits: the **rat race effect** (or labor demand effect) and the **wage effect**.

Unemployed workers face v vacancies opened by firms, and the total number of matches realized is given by an aggregate matching function $m(\overline{e \cdot u}, v) = \omega_m \cdot (\overline{e \cdot u})^{\eta} \cdot v^{1-\eta}$. Labor market tightness $\theta = \frac{v}{e \cdot u}$ is defined as the ratio of vacancies to the aggregate search effort in the labor market.

The individual job-finding probability is $h = e \cdot f(\theta) = e \cdot m(1, \theta)$, where $e = e(B, \theta)$ is the optimal search effort of individuals given benefits and labor market tightness. Effort is a decreasing function of unemployment benefits $\partial e / \partial B < 0$. To further simplify the presentation, we assume that $\frac{\partial e}{\partial \theta} = 0$. The assumption that the elasticity of job search effort with respect to the job-finding rate is close to zero seems reasonable empirically. As emphasized by Shimer [2004] labor market participation and other measures of search intensity are, if anything, slightly countercyclical even after controlling for changing characteristics of unemployed workers over the business cycle. The job-finding probability is an increasing function of θ ($f'(\theta) > 0$). From the definition of the matching function we can also define the vacancy-filling probability for each vacancy opened by the firm $q(\theta) = m(1/\theta, 1)$ which is a decreasing function of labor market tightness $\frac{\partial q(\theta)}{\partial \theta} < 0$.

We denote by n^s the probability that a worker is employed (and by $u = 1 - n^s$ the corresponding unemployment probability). Using the steady state equality of flows in and out of unemployment, we have that

$$n^s = \frac{ef(\theta)}{\lambda + ef(\theta)} \tag{6}$$

where λ is the exogenous separation rate. Following Michaillat [2012], we interpret $n^s = n^s(\theta, e(B))$ as a labor supply that we can represent as an increasing function of θ in a $\{n, \theta\}$ diagram.

A representative firm maximizes profit $\pi = \phi(n) - n \cdot w - \frac{r}{q(\theta)} \cdot \psi \cdot n$ where $\phi(.)$ is total output, n is employment and r is the recruiting cost of opening a vacancy. Firms take labor market tightness as given, and for them it is equivalent to choose employment level or the number of vacancies, given that v vacancies automatically translate into $v \cdot q(\theta)$ job creations. The first-order condition of the firm with respect to employment level n is:

$$\phi'(n) = w + \frac{r\psi}{q(\theta)} \tag{7}$$

Equation (7) implicitly defines a labor demand function $n^d(\theta, w)$ whose properties depend in particular on the assumptions made on $\phi(.)$ and on the wage setting process defining w. These properties are important to determine the sign and magnitude of externalities, as explained below. In particular, note that when technology exhibits diminishing returns to labor, with $\phi'(n) > 0$ and $\phi''(n) < 0$, we have by implicit differentiation of equation (7): $\frac{\partial n^d}{\partial \theta} < 0$. So in this case, labor demand will be a downward sloping function of θ as in Michaillat [2012]. The intuition for this negative relationship between labor demand and labor market tightness is the following: as labor market tightness goes up, the cost of opening vacancies goes up, as it takes longer to fill vacancies. Firms will post fewer vacancies, bringing their level of employment down, which will increase labor productivity and restore the profit from opening vacancies. It is also immediate to see that when technology is linear and in the absence of aggregate demand effects, equation (7) implicitly defines labor demand as a perfectly elastic function of labor market tightness.

Note also that, depending on the wage setting process, labor demand implicitly defined by equation (7) can also be a function of unemployment benefits. If wages are bargained over and workers have limited bargaining power, then wages will react to outside options of workers and thus to variations in unemployment benefits B: $w = w(B)$. As can be seen from equation (7), an increase in B leading to a increase in wages w will, everything else equal, decrease the net return from opening a vacancy and lead to a decrease in labor demand n^d.

We can now define a labor market equilibrium by the condition:

$$n^s(\theta, e(B)) = n^d(\theta, w(B)) \tag{8}$$

Market externalities:

Equilibrium condition (8) defines θ as an endogenous variable, affected by the level of benefits B of unemployed individuals in equilibrium. Because of this equilibrium adjustment of θ in response to a change in UI benefits, the effect of UI on the job finding probability $h = e \cdot f(\theta)$ can be decomposed into two parts, a micro-effect capturing the change in search effort keeping labor market tightness constant and a "market externality", capturing the effect of the change in labor market tightness:

$$\frac{dh}{dB} = \frac{d(e \cdot f(\theta))}{dB} = \underbrace{\frac{\partial e}{\partial B} \cdot f(\theta)}_{\text{Micro effect}} + \overbrace{e \cdot f'(\theta) \cdot \frac{\theta}{B} \cdot \varepsilon_B^\theta}^{\text{Market externality}} \tag{9}$$

where $\varepsilon_B^\theta = \frac{d\theta}{dB}\frac{B}{\theta}$ is the elasticity of labor market tightness with respect to the generosity of UI B. The second term on the right-hand side of equation (9) is the market externality, which is defined as the variation in the job finding rate caused by equilibrium adjustments in labor market tightness, keeping search effort constant.

The reason why we call this effect a "market externality" instead of a mere incidence effect is because, as shown in Landais, Michaillat and Saez [2010], these equilibrium adjustments in labor market tightness have first-order welfare effects when the Hosios condition is not met.

Equilibrium adjustment of θ in response to a change in UI benefits ($\frac{d\theta}{dB}$) is given by fully differentiating equation (8).

$$\frac{d\theta}{dB} = \frac{\frac{\partial n^d}{\partial w}\frac{\partial w}{\partial B} - \frac{\partial n^s}{\partial B}}{\frac{\partial n^s}{\partial \theta} - \frac{\partial n^d}{\partial \theta}} \tag{10}$$

Equation (10) can also be rewritten in terms of elasticities:

$$\varepsilon_B^\theta = \frac{\varepsilon_w^{n^d} \cdot \varepsilon_B^w - \varepsilon_B^{n^s}}{\varepsilon_\theta^{n^s} - \varepsilon_\theta^{n^d}} \tag{11}$$

where the notation ε_Y^X refers to the elasticity of X w.r.t Y. From the previous equation, we can now discuss the forces determining equilibrium adjustments of θ in response to a change in benefits B. We focus in particular on two opposing forces: the rat-race effect (or labor-demand effect), and the wage effect.

Rate race effect

The **rate race effect** is determined by the elasticity of labor-demand ($\varepsilon_\theta^{n^d}$). If labor demand is downward sloping ($\varepsilon_\theta^{n^d} < 0$) then the denominator in (11) is positive. Given that $\varepsilon_B^{n^s} < 0$, it follows that, *conditional on wages*, equilibrium labor market tightness will increase when UI benefits increase $\varepsilon_B^\theta\big|_w > 0$. The more inelastic labor demand is with respect to labor market tightness, the larger the rat race effect. If labor demand is fixed, then the rat race effect is at its maximum: firms will fully compensate a UI-induced decrease in search effort by opening more vacancies to keep the level of employment constant.

Intuitively, a downward sloping labor demand ($\varepsilon_\theta^{n^d} < 0$) captures the fact that the net profits from opening vacancies are a decreasing function of employment. When search effort decreases, it decreases labor supply, which increases the profits of opening vacancies for firms: vacancies increase, which increases labor market tightness, and the probability of finding a job per unit of effort increases for all workers. Landais, Michaillat and Saez [2010] discuss various search and matching models and show under which conditions such "rat race" effect is likely to arise. In particular, Landais, Michaillat and Saez [2010] show that technology can be an important factor. In the presence of diminishing returns to labor, as explained above, labor demand is a downward sloping function of tightness and the larger the diminishing returns to labor, the larger the labor demand effect on equilibrium tightness. When technology is close to linear in labor, labor demand will in general be close to perfectly elastic, and therefore ε_B^θ tends to zero. Note however that diminishing returns is a sufficient but not a necessary condition for the presence of a downward sloping labor demand. Landais, Michaillat and Saez [2010] show for instance that an "aggregate demand model" with a quantity equation for money and nominal wage rigidities will feature a downward sloping labor demand even with linear technology.

The rat race effect will be the only driver of labor market tightness adjustments to the policy when wages do not react to the policy ($\varepsilon_B^w = 0$). Studies estimating spillover effects of active labor market programs such as training programs therefore tend to capture a pure rat race effect as these training programs do not generally affect bargained wages.

Wage effect

If the wage setting process is such that wages depend on outside options of workers, then an increase in UI benefits will increase wages $\varepsilon_B^w > 0$, which will in turn affect the vacancy posting behavior of firms. Higher wages will decrease the return from opening vacancies for firms leading to a decrease in labor demand ($\varepsilon_w^{n^d} < 0$) and in turn, a decrease in labor market tightness. We call this effect the **wage effect** (or job creation effect). The wage effect is going in the opposite direction to the rate race effect. The overall effect of a change in UI benefits on equilibrium labor market tightness will therefore depend on the relative magnitude of these two effects. If the wage effect is large enough, the numerator in (11) may become negative ($\varepsilon_w^{n^d} \cdot \varepsilon_B^w < \varepsilon_B^{n^s} < 0$) and equilibrium labor market tightness will decrease in response to an increase in benefits. If the wage effect is small in magnitude, then the rat race effect will dominate: the numerator in (11) will be positive ($\varepsilon_B^{n^s} < \varepsilon_w^{n^d} \cdot \varepsilon_B^w < 0$) and labor market tightness will increase in response to an increase in UI benefits.

A.2 Identification of market externalities in a two group equilibrium

Identification of the micro effect in equation (9) is relatively straightforward. The ideal experiment is to offer higher unemployment benefits to a randomly selected and small subset of individuals within a labor market and compare unemployment durations between these treated individuals and the other jobseekers. In practice, the micro effect is estimated by comparing individuals with different benefits in the same labor market at a given time, while controlling for individual characteristics.

Identification of market externalities in equation (9) is more complicated, in large part due to the lack of good measures of labor market tightness.[22] We show here how one can use labor market outcomes of different group of workers *in the same labor market* to identify market externalities of UI benefits. We introduce two groups of workers a and b and assume there are p workers of group a who are eligible to unemployment benefits B_a and $1-p$ workers workers of group b who are eligible to unemployment benefit B_b. The group shares p and $1-p$ are exogenously given. We start from a situation where $B_a = B_b$ and look at the effect on the steady state equilibrium of an increase in benefits for workers of group a: $dB_a > 0$.

We denote by n_a^s (resp. n_b^s) the probability that a worker of group a (resp. b) is employed (and by $u_a = 1 - n_a^s$ the corresponding unemployment probability) There are $u = u_a + u_b$ unemployed workers. When unemployed, each individual worker exerts some effort $e_i = e(B_i),\ i = (a, b)$, where e is a decreasing function of benefits received B.

Workers of both groups are assumed to be in the same labor market and **we define a labor market as the place where workers compete for the same job vacancies.** A labor market is therefore characterized by a unique labor market tightness in equilibrium, and matching is random between identical job vacancies posted by firms and all the

[22]A notable exception is Marinescu [2014] who uses very detailed information on vacancies and job applications from `CareerBuilder.com`, the largest American online job board, to compute the effects of UI extensions on aggregate search effort ($e \cdot u$) measured by job applications and on vacancy posting (v) at the state level. She finds a negative effect of UI extensions on job applications but no effect of UI extensions on vacancy posting. Since $\theta = v/(e \cdot u)$, these results imply that more generous UI benefits increase labor market tightness.

