# Temporary and Permanent Layoffs and Time Series of Job Creation, Job Destruction and Unemployment

Ricardo Nieva

University of Minnesota March 2001

Layoffs and recalls are an empirically important source of worker flows in the U.S. manufacturing sector. Besides, the Mortensen and Pissarides model is claimed to match the statistics of Job Creation, Job Destruction and Unemployment provided that the unemployment hazard is low. I extend this model in order to account for the simultaneous existence of permanent and temporary layoffs and to find out if the implied lower probability of leaving permament unemployment dominates the high recall rate of temporary layoffs. In order to do this I modify their matching model so as to assume that employment matches are subject to two types of idiosyncratic shocks: one which is persistent and the other which is purely temporary. I endogenize both the decision of permanent and temporary layoffs. Loosely speaking, bad realizations of the temporary shock will lead to temporary layoffs whereas bad realizations of the persistent shock will lead to permanent layoffs. The model does a fairly good job explaining various empirical regularities of the empirical data on manufacturing. The reason it produces a positive correlation between Job Creation and Job destruction might be related to the inability of the model to reproduce the richness in the dynamics of the temporary unemployment hazard rate pointed out in other in other data. The bounching of recalls around unemployment benefits elapse around the end of the second quarter might generate a slow adjustment of job creation at the onset of a recession. Hence a negative correlation between creation and destruction would be generated.

### 1 Introduction

Job and worker flows are very large in the U.S. economy. Davis et al.(1996) gives empirical evidence of the close relationship between unemployment flows and the unemployment rate. Because of this relationship, the flow approach to labor markets has become increasingly popular as a way to analyze the aggregate labor market. One of the most widely used models that has been developed is the Mortensen and Pissarides matching model of job creation and destruction (1994). One feature of the Mortensen and Pissarides model is that all separations are assumed to be permanent. However, Lilien(1980) and Feldstein(1975) conclude that over 70% percent of workers laid off in U.S. manufacturing were recalled by their former employers. Katz(1986) finds this process to be common outside manufacturing, as well. Anderson and Meyer (1994) also calculate that 28% of all turnover is temporary(defined as temporary layoffs plus recalls). Additionally, the Mass Layoff Statistics program reports that 68% of employers reporting a layoff in the second quarter of 1998 had anticipated some type of recall. In this same report, among all establishments expecting a recall, most employers expected to recall over one-half of the separated employees within six months (U.S. bureau of labor Statistics, October 1998). Finally, Feldstein points out that fluctuations of temporary layoffs are tied to firms' output demand fluctuations. Given the importance of temporary layoffs in the real world, it is clearly important that our models be consistent with their significance if they are to help us understand how the labor market responds to various types of shocks or changes in policies.

Additionally the standard matching model is claimed to match the statistics of Job Creation, Job Destruction and Unemployment provided that the probability of leaving unemployment is lower than the one found in the data(Rogerson and Cole 1996). Intuitively the latter would produce persistence and a negative correlation between Job Creation and Destruction. This would happen because the consequent slow adjustment of the labor market would make persistent the opposite response that this series have when the economy is hit by aggregate shocks. It is then an empirical question if the effect of a high recall rate is dominated by a lower permanent unemployment hazard implied by introducing temporary layoffs.

Hence we extend the model of Mortensen and Pissaridesfor two reasons.

First in order to account for the simultaneous existence of permanent and temporary layoffs. Second to check if for reasonable parameter values the lower permanent hazard rate implied by introducing temporary layoffs dominates the effect of of higher recall rate on the series of Job Creation, Job Destruction and Unemployment.

In order to do this I modify their model so as to assume that employment matches are subject to two types of idiosyncratic shocks: one which is persistent and the other which is purely temporary. I assume that a matched worker and entrepreneur may choose to remain matched even if they do not produce, though doing so entails incurring a cost to maintain the match. I will identify this with a temporary layoff. I then go on to characterize the equilibrium for this extended matching model, and in particular the circumstances in which permanent and temporary layoffs will result. Loosely speaking, bad realizations of the temporary shock will lead to temporary layoffs, whereas bad realizations of the persistent shock will lead to permanent layoffs. I also show how the equilibrium of the model can be determined as the intersection of two equations in two unknowns. This greatly facilitates understanding the model's implications for various changes in the economy.

Finally using the series for Job Creation Destruction and unemployment implied by our model, the latter steady state is calibrated to the U.S. manufacturing Data and then a stochastic version is simulated. Given that most of the data argues that temporary layoffs are more important at a monthly level we calibrate and simulate both a quarterly and a monthly model. In the monthly model we aggregate to build up quarterly series of Job Creation and Destruction to match quarterly data presumably on temporary layoffs constructed by Davis and Haltiwanger(1992).

The model does a fairly good job explaining various empirical regularities however it produces a positive correlation between Job Creation and Job destruction. The reason behind this poor performance might be related to the inability of our setup to match the richness in the dynamics of the temporary unemployment hazard rate found in other empirical sources like Anderson and Meyer. In a context of finite duration of unemployment benefits temporary layoffs occur either the first 2 weeks or as late as in the second quarter around the last unemployment benefits paydate. Hence this pattern of recovery of employment after a recession might produce the desired negative correlation between creation and destruction provided that the effect of the recallers with low temporary hazard rate dominates.

In the following section we describe the model. Section 3 focuses on the data, the calibration of the steady and the simulation of the stochastic version of the model. In section 4 we have the conclusions. Finally, section 5 includes an appendix with the derivation of our key results.

### 2 The Model

### 2.1 The Environment

There is a continuum of identical workers with total mass equal to one with the following preferences:

$$\sum_{t=1}^{\infty} \beta^t (c_t - bn_t), \tag{1}$$

where  $0 < \beta < 1$  is a discount factor,  $c_t$  is consumption and  $n_t$  is time spent working. One can work either one or zero units. The disutility of working is measured by b and consumption can be only nonnegative. We assume that search is costless and that the workers receive payments when matched with an entrepreneur in a productive unit or match. While in a match we allow for the worker to be on temporary layoff. We further assume that there is not on the job search or search while on temporary layoff. This latter assumption is consistent with the fact that most of workers on temporary layoff are recalled by their former employees. Anderson and Meyer (1994) find that 71.7% of layoffs that expected recall were reemployed in the previous job.

There is a continuum of identical entrepreneurs with the following preferences:

$$\sum_{t=1}^{\infty} \beta^t c_t \tag{2}$$

In this economy there is a matching technology that makes entrepreneurs and workers meet and a production technology that may be used for producing output only after the two agents have been matched. We'll begin with the latter.

Production units can be set up costlessly only by entrepreneurs. A entrepreneur-worker match produces  $p + \epsilon + \iota$ . The common aggregate productivity is p. We have  $\epsilon$  and  $\iota$  as idiosyncratic shocks whose realizations are independent also across matches. Each new match starts by assumption with an idiosyncratic pair ( $\epsilon^u, \iota^u$ ), which then evolves stochastically as follows: In each period there is a probability  $\gamma$  that a given match receives a new value for its idiosyncratic  $\epsilon$  component from the cdf  $F(\epsilon)$  with support on  $(-\infty, \epsilon^u]$ . Otherwise it stays with the same value as the last period's. There is persistence in the  $\epsilon$  shocks. With respect to the  $\iota$  component, the match receives a draw every period from a distribution with cdf  $G(\iota)$  epsilon and support on  $(-\infty, \iota^u]$ . Hence the  $\iota$  shock is i.i.d.

The assumption about timing is as follows: At the end of each period a match is in one of two states, dormant(laying off its worker temporarily), or active and producing. At the beginning of a period each match which was productive or dormant in the previous period receives its current values for the idiosyncratic shocks. Given a realization of shocks there is a joint decision between the entrepreneur and the worker to decide between destroying the match, laying off temporarily or producing output. That the decision is taken jointly follows from our assumption that wages are determined by generalized Nash bargaining.

With respect to how entrepreneurs and workers meet, they become matched through a matching function that depends on the number of permanent unemployed searching workers  $u^p$  and number of vacancies (v) posted. Entrepreneurs are the only ones who can create job vacancies. It costs z to post a vacancy.

If in a given period there are v vacancies posted and  $u^p$  unmatched workers searching, the number of matches formed between entrepreneurs and workers is given by the matching function  $m(v, u^p)$ . Any matches that result from search say in period t become productive as of period t+1. The probability then that a given worker is matched with a vacant job is given by:

$$q^u = \frac{m(v, u^p)}{u^p} \tag{3}$$

and the probability that a given vacancy is matched with a searching worker is given by:

$$q^v = \frac{m(v, u^p)}{v} \tag{4}$$

We assume that the matching function m is non-negative, increasing in both arguments, concave and displays constant returns to scale. The latter implies that  $q^u$  and  $q^v$  are functions only of the ratio  $\frac{v}{u^p}$ .

Finally, following the standard literature, we use a generalized Nash bargaining solution for wage determination in which the worker's threat point is equal to the value of being unemployed and the entrepreneur's threat point is the value of an unmatched vacancy.

### 2.2 Equilibrium Analysis

In this subsection we define and characterize the equilibrium for the model. We start by examining the individual decisions taken by matched entrepreneurs and workers.

Let  $J_m(\epsilon, \iota)$  be the value of the match for the entrepreneur given current values of both of the idiosyncratic shocks. It is equal to the maximum of three components: Let  $J_a(\epsilon, \iota)$  be the value of the match for the entrepreneur if it is active and producing.  $J_d(\epsilon, \iota)$  stands for the value of the match for the entrepreneur if it is dormant or the worker is on temporary layoff. The third component is the value of destroying the match, which is equal to zero in equilibrium. The derivation of the results are simpler if we assume this condition (see below unmatched entrepreneur's decision problem and definition of equilibrium). The corresponding equations are:

$$J_m(\epsilon,\iota) = max(J_a(\epsilon,\iota), J_d(\epsilon,\iota), 0)$$
(5)

$$J_a(\epsilon,\iota) = p + \epsilon + \iota - w(\epsilon,\iota) + \beta \gamma E(J_m(.,.)) \cdots$$

$$+\beta(1-\gamma)E(J_m(\epsilon,.)/\epsilon) \tag{6}$$

$$J_d(\epsilon, \iota) = -w(\epsilon, \iota) \cdots +\beta\gamma E(J_m(., .)) + \beta(1 - \gamma)E(J_m(\epsilon, .)/\epsilon)$$
(7)

where  $E((\epsilon, .)/\epsilon)$  is the expectation of  $(\epsilon, .)$  given  $\epsilon$  and  $E(J_m(., .))$  is the expectation over the two arguments. Note that we have that the entrepreneur gives a payment to the worker on temporary layoff as is standard in the wage bargaining literature.

In the case of the worker,  $V^{mw}(\epsilon, \iota)$  is the value of the match for the worker given current values of both of the idiyosincratic shocks. It is equal to the maximum of three components: Let  $V^e(\epsilon, \iota)$  be the value of the match for the worker if employed and producing. The variable  $V^{tl}(\epsilon, \iota)$  stands for the value of the match for the worker if it is dormant or the worker is on temporary layoff. The third component is the value of destroying the match for the worker or the value of unemployment denoted as  $V^u$ . Formally we have:

$$V^{mw}(\epsilon,\iota) = max(V^{e}(\epsilon,\iota), V^{tl}(\epsilon,\iota), V^{u})$$
(8)

$$V^{e}(\epsilon,\iota) = w(\epsilon,\iota) - b + \beta\gamma E(V^{mw}(.,.)) + \beta(1-\gamma)E(V^{mw}(\epsilon,.)/\epsilon)$$
(9)

$$V^{tl}(\epsilon,\iota) = w(\epsilon,\iota) + \beta\gamma E(V^{mw}(.,.)) + \beta(1-\gamma)E(V^{mw}(\epsilon,.)/\epsilon)$$
(10)

$$V^{u} = \beta q^{u} V^{mw}(\epsilon^{u}, \iota^{u}) + \beta (1 - q^{u}) V^{u}$$

$$\tag{11}$$

$$q^u = \frac{m(v, u^p)}{u^p} \tag{12}$$

Let's define the total match surplus  $S_m(\iota, \epsilon)$  as:

$$S_m(\epsilon,\iota) = V^{mw}(\epsilon,\iota) + J_m(\epsilon,\iota) - V^u$$
(13)

The wage is set to split the surplus in fixed proportions at all times, so:

$$V^{mw}(\epsilon,\iota) - V^u = X \left[ V^{mw}(\epsilon,\iota) + J_m(\epsilon,\iota) - V^u \right]$$
(14)

where X is a constant between 0 and 1.