(potentially different) workers who apply for these identical vacancies. From the firms' point of view, this means that when opening vacancies, firms take as given labor supply of group a and group b, and opening v vacancies translates into $p \cdot n_a/q(\theta)$ jobs of workers from group a and $(1-p)n_b/q(\theta)$ jobs of workers from group b. Wages are determined at the individual level, once the match is done and depends on the outside option of each worker. We therefore allow for two different wage levels w_a and w_b for both groups of workers in equilibrium.

This definition of labor market is the most natural definition from a search theoretic standpoint. As labor market tightness (and not the wage rate) is the "price" variable equating labor supply and labor demand in labor market characterized by search frictions, our definition of a labor market strictly follows the *law of one price*. From an empirical perspective, this definition captures the fact that a labor market is the place where workers compete for the same jobs.

As in the one group case before, firms choose the level of employment that maximizes profits, which is equivalent to choosing the number of vacancies to open in order to maximize profits (taking labor market tightness as given). There is only one labor market tightness for the two groups of workers, so opening v vacancies translates into $p \cdot n_a/q(\theta)$ jobs of workers from group a and $(1-p) \cdot n_b/q(\theta)$ jobs of workers from group b. We can therefore write firms profits as:

$$\pi = \phi\Big(p \cdot n_a, (1-p) \cdot n_b\Big) - p \cdot n_a \cdot w_a - (1-p) \cdot n_b \cdot w_b - \frac{r}{q(\theta)} \cdot \psi \cdot (p \cdot n_a + (1-p) \cdot n_b) \quad (12)$$

$$p\left\{\frac{\partial \phi}{\partial n_a} - w_a - \frac{r\psi}{q(\theta)}\right\} + (1-p)\left\{\frac{\partial \phi}{\partial n_b} - w_b - \frac{r\psi}{q(\theta)}\right\} = 0 \quad (13)$$

Similarly to equation (7), equation (13) implicitly defines the optimal employment level demanded by firms as a function of labor market tightness θ. Importantly, equation (13) defines the optimal employment level $n^d = pn_a^d + (1-p)n_b^d$ as a weighted sum of the optimal employment level of workers of group a and group b. In other words, the labor demand curve in the two-group case is the weighted sum of the demand curve for workers of group a and the demand curve for workers of group b.

Equilibrium in the labor market is now defined by the following condition:

$$pn_a^d(\theta, w_a) + (1-p)n_b^d(\theta, w_b) = pn_a^s(\theta, B_a) + (1-p)n_b^s(\theta, B_b) \quad (14)$$

Equilibrium condition (14) defines θ as an endogenous variable, *affected by the level of* *benefits B_a and B_b of both groups of unemployed individuals* in equilibrium. Let us start from a situation where $B_a = B_b = B$ and workers of both groups are identical so that $e_a = e_b$, and investigate the effect of a small change $dB_a > 0$ on hazard rates of workers of group a and group b. Because of the equilibrium adjustment of θ in response to a change in UI benefits B_a, the effect of UI on the job finding probability of workers of group a, $e_a \cdot f(\theta)$ can again be decomposed into two parts, a micro-effect capturing the change in search effort of workers of group a keeping labor market tightness constant and a “market externality”, capturing the effect of the change in labor market tightness:

$$\frac{dh_a}{dB_a} = \frac{d(e_a \cdot f(\theta))}{dB_a} = \underbrace{\frac{\partial e_a}{\partial B_a} \cdot f(\theta)}_{\text{Micro effect}} + \overbrace{e_a \cdot f'(\theta) \cdot \frac{\theta}{B} \cdot \varepsilon^{\theta}_{B_a}}^{\text{Market externality}} \tag{15}$$

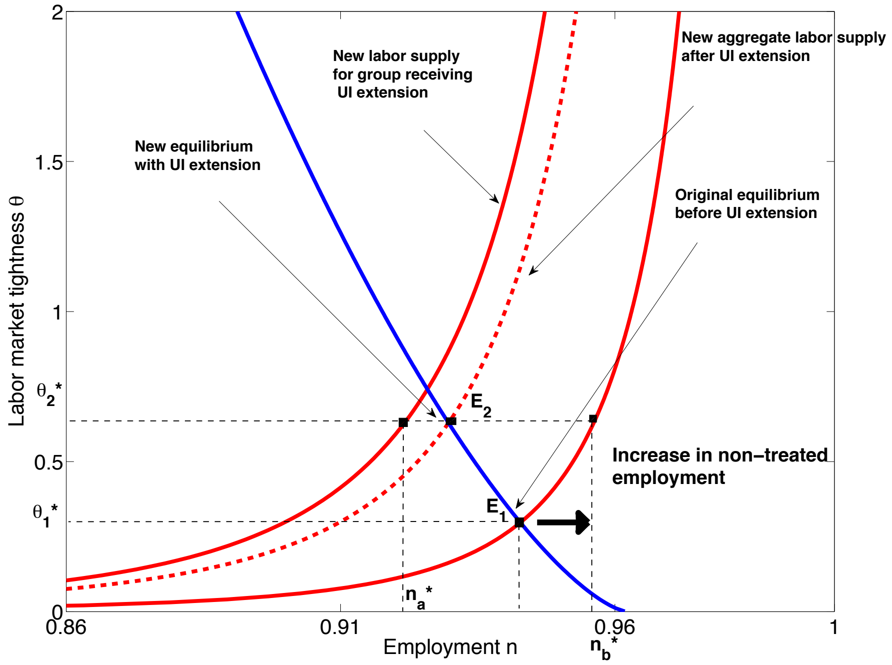
But workers of group b also experience a change in their job finding probability, even if their unemployment benefits are unaffected, due to the equilibrium adjustment of θ in response to a change in UI benefits B_a:

$$\frac{dh_b}{dB_a} = \frac{d(e_b \cdot f(\theta))}{dB_a} = e_b \cdot f'(\theta) \cdot \frac{\theta}{B} \cdot \varepsilon^{\theta}_{B_a} \tag{16}$$

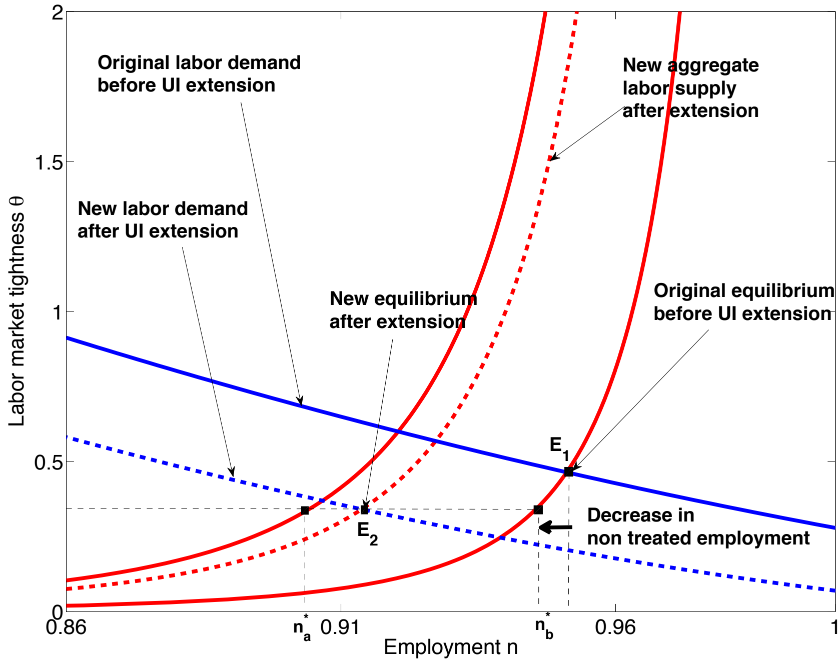
Equation (16) shows that the effect of a change in benefits B_a for a treated group of workers on the job finding probability of non-treated workers of group b identifies the market externality. This result motivates our empirical strategy. By looking at how the job finding probability of non-treated workers varies in response to a change in unemployment benefits of similar workers *in the same labor market*, one can identify equilibrium adjustments in labor market tightness.

Figure 5: MARKET EXTERNALITIES OF UI EXTENSIONS IN AN EQUILIBRIUM SEARCH-AND-MATCHING MODEL WITH TWO GROUPS OF WORKERS:

A. Rigid wages & diminishing returns



B. Flexible wages & close to linear technology



Notes: Both panels describe the effect on labor market equilibrium of a change in benefits for one group of workers (group a), when firms cannot discriminate vacancies between the two groups of workers. In both panel, we start from equilibrium E_1, where all workers get the same UI benefits. A group of workers then receives a higher level of benefits, which shifts their labor supply to the left. The new aggregate labor supply is a weighted average of labor supply of both groups, depicted by the dashed red line. In case of rigid wages (panel A) as in the model of Michaillat [2012], labor demand is not affected, and, if returns to labor are decreasing, the new equilibrium E_2 is characterized by higher labor market tightness θ_2^* and positive market externalities on workers of group b. When wages adjust to the change in benefits (panel B), firms reduce their vacancy openings, and if returns to labor are almost constant, it can lead to a decline in θ and negative externalities on workers of group b.

We now explain how market externalities in the two group experiment relate to market externalities in the one group experiment where all workers of the labor market are treated. Equilibrium adjustments in tightness in the two group experiment is given by implicitly differentiating equilibrium condition (14):

$$\frac{d\theta}{dB_a} = p\frac{\frac{\partial n_a^d}{\partial w_a}\frac{\partial w_a}{\partial B_a} - \frac{\partial n_a^s}{\partial B_a}}{\frac{\partial n^s}{\partial \theta} - \frac{\partial n^d}{\partial \theta}} \tag{17}$$

When we start from $n_a = n_b$, we can rewrite equation (17) in terms of elasticities:

$$\begin{aligned} \varepsilon_{B_a}^{\theta} &= p \cdot \frac{\varepsilon_w^{n_a^d} \cdot \varepsilon_{B_a}^{w_a} - \varepsilon_{B_a}^{n_a^s}}{\varepsilon_\theta^{n^s} - \varepsilon_\theta^{n^d}} \\ &= p \cdot \varepsilon_B^{\theta} \end{aligned} \tag{18}$$

A few points are worth noting about equation (18). First, equilibrium adjustments in labor market tightness in the two group experiment increase with the size of the treated group. The larger p, the larger the market externalities. Second, as p tends to 1, $\varepsilon_{B_a}^{\theta}$ tends to ε_B^{θ}, so that market externalities identified on group b will tend to capturing the effect of treating the entire labor market. Third, market externalities identified through the change in the job finding probability of workers of group b still capture the wage effect even if wages are bargained at the individual level. The intuition is that within a labor market, there is random matching. The expected profit of opening vacancies is the weighted average of the profits of opening vacancies for each group of workers. Therefore the increase in bargained wages of workers of group a will reduce the expected profit of opening vacancies and will then affect overall vacancy posting in the market. Finally, the above have assumed that the two types of workers were perfectly equivalent and initially earn the same wage. In that case, the firm's profit-maximizing employment level does not depend on the mix of workers. If there is imperfect substitution and/or the two types of workers get initially different wages, employment depends on the mix of workers of both types in equilibrium. An extra term kicks in in formula 17. Graphically, the labor demand curve shifts as result of an increase in B_a.[23]

In figure 5, we offer a graphical representation of market externalities of UI extensions in the two group model, and we illustrate how different assumptions about the production

[23]Note that the direction of the labor-demand shift is a priori unclear. An increase in B_a may change the employment mix such that opening up new vacancies may in fact be profitable for the firm (shifting labor demand to the right). To see this, consider the simple case when workers are perfect substitutes but initially group a gets a higher wage than group b. When an increase in B_a strongly decreases labor supply of group a but does not affect wages of group a, the expected wages costs of a randomly matched worker will decrease, thus firms will increase employment. However, these effects are second order as labor demand is affected only indirectly through the impact of B_a on n_a^s.

function and the wage setting process affect the sign and magnitude of externalities. Both panels describe the effect on labor market equilibrium of a change in benefits for one group of workers (group a), when firms cannot discriminate vacancies between the two groups of workers. In both panel, we start from equilibrium E_1, where all workers get the same UI benefits. Workers of group a then receive a higher level of benefits, which shifts their labor supply to the left. The new aggregate labor supply is a weighted average of labor supply of both groups, depicted by the dashed red line. In case of rigid wages (panel A) as in the model of Michaillat [2012], labor demand is not affected, and, if returns to labor are decreasing, the new equilibrium E_2 is characterized by higher labor market tightness θ_2^* and positive market externalities on workers of group b. When wages adjust to the change in benefits (panel B), firms reduce their vacancy openings, and if returns to labor are almost constant, it can lead to a decline in θ and negative externalities on workers of group b.