Since firms have the option of destroying matches at no cost, the latter exists as long as its value is above zero. Note that we are making use of the equilibrium condition which requires that the value of a destroyed match is zero to the entrepreneur. Hence matches are destroyed when the productivity pair shock  $(\epsilon, \iota)$  arises that makes  $J_m(\epsilon, \iota) = (1 - X)S_m(\epsilon, \iota)$  negative. Also it is not always optimal to layoff temporarily when the match is hit by a bad idiosyncratic shock because the opportunity cost of employment might be high enough to make the value of the surplus of a dormant match less or equal to zero. Hence the opportunity cost of employment plays the role of a fixed cost that has to be paid in terms of total surplus in order to mantain the match active or dormant.

Let suppose that  $(\epsilon, \iota)$  are such that  $S_m(\epsilon, \iota) = S_a(\epsilon, \iota)$ , then

$$S_m(\epsilon,\iota) = V^e(\epsilon,\iota) + J_a(\epsilon,\iota) - V^u + \beta q^u V^u - \beta q^u V^u$$
(15)

After manipulating we get

$$S_m(\epsilon,\iota) = S_a(\epsilon,\iota) = p + \epsilon + \iota - b + \beta \gamma E(S_m(.,.)) \cdots + \beta (1-\gamma) E(S_m(\epsilon,.)/\epsilon) - \beta q^u X S(\epsilon^u,\iota^u)$$
(16)

See appendix for derivation.

If  $(\epsilon, \iota)$  take values so that  $S_m(\epsilon, \iota) = S_d(\epsilon, \iota)$ , then

$$S_m(\epsilon,\iota) = V^{tl}(\epsilon,\iota) + J_d(\epsilon,\iota) - V^u(\epsilon,\iota) + \beta q^u V^u - \beta q^u V^u$$
(17)

After simplifying we get

$$S_d(\iota, \epsilon) = \beta \gamma E(S_m(., .)) \cdots + \beta (1 - \gamma) E(S_m(\epsilon, .)/\epsilon) - \beta q^u X S(\iota^u, \epsilon^u)$$
(18)

So we get that:

$$S_m(\epsilon,\iota) = max(S_a(\epsilon,\iota), S_d(\epsilon,\iota)), 0)$$
(19)

We can show using the standard dynamic programming arguments that there exists a unique value function  $S_m(\epsilon, \iota)$  that is nondecreasing in both of its arguments. The latter equations map the space of continuous nondecreasing bounded functions into itself given  $q^u$ . Given that this space with the supnorm is a complete normed vector space and that satisfies Blackwell's sufficient conditions for a contraction mapping, our claim holds. This is going to imply a unique characterization for the optimal decision rules for the entrepreneur in the plane  $(\epsilon, \iota)$ :

We assume that  $S_d(\epsilon, \iota)$  is positive for some value of its arguments. Intuitively note that if  $q^u$  is low enough this would be true.

To make the exposition transparent let us first analize for which values of the two idiosyncratic shocks the decision of laying off permanently would be prefered over the temporary one. First note that there exists  $\epsilon^*$  such that  $S_d(\epsilon^*, \iota) = 0$  for all  $\iota$ . This happens because as we will see soon  $E(S_m(\epsilon, .)/\epsilon)$ is strictly increasing in  $\epsilon$ . So for  $\epsilon$  greater than  $\epsilon^*$  the option of temporary layoff is positive. Hence entrepreneurs prefer temporary layoffs to permanent ones. In the plane  $(\epsilon, \iota)$  this implies that to the left of a vertical line crossing the  $\epsilon$  axis at the value  $\epsilon^*$ , the option of permanent layoff is higher than the option of temporary layoff and conversely to the left of this line.

Now we show when it is preferable to mantain the match active instead of dormant or equivalently, laying off the worker temporarily. Given  $\epsilon$  there exists  $\iota^{tl}(\epsilon)$  such that  $S_a(\epsilon, \iota^{tl}(\epsilon)) = S_d(\epsilon, \iota^{tl}(\epsilon))$ . Note that conditional on  $\epsilon$ ,  $S_a(\epsilon, \iota)$  is strictly inceasing in  $\iota$  and  $S_d(\epsilon, \iota)$  is constant. This implies after subtracting  $S_d(\epsilon, \iota)$  from  $S_a(\epsilon, \iota)$  for a given value of  $\epsilon$ :

$$\iota^{tl}(\epsilon) = -p - \epsilon + b \tag{20}$$

In the plane  $(\epsilon, \iota)$  the latter implies a diagonal. Above it  $S_a(\epsilon, \iota)$  is bigger than  $S_d(\epsilon, \iota)$ . The converse happens below it. The slope of this line is -1.

Finally we explain for which values of  $(\epsilon, \iota)$  it is preferable to mantain the match active instead of laying off permanently and viceversa. Given  $\epsilon$  there exists  $\iota^{pl}(\epsilon)$  such that  $S_a(\epsilon, \iota^{pl}(\epsilon)) = 0$ . In particular at  $\epsilon^* S_a(\epsilon^*, \iota^{pl}(\epsilon^*)) = 0$ . Also  $S_d(\epsilon^*, \iota) = 0$  for all  $\iota$  or as we discussed before at  $\epsilon^*$  the entrepreneur is indifferent between laying off permanently or temporarily when  $\iota$  is low enough. Hence at this reservation value of  $\epsilon$  the threshold for laying off permanently  $\iota^{pl}(\epsilon^*)$  is the same as the one for laying off temporarily  $\iota^{tl}(\epsilon^*)$  when the match is hit by a temporary idiosyncratic shock.

It is intuitively clear that because  $E(S_m(\epsilon, .)/\epsilon)$  is strictly increasing in  $\epsilon$ ,  $\iota^{pl}(\epsilon)$  is strictly decreasing in the same variable. We can characterize even more precisely  $\iota^{pl}(\epsilon)$ . Formally we have after solving for  $\iota^{pl}(\epsilon)$  from  $S_a(\epsilon, \iota^{pl}(\epsilon)) = 0$ :

$$\iota^{pl}(\epsilon) = -p - \epsilon + b - \beta \gamma E(S_m(.,.)) -\beta(1-\gamma)E(S_m(\epsilon,.)/\epsilon) + \beta \frac{vq^v}{u^p} XS(\iota^u, \epsilon^u)$$
(21)

Note that in the latter equation we have used the fact that  $q^u = \frac{vq^v}{u^p}$ . When differentiating with respect to  $\epsilon$  all what matters is  $-\beta(1-\gamma)E(S_m(\epsilon,.)/\epsilon)$  and  $-\epsilon$ .

if  $\epsilon \geq \epsilon^*$  we have:  $S_m(\epsilon, \iota) = S_a(\epsilon, \iota)$  if  $\iota \geq \iota^{tl}(\epsilon)$ ;  $S_m(\epsilon, \iota) = S_d(\epsilon, \iota)$  if  $\iota \leq \iota^{tl}(\epsilon)$ 

After integrating by parts over the implied ranges we get that for given epsilon:

$$E(S_m(\epsilon,.)/\epsilon) = \iota^{tl}(\epsilon) - \iota^{pl}(\epsilon) + \int_{\iota^{tl}(\epsilon)}^{\iota^u} S_{a_2}(\epsilon,y)(1 - G(y))dy$$
(22)

where  $S_{a_2}(\epsilon, y)$  is the partial derivative with respect to the second argument equal to 1 (See Apendix for details of the derivation). After differentiating the implicit function  $\iota^{pl}(\epsilon)$  with respect to  $\epsilon$ . we get:

$$\iota_{\epsilon}^{pl}(\epsilon) = -1 - \frac{\beta(1-\gamma)(1-G(\iota^{tl}(\epsilon)))}{1-\beta(1-\gamma)}$$

or using  $\iota^{tl}(\epsilon) = -p - \epsilon + b$  we have:

$$\iota_{\epsilon}^{pl}(\epsilon) = -1 - \frac{\beta(1-\gamma)(1-G(-p-\epsilon+b))}{1-\beta(1-\gamma)}$$
(23)

Hence the slope is strictly less than minus one.

if  $\epsilon \leq \epsilon^*$  and  $\iota \geq \iota^{pl}(\epsilon)$  then  $S_m(\epsilon, \iota) = S_a(\epsilon, \iota)$ . If  $\iota \leq \iota^{pl}(\epsilon)$ ,  $S_m(\epsilon, \iota) = 0$ . In this case it can be shown in an analogous way as the derivation of equation 22 that:

$$E(S_m(\epsilon,.)/\epsilon) = \int_{\iota^{pl}(\epsilon)}^{\iota^u} S_{a_2}(\epsilon,y)(1-G(y))dy$$
(24)

Using again the fact that  $S_{a_2}(\epsilon, y) = 1$  we get after differentiating 21:

$$\iota_{\epsilon}^{pl}(\epsilon) = \frac{-1}{1 - \beta(1 - \gamma)(1 - G(\iota^{pl}(\epsilon)))}$$
(25)

Note that this slope is also strictly less that -1. Also at  $\epsilon^*$  there is going to be a kink. Figure 1 summarizes the previous discussion by partioning the state space into various regions. Area 3 is the area where it is optimal to be active. In area 2, laying off temporarily is the best option and in area 1 it is better to destroy the match and to layoff permanently.

Now we can describe the unmatched entrepreneur's decision problem. As we said before entrepreneurs are the only ones who can create job vacancies. Let the value for an entrepreneur of posting a vacancy be the following:

$$V(q^{v}, \epsilon_{u}, \iota_{u}) = -z + \beta q^{v} J_{m}(\epsilon_{u}, \iota_{u})$$
(26)

Note that for the latter expression we have used the assumption that new matches begin with the highest productivity.

Entrepreneurs will post vacancies as long as the value of the vacancy is positive. As we will see later, in equilibrium, entrepreneurs who post vacancies must earn zero expected return net of their costs z.



Figure 1: Optimal decision rules in the plane (epsilon,iota)

Next we solve implicitly for  $\epsilon^*$ . As in the standard model this is going to be the key variable for showing the existence of an equilibrium. Implicitly we are claiming that if we know  $\epsilon^*$  and  $q^u = \frac{vq^v}{u^p}$ , we can derive the whole regions that characterize optimal layoff behavior. Also it can be shown that there is positive relationship between  $\epsilon^*$  and  $\iota^{pl}(\epsilon)$  for all  $\epsilon$ (see appendix(g)).

However, the interpretation of  $\epsilon^*$  is somewhat different. It will be the reservation value of the persistent  $\epsilon$  idiosyncratic shock that makes firms switch their layoff type. So firms with  $\epsilon \geq \epsilon^*$  will layoff temporarily if hit by a low temporary  $\iota$  shock. The other ones with persistent bad draws of  $\epsilon$  will instead layoff permanently if hit by a bad i.i.d.  $\iota$  shock. Define  $\epsilon^{pl}$  as the value of  $\epsilon$  such that  $\iota^{pl}(\epsilon^{pl}) = \iota^u$  (see graph). If  $\epsilon \leq \epsilon^{pl}$  firms will layoff permanently whatever value of  $\iota$ .

For deriving  $\epsilon^*$  as an implicit function of all the exogenous variables we first show that given  $\epsilon^*$ ,  $\iota^{pl}(\epsilon, \epsilon^*)$  can be found. Recall that  $\iota^{tl}(\epsilon)$  only depends on p and b.