Implications for the wedge between micro and macro effects of UI

We are interested in recovering from the two group experiment, the wedge between micro and macro effects of treating the whole labor market. More specifically, starting from equation (9), we are interested in the wedge $W = 1 - e^M/e^m$ where $e^M = \frac{dh}{dB}$ is the total effect on job finding rate of treating the whole market by an increase dB in UI benefits ("macro effect") and e^m is the "micro effect" from equation (9) (*i.e.* the effect of an increase dB in UI benefits on individual job finding rate).

From equation (9) we know that $W = \frac{e^X}{e^m}$, where $e^X = e \cdot f'(\theta) \cdot \frac{\theta}{B} \cdot \varepsilon_B^\theta$ is the market externality of treating the whole labor market. From equations (16) and (18), we know that in the two group experiments, starting from a situation where both groups have the same benefits and search effort

$$\frac{dh_b}{dB_a} = p \cdot e^X \tag{19}$$

In other words, the effect of changing benefits for workers of group a on the job finding rates of workers of group b identifies p times the externality of treating all workers, where p is the fraction of workers of group a in the labor market.

In the two group experiment, again starting from a situation where both groups have the same benefits and search effort, we also know that the micro effect e^m will be the same than when treating the whole market. This means that the micro effect $\frac{\partial e}{\partial B} \cdot f(\theta)$ from equation (9) is equal to the micro effect from equation (15): $\frac{\partial e_a}{\partial B_a} \cdot f(\theta)$. And from equations (15) and (16), we know that the micro effect will be identified in the two group experiment as

$$e^m = \frac{dh_a}{dB_a} - \frac{dh_b}{dB_a} \tag{20}$$

In other words, the micro effect is identified by the effect of the change in UI benefits on the job finding rate of workers of group a minus the effect on the job finding rate of workers of group b. It follows from equations (19) and (20) that we can identify the wedge W of treating the whole market in the two group experiment:

$$W = \frac{1}{p} \cdot \frac{\frac{dh_b}{dB_a}}{\frac{dh_a}{dB_a} - \frac{dh_b}{dB_a}} \tag{21}$$

Using the fact that we start from a situation where $B_a = B_b$ and $h_a = h_b$, and under the approximation that hazard rates are somewhat constant over a spell so that the duration of unemployment $D \approx 1/h$ we can rewrite equation 21 in terms of responses of unemployment duration:

$$W = \frac{1}{p} \cdot \frac{\frac{dD_b}{dB_a}}{\frac{dD_a}{dB_a} - \frac{dD_b}{dB_a}} \tag{22}$$

A.3 Market externalities across labor markets

In most quasi-experiments involving variations in the generosity of unemployment benefits, treatment is restricted to some but not all labor markets. The REBP program is no exception. The program extended the duration of UI benefits for individuals above age 50 in specific regions meeting specific criteria. A firms can adjust to the policy not only by changing the number of vacancy it opens in the treated labor market, but also by changing the number of vacancies it opens in other labor markets where there exists close substitutes to the treated population. In other words, there exist "non-treated" labor markets that, due to their (geographic or technological) proximity to the treated labor market, will also be affected by the policy in equilibrium. We show here how the existence of other labor markets will affect market externalities. First, we show how (and discuss why) equilibrium labor market conditions in other markets will be affected. Then, we discuss how the existence of other markets affect the magnitude of market externalities in the treated market.

How are other labor markets affected by a change in UI policy in one labor market? We focus again on a two group model, but now group a and group b are assumed to be in two different labor markets. This means that firms can perfectly discriminate between the two groups of workers when they open vacancies. In practice, there will be vacancies v_a to which only workers of group a will apply and vacancies v_b to which only workers of group b will apply. The ability of firms to direct their search by tailoring the characteristics of vacancies to each group of workers means that there will be in effect two labor markets with two labor market tightness in equilibrium.

Firms' profits are now equal to:

$$\pi = \phi\Big(p \cdot n_a, (1-p)\cdot n_b\Big) - p \cdot n_a \cdot w_a - (1-p)\cdot n_b \cdot w_b - r \cdot \psi \cdot \left\{ \frac{p \cdot n_a}{q(\theta_a)} + \frac{(1-p)\cdot n_b}{q(\theta_b)} \right\} \quad (23)$$

For the firm, the optimal choice of vacancies to open for group a and group b is equivalent to the optimal choice of n_a and n_b, as v_a vacancies translate into $n_a/q(\theta_a)$ jobs for workers of group a (and v_b vacancies translate into $n_b/q(\theta_b)$ jobs for workers of group b). The optimal labor demand of firms for workers of group a, n_a^d, and for workers of group b, n_b^d, is then implictely defined by the two following first-order conditions:

$$\frac{\partial \phi}{\partial n_a} = \left\{ w_a + \frac{r\psi}{q(\theta_a)} \right\} \quad (24)$$

$$\frac{\partial \phi}{\partial n_b} = \left\{ w_b + \frac{r\psi}{q(\theta_b)} \right\} \quad (25)$$

When technology is such that the marginal product of labor for group a (resp. group b) depends on the level of employment of workers of group b (resp. group a), n_a^d (resp. n_b^d) will be a function of n_b (resp. of n_a). Equilibrium conditions in the two labor markets can therefore be written as: $n_a^d(w_a, \theta_a, n_b) = n_a^s(\theta_a, B_a)$ and $n_b^d(w_b, \theta_b, n_a) = n_b^s(\theta_b, B_b)$. In particular, if n_a and n_b are substitutes and there are diminishing returns to both n_a and n_b, then $\frac{\partial^2 \phi}{\partial n_b \partial n_a}$ will be negative. This means that, when the employment of workers of group a decreases (say, as a result of the REBP), the marginal product of workers of group b, $\frac{\partial \phi}{\partial n_b}$, will increase. Firms will respond by posting more vacancies v_b. This will in turn increase labor market tightness θ_b, bringing up the cost of opening vacancies in the market for group b workers, and decrease the productivity of group b workers, until condition (25) is met again. A decrease in the employment of workers of group a is therefore met by an increase in the employment of workers of group b, when workers are substitutes. The larger the elasticity of substitution σ between group a and group b workers, the larger this substitution effect.

A change in UI benefits B_a for workers of group a in one given market can therefore create market externalities on workers of group b, who are in a separate labor market. These market externalities are given by:

$$\frac{dh_b}{dB_a} = \frac{d(e_b f(\theta_b))}{dB_a} = e_b f'(\theta_b) \frac{d\theta_b}{dB_a} \quad (26)$$

where the equilibrium adjustment in tightness $\frac{d\theta_b}{dB_a}$ determines the size of market externality. To calculate $\frac{d\theta_b}{dB_a}$, we implicitly differentiate the system of equilibrium conditions for the two market "prices", θ_a and θ_b, with respect to B_a, using the fact that n_a^d and n_b^d are implicitly given by equations (24) and (25). Note that supply of and demand for type b workers does not directly depend on B_a but only indirectly through changes in θ_a and θ_b. In contrast, type a workers are also directly affected by changes in B_a: labor demand is affected through the wage effect and labor supply through the effect on search effort.

Implicitly differentiating this system yields:

$$\frac{\partial \theta_b}{\partial B_a} = \frac{p\phi_{ba}\left[-\frac{\partial n_a^s}{\partial \theta_a}\frac{\partial w_a}{\partial B_a} - \frac{\partial n_a^s}{\partial B_a}\frac{q'(\theta_a)}{q^2(\theta_a)}r\psi\right]}{\Delta} \tag{27}$$

where $\Delta = \left[\phi_{aa}p\frac{\partial n_a^s}{\partial \theta_a} + \frac{q'(\theta_a)}{q^2(\theta_a)}r\psi\right]\left[\phi_{bb}(1-p)\frac{\partial n_b^s}{\partial \theta_b} + \frac{q'(\theta_b)}{q^2(\theta_b)}r\psi\right] - \phi_{ab}^2(1-p)p\frac{\partial n_b^s}{\partial \theta_b}p\frac{\partial n_a^s}{\partial \theta_a} > 0$, since $\phi_{aa}\phi_{bb} - \phi_{ab}^2 > 0$.

A few points are important to note about equations (26) and (27). First, the existence of market externalities *across* labor markets is entirely driven by the substitution effect. This can be easily seen from the right-hand-side of equation (27), which is proportional to the cross-derivative of the production function. When $\phi_{ab} = 0$, the marginal product of type b is independent of type a employment, an increase in B_a leaves labor market tightness for market b unchanged, and group b is entirely unaffected by the increase in B_a.[24] In contrast, when $\phi_{ab} < 0$, so that the two types of workers are substitutes, a larger B_a increases θ_b. There are two reasons. First, a higher B_a may trigger an increase in w_a, so that type a workers will be more expensive. Second, a higher B_a lowers search effort of type a workers and vacancies become relatively easier to fill with type b workers than type a workers. Firms will shift their labor demand towards type b and equilibrium tightness in the market for workers of group b will go up. The higher the elasticity of substitution, the larger (in absolute value) is ϕ_{ab} and therefore the larger the market externality on the non-treated labor market.

In terms of empirical identification, the existence of market externalities *across* labor markets through substitution effects means that one needs to be very cautious when choosing the control labor markets for the analysis. The control labor markets must be chosen so as to provide a good counterfactual for what would have happened in the treated labor market in the absence of REBP. At the same time, they must not offer substitution opportunities from the treated labor market.

The second point worth noting is that market externalities on workers of group b, who are now in a separate labor market, are different from market externalities in the treated

[24]Note again that, with a linear technology, we have $\phi_{ab} = 0$, and we should see no spillover effects across labor markets in that case.

labor market (workers of group a), contrary to the case where matching was random and the two groups of workers were in the same labor market. This means that in practice, the effect of REBP on the job finding probability of non-treated workers who are not in the same labor market cannot directly identify the market externalities of interest in the treated labor market.