For  $\epsilon \geq \epsilon^*$ , using equation (21) and (22), we have:

$$\iota^{pl}(\epsilon) = -p - \epsilon + b - \beta \gamma E(S_m(.,.)) -\beta(1-\gamma)(\iota^{tl}(\epsilon) - \iota^{pl}(\epsilon) + \int_{\iota^{tl}(\epsilon)}^{\iota^u} S_{a_2}(\epsilon, y)(1 - G(y))dy) +\beta \frac{vq^v}{u^p} XS(\iota^u, \epsilon^u)$$
(27)

Note that for  $\iota^{tl}(\epsilon)$  we could have used its equivalent  $-p - \epsilon + b$ . Using equation 27 let us subtract  $\iota^{pl}(\epsilon^*)$  from  $\iota^{pl}(\epsilon)$  so that we cancel out  $-\beta\gamma E(S_m(.,.))$  and  $\beta \frac{vq^v}{u^p}X$ . Hence after using using  $S_{a_2} = 1$  we get:

$$\iota^{pl}(\epsilon,\epsilon^*) - \iota^{pl}(\epsilon^*,\epsilon^*) = -\epsilon + \epsilon^* - \beta(1-\gamma)(\iota^{tl}(\epsilon) - \iota^{pl}(\epsilon,\epsilon^*) + \int_{\iota^{tl}(\epsilon)}^{\iota^u} (1-G(y))dy) + \beta(1-\gamma)(\iota^{tl}(\epsilon^*) - \iota^{pl}(\epsilon^*,\epsilon^*) + \int_{\iota^{tl}(\epsilon^*)}^{\iota^u} (1-G(y))dy)$$

But  $\iota^{pl}(\epsilon^*, \epsilon^*) = \iota^{tl}(\epsilon^*) = -p - \epsilon^* + b$ . Also given that the integrands are the same the difference of the integral from  $\iota^{tl}(\epsilon)$  to  $\iota^u$  and the integral from  $\iota^{tl}(\epsilon^*)$  to  $\iota^u$  is equal to the integral from  $\iota^{tl}(\epsilon)$  to  $-p - \epsilon^* + b = \iota^{tl}(\epsilon^*)$ . So after cancelling terms and solving for  $\iota^{pl}(\epsilon, \epsilon^*)$  we get:

$$\iota^{pl}(\epsilon,\epsilon^*) = -p - \epsilon + b - \frac{\beta(1-\gamma)}{1-\beta(1-\gamma)} \int_{\iota^{tl}(\epsilon)}^{-p-\epsilon^*+b} (1-G(y))dy$$
(28)

For  $\epsilon \leq \epsilon^*$  from 21 and 24 we get:

$$\iota^{pl}(\epsilon) = -p - \epsilon + b - \beta \gamma E(S_m(.,.)) -\beta(1-\gamma) \int_{\iota^{pl}(\epsilon)}^{\iota^u} S_{a_2}(\epsilon, y) (1 - G(y)) dy + \beta \frac{vq^v}{u^p} X S(\iota^u, \epsilon^u)$$
(29)

Using the latter equation let us subtract  $\iota^{pl}(\epsilon^*)$  from  $\iota^{pl}(\epsilon)$  so that we cancel out  $-\beta\gamma E(S_m(.,.))$  and  $\beta \frac{vq^v}{u^p}X$ . Hence after using using  $S_{a_2} = 1$  we get:

$$\iota^{pl}(\epsilon,\epsilon^*) - \iota^{pl}(\epsilon^*,\epsilon^*) = -\epsilon + \epsilon^* - \beta(1-\gamma) \int_{\iota^{pl}(\epsilon)}^{\iota^u} (1-G(y)) dy + \beta(1-\gamma) \int_{\iota^{pl}(\epsilon^*)}^{\iota^u} (1-G(y)) dy$$

But  $\iota^{pl}(\epsilon^*, \epsilon^*) = \iota^{tl}(\epsilon^*) = -p - \epsilon^* + b$ . Also given that the integrands are the same the difference of the integral from  $\iota^{pl}(\epsilon)$  to  $\iota^u$  and the integral from  $\iota^{pl}(\epsilon^*)$  to  $\iota^u$  is equal to the integral from  $-p - \epsilon^* + b = \iota^{pl}(\epsilon^*, \epsilon^*)$  to  $\iota^{pl}(\epsilon, \epsilon^*)$ . So after cancelling terms and solving for  $\iota^{pl}(\epsilon, \epsilon^*)$  we get:

$$\iota^{pl}(\epsilon,\epsilon^*) = -p - \epsilon + b + \beta(1-\gamma) \int_{-p-\epsilon^*+b}^{\iota^{pl}(\epsilon,\epsilon^*)} (1 - G(y)) dy$$
(30)

Note that now  $\iota^{pl}(\epsilon, \epsilon^*)$  depends also on  $\epsilon^*$ . This latter variable enters in the upper and lower bound of the definite integral in the right side of equation 28.

In conclusion, if we know  $\epsilon^*$  and  $q^u = \frac{vq^v}{u^p}$ , we can derive the whole regions that characterize optimal layoff behavior in a unique way. Note that  $\iota^{pl}(\epsilon, \epsilon^*)$  has now two arguments. This is not the case for  $\iota^{tl}(\epsilon)$ .

Now we solve for  $\epsilon^*$  as an implicit function of all the exogenous variables. Note that at  $\epsilon^*$ ,  $\iota^{tl}(\epsilon^*) = \iota^{pl}(\epsilon^*)$  and  $S_m(\epsilon^*, \iota(\epsilon^*)) = S_a(\epsilon^*, \iota(\epsilon^*)) = S_d(\epsilon^*, \iota(\epsilon^*)) = 0$ , hence:

$$0 = \beta \gamma E(S_m(.,.)) + \beta (1-\gamma) \int_{-p-\epsilon^*+b}^{\iota^u} S_{a_2}(x,y)(1-G(y))dy -\beta \frac{vq^v}{u^p} X S(\epsilon^u,\iota^u)$$
(31)

So we need to solve  $E(S_m(.,.))$  and  $S(\epsilon^u, \iota^u)$  in terms of  $\epsilon^*$ . For the case of  $E(S_m(.,.))$  we have:

$$E(S_m(.,.)) = \int_{-\infty}^{\epsilon^{p^l}(\epsilon^*,\iota^u)} \int_{-\infty}^{\iota^u} 0 dy dF(x) + \int_{\epsilon^{p^l}(\epsilon^*,\iota^u)}^{\epsilon^*} \int_{\iota^{p^l}(x,\epsilon^*)}^{\iota^u} S_{a_2}(x,y)(1-G(y)) dy dF(x) + \int_{\epsilon^*}^{\epsilon^u} \iota^{tl}(x) - \iota^{pl}(x,\epsilon^*) + \int_{\iota^{tl}(x)}^{\iota^u} S_{a_2}(x,y)(1-G(y)) dy dF(x)$$
(32)

Note that we have used the definition of  $S_m(\epsilon, \iota)$  and equations (29) and (30). This expression could we simplified if we use the fact  $S_{a_2}(\epsilon, y) = 1$ .

The only term that we don't know is  $\epsilon^{pl}(\iota^u)$  that is the value given  $\iota = \iota^u$ , such that  $S_m(\epsilon^{pl}, \iota^u) = S_a(\epsilon^{pl}, \iota^u) = 0$ . To get this value first note that the latter implies using equation 24:

$$0 = S_m(\epsilon^{pl}, \iota^u) = S_a(\epsilon^{pl}, \iota^u) =$$

$$p + \epsilon^{pl} + \iota^u - b + \beta \gamma E(S_m(., .))$$

$$+\beta(1 - \gamma) \int_{\iota^{pl}(\epsilon^{pl}, \epsilon^*) = \iota^u}^{\iota^u} (1 - G(y)dy - \beta q^u X S(\epsilon^u, \iota^u)$$
(33)

Also at  $\epsilon^*$  and at  $\iota^{pl}(\epsilon^*, \epsilon^*) = \iota^{tl}(\epsilon^*)$  we have:

$$0 = S_m(\epsilon^*, \iota^{tl}(\epsilon^*)) = S_a(\epsilon^*, \iota^{tl}(\epsilon^*)) = S_d(\epsilon^*, \iota^{tl}(\epsilon^*)) =$$

$$p + \epsilon^* + \iota^{pl}(\epsilon^*) - b + \beta\gamma E(S_m(., .))$$

$$+\beta(1-\gamma) \int_{\iota^{pl}(\epsilon^*, \epsilon^*)}^{\iota^u} (1 - G(y)) dy - \beta q^u X S(\epsilon^u, \iota^u)$$
(34)

Substracting the latter equation from the former and rearranging we get:  $\epsilon^{pl}$  as a function of  $\epsilon^*$ 

$$\epsilon^{pl}(\epsilon^*, \iota^u) = -p - \iota^u + b + \beta(1 - \gamma) \int_{-p - \epsilon^* + b}^{\iota^u} (1 - G(y)) dy$$
(35)

Finally, using the zero profit condition for the value of posting a vacancy, we get that  $J_m(\iota, \epsilon) = \frac{c}{\beta q^v}$ . Additionally,  $J_m(\iota, \epsilon) = (1 - X)S(\iota, \epsilon)$ . Hence we get that  $-\beta \frac{vq^v}{u^p}S(\iota^u, \epsilon^u)X = -\frac{Xc}{1-X}\frac{v}{u^p}$ . So we get an inplicit function of  $\epsilon^*$  for given  $\frac{v}{u^p}$ . We will call this as in standard in the literature, the Job Destruction condition. It can be shown that this equation is strictly increasing in  $\frac{v}{u^p}$  (See Appendix for the sign of the partial derivative of  $\epsilon^*$  with respect to  $\frac{v}{u^p}$ ).

The Job Creation curve is going to give us the second equation to solve for  $\frac{v}{u^p}$  and  $\epsilon^*$ . Note that

$$S_m(\epsilon^u, \iota^u) - S_m(\epsilon^*, \iota^{tl}(\epsilon^*)) = \epsilon^u + \iota^u + \frac{\beta(1-\gamma)}{1-\beta(1-\gamma)} \int_{-p-\epsilon^u+b}^{-p-\epsilon^*+b} (1-G(y)) dy (36)$$

Hence, after using the zero profit condition and  $J_m(\iota, \epsilon) = (1 - X)S(\iota, \epsilon)$ we get to:

$$q^{v}\left(\frac{v}{u^{p}}\right) = \frac{z}{\beta(1-X)\left(S_{m}(\epsilon^{u},\iota^{u}) - S_{m}(\epsilon^{*},\iota(\epsilon^{*}))\right)}$$
(37)

It is clear that in this latter equation "the Job Creation condition"  $\frac{v}{u^p}$  is strictly decreasing in  $\epsilon^*$  (see appendix). A solution for these two variables is given in figure 2 by the intersection of destruction and creation equation in the plane  $(\epsilon^*, \frac{v}{u^p})$ .

The latter analysis greatly facilitates understanding the model's implications for various changes in the economy. The effect of a higher value of the aggregate productivity component in the economy, p, can be decomposed in its effects on  $\epsilon^*$  and  $\frac{v}{u^p}$  through its effects on the Job Destruction and Job creation curve.

As we explain in the appendix(d) a higher p shifts the job destruction curve to the left or decreases  $\epsilon^*$ . This happens because now the surplus of any match is higher for given  $\frac{v}{u^p}$ . This implies a lower reservation value of the persistent  $\epsilon$  idiosyncratic shock that makes firms switch their layoff type in good times. Figure 2: Joint determination of v/u and epsilon\*



This implies a lower reservation value of the persistent  $\epsilon$  idiosyncratic shock that makes firms switch their layoff type in good times. However the Job Creation curve shifts to the right because now new maches are more productive, hence the only way to prevent more vacancy posting so that to hold  $\frac{v}{u^p}$  constant in equation 36 is to make more probable the decision to layoff permanently that temporarily through a higher  $\epsilon^*$ . So the final effect on the latter variable is undetermined. Following an analogous argument  $\frac{v}{u^p}$ goes up. When we calibrate in the empirical section the model to the US data  $\epsilon^*$  is countercyclical but almost constant to changes in p. The last thing to analyze would be the final effect on  $\iota^{pl}$  that together with  $\epsilon^*$  characterize completely the optimal decision rules given the current values of the two idiosyncratic shocks. A way to facilitate this analysis is using the claim that given the structural parameters and  $\frac{v}{u^p}$  we can determine uniquely  $\iota^{pl}$  through  $\epsilon^*$ . So if in the US economy changes in p almost don't affect  $\epsilon^*$  then the effect on  $\iota^{pl}$  depends only on the partial derivative of  $\iota^{pl}$  with respect to p as defined in equations 27 and 28 for all  $\epsilon$ . In the appendix(g) we show that  $\iota_p^{pl}$  is negative. Hence for the US economy our model implies countercyclicality in job reallocation and also in temporary layoffs. Both implications are consistent with the data (Feldstein 1975)

A higher value of  $\gamma$  shifts the creation curve to the left. In the Appendix(e) we show that the effect on the destruction curve is undetermined. Hence  $\epsilon_{\gamma}^{*}$  and  $\frac{v}{u^{p}\gamma}$  are undetermined. However The Job Destruction curve shifts to the left for the US economy(see appendix). So  $\epsilon_{\gamma}^{*}$  is negative for the US economy.  $\frac{v}{u^{p}\gamma}$  is also negative for the calibrated model.

'Finally an increase in z shifts the destruction curve to the right and the creation curve to the left.  $\frac{v}{u^p c}$  is negative however  $\epsilon_z^*$  is undetermined. For the calibrated model this derivative is negative(see appendix(f))

To define an equilibrium we need to describe the laws of motion for permanent and temporary unemployment. We need first to define two measures, one for active matches and another one for dormant matches. Let  $\phi_t^1$  be the beginning of period t distribution of pairs  $(\epsilon, \iota)$  across prexisting active matches after new realizations but before exit decisions.  $\phi_t^2$  is defined analogously for the case of prexisting dormant matches. Let  $NM_t$  be the mass of new matches formed last period. Recall that any matches that result from the search in period t-1 become productive as of period t. Hence, if there are  $u_{t-1}^p$  permanent unemployed workers in period t and  $v_{t-1}$  vacancies posted,

then the law of motion for  $u_t^p$  is given by:

$$u_t^p = \lambda_t^{p_1}(\phi_t^1) + \lambda_t^{p_2}(\phi_t^2) + u_{t-1}^p - u_{t-1}^p \frac{m(u_{t-1}^p, v_{t-1})}{u_{t-1}^p}$$
(38)

where the last term in the right hand side corresponds to  $NM_t$ .  $\lambda_t^{p_1}$  is the amount of job destruction in period t that goes to permanent unemploment(or prexisting active matches that given their new shocks are destroyed at the beginning of period t) as a function of  $\phi_t^1$ . The term  $\lambda_t^{p_2}$  stands for the additional flow to permanent unemployment coming from dormant matches that given their new shocks are destroyed. Note that job destruction is not a constant fraction of matches that are active in a given period as in the standard matching model. According to our assumptions, a fraction  $\gamma$  of active matches receives new draws from each of the two shocks distributions and have a specific probability of destroying the match. However, a fraction  $(1 - \gamma)$  stays with the same  $\epsilon$  shock and depending on this specific value they are going to have different probabilities of getting destroyed. The latter implies that the amount of destruction depends both on  $\epsilon$  and the mass of preexisting active matches that had that same  $\epsilon$  in the previous period. In our model the Job Destruction rate is not a constant fraction of preexisting active matches.

For the case of temporary unemployed workers  $u_t^t$  we have:

$$u_t^t = \lambda_t^t(\phi_t^1) + u_{t-1}^t - r_t(\phi_t^2) - \lambda_t^{p_2}(\phi_t^2)$$
(39)

where  $\lambda_t^t$  is the amount of job destruction in period t that goes to temporary unemployment (or active matches that given their new shocks are chosen to be dormant) as a function of  $\phi_t^1$ . The amount of recalls is denoted by r as a function of the measure of matches that were on temporary layoff. Finally  $\lambda_t^{p^2}$  is the amount of dormant matches that after new shocks are chosen to be destroyed, as a function of  $\phi_t^2$ .

Unemployment in a given period,  $u_t$ , is going to be the sum of  $u_t^p$  and  $u_t^t$ . Formally: Let  $\phi$  be equal to the sum of  $\phi^1$  and  $\phi^2$ .

$$u_t^p = 1 - NM_t - \int_{-\infty}^{\epsilon^u} \int_{\iota^*(\epsilon)}^{\infty} d\phi_t(x, y)$$
(40)

$$u_t^t = \lambda_t^t(\phi_t^1) + \int_{\epsilon^*}^{\epsilon^u} \int_{-\infty}^{\iota^*(\epsilon)} d\phi_t^2(x, y)$$

$$\tag{41}$$

$$\lambda_t^{p1} = \int_{-\infty}^{\epsilon^*} \int_{-\infty}^{\iota^*(\epsilon)} d\phi_t^1(x, y) \tag{42}$$

$$\lambda_t^{p_2} = \int_{-\infty}^{\epsilon_*} \int_{-\infty}^{\iota^*(\epsilon)} d\phi_t^2(x, y) \tag{43}$$

$$\lambda_t^t = \int_{\epsilon_*}^{\epsilon_u} \int_{-\infty}^{t^*(\epsilon)} d\phi_t^1(x, y)$$
(44)

$$r_t = \int_{-\infty}^{\epsilon^u} \int_{\iota_*(\epsilon)}^{\infty} d\phi_t^2(x, y)$$
(45)

Finally, the amount of Job Destruction (JD) is going to be given by the mass of matches that become destroyed plus the mass of matches in which the entrepreneur decides to layoff the worker temporarily. The latter source only makes sense if the match in the previos period was active.

The amount of Job Creation (JC) is going to be given by new matches and recalls (dormant matches in the previous period that decide to produce in the following period).

Formally we have:

$$JD_t = \lambda_t = \lambda_t^{p_1} + \lambda_t^t \tag{46}$$

$$JC_t = y_{t-1}u_{t-1}^p + r_t (47)$$

#### 2.2.1 Definition of Equilibrium

We are ready to define an equilibrium in this economy; An equilibrium is a list  $\{NM_t\}, \{\phi_t^1\}, \{\phi_t^2\}, \{u_t^p\}, \{u_t^t\}, \{v_t\}, \text{functions } J_m(\epsilon, \iota), J_a(\epsilon, \iota), J_d(\epsilon, \iota), V^{mw}(\iota, \epsilon), V^e(\iota, \epsilon), V^{tl}(\iota, \epsilon)), V^u, V(q^v, \epsilon_u, \iota_u), \iota^{pl}(\epsilon), \iota^{tl}(\epsilon) \text{ and a number } \epsilon^* \text{ s.t:}$ a) $J_m(\epsilon, \iota) = max(J_a, J_d, 0)$ 

b)
$$V^{mw}(\iota, \epsilon) = max(V^e(\iota, \epsilon), V^{tl}(\iota, \epsilon), V^u)$$

c) $\epsilon^*, \iota^{pl}(\epsilon), \iota^{tl}(\epsilon)$  are optimal decisions rule for exiting, laying off temporarily or permanently.

d) $V(q^v, \epsilon_u, \iota_u) = -z + \beta q^v J_m(\epsilon_u, \iota_u)$ e) $V(q_t^v, \epsilon_u, \iota_u) = 0$  for all t. f) $V^{mw}(\epsilon, \iota) - V^u(\epsilon, \iota) = X(V^{mw}(\epsilon, \iota) + J_m(\epsilon, \iota) - V^u(\epsilon, \iota))$ 

g) $\phi_{t+1}^1 \phi_{t+1}^2$ ,  $u_{t+1}^p$  and  $u_{t+1}^t$  are consistent with  $\phi_t^1 \phi_t^2$ ,  $u_t^p$  and  $u_t^t$  respectively and the stochastic structure.

A Stationary Equilibrium is an equilibrium such that  $NM_{t+1}$  is equal to  $NM_t$ ,  $\phi_{t+1}^1$  equal  $\phi_t^1$  and  $\phi_{t+1}^2$  equal  $\phi_t^2$  for all t.

### 2.3 Model with agregate shocks

In what follows we study an equilibrium in which wages depend only upon the aggregate technologically shock and not on the level of permanent unemployment. For an easy proof in a simple model see Rogerson, Cole(1996).

We assume that  $p_t$  is an aggregate technology shock that follows a symmetric two state markov chain in which  $l(=l_{11} = l_{22})$  with the probability of remaining in the same state for two consecutive periods. We assume that  $p_1 > p_2$ , being  $p_1$  the good state.

The respective Bellman equation for the total match surplus is now defined of terms of value functions that depend not only on the two idiosyncratic shocks but on the aggregate productivity compontent p. For details of derivation see appendix:

$$S_m(p_j,\iota,\epsilon) = max(S_a(p_j,\iota,\epsilon), S_d(p_j,\iota,\epsilon), 0)$$
(48)

for j = 1, 2 where

$$S_{a}((p_{j}\iota,\epsilon) = p_{j} + \epsilon + \iota - b + \sum_{i=1}^{2} l_{ji}(\beta\gamma E(S_{m}(p_{i},\iota,\epsilon))) + \beta(1-\gamma)E(S_{m}(p_{i},\iota,\epsilon)/\epsilon) - \beta q_{j}^{u}XS(p_{i},\iota^{u},\epsilon^{u}))$$
(49)

$$S_d(p_j, \iota, \epsilon) = \sum_{i=1}^2 l_{ji}(\beta \gamma E(S_m(p_i, \iota, \epsilon))) + \beta(1-\gamma)E(S_m(p_i, \iota, \epsilon)/\epsilon) - \beta q_j^u XS(p_i, \iota^u, \epsilon^u))$$
(50)

for j = 1, 2.

Numerical results indicate that the comparative statics of changes in the aggregate productivity component are robust when these are anticipated.

The definition of equilibrium for the stochastic version follows directly in the same way as before with additional value functions contingent upon a vector  $(p_j, \epsilon, \iota)$ .

#### 2.3.1 Definition of Equilibrium with Aggregate Shocks

An Recursive Competitive Equilibrium is a list functions  $u^p(p_j, \phi^1, \phi^2)$ ,  $u^t(p_j, \phi^1, \phi^2)$ ,  $v(p_j, \phi^1, \phi^2)$ ,  $NM(p_j, \phi^1, \phi^2)$ ,  $q^u(p_j, \phi^1, \phi^2)$ ,  $q^v(p_j, \phi^1, \phi^2)$ ,  $w(p_j, \epsilon, \iota, \phi^1, \phi^2)$ ,  $J_m(p_j, \epsilon, \iota, \phi^1, \phi^2)$ ,  $J_a(p_j, \epsilon, \iota, \phi^1, \phi^2)$ ,  $J_d(p_j, \epsilon, \iota, \phi^1, \phi^2)$ ,  $V^{mw}(p_j, \iota, \epsilon, \phi^1, \phi^2)$ ,  $V^e(p_j, \iota, \epsilon, \phi^1, \phi^2)$ ,  $V^{tl}(p_j, \epsilon, \iota, \phi^1, \phi^2)$ ,  $V^u(p_j, \iota, \phi^1, \phi^2)$ ,  $V(p_j, q^v, \epsilon_u, \iota_u, \phi^1, \phi^2)$ ,  $\iota^{pl}(p_j, \epsilon, \iota, \phi^1, \phi^2)$ ,  $\iota^{tl}(p_j, \epsilon, \iota, \phi^1, \phi^2)$ , a number  $\epsilon^*(p_j, \phi^1, \phi^2)$  and  $T(p_j, \phi^1, \phi^2)$  for j=1,2 such that: a)(Optimization) Taking the functions  $q^u(p_j, \phi^1, \phi^2)$ ,  $q^v(p_j, \phi^1, \phi^2)$ ,  $w(p_j, \epsilon, \iota, \phi^1, \phi^2)$  as given  $J_m(p_j, \epsilon, \iota, \phi^1, \phi^2)$ ,  $V^{mw}(p_j, \iota, \epsilon, \iota, \phi^1, \phi^2)$  satisfy the appropiate Bellman equations.

b)(Optimal decision rules)  $\epsilon^*(p_j), \iota^{pl}(p_j, \epsilon), \iota^{tl}(p_j, \epsilon)$  are optimal decisions rule for exiting, laying off temporarily or permanently.

c)(Free Entry)  $0 = -z + \beta q^v(p_j, \phi^1, \phi^2) \sum_{i=1}^2 l_{ji} J_m(p_i, \epsilon^u, \iota^u, \phi^{1'}, \phi^{2'})$  for all  $(p_j, \phi^1, \phi^2)$ , where  $(p_j, \phi^{1'}, \phi^{2'})$  is next period's value for the aggregate state variables.

f)(Bargaining)  $V^{mw}(p_j, \epsilon, \iota, \phi^1, \phi^2) - V^u(p_j, \epsilon, \iota, \phi^1, \phi^2) =$ X  $(V^{mw}(p_j, \epsilon, \iota, \phi^1, \phi^2) + J_m(p_j, \epsilon, \iota, \phi^1, \phi^2) - V^u(p_j, \phi^1, \phi^2))$ for j=1,2

g)(Rational Expectations) For each  $(p_j, \phi^1, \phi^2)$  and when appicable for each  $(\iota, \epsilon)$ , decisions generate a distribution over next period's state which is equal to the distribution given by  $T(p_i, \phi^1, \phi^2)$ 

In this section we have formulated a matching model in which temporary and permanent layoffs exist simultaneously. The key issue in obtaining this result is to assume that individual employment matches are subject to two shocks, one of which is persistent and one of which is not. Low values of the persistent shocks will lead to permanent separations whereas low values of the temporary shock will lead to temporary layoffs. In the subsequent sections I will use this model to carry out a quantitative analysis of labor market dynamics.