Equation (27) shows that when there are multiple markets, one of them being treated and others not being treated, there will be market externalities in non-treated markets but these externalities cannot directly identify market externalities in the treated market. What can we say then about market externalities in the treated market in this case? How does the existence of substitution opportunities across labor markets affect market externalities in the treated market?

Recall from equation (9) that market externalities within the treated market depend on the impact of the increase in B_a on tightness in the treated market. This can be inferred from implicit differentiation θ_a with respect to B_a using the two above equilibrium equations. This yields:

$$\frac{\partial\theta_a}{\partial B} = p\frac{-\left[\phi_{aa}\frac{\partial n_a^s}{\partial B} - \frac{\partial w_a}{\partial B}\right]\left[\phi_{bb}(1-p)\frac{\partial n_b^s}{\partial\theta_b} + \frac{q'(\theta_b)}{q^2(\theta_b)}r\psi\right] + (1-p)\phi_{ba}^2\frac{\partial n_a^s}{\partial B}\frac{\partial n_b^s}{\partial\theta_b}}{\Delta} \tag{28}$$

It is straightforward to verify that equation (28) reduces to (10) when we set $p = 1$.[25] In the absence of any factors that could substitute for the treated workers, the results from the one-group equilibrium apply. In contrast, when there are many substitution possibilities and the share of the treated market in the aggregate economy is tiny (p goes to zero), the externality on the treated market gets negligible.[26] In other words, when the treated market gets small relative to the aggregate economy, variations in labor market tightness in the treated market in response to a change in UI benefits– and hence market externalities of UI benefits– become negligible.

The existence of substitution opportunities across labor markets therefore bears important consequences for the interpretation of quasi-experimental results on externalities using variations in unemployment benefits. When the experiment / policy variation is such that the treated population of workers represent a relatively small labor market and there exists non-treated labor markets that offer available substitutes for the treated workers, market externalities in the treated labor market will be relatively small. And

[25]To see this, notice that the first order condition $(\phi_a(n_a^d, n_b^d) - w_a(B) - r\psi/q(\theta_a) = 0$ imply the partial derivative $\partial n_a^d/\partial w_a = 1/\phi_{aa}$ and $\partial n_a^d/\partial\theta_a = -(q'(\theta_a)/q^2(\theta_a))\cdot(r\psi/\phi_{aa})$. Similarly, for group b.

[26]This assumes that type-a workers are not essential for production, $\phi_{aa}(0, n_b^d) > -\infty$. In that case, as p goes to zero, the numerator of equation (28) goes to zero, while the denominator stays positive.)

estimated equilibrium adjustments in labor market tightness in such a context should be interpreted as a clear lower bound on the equilibrium adjustments in labor market tightness that would occur if the whole population of workers were to be treated.

A.4 Endogenous layoffs

The separation rate λ as been assumed exogenous. But in practice λ might be endogenous to UI benefits ($\lambda = \lambda(B)$) and there is indeed evidence that the separation rate increased for eligible workers during the REBP period (Winter-Ebmer [1996]), implying that $\partial\lambda_a/\partial(B_a) > 0$. How will the response of the separation rate to UI benefits affect market externalities of UI? From the definition of labor supply given in equation 6, $n^s = \frac{ef(\theta)}{\lambda+ef(\theta)}$, which follows from the equality of flows in and out of unemployment in the steady-state, it appears clearly that an increase in the separation rate λ will shift labor supply downwards everything else equal. For a given search effort level, and for a given labor market tightness, an increase in the separation rate means that the stock of unemployed will be larger in the steady state and therefore the probability of finding a job (n^s) will be lower. An increase in the separation rate is equivalent to a downward shift in labor supply and its effect on labor supply is comparable to that of a decrease in search effort. If both search effort and the separation rate are responsive to UI benefits, the effect of a change in benefit of workers of group a on labor supply of group a is the sum of a search effort effect ($e'_a \cdot \lambda_a$) and of a separation rate effect ($e_a \cdot \lambda'_a$):

$$\frac{\partial n^s_a}{\partial B_a} = \frac{[e'_a \cdot \lambda_a - e_a \cdot \lambda'_a] f(\theta)}{(\lambda_a + e_a f(\theta))^2}$$

In the context of REBP, because the separation rate effect $e_a \cdot \lambda'_a > 0$ is significantly positive, the downward shift in labor supply of treated workers will be even stronger than if only search effort had reacted to the policy.

But an increase in the separation rate λ also increases recruiting costs of firms. As new jobs have a higher probability of being terminated, the net present value of a job decreases. This will create a downward shift of n^d that can easily be seen in equation (7) which implicitly determines labor demand of firms n^d as a decreasing function of the layoff rate: $\partial n^d/\partial\lambda \leq 0$. So the overall effect on labor market tightness of a change in benefits for workers of group a when layoffs are endogenous is:

$$\frac{d\theta}{dB_a} = p \frac{\frac{\partial n^d_a}{\partial w_a}\frac{\partial w_a}{\partial B_a} + \frac{\partial n^d_a}{\partial \lambda_a}\frac{\partial \lambda_a}{\partial B_a} - \frac{\partial n^s_a}{\partial B_a}}{\frac{\partial n^s}{\partial \theta} - \frac{\partial n^d}{\partial \theta}} \tag{29}$$

where $\frac{\partial n^d_a}{\partial \lambda_a}\frac{\partial \lambda_a}{\partial B_a}$ is the layoff rate effect on labor demand. The overall effect of endogenous layoffs on equilibrium adjustments in labor market tightness $\frac{d\theta}{dB_a}$ is therefore ambiguous, as can be seen by comparing equation (29) to equation (17). The presence of endogenous layoffs creates a negative layoff rate effect on labor demand ($\frac{\partial n_a^d}{\partial \lambda_a} \frac{\partial \lambda_a}{\partial B_a} \leq 0$), which will tend to reduce labor market tightness, but it also increases the magnitude of the shift in labor supply $\frac{\partial n_a^s}{\partial B_a}$ as discussed earlier, which will tend to increase labor market tightness. The relative magnitude of these two effects will therefore determine if endogenous layoffs deepens or attenuates the effect of UI on equilibrium labor market tightness.

B Defining labor markets using vacancy data

Identifying which workers are competing for the same vacancies workers satisfying the REBP-eligibility requirements is critical to determine and define the relevant labor markets that are affected by externalities of the REBP program. As explained in section A.2, when treated and non-treated workers are in the same labor market, i.e. competing for the same vacancies, the effect of the program on non-treated workers can identify equilibrium labor market tightness in the labor market. When treated and non-treated workers are competing for different vacancies, there are in practice two search markets for labor, and the effect of the program on non-treated workers cannot directly identify equilibrium adjustments in the treated market.

To determine which workers are competing for the same vacancies as REBP eligible workers, we use detailed micro data on the universe of job vacancies posted in public employment agencies available for the period 1994-1998. (Vacancies posted in public employment agencies represent 30% to 40% of all posted vacancies). This data set has two important features. First, the data records for each vacancy all the detailed information about the characteristics of the vacancy. This includes the firm identifier of the firm posting the vacancy, the date (in month) at which the vacancy is opened and the date at which it is closed, the reason for closing the vacancy (the vacancy has been filled, search has been abandoned, etc.), the identifier of the public employment service where the vacancy is posted, the industry and job classifications of the job, details on the duration and type of the contract (full-time,/part-time tenured/non-tenured, seasonal job, etc.), the age requirement if any, the education requirement if any, the gender requirement if any, and the posted wage or range of wage if any. Second, the data contains the personal identifier of the person who filled the vacancy if the vacancy is filled. This personal identifier enables us to match this vacancy data to the ASSD and determine the characteristics and REBP eligibility status of the person filling the vacancy.

Our strategy consists in using all the information that we have on each vacancy, and estimate how well the characteristics of each vacancy predicts the REBP eligibility status of the worker who fills the vacancy. If there is perfect discrimination in vacancies between eligible and non-eligible workers, then eligible and non-eligible workers will be competing for two different sets of vacancies and will effectively be in two different labor markets from a search-theoretic perspective. Empirically, this means that characteristics of vacancies for eligible and non-eligible workers are different, and therefore characteristics of vacancies should predict very well whether the individual filling the vacancy is eligible to REBP or not. To the contrary, if eligible and non-eligible workers are in the same job-search market, they will compete for the same vacancies. When opening a vacancy in this market, and conditional on search effort of eligible and non-eligible workers, a firm will be randomly matched to an eligible or to a non-eligible worker. In other words, conditional on search effort of eligible and non-eligible workers, matching is random across eligible and non-eligible workers and vacancies in this market will be filled (randomly) by eligible or non-eligible workers. In this case, the characteristics of a vacancy will have very little predictive power on the eligibility status of the worker who fills it.

To implement this strategy, we take all vacancies opened by firms located in REBP regions that ended up being filled (by REBP eligible or non-eligible male workers) during 1994 to 1998. (Before this period, the quality of the data is too weak and thus cannot be used for our analysis.) We estimate the following latent variable model:

$$Y_i^* = X_i'\beta + \epsilon_i$$
$$Y_i = \begin{cases} 0 & \text{if} \quad Y_i^* < 0 \\ 1 & \text{if} \quad Y_i^* \geq 0 \end{cases}$$

where Y_i is a dummy variable indicating whether the worker filling vacancy i is eligible to REBP or not, and X_i is a vector of all the characteristics of vacancy i. These characteristics are the two-digit industry code of the firm opening the vacancy, the two-digit occupation code of the job, the duration of the contract (temporary contract, unlimited contract, seasonal job, holiday work, etc.), whether the job is full-time, part-time or flexible hours, whether the job hours are negotiable or not, whether the job implies shift work, whether it implies night or extra hours work, whether the job is an apprenticeship, the size of the firm (in 5 categories), the age required for the job if any, and the level of education required for the job (in 17 categories) if any. We estimate this model using a logit. We run the model separately for various categories of non-eligible workers (35 to 40 years old workers, 40 to 45 years old workers, 45 to 50 years old workers, and 50-54 years old non-eligible workers) in order to compare each of these categories of workers to REBP eligible workers. For each of the categories of non-eligible workers, we then analyze the predictive power of the model using various goodness-of-fit measures.

In figure 1 panel A, we start by plotting the p-value of two standard goodness-of-fit tests for the logit model, the Pearson's χ^2 goodness of fit test and the Hosmer-Lemeshow χ^2 goodness of fit test, for different categories of non-eligible workers. A low p-value for the test indicates a poor fit of the data. Both tests suggest that the model fits the data very well for comparing eligible workers to non-eligible workers aged 35 to 40, but tend to perform more and more poorly as we use non-eligible workers that are older. When comparing eligible workers to non-eligible workers aged 50 to 54, the p-value is very close to zero, and the goodness-of-fit of the model is extremely poor. This suggests that the predictive power of vacancy characteristics on eligibility is very good when comparing workers that are below 50 to eligible workers, but very low when comparing eligible and non-eligible workers aged 50 to 54. In other words, workers age below 50 seem to fill vacancies that have characteristics that are very different from the vacancies filled by eligible workers. But eligible and non-eligible workers above 50 seem to fill vacancies that have very similar characteristics. This suggests that workers aged below 50 are likely to be in a different job search market than eligible workers, but non-eligible workers aged 50 to 54 are very likely to compete for the same vacancies as eligible workers.

In panel B of figure 1, we plot the fraction of observations that are incorrectly predicted by the model (*i.e.* the predicted eligibility status to REBP is different from the true eligibility status of the worker filling the vacancy) for all categories of non-eligible workers. The fraction of misclassified observations is less than 7.5% for the model comparing eligible workers to non-eligible workers aged 30 to 40, but increases up to more than 25% for the model comparing eligible workers to non-eligible workers aged 50 to to 54. We also plot the fraction of type I errors, *i.e.* the fraction of true non-eligible workers that are predicted as being eligible to REBP by the model. Type I errors are particularly relevant in our context. They provide information about how likely it is that a non-eligible worker is competing for a vacancy that has been "tailored" to eligible workers based on its characteristics. In this sense, type I errors provide direct information about the intensity of the competition that eligible workers receive from various groups of non-eligible workers when a vacancy is opened in "their" search market. The figure indicates that type I errors seem to be particularly severe when comparing eligible workers to non-eligible workers aged 50 to 54. Because classification is sensitive to the relative sizes of each component group, and always favors classification into the larger group, the classification error measures of panel B should still be interpreted with caution. We therefore tend to prefer goodness-of-fit measures presented in panel A.

These results help inform our identification strategy and choose the proper groups of non-eligible workers to identify the presence of externalities. The results indicate that it is much more likely for non-eligible workers aged 50 and over to compete for the same vacancies as eligible workers than for non-eligible workers aged below 50. This means that non-eligible workers aged 50 and above are likely to be in the same job-search market as eligible workers, while non-eligible workers aged below 50 tend to compete for different vacancies and are therefore in a different job-search market. This means that the effect of REBP on job-finding probabilities of eligible workers aged 50 and above is more likely to identify variations in labor market tightness in the job-search market of REBP-treated workers. As explained in section A.2, these variations in labor market tightness in the job-search market of REBP-treated workers capture both the rat race effect and the wage effect of UI, and are the relevant variations to consider to identify the equilibrium effect of variations in UI in a given labor market.

Non-eligible workers below 50 years old, to the contrary, seem to be competing for different vacancies than workers eligible to REBP. This means that they are more likely to operate in a different search market than workers eligible to REBP. The effect of REBP on their job finding probability is therefore more likely to identify externalities across search markets. In section A.3, we have shown that such externalities stem from substitution effects, and cannot directly identify the effect of REBP on the labor market tightness in the search market of treated workers.

Overall, the vacancy data is useful to determine the scope of the different job search markets. This analysis indicates that the externalities that we may find on non-eligible workers may be very different in nature and in magnitude across different groups of non-eligible workers. Non-eligible workers aged 50+ are more likely to experience larger externalities stemming from equilibrium adjustments in labor market tightness in the search market of workers eligible to REBP. Non-eligible workers that are younger than 50 are more likely to experience externalities stemming from substitution effects across search markets.

C Additional tables and figures

Standard errors To correct for the presence of common random effects, we cluster standard errors at the region-year level. We have checked sensitivity of inference in three ways. First, we allow for clustering by markets defined as county-by-industry-by-education cells (see appendix C, table 6). Results indicate that standard errors are robust to clustering by markets. Second, clustering by market is fully flexible in terms of clustering in time but assumes no correlation across markets or space. Conley [1999] proposes a more flexible approach to inference that allows for arbitrary tempo-spatial dependence in shocks within

Table 6: Sensitivity of Baseline Results to Inference Assumptions

	(1) Unemployment duration	(2) Non-employment duration	(3) Spell > 100 wks	(4) Spell > 26 wks
β_0	43.37	29.17	0.240***	0.237***
Baseline cluster	(5.069)***	(5.444)***	(0.0293)***	(0.0240)***
Market cluster	(4.581)***	(4.867)***	(0.0247)***	(0.0278)***
Spatial HAC	(4.319)***	(4.785)***	(0.0230)***	(0.0250)***
Permutation	(1.143)***	(0.930)***	(0.0077)***	(0.0099)***
γ_0	-3.740	-2.327	-0.0130	-0.0165
Baseline cluster	(0.758)***	(0.629)***	(0.00311)***	(0.00660)**
Market cluster	(0.798)***	(1.004)**	(0.00231)***	(0.00585)***
Spatial HAC	(0.862)***	(1.012)**	(0.00287)***	(0.00889)*
Permutation	(1.528)**	(1.124)**	(0.00519)**	(0.00880)*
N	262344	232135	262344	262344

Notes: * p<0.10, ** p<0.05, *** p<0.010. This table reports the main result from Table 2. Numbers in parentheses display standard errors. Baseline standard errors allow for clustering at the region * year level. Market cluster standard errors allow for clustering at the level of the market, i.e. a county × education × industry cell – this is the classification we use to detect market externalities in Table 5 of the paper. Spatial HAC standard errors allow for any correlation in errors in a circle of 33 kilometers around a job seeker's location, and zero correlation beyond that. Spatial HAC standard errors also allow for full correlation between spells starting in the same quarter, one half correlation between spells that start one quarter apart, and no correlation beyond. Permutation standard errors are based on 235 placebo estimates of simulations of the REBP program during non-REBP time periods.

Source: Own calculations, based on ASSD.

a distance and an autocorrelation cutoff, so-called spatial HAC standard errors. We report results that use a distance cutoff of 33 km – the median commuting distance for job seekers in Austria – and an autocorrelation cutoff of two quarters. Spatial HAC standard errors are similar to our baseline standard errors. Third, both clustering on market and spatial HAC standard errors rely on assumptions regarding the tempo-spatial dependence of standard errors. Permutation is a way to assess sensitivity to these assumptions. Permutation works as follows: we first construct a set of 235 placebo REBP estimates on non-REBP periods and then conduct inference using the distribution of placebo REBP effects. Permutation based standard errors for the market externality are somewhat larger than baseline standard errors, and substantially smaller for the effect of REBP on the eligible. But our inference remains robust to adopting this permutation procedure.[27]

[27] Kline and Moretti [2014] have adopted the spatial HAC approach in their analysis of the Tennesess Valley Authority. Chetty et al. [2014] use permutation to study sensitivity of inference in active savings decisions in a regression discontinuity design. Lalive, Wuellrich and Zweimueller [2013] use permutation to test sensitivity of disabled employment to financial incentives in a threshold design.

Table 7: Sensitivity analysis to sample restrictions

	(1)	(2)	(3)	(4)	(5)	(6)
	Unemployment duration			Non-empl. duration	Spell >100 wks	Spell >26 wks
	A. Men, 46 to 59, excluding steel sector					
β_0	50.20***	44.84***	43.82***	33.60***	0.254***	0.222***
	(3.607)	(3.300)	(3.210)	(5.165)	(0.0192)	(0.0155)
γ_0	-2.680***	-2.133***	-3.222***	-2.514***	-0.00912***	-0.0139**
	(0.782)	(0.657)	(0.608)	(0.527)	(0.00240)	(0.00545)
N	378556	369477	369477	304664	369477	369477
	B. Men and women, 46 to 54, excluding steel sector					
β_0	55.93***	52.28***	51.80***	40.59***	0.297***	0.238***
	(3.549)	(3.472)	(3.319)	(5.147)	(0.0192)	(0.0163)
γ_0	-2.241***	-1.307**	-3.217***	-1.892***	-0.0103***	-0.0106**
	(0.781)	(0.648)	(0.682)	(0.608)	(0.00297)	(0.00522)
N	359901	351433	351433	296768	351433	351433
	C. Men, 46 to 54, including steel sector					
β_0	47.33***	43.82***	43.85***	30.58***	0.242***	0.238***
	(5.534)	(5.108)	(5.045)	(5.603)	(0.0290)	(0.0237)
γ_0	-2.248***	-1.809**	-3.581***	-2.228***	-0.0119***	-0.0158**
	(0.825)	(0.730)	(0.785)	(0.632)	(0.00304)	(0.00700)
N	284099	278021	278021	245621	278021	278021
Educ., industry, citizenship, marital status		×	×	×	×	×
Region-specific trends			×	×	×	×

Notes: S.e. clustered at the year×region level in parentheses. * p<0.10, ** p<0.05, *** p<0.010.
All duration outcomes are expressed in weeks. The table presents estimates of the model presented in equation (3) where we explore the sensitivity of our baseline results to various sample restrictions. β_0 identifies the effect of REBP on eligible unemployed, while γ_0 identifies spillovers of REBP on non-eligible unemployed in REBP counties. In column (1), we estimate this model without any other controls. In column (2) we add a vector of controls X which includes education, 15 industry codes, family status, citizenship and tenure in previous job. In column (3) to (6) we add controls for preexisting trends by region. Column (5) uses as an outcome the duration of total non-employment (conditional on finding employment at the end of the unemployment spell). Columns (6) and (7) use as an outcome the probability of experiencing unemployment spells longer than 100 weeks and 26 weeks respectively. In panel A, the estimation sample includes all men age 46 to 59. In panel B, the sample includes all men and women age 46 to 54. In panel C, the sample is the same as our baseline sample but also includes workers who ever worked in the steel sector.

Table 8: ROBUSTNESS TO REBP-COUNTIES-SPECIFIC SHOCKS: Externalities on non-eligible aged 50 to 54 using unemployed aged 30 to 39 in REBP counties as a control

	(1)	(2)	(3)	(4)	(5)	(6)
	Unemployment duration		Non-empl. duration		Spell >26 wks	
β_0	54.32***	50.81***	30.30***	30.29***	0.312***	0.275***
	(7.480)	(6.784)	(7.639)	(7.192)	(0.0432)	(0.0362)
γ_0 (externality)	-7.878**	-6.466*	-7.643***	-6.347**	-0.0742***	-0.0554**
	(3.880)	(3.437)	(2.156)	(2.461)	(0.0222)	(0.0213)
Educ., marital status, industry, citizenship		×		×		×
N	182689	180098	170388	168163	182689	180098

Notes: S.e. clustered at the year×county level in parentheses. * p<0.10, ** p<0.05, *** p<0.010. All duration outcomes are expressed in weeks. We use the same strategy as in table 2 but we use men aged 30 to 39 in REBP counties as a control instead of men 50 to 54 in non-REBP counties. We run on a sample restricted to unemployed aged 30 to 39 and 50 to 54 a diff-in-diff specification equivalent to equation (3) where we replace $\mathbb{M}$ by $\mathbb{A} = \mathbb{1}[Age > 50]$. This specification enables us to fully control for shocks to the labor markets of REBP counties contemporaneous to REBP.