### 3 Empirical Analysis

### 3.1 The Data

We use the same data as Cole and Rogerson(1996) based on Davis Haltiwanger and Shuh(1996) work. We use as an employment measure the citybase series for workers on payroll for the manufacturing sector(1972:2-1988:4). Job creation and job destruction series are based on quarterly employment information using the following definitions. 1)Job creation in period t  $(JC_t)$ : Sum of all employment gains at establishments experiencing positive net employment gains between t-1 and t.2)Job destruction in period t  $(JD_t)$ :Sum of all employment losses at establishments experiencing negative net employment gains between t-1 and t. These series are linked through the following definition:

$$e_t - e_{t-1} = JC_t - JD_t \tag{51}$$

where  $e_t$  is the employment at the time t. In our first table we present a summary statistics that were constucted after adjusting the data seasonally and filtering.

In the second table we present a larger set of facts that would have to be matched when introducing temporary layoffs. First note that series of job destruction and creation for longer horizons than one quarter are presented. These are redefined series of job creation and destruction that result from requiring that deletions or additions to payroll persist for some specified horizon.

For matching the importance of temporary layoffs we would have to match a 25% decrease in the mean of Job Destruction that results when we go from the series of horizon zero to horizon one. Our model could not account for the respective 25% decrease in the mean of Job Creation.

We will use two versions of our model. In one version periods are quarters. We will call this the non aggregated model. It is straightforward to check that the definition of the variables we study in the data have their consistent counterpart in the first version of the model. In the second version periods will be months and we will aggregate to build up quarterly series of Job Creation and Destruction. The procedure is explained in the appendix. As we pointed out in the introduction the latter version is the most relevant one given that temporary layoffs are more important at a monthly level.

### **3.2** Calibration of the steady state

For the calibration of the steady state to the U.S. facts we assume that the idiosyncratic shock  $\epsilon$ 's distribution F is taken to be uniform over the interval [-e,e], being e a positive number. Analogously G is uniform over[-i,i]. The matching function chosen is  $Au^{\theta}v^{1-\theta}$ , so the unemployment elasticity is equal to  $\theta$ . Using the zero profit the job matching rate per searching worker in equilibrium is given by:

$$q^{u} = A\left(\frac{A\beta J_{m}(p_{i}, \epsilon^{u}, \iota^{u})}{z}\right)^{\frac{1-\theta}{\theta}}$$
(52)

For the quarterly model the parameters were chosen as follows. The value of  $\theta$  is set to be 0.5, midway between the estimate of Blanchard and Diamond(1989) using U.S data and that of Pissarides(1986) from U.K. data. The quarterly discount factor is set to be 0.99. For lack of information the bargaining power parameter X was set to 0.5. The other parameters were set so as to match the following facts in the U.S. data:

1) The support of  $\iota$  i=.16 matches approximately a decrease of 25% in the mean of job destruction when we don't consider deletions to payroll that are reversed after one quarter(actual value matched in the quarterly model is 23%).

2)  $\gamma = .3$  would match a job destruction rate of .55 (actual.0511)

3) The support of  $\epsilon = .02$  matches a 8.5% level of manufacturing unemployment.

4) The cost of posting a vacancy, z=.544 would be consistent with the fraction .4615 of the value of the most productive job that is spent on advertizing costs(Millard and Mortensen 1996).

5)The scale parameter of the matching function A would be chosen so as to match an average duration of an unemployment spell of 1.667 quarters or equivalently an average unemployment hazard of .6 as in the data. This average duration was obtained in our model through a weighted average of the permanent unemployment hazard rate and the temporary hazard rate. The weights are given by the steady state values of permanent and temporary unemployment respectively (For the calculation of the temporary hazard rate see below). The value obtained is 1.27. Note that in the monthly model we choose A to match the average duration of a vacancy. We don't do the same in the quartely model because this duration is empirically less than one quarter.

6)The value of leisure was set equal to .86 in so as to match the variability of unemployment in the stochastic simulation of the model to the US data.

Finally p, the common worker productivity, was the numeraire set equal to 1.

The implied quarterly temporary unemployment hazard was .9506 or 1.052 quarters duration of a temporary unemployment that is somewhat consistent with the data of Anderson and Meyer. Actually their data might not be comparable with the quarterly model because the rates they calculate are weekly hazard rates. They would take into account in calculating these rates unemployment spell of less than one quarter that would not be taken into account into our quarterly model. A better framework for comparison, although still not quite accurate, would be our monthly model.

The rate in our quarterly model was calculated as the percentage of temporary layoffs in one quarter that is recalled the next one. The corresponding population permanent unemployment hazard is .5411. In our calibrated model of 8.5% of unemployment 15.06% was temporary and the rest was permanent.

For the agggregated model the parameters were chosen as follows: As before the value of  $\theta$  is set to be 0.5, the monthly discount factor is set to be 0.9975. Again the bargaining power parameter X was set to 0.5. The other parameters were set so as to match the following facts in the U.S. data:

1) The support of  $\iota$  .188 matches approximately a decrease of 25% in the mean of job destruction when we don't consider deletions to payroll that are reversed after one quarter. See appendix for the aggregation of the series of job creation and destruction from the monthly model.

2)  $\gamma = .0293$  would match a proximately a quarterly job destruction rate of .55.

3) The support of  $\epsilon$  e=.046 matches approximately a 8.5% level of manufacturing unemployment.

4) The cost of posting a vacancy, z=.57 would be consistent with the fraction .4615 of the value of the most productive job that is spent on advertizing

costs(Millard and Mortensen 1996).

5) The scale parameter of the matching function A would be chosen so as to match an average duration of a vacancy of 45 days that implies a monthly  $q^{v}$ =.666. We obtained A=.345.

6)The value of leisure was set equal to .85 so as to match the variability of unemployment in the stochastic simulation of the model to the US data

Again p, the common worker productivity, was the numeraire set equal to 1.

The implied monthly temporary unemployment hazard was .9382 aproximately a month and three days or .365 quarters. The temporary unemployment hazard rate was calculated as the percentage of temporary layoffs in one month that is recalled the next one. According to this results the monthly model does not a good job in matching its empirical counterpart at least in Anderson and Meyer(1994) calculations when they refer to the average duration of unemployment spells that end in recall. Note as we said before that this comparison is not that accurate because the hazard rates the authors calculate are weekly. The data they use is taken from workers claiming unemployment insurance. So the beginning and end of a spell is associated with the date at which benefits were received, claimed or actually begun according to the worker response (3 measures of spell) and the last date this payments were received .In the paper one can find 8 weeks to be the average duration for spells ending in recall. However we add two weeks because the measure of spell used for this calculation was the one that considers the beginning of a spell the time at which benefits were claimed; but in average it takes two weeks to present the claim.

When we go from a quarterly model to a monthly model we are really changing the persistence of the "temporary" shock from three months to one month. As a result it is much harder to get temporary layoffs to last very long. More generally what we could consider is a model with two shocks that have differing persistence. We have chosen the special case where one of the shocks has no persistence in order to keep the computations more tractable. But in general one could consider the more general case in which case one could get higher temporary layoff durations in the monthly model.

Among other results we got that the corresponding permanent monthly unemployment hazard,  $q^u$ , is .1743 or a permanent unemployment spell of 1.83 quarters consistent with the Anderson and Meyer measures of new job finding rate. Note that in this case our model and the mentioned authors' measures are comparable. The implied average duration of an unemployment spell was 3.14 months or aproximately 1 quarter. Finally of 8.5% of unemployment 16.34% was temporary and the rest was permanent.

#### 3.3 Simulations

For the simulations we assume that  $p_t$  is an aggregate technology shock that follows a symmetric two state markov chain in which  $l(= l_{11} = l_{22})$  is the probability of remaining in the same state for two consecutive periods. We assume that  $p_1 > p_2$ , being  $p_1$  the good state. See Appendix for formal derivation of the respective functional equations.

The probability of remaining in the same state for two consecutive periods 111 would be set equal to .973 and .985 for the non aggregated and aggregated model respectively. The size of the shock, pd, was set equal to .012 in both models, where p1=p+pd,p2=pd-pd. This numbers were obtained after simulating and taking logs of quarterly productivity values using a monthly two state symmetric markov chain with productivity values equals to p1 and p2. Given p arbitrarily, in our case equal to one, 111 and pd were chosen so as to match the autocorrelation and standard deviation of logged USA quarterly labour poductivity from 1947 to 1991(Mortensen and Pissarides 1994). Quarterly productivity in the aggregated model was set equal to the average productivity of the respective 3 month productivity draws.

To obtain statistics we simulate the aggregated model for 1500 months that are equivalent to 500 quarters. For the non aggregated model we simulate the model for only 500 periods where one period equals one quarter. Then we compute the quarterly series of creation and destruction as defined in equations 42 and 43 and as explained in the appendix for the aggregated model. We discard the first 100 observations and then logged and filtered (Hoedrick and Presscott) the series consisting of 400 observations.

For comparison we also present the results for the standard quarterly matching model reported by Rogerson and Cole(1996). We also present results when we used our quarterly model setting parameters so as not to have temporary layoffs. For the latter benchmark model we set the support of the iid idiosyncratic shock such as to match no temporary layoffs(i=.1315) in steady state. A=1.36 matched the unemployment, the support of  $\epsilon$ , e=.03,

matched the job destruction rate, z matched the fraction .4615 of the value of the most productive job that is spent on advertizing costs. The other values of the parameters were the ones we obtained when we calibrated the quarterly model. Note that for the benchmark model the change in the variables is "small". By small we mean that, say, the ratio of the support of the iid shock to the persistent shock is still around 4. We can see the implied statistics in the sixth column of table 1.

Adding temporary layoffs doesn't change the results much in comparison to the benchmark model. It increases somewhat the positive correlation between creation and destruction and increases the variability of job destruction. Also the autocorrelation in the three series is diminished but not significantly.

However if we take Rogerson and Cole results as a benchmark it is clear that adding temporary layoffs produces a positive correlation between creation and destruction.

We did another excercise to reproduce Rogerson and Cole results and we found that in order to do this we have to reduce the support of  $\iota$ . For this purpose we followed a somewhat similar procedure as when setting parameter values for our benchmark model. The difference is that we set additionally  $\gamma$  so that to make  $\iota$  close to zero.

The reason why reducing the support of iota takes us to the Rogerson and Cole results or the standard Mortensen and Pissarides results is in line with all of this authors intuition about the reasons for a negative correlation between creation and destruction.

This is related to the asymptry in the response of Job destruction to an aggregate shock. In Rogerson and Cole terms this refers to  $\lambda_0$ . When the support of iota is zero and we calibrate the model to the US facts as Mortensen and Pissarides did, the effect of the arrival rate of the persistent shock creates the asymptry in the response of job destruction to an aggregate shock. Job destruction is more volatil than creation when the economy is hit by a bad aggregate shock. Hence this creates a negative correlation between creation and destruction. However as as Rogerson and Cole point out this comes at expenses of the autocorrelation of the three series (see fourth column of table 1).

In other words if temporary layoffs are empirically important and for their existence we need the iid shocks to be large enough, then in this context the standard Mortensen and Pissarides Model does a poor job in terms of trying to replicate the statistics.

One of the results we get is that the correlation between job creation and destruction is positive. This implies that for the US Data the lower permanent unemployment hazard rate implied by introducing temporary layoffs in the Mortensen and Pissarides matching model is dominated by the high recall rate of temporary layoffs. Hence a positive correlation is generated.

The puzzle that remains is why don't we get the desired negative correlation if temporary layoffs are empirically important. We will claim that the inability of our model to replicate the richness in the dynamics of the temporary unemployment hazard rate pointed out in the previous section is behind the poor performance of our model in replicating the statistics of job creation and destruction.

Before laying out our explanation we present the implications that aggregate shocks have to the following measures over the cycle in our calibrated quarterly model: The fraction of layoffs that are temporary, the temporary and permanent unemployment hazard rate, the unemployment hazard rate and the probability of a permanent layoff for a temporary layoff. For exposition purposes we assume that the draw of aggregate shocks is characterized by a long period of consecutive bad realizations so that the economy, abusing the use of language, tends to to a "steady state". Note that in an stochastic environment it is not correct to make use of the notion of steady state. See figure 4

Definetely what is causing the average hazard rate to go up slightly is the increase of the importance of temporary layoffs over total unemployment even when the permanent unemployment hazard rate goes down. Also note that we don't get that richness in the temporary unemployment hazard rate when the economy fluctuates when hit by aggregate shocks.