Table 9: EXTERNALITIES ON NON-ELIGIBLE UNEMPLOYED BY INITIAL LEVEL OF LABOR MARKET TIGHTNESS

REBP effect on non-treated	(1) Unemployment duration	(2) Non-empl. duration	(3) Spell >100 wks	(4) Spell >26 wks
	All non-eligible			
$\gamma_0^{High\ \theta}$ ($\theta \geq P50$)	0.728	-1.650	0.00877	-0.0208
	(1.411)	(1.088)	(0.00571)	(0.0125)
$\gamma_0^{Low\ \theta}$ ($\theta < P50$)	-2.250***	-1.809**	-0.00457*	-0.00936
	(0.726)	(0.733)	(0.00255)	(0.00657)
F-Test $\gamma_0^{Low\ \theta} = \gamma_0^{High\ \theta}$	[0.0635]	[0.910]	[0.0530]	[0.422]
N	262109	231940	262109	262109
	Non-eligible 50+			
$\gamma_0^{High\ \theta}$ ($\theta \geq P50$)	-1.317	-2.788	0.00878	-0.0309
	(4.073)	(2.745)	(0.0181)	(0.0204)
$\gamma_0^{Low\ \theta}$ ($\theta < P50$)	-7.539***	-5.999**	-0.0167**	-0.0312*
	(2.334)	(2.407)	(0.00801)	(0.0180)
F-Test $\gamma_0^{Low\ \theta} = \gamma_0^{High\ \theta}$	[0.0530]	[0.320]	[0.114]	[0.992]
N	122174	102598	122174	122174
Educ., marital status, industry, citizenship	×	×	×	×

Notes: S.e. clustered at the year×region level in parentheses. * p<0.10, ** p<0.05, *** p<0.010. Sample restricted to male workers working in non-steel related sectors. All duration outcomes are expressed in weeks. The table presents estimates of the effects of REBP on non-eligible workers broken down by the initial level of labor market tightness in county×industry×education cells. Initial labor market tightness is obtained by dividing the average monthly number of vacancies posted in 1990 (the first year for which we have some vacancy information by county) in each county×industry×education cell, by the average monthly number of unemployed in the same county×industry×education cell. $\gamma_0^{High\ \theta}$ identifies externalities of REBP on non-treated workers in REBP county×industry×education cells where labor market tightness was above the median level of tightness in 1990. $\gamma_0^{Low\ \theta}$ identifies externalities of REBP on non-treated workers in REBP county×industry×education cells where labor market tightness was below the median level of tightness in 1990.

D Wages

D.1 Effect of REBP on reemployment wages

As highlighted in section I and explained formally in appendix section A, one of the key requirement for externalities to be positive on non-eligible workers is that wages do not react much to outside options of workers. Here, we investigate explicitly this question by looking at the effect of REBP on reemployment wages and other characteristics of jobs at reemployment.[28]

The identification of the effect of REBP on wages is very different from our previous market externality analysis, as we now wish to compare eligible workers to non-eligible workers (rather than non-eligible in treated and non treated markets). The identification of the effect of REBP on wages is difficult for at least three reasons. First, REBP treatment is correlated with longer unemployment duration, which may directly affect wages through duration dependence effects. If reemployment wages depend on the duration of the unemployment spell $w = w(D, B)$ (because of human capital depreciation, or discrimination from the employers), then the effect of a change in benefits B on reemployment wage can be decomposed into two effects:

$$\frac{dw}{dB} = \underbrace{\frac{\partial w}{\partial D} \cdot \frac{\partial D}{\partial B}}_{\text{Duration effect}} + \overbrace{\frac{\partial w}{\partial B}}^{\text{Reservation wage effect}}$$

If reemployment wages decline over the duration of a spell ($\frac{\partial w}{\partial D} < 0$), the total effect of an increase in benefits on reemployment wages might be zero or even negative even though the reservation wage effect is positive.

The second issue is that REBP treatment affects the probability of entering into unemployment and REBP recipients may therefore be selected along unobserved characteristics that are correlated with wages. Treatment is also correlated with the probability of ever reentering the labor force, which creates additional selection issues when looking at reemployment wages.

The third issue is that REBP affects labor market tightness, which will in turn affect the bargaining power of workers. It is thus difficult to separate what is the pure reservation wage effect from other equilibrium effects affecting wages.

We try to address these issues in the following analysis, but we want to stress that our analysis remains tentative. To deal with the first issue, we follow the methodology of Schmieder, von Wachter and Bender [2012*a*] and estimate the effect of variations in benefits on reemployment wages *conditional on unemployment duration*. We do this first

[28]Note that Lalive [2007] discusses the effects of benefit extension programs on re-employment wages without conditioning on elapsed unemployment duration.

in the diff-in-diff setting of equation 3, and then in a RD setting taking advantage of the age eligibility discontinuity at 50 and experience eligibility discontinuity at 15 years. Note that in both cases, the identifying assumption requires that there is no correlation between unobserved heterogeneity and unemployment benefits *conditional on unemployment duration* which is a much stronger assumption than in the standard diff-in-diff or RD assumptions where we only need that the correlation between unobserved heterogeneity and unemployment benefits is zero.

We plot in appendix figure 6 post-unemployment wages conditional on the duration of the unemployment spell in REBP and non-REBP counties for eligible workers (aged 50 to 54 with more than 15 years of experience). The difference between REBP and non-REBP counties at each duration point in panel B (when REBP was in place) compared to the same difference in panel A (when REBP was not in place) gives us a diff-in-diff estimate of the effect of REBP on reemployment wages conditional on spell duration. This evidence suggests that there was no effect of REBP on reemployment wages.

We formally assess this result in appendix table 10 by running a simple diff-in-diff model where we compare workers eligible to REBP (treatment) to non-eligible workers (control). Each panel uses a different control group. In panel A, we use workers aged 50 to 54 with more than 15 years of experience but residing in non-REBP regions. In panel B we use workers aged 50 to 54 residing in REBP regions but with less than 15 years of experience. In panel C we use workers aged 46 to 49 with more than 15 years of experience and residing in REBP regions. In column (1), we estimate the model without further controls. In column (2) we add a vector of controls including education, 15 industry codes, family status, citizenship and tenure in previous job. These specifications tend to deliver a negative effect of REBP on reemployment wages. This negative effect may well be driven by selection into unemployment. We know from table 3 that REBP has affected the inflow rate into unemployment of eligible workers. This means that the selection of eligible workers may be different during REBP. We try to control for this using pre-employment wages. In column (3) we add a rich set of pre-unemployment wage dummies to control for potential differential self-selection into unemployment due to REBP. As explained above, the negative effect on reemployment wages found in column (1) and (2) can also be due to duration dependence effects. In column (4) we allow for an effect of longer unemployment spells during on reemployment wages (because of skill depreciation, employer discrimination, etc.). Following the methodology of Schmieder, von Wachter and Bender [2012*a*], we condition on the duration of unemployment using a rich set of dummies for the duration of unemployment prior to finding a new job. In this preferred specification of column (4), irrespective of the control group we are using, we always find no significant effect of REBP on reemployment wages.

To complement our diff-in-diff approach, we also focus on the age eligibility discontinuity at 50 in REBP counties and estimate RD effects of the REBP extensions controlling for the effect of duration on reemployment wages by adding a rich set of dummies for the duration of the spell prior to finding the job.

$$E[Y|A=a] = \sum_{p=0}^{\bar{p}} [\gamma_p (a-k)^p + \nu_p (a-k)^p \cdot \mathbb{1}[A \geq k]] + \sum_{t=0}^{T} \mathbb{1}[D=t] \tag{30}$$

where Y is real reemployment wage, A is age at the beginning of the unemployment spell, $k = 50$ is the age eligibility threshold, and D is the duration of the unemployment spell prior to finding the new job. We use a third-order polynomial specification. Results are displayed in appendix figure 7, where we have estimated this model for six periods to look at the dynamics of the wage response. Before REBP, we can detect no sign of discontinuity at age 50 in reemployment wages. But interestingly, we can detect a small discontinuity at the beginning of REBP (1988-1990). This discontinuity increases over time and is the largest in 1991-1993, at the peak of REBP. The implied RD estimate of the elasticity of wages with respect to UI benefits is .14 (.04). This discontinuity then decreases and disappears when REBP is over. This suggests that wages are relatively rigid in the short run, but that in the longer run, wages might adjust to variations in outside options of workers. Note, however, that the McCrary test rejects continuity of the probability density function of the assignment variable (age) at the cutoff (50 years) during REBP. This implies that the wage effects could also partly be driven by selection (sorting) at the 50 years age cut-off.

We finally exploit the experience eligibility discontinuity in REBP counties using the same methodology. Results are displayed in appendix figure 9. The figure displays for REBP regions the relationship between experience in the past 25 years at the beginning of unemployment spell and reemployment wages for workers aged 50 to 54. We use the discontinuity created by the fact that workers with more than 15 years of experience are eligible for REBP extensions while workers with less than 15 years are not eligible. The graph shows the average reemployment wage for each bin of 6 months of past experience for all non REBP years and for all REBP years. We also estimate a model of the form: $E[Y|E=e] = \sum_{p=0}^{\bar{p}} \gamma_p (a-k)^p + \nu_p (a-k)^p \cdot \mathbb{1}[E \geq k] + \sum_{t=0}^{T} \mathbb{1}[D=t]$, where Y is real reemployment wage, E is experience at the beginning of the unemployment spell, $k = 15$ is the experience eligibility threshold, and D is the duration of the unemployment spell prior to finding the new job. The graph plots the predicted values of this regression for all non REBP years and for all REBP years using a 3rd order polynomial for the regressions. Here, we find no evidence of an effect of REBP on reemployment wages. Note again however that McCrary tests rejects continuity in the probability density function of the assignment variable (experience) at the cutoff (15 years) during REBP.

Overall, this evidence, although tentative, suggests that wages of eligible workers did not strongly respond to REBP, which is in line with the market externalities that we find.

Yet, we cannot exclude that these results are confounded by selection, nor can we exclude that wages would have adjusted in the very long run.

D.2 Implications of these results for the wage setting process

What can we learn on the wage setting process from this empirical evidence? Is this evidence, combined with other available evidence, compatible with Nash bargaining?

Note that union membership is not extremely high in Austria, and the wage setting process is less centralized and rigid than in most continental European countries. Austria has (formally) a decentralized system of wage negotiations. 400 collective agreements determine a minimum wage in the particular sector/occupation where the contract applies and the wage growth for effective wages, leaving some room for individual bargaining.

In a standard DMP model with Nash bargaining, the wage w is a weighted average of the productivity of the worker Π (which determines the reservation price of the employer) and of the value of remaining unemployed z (which determines the reservation price of the unemployed):

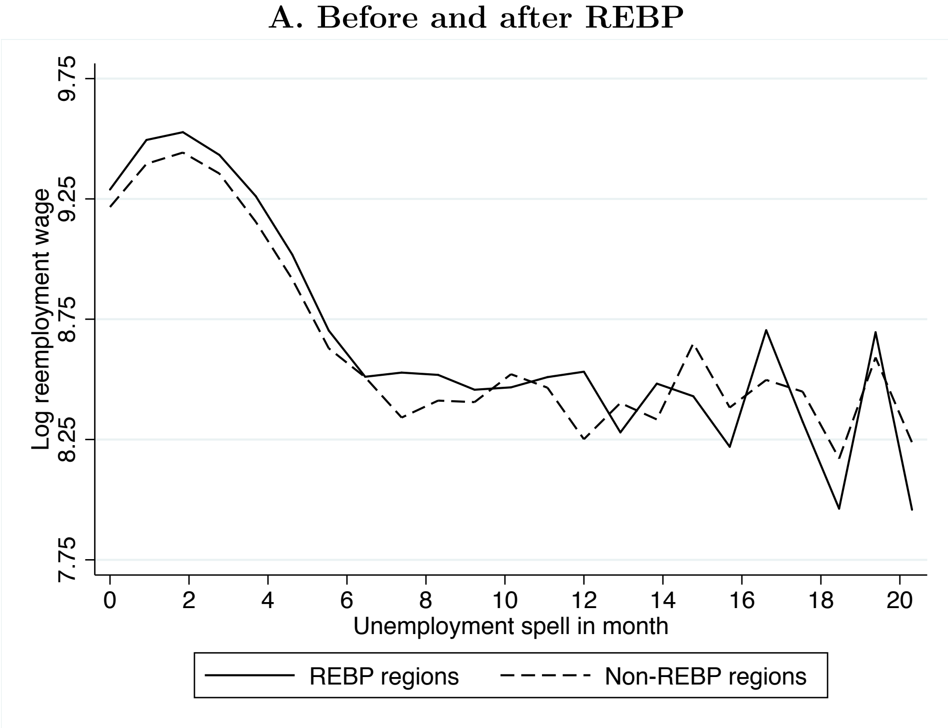
$$w = \beta\Pi + (1-\beta)z$$

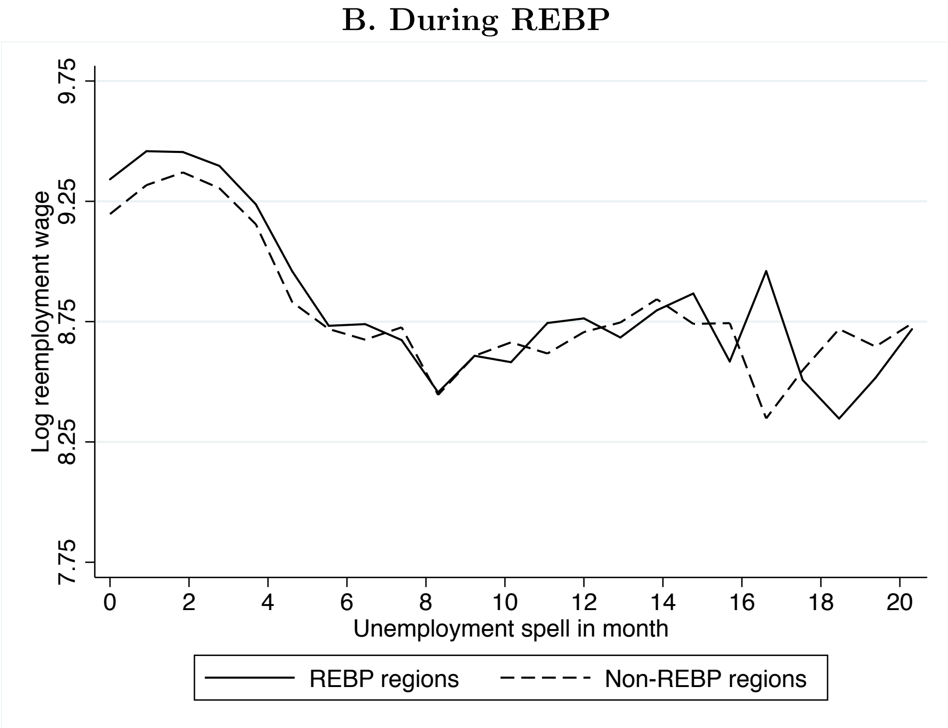
The weight β corresponds to the bargaining power of the unemployed. Therefore $\frac{dw}{d\Pi} = \beta$ and $\frac{dw}{dz} = 1-\beta$. In other words, the bargaining power of the workers could be identified by the variation of wages to a change in Π or z. The main problem is that we never observe p nor $z = z(B, X)$, which depends not only on unemployment benefits B but also on many other different things such as the disutility of work, etc. The Nash bargaining model is therefore fundamentally non-identifiable. Are there nevertheless credible values of Π, z and β that would rationalize the empirical evidence presented here? First, all the evidence in the macro literature (see, for instance, Shimer [2005] and Hagedorn and Manovskii [2008]) suggests that wages do not react much to productivity shocks, so that $\frac{dw}{d\Pi}$ is likely to be small. This, implies that β is small. But if β is small, then wages should react a lot to variations in the outside options of workers, *i.e.* the value of remaining unemployed: $\frac{dw}{dz}$ and $\varepsilon_z = \frac{dw}{dz} \cdot \frac{z}{w}$ should be large. Of course, we never directly observe ε_z. We only observe the variation of wages to a change in unemployment benefits $\frac{dw}{dB} \cdot \frac{B}{w} = \varepsilon_z \cdot \frac{\partial z}{\partial B} \cdot \frac{B}{z}$. Given that we found $\frac{dw}{dB} \cdot \frac{B}{w} \approx 0$, it is difficult to believe that ε_z is very large, unless $\frac{\partial z}{\partial B} \cdot \frac{B}{z} << 1$. In other words, it is difficult to reconcile the small elasticity of w w.r.t z and the small elasticity of w w.r.t p in the Nash bargaining model. The only solution is to assume that $\frac{B}{z} << 1$ as in Hagedorn and Manovskii [2008]. But two pieces of evidence argue against such an assumption. First, if we follow their preferred calibration for β, our largest estimate of ε_z would imply[29] that $B \leq .05 \cdot z$ which seems absurdly low. In other words the value of remaining unemployed would be more than 20 times larger than the value of the unemployment benefits received by an unemployed. Second, if $\frac{B}{z} << 1$,

[29] Assuming an additive specification $z = B + f(X)$ so that $\frac{\partial z}{\partial B} = 1$.

this in turn implies that accounting profits of firms $\Pi - w$ are small, so that even small increases in w have very large effects on vacancy openings by firms, driving labor market tightness down. This means that the "wage externality" would be very large, shocking labor demand down as in figure 5 panel B. This would also mean that the externalities of large unemployment extension programs like REBP would likely go in the opposite direction compared to our estimates. Overall, it seems reasonable to think that the Nash bargaining model is maybe not the best way to describe the data. A model of wage setting with some wage stickiness, at least in the short to medium run seems more appropriate. Still, it does not mean that Nash bargaining is not appropriate to describe the longer run. Indeed, the effects of REBP on wages seems to build up slightly over time and with treatment intensity. In the very long run, wages may adjust more to B than what we observe in the REBP experiment, suggesting that $\frac{dw}{dz}$ can be larger in the long run. This has important implications for the design of UI policies.

Figure 6: Reemployment wages conditional on duration of unemployment spell in REBP and non-REBP counties





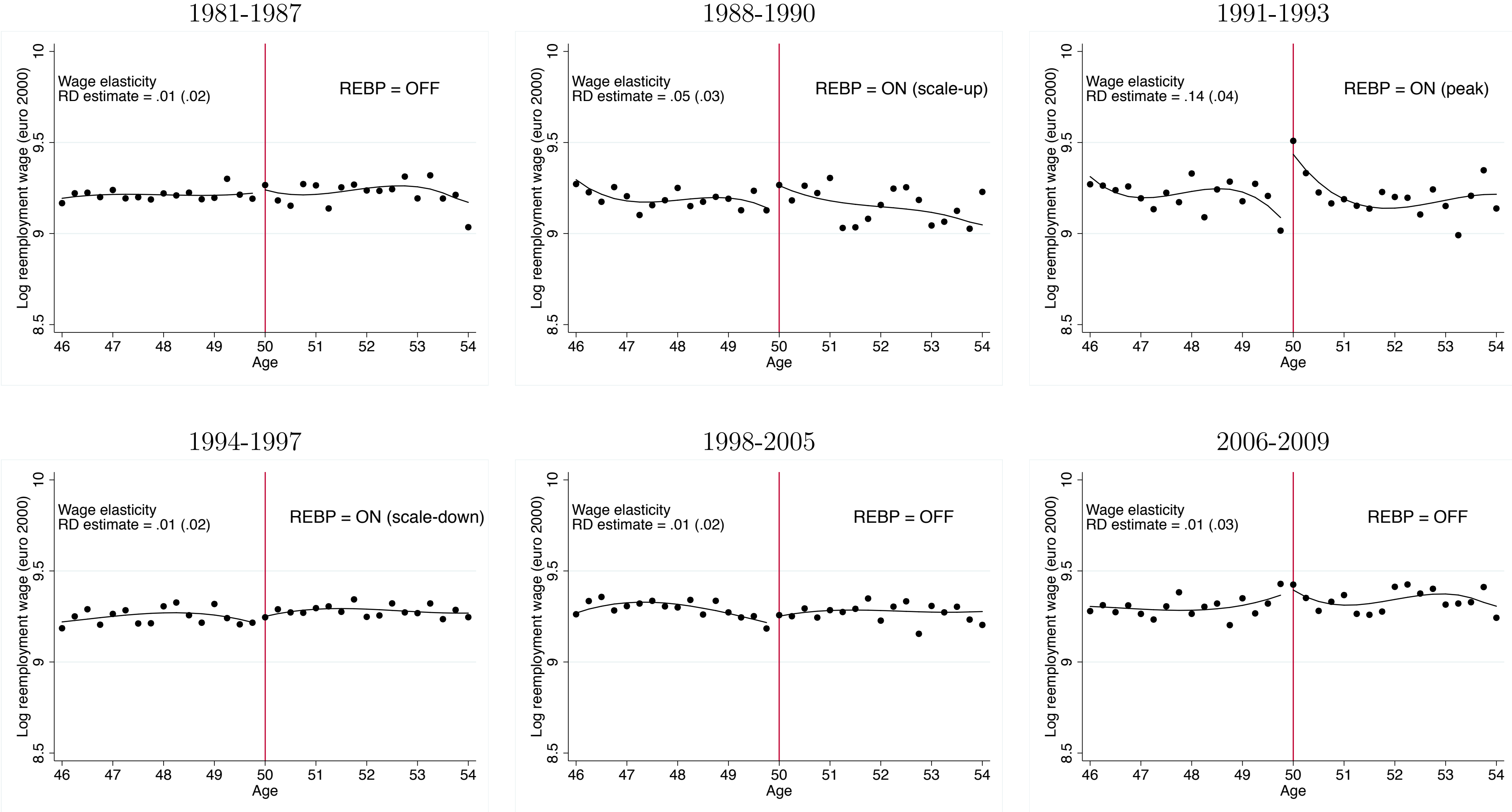
Notes: the figure plots post-unemployment wages conditional on the duration of the unemployment spell in REBP and non-REBP counties for workers aged 50 to 54 with more than 15 years of experience in the past 25 years prior to becoming unemployed. Following the methodology of Schmieder, von Wachter and Bender [2012*a*], by conditioning on the duration of unemployment, we control for the fact that REBP eligible workers experienced longer unemployment spells during the REBP period, which may impact reemployment wages if the distribution of wages depend on time spent unemployed (because of skill depreciation or discrimination from employers for instance). The difference between REBP and non-REBP counties at each duration point in panel B (when REBP was in place) compared to the same difference in panel A (when REBP was not in place) gives us a diff-in-diff estimate of the "reservation wage" effect. This evidence suggests that there was no significant reservation wage effect of REBP.