In figure 5 we present the dynamics of the same rates when we use the monthly model. This latter model as we said before is more adequate if we want to compare our results with those of Anderson and Meyer. We find a similar pattern as in the quarterly model.

I offer the following explanation. First the monthly temporary hazard rate should be lower around 1/3. This could be obtained if as we said before we introduce finite duration unemployment benefits. This would help in producing less of a positive correlation. However the crucial point is to see

that the weekly hazard rates reported by Anderson and Meyer are kind of u shaped. The first weeks they are high with a lower peak in the third month and a peak around the weeks of benefits exhaustion of the same magnitude as the one of the first weeks(figure IV in their paper). Hence most of recalls would not occur after one quarter as in our quarterly model but either as early in the first month or as late as after two quarters. A model that would imply this would still generate an average temporary unemployment duration of 1 quarter to be consistent with the facts. However it is possible that the effect on job creation of longer spells of temporary unemployment that end up in recall might dominate the initial high recall rate.





If so we would obtain the desired negative correlation between job creation and destruction. We want to emphasize that to be recalled the last week of unemployment benefits it is necessary for this workers on temporary layoff to have very low hazard rates the first weeks. It is intuitively clear that extending our model for the presence of finite duration unemployment benefits would generate the adequate framework to answer the latter question. Matches with persistent good draws of the persistent idiosyncratic shock would be recalled faster in comparison to the ones with lower persistent idiosyncratic shocks. The U shaped hazard rate of temporary layoffs as a function of the number of weeks before benefits exhaustion would be a natural implication.

Finally two last things deserve comment with respect to the duration of benefits. The data for Missoury and Pennsylvania have benefits duration of 23 and 35 wekks respectively. In quarters this implies between two and three quarters. By law if there is recession emergency funds from the federal government could be provided to finance more weeks of unemployment insurance. If there are less recalls that ocurr the first weeks than the ones that occur at a high rate near benefits exhaustion then it is possible that temporary layoffs have a quarterly recall rate closer to 1/3. Recall this is the hazard rate necessary for the matching model to match the facts.

Stat	$Mod_{quart}$	$Mod_{month}$	$MortPiss_{ColeRog}$	Data	$Mod_{Bench}$
STDe	.013	.011	.017	.030	.011
STDJC	.15	.131	.121	.117	.098
STDJD	.18	.144	.147	.197	.126
CORRJDJC	.58	.603	-0.43	65	.461
$CORRe_te_{t-1}$	.776	.73	.47	.90	.807
$CORRJC_tJC_{t-1}$	.728	.67	.17	.51	.820
$CORRJD_tJD_{t-1}$	.635	.59	07	.65	.582

#### Table 1: Statistics

### 4 Conclusions

In this paper we have formulated a matching model in which temporary and permanent layoffs exist simultaneously. The key issue in obtaining this result is to assume that individual employment matches are subject to two shocks, one of which is persistent and one of which is not. Low values of the persistent shocks will lead to permanent separations whereas low values of the temporary shock will lead to temporary layoffs.

The calibrated model though very simple does a good job replicating basic empirical regularities of Davis and Haltiwanger Data(1996). However we get that the correlation between job creation and destruction is positive. This implies that for the US Data the lower permanent unemployment hazard rate implied by introducing temporary layoffs in the Mortensen and Pissarides matching model is dominated by the high recall rate of temporary layoffs. Hence a positive correlation is generated.

However extending the model for allowing for limited duration of unemployment benefits would generate a more richer dynamics of the temporary layoff recall rate that is consistent with the more detailed data of Anderson and Meyer. In particular it would match the fact that recalls occur either the first month or after the seventh month or around the exhaustion of unemployment benefits. This lower temporary unemployment hazard rate might dominate the high recall rate the first weeks after the start of the temporary unemployment spell. Hence matching the facts.

## 5 Appendix

a)Claim 1:

$$S_m(\epsilon,\iota) = max(S_a(\epsilon,\iota), S_d(\epsilon,\iota), 0)$$

If  $(\epsilon, \iota)$  are such that  $S_m(\epsilon, \iota) = S_a(\epsilon, \iota)$ , then

$$S_{m}(\epsilon, \iota) = V^{e}(\epsilon, \iota) + J_{a}(\epsilon, \iota) - V^{u} + \beta q^{u} V^{u} - \beta q^{u} V^{u} = \cdots$$

$$w(\iota, \epsilon) - b + \beta \gamma E(V^{mw}(., .)) + \beta(1 - \gamma)E(V^{mw}(\epsilon, .)/\epsilon) \cdots$$

$$+p + \epsilon + \iota - w(\iota, \epsilon) + \beta \gamma E(J_{m}(., .)) + \beta(1 - \gamma)E(J_{m}(\epsilon, .)/\epsilon) \cdots$$

$$-(\beta q^{u} V^{mw}(\epsilon^{u}, \iota^{u}) + \beta(1 - q^{u})V^{u}) \cdots$$

$$+\beta q^{u} V^{u} - \beta q^{u} V^{u} \qquad (53)$$

Using  $J_m(\iota, \epsilon) = (1 - X)S_m(\iota, \epsilon)$  we get after simplifying to the desired conclusion. The derivation is analogous for the case where  $(\epsilon, \iota)$  are such that  $S_m(\epsilon, \iota) = S_d(\epsilon, \iota)$ .

b)Claim 2:

Derivation of equation 22: if  $\epsilon \geq \epsilon^*$  we have:  $S_m(\epsilon, \iota) = S_a(\epsilon, \iota)$  if  $\iota \geq \iota^{tl}(\epsilon)$ ;  $S_m(\epsilon, \iota) = S_d(\epsilon, \iota)$  if  $\iota \leq \iota^{tl}(\epsilon)$ . We can write:

$$E(S_m(\epsilon,.)/\epsilon) = \int_{\iota^{tl}(\epsilon)}^{\iota^u} S_a(\epsilon,y) dG(y) + \int_{-\infty}^{\iota^{tl}(\epsilon)} S_d(\epsilon,y) dG(y)$$
(54)

After integrating by parts over the implied ranges we get that for a given value of  $\epsilon$ :

$$E(S_m(\epsilon, .)/\epsilon) = S_a(\epsilon, y)G(y)|_{\iota^{tl}(\epsilon)}^{\iota^u} - \int_{\iota^{tl}(\epsilon)}^{\iota^u} S_{a_2}(\epsilon, y)G(y)dy + S_d(\epsilon, y)G(y)|_{-\infty}^{\iota^{tl}(\epsilon)} - \int_{-\infty}^{\iota^{tl}(\epsilon)} S_{d_2}(\epsilon, y)G(y)dy$$
(55)

Given that  $S_a(\epsilon, \iota^{tl}(\epsilon)) = S_d(\epsilon, \iota^{tl}(\epsilon))$  this expressions cancel out. Additionally,  $S_d(\epsilon, -\infty)G(-\infty) = 0$  and  $S_{d_2}(\epsilon, y) = 0$  imply:

$$E(S_m(\epsilon, .)/\epsilon) = S_a(\epsilon, \iota^u)G(\iota^u) - \int_{\iota^{tl}(\epsilon)}^{\iota^u} S_{a_2}(\epsilon, y)G(y)dy$$
(56)

but  $S_a(\epsilon, \iota^{pl}(\epsilon)) = 0$ , by definition of  $\iota^{pl}(\epsilon)$ . Note also that  $G(\iota^u) = 1$ , so after integrating the first term in the right side of the previous equation we get:

$$E(S_m(\epsilon, .)/\epsilon) = \int_{\iota^{pl}(\epsilon)}^{\iota^u} S_{a_2}(\epsilon, y) dy - \int_{\iota^{tl}(\epsilon)}^{\iota^u} S_{a_2}(\epsilon, y) G(y) dy = \int_{\iota^{pl}(\epsilon)}^{\iota^{tl}(\epsilon)} S_{a_2}(\epsilon, y) dy + \int_{\iota^{tl}(\epsilon)}^{\iota^u} S_{a_2}(\epsilon, y) (1 - G(y)) dy = \iota^{tl}(\epsilon) - \iota^{pl}(\epsilon) + \int_{\iota^{tl}(\epsilon)}^{\iota^u} S_{a_2}(\epsilon, y) (1 - G(y)) dy$$
(57)

Note that in the last equality we have used the fact that  $S_{a_2}(\epsilon, y) = 1$ when solving for the definite integral in the first term of the third equality. c)Claim 3:

Let the Job destruction equation 29 be:

$$0 = \beta \gamma E(S_m(.,.)) + \beta (1-\gamma) E(S_m(\epsilon^*,.)/\epsilon^*) - \frac{Xz}{1-X} \frac{v}{u^p}$$
(58)

where

$$E(S_m(.,.)) = \int_{-\infty}^{\epsilon^{pl}(\epsilon^*,\iota^u)} \int_{-\infty}^{\iota^u} 0 dy dF(x) + \int_{\epsilon^{pl}(\epsilon^*,\iota^u)}^{\epsilon^*} \int_{\iota^{pl}(x,\epsilon^*)}^{\iota^u} S_{a_2}(x,y)(1-G(y)) dy dF(x) + \int_{\epsilon^*}^{\epsilon^u} \iota^{tl}(x) - \iota^{pl}(x,\epsilon^*) + \int_{\iota^{tl}(x)}^{\iota^u} S_{a_2}(x,y)(1-G(y)) dy dF(x)$$
(59)

and

$$E(S_m(\epsilon^*,.)/\epsilon^*) = \int_{\iota^{pl}(\epsilon^*)}^{\iota^u} S_{a_2}(\epsilon^*,y)(1-G(y))dy$$
(60)

Let

$$R(\epsilon^*,...) = \beta \gamma E(S_m(.,.)) + \beta (1-\gamma) E(S_m(\epsilon^*,.)/\epsilon^*)$$
(61)

then  $\epsilon^*_{\frac{v}{u^p}}$ , the partial derivative of  $\epsilon^*$  with respect to  $\frac{v}{u^p}$ , is positive and is given by:  $\epsilon_{up}^* = \frac{\frac{X_c}{1-X}}{R_{\epsilon^*}}$ . We just need to show that  $R_{\epsilon^*}$  is positive. Note that:  $E(S_m(\epsilon^*,.)/\epsilon^*)_{\epsilon^*} =$ 

 $1-G(-p-\epsilon^*+b)$  and again  $S_{a_2}(\epsilon^*, y) = 1$ . We will calculate next  $E(S_m(.,.))_{\epsilon^*}$ .

After integrating by parts and simplifying we get:

$$E(S_m(.,.)) = -\int_{\epsilon^{pl}(\epsilon^*,\iota^u)}^{\epsilon^*} \frac{(1 - G(\iota^{pl}(x,\epsilon^*)))}{1 - \beta(1 - \gamma)(1 - G(\iota^{pl}(x,\epsilon^*)))} F(x) dx -\frac{1}{1 - \beta(1 - \gamma)} \int_{\epsilon^*}^{\epsilon^u} (1 - G(\iota^{tl}(x))) F(x) dx +\frac{\beta(1 - \gamma)}{1 - \beta(1 - \gamma)} \int_{-p - \epsilon^u + b}^{-p - \epsilon^u + b} (1 - G(y)) dy + \int_{-p - \epsilon^u + b}^{\iota^u} (1 - G(y)) dy$$
(62)

After derivating with respect to  $\epsilon^*$  the terms to the right of the previous equation become after manipulating equal to:

$$term1_{\epsilon^{*}} = \int_{\epsilon^{pl}(\epsilon^{*},\iota^{u})}^{\epsilon^{*}} \frac{G_{\iota}(\iota^{pl}(x,\epsilon^{*}))\beta(1-\gamma)(1-G(-p-\epsilon^{*}+b))}{(1-\beta(1-\gamma)(1-G(\iota^{pl}(x,\epsilon^{*})))^{3}}F(x)dx$$
$$-\frac{F(\epsilon^{pl}(\epsilon^{*},\iota^{u}))(1-G(\iota^{pl}(\epsilon^{pl}(\epsilon^{*},\iota^{u}),\epsilon^{*})))}{1-\beta(1-\gamma)(1-G(\iota^{pl}(\epsilon^{*},\epsilon^{*})))}\epsilon_{\epsilon^{*}}^{pl}(=0) + \frac{F(\epsilon^{*})(1-G(-p-\epsilon^{*}+b))}{1-\beta(1-\gamma)(1-G(\iota^{pl}(\epsilon^{*},\epsilon^{*})))} > 0$$
$$term2_{\epsilon^{*}} = \frac{F(\epsilon^{*})(1-G(-p-\epsilon^{*}+b))}{1-\beta(1-\gamma)} > 0$$
$$term3_{\epsilon^{*}} = -\frac{\beta(1-\gamma)(1-G(-p-\epsilon^{*}+b))}{1-\beta(1-\gamma)} < 0$$

However,  $\beta(1-\gamma)E(S_m(\epsilon^*,.)/\epsilon^*)_{\epsilon^*}$  is positive and greater than  $\beta\gamma$  the third term. Hence the job destruction curve displays a positive relationship between  $\epsilon^*$  and  $\frac{v}{u^p}$ .

d)Comparative statics of the aggregate component p.

-Differentiantion of the Job Destruction Condition (equation 30) with respect to p yields (holding  $\frac{v}{u}$  constant):

$$0 = R_{\epsilon^*} \epsilon_p^* + R_p$$
  

$$\epsilon_p^* = -\frac{R_p}{R_{\epsilon^*}} < 0$$
(63)

This partial derivative is negative because:

$$R_{p} = \int_{\epsilon^{pl}}^{\epsilon^{*}} -(1 - G(\iota^{pl}))\iota_{p}^{pl}dF(x) + \left(\int_{\iota^{pl}(\epsilon^{pl})}^{\iota^{u}} (1 - G(y))dy\right)f(\epsilon^{pl})\epsilon_{p}^{pl}$$
$$+ \int_{\epsilon^{*}}^{\epsilon^{u}} (G(-p - \epsilon^{*} + b) - G(-p - x + b))\frac{\beta(1 - \gamma)}{1 - \beta(1 - \gamma)} + G(-p - x + b)dF(x)$$
$$+ (1 - G(-p - \epsilon^{*} + b)) > 0(64)$$

We show in g that  $\iota_p^{pl}$  is negative. Also the second term in the right side is zero. Hence an increase in p shifts the job destruction curve to the left.

-Differentiantion of the Job Creation Condition(equation 36) with respect to p yields (holding  $\frac{v}{u}$  constant):

$$0 = \frac{z\beta(1 - G(-p - \epsilon^* + b))}{(1 - \beta(1 - \gamma))(1 - X)^2(S_m(\epsilon^u, \iota^u) - S_m(\epsilon^*, \iota(\epsilon^*)))^2}\epsilon_p^* - \frac{1 + \frac{\beta(1 - \gamma)}{1 - \beta(1 - \gamma)}(G(-p - \epsilon^* + b) - G(-p - x + b))}{(1 - X)^2(S_m(\epsilon^u, \iota^u) - S_m(\epsilon^*, \iota(\epsilon^*)))^2}$$
(65)

Hence  $\epsilon_p^* > 0$  or an increase in p shifts the Job Creation curve to the right. The general equilibrium effect on  $\frac{v}{u}$  is positive however it is undetermined for  $\epsilon^*$ . Analitically we have respectively after differentianting the Job Destruction (equation 30) and Job Creation(equation 36) condition with respect to p:

$$0 = R_{\epsilon^*} \epsilon_p^* + R_p - \frac{v}{u_p} \frac{Xz}{1 - X}$$
 (66)

$$q_{\frac{v}{u}}^{v}\frac{v}{u_{p}} = \frac{z\beta(1-G(-p-\epsilon^{*}+b))}{(1-\beta(1-\gamma))(1-X)^{2}(S_{m}(\epsilon^{u},\iota^{u})-S_{m}(\epsilon^{*},\iota(\epsilon^{*})))^{2}}\epsilon_{p}^{*} - \frac{1+\frac{\beta(1-\gamma)}{1-\beta(1-\gamma)}(G(-p-\epsilon^{*}+b)-G(-p-x+b))}{(1-X)^{2}(S_{m}(\epsilon^{u},\iota^{u})-S_{m}(\epsilon^{*},\iota(\epsilon^{*})))^{2}}$$
(67)

After solving for  $\frac{v}{u}$  we get an expression in terms of  $\epsilon_p^*$ :

$$\epsilon_{p}^{*}(R_{\epsilon^{*}}q_{\frac{v}{u}}^{\frac{v}{u}}\frac{1-X}{Xz} - \frac{z\beta(1-G(-p-\epsilon^{*}+b))}{(1-\beta(1-\gamma))(1-X)^{2}(S_{m}(\epsilon^{u},\iota^{u}) - S_{m}(\epsilon^{*},\iota(\epsilon^{*})))^{2}}) = -R_{p}\frac{1-X}{Xz}q_{\frac{v}{u}}^{v} - z\frac{1+\frac{\beta(1-\gamma)}{1-\beta(1-\gamma)}(G(-p-\epsilon^{*}+b)-G(-p-x+b))}{(1-X)^{2}(S_{m}(\epsilon^{u},\iota^{u}) - S_{m}(\epsilon^{*},\iota(\epsilon^{*})))^{2}} (68)$$

So  $\epsilon_p^*$  is undetermined. Our numerical results for the US. indicate that this is negative but close to zero for a size of the productivity shock calibrated to mimic the time series of the log of quarterly labour productivity for the US economy. Or in other words enough to make temporary layoffs countercyclical

e)Comparative statics of  $\gamma$ .

-Differentiantion of the Job Destruction Condition(equation 30) with respect to  $\gamma$  yields (holding  $\frac{v}{u}$  constant):

$$0 = R_{\epsilon^*} \epsilon^*_{\gamma} + R_{\gamma}$$
  

$$\epsilon^*_{\gamma} = -\frac{R_{\gamma}}{R_{\epsilon^*}}$$
(69)

The sign of the last expression depends on  $R_{\gamma}$ , that it is equal to:

$$R_{\gamma} = \gamma \beta \int_{\epsilon^{pl}}^{\epsilon^{*}} -(1 - (G(\iota^{pl}))\iota_{\gamma}^{pl} dF(x))$$
$$-(\int_{\iota^{pl}(\epsilon^{pl})}^{\iota^{u}} (1 - G(y)) dy) f(\epsilon^{pl}) \epsilon_{\gamma}^{pl}$$
$$\beta \int_{\epsilon^{pl}}^{\epsilon^{*}} \int_{\iota^{pl}(\epsilon^{pl})}^{\iota^{u}} (1 - G(y)) dy dF(x)$$

$$+\beta\gamma \int_{\epsilon^{*}}^{\epsilon^{u}} \frac{\beta \int_{-p-x+b}^{-p-\epsilon^{*}+b} (1-G(y)) dy}{(1-\beta(1-\gamma))^{2}} dF(x)$$
  
$$\beta \int_{\epsilon^{*}}^{\epsilon^{u}} \iota^{tl}(x) - \iota^{pl}(x) + \int_{\iota^{tl}(x)}^{\iota^{u}} (1-G(y)) dy dF(x)$$
  
$$-\beta \int_{-p-\epsilon^{*}+b}^{\iota^{u}} (1-G(y)) dy$$
(70)

After integrating by parts and simplifying we get:

$$R_{\gamma} = \int_{\epsilon^{pl}}^{\epsilon^{*}} \frac{\gamma \beta^{2} (1 - (G(\iota^{pl})))}{1 - \beta (1 - \gamma) (G(\iota^{pl}))} \int_{-p - \epsilon^{*} + b}^{\iota^{pl}} (1 - G(y)) dy dF(x) + \int_{\epsilon^{*}}^{\epsilon^{u}} \frac{\beta (1 - \gamma)}{(1 - \beta (1 - \gamma))^{2}} \int_{-p - x + b}^{-p - \epsilon^{*} + b} (1 - G(y)) dy dF(x) -\beta \int_{\epsilon^{pl}}^{\epsilon^{*}} \frac{1 - G(\iota^{pl})}{1 - \beta (1 - \gamma) G(\iota^{pl})} F(x) dx$$
(71)

Note that the first and the third term go to zero when  $\epsilon^*$  goes down or gets closer to  $\epsilon$  such that  $\iota^u = -p - \epsilon + b$ . Hence for  $\epsilon^*$  close enough to the latter value  $R_{\gamma}$  is positive therefore  $\epsilon^*_{\gamma}$  holding  $\frac{v}{u}$  constant is negative. In the numerical analysis we claim that for the model calibrated to the US economy this is the case. Hence an increase in  $\gamma$  would shift the job destruction curve to the left.

-Differentiantion of the Job Creation Condition(equation 33) with respect to  $\gamma$  yields (holding  $\frac{v}{u}$  constant):

$$0 = \frac{z\beta(1 - G(-p - \epsilon^* + b))}{(1 - \beta(1 - \gamma))(1 - X)^2(S_m(\epsilon^u, \iota^u) - S_m(\epsilon^*, \iota(\epsilon^*)))^2}\epsilon_{\gamma}^* + \frac{\beta\int_{-p - \epsilon^u + b}^{-p - \epsilon^* + b}(1 - G(y))dy}{(1 - \beta(1 - \gamma))^2(1 - X)^2(S_m(\epsilon^u, \iota^u) - S_m(\epsilon^*, \iota(\epsilon^*)))^2}$$
(72)

We get that  $\epsilon_{\gamma}^{*}$  holding  $\frac{v}{u}$  constant is negative so the Job Creation curve shifts to the left. Taking into account the general equilibrium effects, for the US data, we have that  $\epsilon_{\gamma}^{*}$  is negative(the same happens when holding  $\frac{v}{u}$  constant). When we solved for the analytical derivative it was sufficient for  $R_{\gamma}$  to be positive to get this result. Even if  $R_{\gamma}$  was positive if the job creation curve shifts enough to the left we would get the mentioned result. In numerical exercises we found structural parameters such that  $\epsilon_{\gamma}^*$  was positive hence this implies a negative value for  $R_{\gamma}$  for this parameter values.

With respect to  $\frac{v}{u_{\gamma}}$  its value is undetermined. Analitically we have after differentianting the Job Destruction (equation 30) and Job Creation(equation 36) condition with respect to  $\gamma$ , solving for  $\epsilon_{\gamma}^*$  and rearranging:

$$\frac{v}{u_{\gamma}} * (negative term) = \frac{R_{\epsilon^*} \int_{-p-\epsilon^u+b}^{-p-\epsilon^*+b} (1-G(y)) dy}{(1-\beta(1-\gamma))(1-G(-p-\epsilon^*+b))} - R_{\gamma}$$
(73)

If  $\epsilon^*$  goes down or gets closer to  $\epsilon$  such that  $\iota^u = -p - \epsilon + b$ . then the last term becomes positive as we explained before. However the first expresion doesn't go to zero because  $R_{\epsilon^*}$  and  $(1 - G(-p - \epsilon^* + b))$  go to zero. Note that  $\int_{-p-\epsilon^u+b}^{-p-\epsilon^u+b}(1 - G(y))dy$  is bounded. However for the US data  $\frac{v}{u\gamma}$  is negative. So the shift in the job creation curve dominates the effect of the shift of the job destruction curve.

f)Comparative statics of z.

-Differentiantion of the Job Destruction Condition(equation 30) with respect to z yields (holding  $\frac{v}{u}$  constant):

$$0 = R_{\epsilon^*} \epsilon_z^* - \frac{v}{u} \frac{X}{1 - X}$$

$$\tag{74}$$

Hence  $\epsilon_z^*$  is positive, ie the Job Destruction curve shifts to the right.