Table 10: Diff-in-diff estimates of the effects of REBP on wages

	(1)	(2)	(3)	(4)
	log reemployment wage			
	A. Control: eligible workers 50-54 in non-REBP regions			
REBP × eligible	-0.0291**	-0.0403**	-0.0589***	-0.00895
	(0.0133)	(0.0153)	(0.0183)	(0.0123)
N	77743	76501	75594	76501
	B. Control: non-eligible workers 50-54 in REBP regions			
REBP × eligible	-0.101	-0.0913	-0.0473	-0.0891
	(0.0820)	(0.0820)	(0.0867)	(0.0591)
N	23278	22996	22781	22996
	C. Control: non-eligible workers 46-50 in REBP regions			
REBP × eligible	0.00550	-0.0144	-0.0313	0.000967
	(0.0228)	(0.0286)	(0.0240)	(0.0242)
N	46701	46251	45826	46227
Educ., marital status, industry, citizenship		×	×	×
Pre-unemployment wage dummies			×	
Set of dummies for duration of U spell				×

Notes: Standard errors are clustered at the year×region level. * p<0.10, ** p<0.05, *** p<0.010. The table investigates the impact of REBP on real reemployment wages. The specification is a diff-in-diff where we compare workers eligible to REBP (treatment) to non-eligible workers (control). Each panel uses a different control group. In panel A, we use workers aged 50 to 54 with more than 15 years of experience but residing in non-REBP regions. In panel B we use workers aged 50 to 54 residing in REBP regions but with less than 15 years of experience. In panel C we use workers aged 46 to 50 with 15 years of experience and residing in REBP regions. Column (1) runs a basic diff-in-diff specification using log reemployment wages as an outcome with no additional controls. In column (2) we add a vector of controls including education, 15 industry codes, family status, citizenship and tenure in previous job. In column (3) we add a rich set of pre-unemployment wage dummies to control for potential differential self-selection into unemployment due to REBP. In column (4), following the methodology of Schmieder, von Wachter and Bender [2012*a*], we condition on the duration of unemployment using a rich set of dummies for the duration of unemployment prior to finding a new job. This is in order to control for the fact that REBP eligible workers experienced longer unemployment spells during the REBP period, which may impact reemployment wages if the distribution of wages depend on time spent unemployed (because of skill depreciation or discrimination from employers for instance).

Figure 7: RD evidence on wage bargaining over time: relationship between age and reemployment wages in REBP counties



Notes: the figure displays for REBP regions the relationship between age at the beginning of unemployment spell and reemployment wages for workers with more than 15 years of experience in the past 25 years prior to becoming unemployed. Workers aged 50 or more are eligible for REBP extensions while workers aged less than 50 are not eligible. We follow the methodology of Schmieder, von Wachter and Bender [2012*a*] and estimate RD effects of the extensions controlling for duration by adding a rich set of dummies for the duration of the spell prior to finding the job. $E[Y|A=a] = \sum_{p=0}^{\bar{p}} \gamma_p (a-k)^p + \nu_p (a-k)^p \cdot \mathbb{1}[A \geq k] + \sum_{t=0}^{T} \mathbb{1}[D=t]$, where Y is real reemployment wage, A is age at the beginning of the unemployment spell, $k=50$ is the age eligibility threshold, and D is the duration of the unemployment spell prior to finding the new job. The graph plots the predicted values of this regression for 6 periods: before REBP 1981-1987, at the beginning of REBP (1988-1990), at the peak of REBP (1991-1993), when REBP was scaled down (1994-1997) and then for two periods after the end of REBP (1998-2005 and 2006-2009). All regressions use a 3rd order polynomial specification. Note that for all periods, we ran a McCrary test, which ruled out the presence of a discontinuity in the probability density function of the assignment variable (age) at the cutoff (50 years), except for the 1991-1993 where a discontinuity can be detected.

Figure 8: Probability density function of age at the start of an unemployment spell in REBP and non-REBP counties

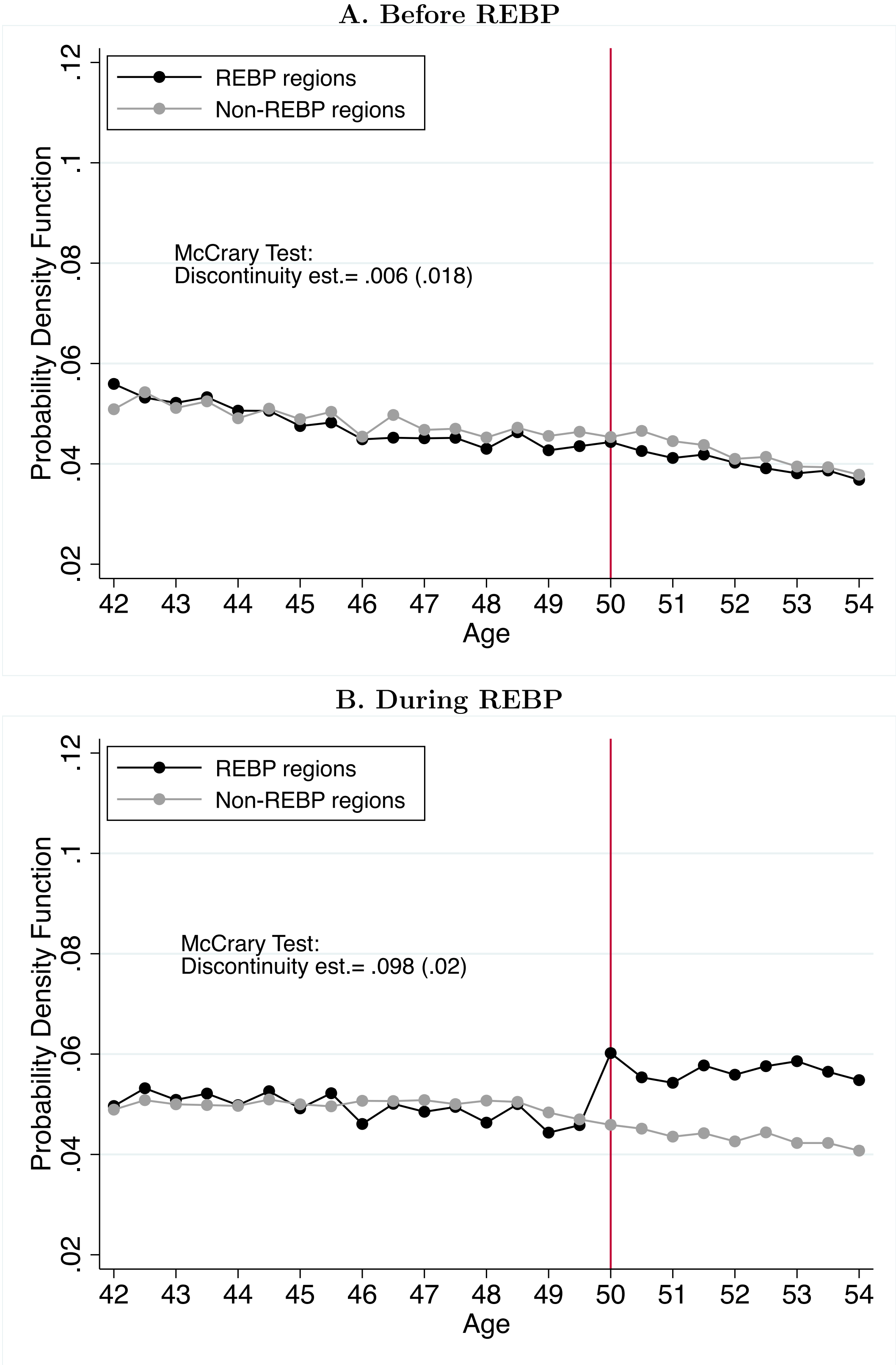
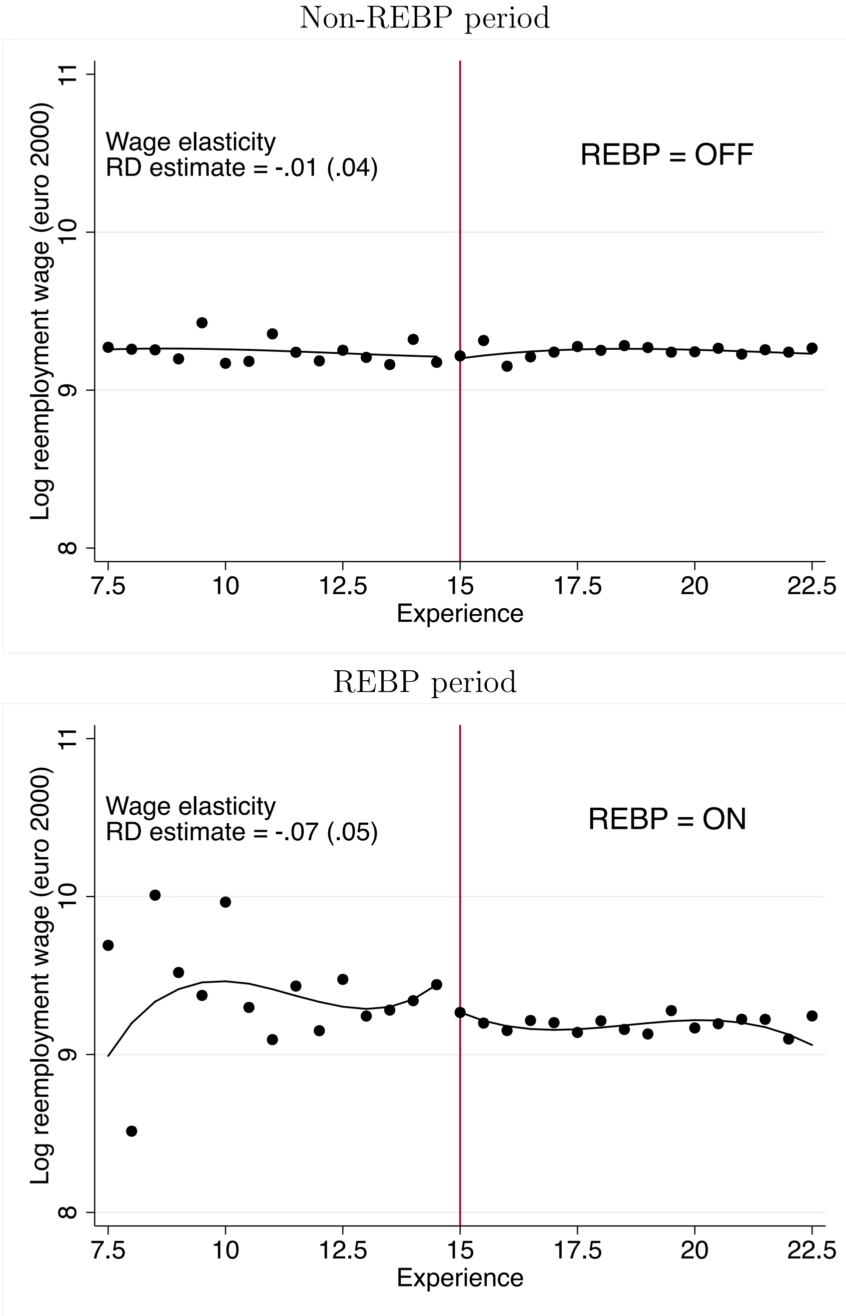


Figure 9: RD EVIDENCE ON WAGES USING EXPERIENCE CUTOFF: RELATIONSHIP BETWEEN EXPERIENCE AND REEMPLOYMENT WAGES IN REBP COUNTIES



Notes: the figure displays for REBP regions the relationship between experience in the past 25 years at the beginning of unemployment spell and reemployment wages for workers aged 50 to 54. Workers with more than 15 years of experience are eligible for REBP extensions while workers with less than 15 years are not eligible. We follow the methodology of Schmieder, von Wachter and Bender [2012*a*] and estimate RD effects of the extensions controlling for duration by adding a rich set of dummies for the duration of the spell prior to finding the job. $E[Y|E=e] = \sum_{p=0}^{\bar{p}} \gamma_p (a-k)^p + \nu_p (a-k)^p \cdot \mathbb{1}[E \geq k] + \sum_{t=0}^{T} \mathbb{1}[D=t]$, where Y is real reemployment wage, E is experience at the beginning of the unemployment spell, $k = 15$ is the experience eligibility threshold, and D is the duration of the unemployment spell prior to finding the new job. The graph plots the predicted values of this regression for all non REBP years and for all REBP years using a 3rd order polynomial for the regressions.