-Differentiantion of the Job Creation Condition(equation 33) with respect to z yields (holding  $\frac{v}{u}$  constant):

$$0 = \frac{z\beta(1 - G(-p - \epsilon^* + b))}{(1 - \beta(1 - \gamma))(1 - X)^2(S_m(\epsilon^u, \iota^u) - S_m(\epsilon^*, \iota(\epsilon^*)))^2}\epsilon_z^* + \frac{1}{\beta(1 - X)(S_m(\epsilon^u, \iota^u) - S_m(\epsilon^*, \iota(\epsilon^*)))}$$
(75)

So  $\epsilon_z^*$  is negative or the Job Creation curve shifs to the right. Hence after taking into account general equilibrium effects  $\frac{v}{u_z}$  is negative and  $\epsilon_z^*$  is undetermined. Analitically we have after differentianting the Job Destruction (equation 30) and Job Creation(equation 36) condition with respect to z, solving for  $\frac{v}{u_z}$  and rearranging:

$$\epsilon_{z}^{*}(R_{\epsilon^{*}}q_{\frac{v}{u}}^{v} - \frac{Xz}{1-X}\frac{z\beta(1-G(-p-\epsilon^{*}+b))}{(1-\beta(1-\gamma))(1-X)^{2}(S_{m}(\epsilon^{u},\iota^{u}) - S_{m}(\epsilon^{*},\iota(\epsilon^{*})))^{2}}) = \frac{Xz}{1-X}\frac{1}{\beta(1-X)(S_{m}(\epsilon^{u},\iota^{u}) - S_{m}(\epsilon^{*},\iota(\epsilon^{*})))} + \frac{X}{1-X}\frac{v}{u}q_{\frac{v}{u}}^{v}(76)$$

The first expression in the right hand side is positive and the second expression is negative because  $q_{\frac{v}{u}}^{v}$  is negative. In the left hand side  $\epsilon_{z}^{*}$  multiplies a negative expression. Hence  $\epsilon_{z}^{*}$  is undetermined. For the US economy our numerical results show that this derivative is negative.

g)Partial derivative of  $\iota^{pl}$  with respect to p holding  $\epsilon^*$  constant: If  $\epsilon \geq \epsilon^*$  we have after differentialing eequation 28:

$$\mu_p^{pl} = -1 - \frac{\beta(1-\gamma)(G(-p-\epsilon^*+b) - G(-p-\epsilon+b))}{1-\beta(1-\gamma)}$$
(77)

If  $\epsilon \leq \epsilon^*$  we have after differentialing eequation 27:

$$\iota_p^{pl} = \frac{-1 + \beta(1 - \gamma)(1 - G(-p - \epsilon^*))}{1 - \beta(1 - \gamma)(1 - G(\iota^{pl}))}$$
(78)

Hence  $\iota_p^{pl}$  is negative.

h)Partial derivative of  $\iota^{pl}$  with respect to  $\gamma$  holding  $\epsilon^*$  constant: If  $\epsilon \geq \epsilon^*$  we have after differentialing eequation 28:

$$\iota_{\gamma}^{pl} = \frac{\beta \int_{-p-\epsilon+b}^{-p-\epsilon^*+b} (1 - G(y)) dy}{(1 - \beta(1 - \gamma))^2}$$
(79)

So  $\iota_p^{pl}$  is negative if  $\epsilon \ge \epsilon^*$  If  $\epsilon \le \epsilon^*$  we have after differentiating eequation 27:

$$\ell_{\gamma}^{pl} = -\frac{\beta \int_{-p-\epsilon^*+b}^{\iota^{pl}} (1-G(y)) dy}{1-\beta(1-\gamma)(1-G(\iota^{pl}))}$$
(80)

We have that  $\iota_p^{pl}$  is negative if  $\epsilon \leq \epsilon^*$ .

i)Redefinition of series of Job Creation and Destruction for the quarterly non aggregated model:

For the calibration of the steady state we need to match a decrease in the mean of job destruction when we don't account for destruction that is reversed after one period. For this objective we will redefine JD and JC. We also redefine Job Creation because it might be that a decrease in the mean of job creation when we don't account for creation that is reversed after one period is due to temporary layoffs. Actually there was no reasonable parametrarization that could match the latter redefined series of Job Creation.

Following Rogerson and Cole (1996) we consider Job Destruction and Job Creation series that result from requiring that destruction persist for some specified horizon. In that way we are consistent with the data collected by Davis and Haltiwanger (1992). Along this line let's explain now how to calculate series using, say horizons zero, one, two, four and eight quarters. Zero corresponds to the measures we have been working so far.

Horizon 1

$$JD_t^1 = JD_t^0 - Del_t^1 \tag{81}$$

where  $Del_t^1$  are deletions from payroll or job destruction that don't persist after one period.

Let  $Del_t^1 = a + a'$  where

$$a = \gamma \lambda_t^t \int_{-\infty}^{\epsilon_u} \int_{\iota^*(\epsilon)}^{\infty} g(\iota) f(\epsilon) d\epsilon d\iota$$
(82)

$$a' = \int_{\epsilon^*}^{\infty} (1 - \gamma) \left[ \int_{\iota^*(\epsilon)}^{\infty} g(\iota) d\iota \right] \int_{-\infty}^{\iota^*(\epsilon)} \phi_t^1 d\iota d\epsilon$$
(83)

Note that a refers to the fraction  $\gamma$  of jobs that were active during period t-1, at the end of period decide to stay on temporary layoff during period t and are recalled at t+1 after receiving new realization of both shocks. The other fraction  $(1-\gamma)$  are recalled at t+1 after receiving a new realization only of the  $\iota$  shock. The latter refers to the a' component.

$$JC_{t+1}^1 = JC_{t+1}^0 - Ad_{t+1}^1$$
(84)

$$Ad_{t+1}^{1} = Adr_{t+1} + AdNew_{t+1}$$
(85)

Where  $Adr_{t+1}$  and  $AdNew_{t+1}$  are additions to payroll or job creation that don't persist after one period.  $Adr_{t+1}$  corresponds to recall at t + 1 and  $AdNew_{t+1}$  corresponds to new matches at t + 1  $(q^u u_t^p)$ .

$$AdNew_{t+1} = \gamma q^{u} u_{t}^{p} \left[ 1 - \int_{-\infty}^{\epsilon_{u}} \int_{\iota^{*}(\epsilon)}^{\infty} g(\iota) f(\epsilon) d\epsilon d\iota \right]$$
$$+ (1 - \gamma) q^{u} u_{t}^{p} \left[ 1 - \int_{\iota^{*}(\epsilon^{\mu})}^{\infty} g(\iota) d\iota \right]$$
(86)

Where the terms in brackets with integrals are probabilities of the match not continuing active (either match is destroyed or mantained dormant).

$$Adr_{t+1} = \gamma r_{t+1} \left[ 1 - \int_{-\infty}^{\epsilon_u} \int_{\iota^*(\epsilon)}^{\infty} g(\iota) f(\epsilon) d\epsilon d\iota \right] + \int_{-\infty}^{\infty} (1 - \gamma) \left[ 1 - \int_{\iota^*(\epsilon)}^{\infty} g(\iota) d\iota \right] \int_{\iota^*(\epsilon)}^{\infty} \phi_t^2 d\iota d\epsilon$$
(87)

j)Construction of series of Job creation and Destruction from the monthly model:

For computing the aggregated series of job destruction in quarter T we trace matches that were active at the end of month t and survive at the end of month t+3. Note that month t+3 corresponds to quarter T. t+6 corresponds to quarter T+1 and so on. Matches that were on temporary layoff within quarter T but were recalled on month t+3 are included as survivors. Job

destruction in quarter T is going to be matches active at the end of month t or equivalently at the end of quarter T-1 minus matches that survived at the end of month t+3 or equivalently at the end of quarter T .

The aggregate quarterly series of job creation at quater T is going to be employment at T or equivalently at month t+3 minus matches that were active at the end of montht t that survived at the end of month t+3 or equivalently at the end of quarter T.

A similar reasoning is used to compute aggregated quarterly series for  $JD_t^1$  and  $JC_t^1$  as defined in g)

k)A stochastic model of Job Creation and Destruction:

In what follows we study an equilibrium in which wages depend only upon the aggregate technologically shock and not on the level of permanent unemployment. For an easy proof in a simple model see Rogerson, Cole(1996).

We assume that  $p_t$  is an aggregate technology shock that follows a symmetric two state markov chain in which  $l(=l_{11} = l_{22})$  with the probability of remaining in the same state for two consecutive periods. We assume that  $p_1 > p_2$ , being  $p_1$  the good state.

 $J_m = max(J_a, J_d, 0)$  is redefined as follows:

$$J_m(p_j, \epsilon, \iota) = max(J_a(p_j, \epsilon, \iota), J_d(p_j, \epsilon, \iota), 0)$$
(88)

where

$$J_{a}(p_{j},\epsilon,\iota) = p_{j} + \epsilon + \iota - w(p_{j},\epsilon,\iota) + \sum_{i=1}^{2} l_{ji}(\gamma\beta E(J_{m}(p_{i},.,.) + (1-\gamma)\beta E(J_{m}(p_{i},.,.)/\epsilon)) (89) J_{d}(p_{j},\epsilon,\iota) = -w(p_{j},\epsilon,\iota) + \sum_{i=1}^{2} l_{ji}(\gamma\beta E(J_{m}(p_{i},.,.) + (1-\gamma)\beta E(J_{m}(p_{i},.,.)/\epsilon)) (90)$$

for j = 1, 2.

The value of the match for the worker would be for j = 1, 2:

$$V^{mw}(p_j,\iota,\epsilon) = max(V^e(p_j,\iota,\epsilon), V^{tl}(p_j,\iota,\epsilon), V^u(p_j))$$
(91)

where

$$V^{e}(p_{j},\iota,\epsilon) = w(p_{j},\iota,\epsilon) - b + \sum_{i=1}^{2} l_{ji}(\gamma\beta E(V^{mw}(p_{i},\iota,\epsilon))) + (1-\gamma)\beta E(V^{mw}(p_{i},\iota,\epsilon)/\epsilon))$$
(92)

$$V^{tl}(p_j, \iota, \epsilon) = w(p_j, \epsilon, \iota) + \sum_{i=1}^{2} l_{ji}(\gamma \beta E(V^{mw}(p_i, \iota, \epsilon))) + (1 - \gamma)\beta E(V^{mw}(p_i, \iota, \epsilon)/\epsilon))$$
(93)

$$V^{u}(p_{j}) = \sum_{i=1}^{2} l_{ji}(\beta y_{j}V^{mw}(p_{i}, \iota^{u}, \epsilon^{u}) + (1 - q_{j}^{u})\beta V^{u}(p_{i}))$$
(94)

where

$$q_j^u = \frac{m(v(p_j), u^p(p_j))}{u^p(p_j)}$$
(95)

Note that  $q_j^u$  can be calculated using the following redefined equilibrium condition:

$$0 = V_j(q_j^v, \epsilon^u, \iota^u) = -z + \beta q_j^v \sum_{i=1}^2 l_{ji} J_m(p_i, \epsilon^u, \iota^u)$$
(96)

for each aggregate state j = 1, 2.

To see this let us assume that the matching fuction is of the form  $Au^{\theta}v^{1-\theta}$ , where  $\theta$  is a number between zero and one.Note that u stands for permanent unemployment only in this derivation. We can write:

$$q_j^u = A(\frac{v_j}{u_j})^{1-\theta} \tag{97}$$

After rearranging, we get:

$$\frac{v_j}{u_j} = \left(\frac{q_j^u}{A}\right)^{\frac{1}{1-\theta}} \tag{98}$$

Expressing  $q_j^v$  in terms of the matching function in equation (53) yields:

$$0 = -z + \beta A(\frac{u_j}{v_j})^{\theta} \sum_{i=1}^2 l_{ji} J_m(p_i, \epsilon^u, \iota^u)$$
(99)

After solving for  $\frac{v_j}{u_j}$ , we get:

$$\frac{v_j}{u_j} = \left(\frac{A\beta \sum_{i=1}^2 l_{ji} J_m(p_i, \epsilon^u, \iota^u)}{z}\right)^{\frac{1}{\theta}}$$
(100)

Equalizing equations (55) and (57) and after rearranging yields:

$$q_j^u = A(\frac{A\beta \sum_{i=1}^2 l_{ji} J_m(p_i, \epsilon^u, \iota^u)}{z})^{\frac{1-\theta}{\theta}}$$
(101)

Finally, generalized Nash bargaining implies that in equilibrium the following must hold:

$$V^{mw}(p_j, \epsilon, \iota) - V^u(p_j, \epsilon, \iota) = X \left[ V^{mw}(p_j, \epsilon, \iota) + J_m(p_j, \epsilon, \iota) - V^u(p_j, \epsilon, \iota) \right]$$
 for j = 1,2.

The respective Bellman equation fo the tota match surplus is:

$$S_m(p_j,\iota,\epsilon) = max(S_a(p_j,\iota,\epsilon), S_d(p_j,\iota,\epsilon), 0)$$
(103)

for j = 1,2 where

$$S_{a}((p_{j}\iota,\epsilon) = p_{j} + \epsilon + \iota - b + \sum_{i=1}^{2} l_{ji}(\beta\gamma E(S_{m}(p_{i},\iota,\epsilon))) + \beta(1-\gamma)E(S_{m}(p_{i},\iota,\epsilon)/\epsilon) - \beta q_{j}^{u}XS(p_{i},\iota^{u},\epsilon^{u}))$$
(104)

$$S_d(p_j, \iota, \epsilon) = \sum_{i=1}^{\infty} l_{ji}(\beta \gamma E(S_m(p_i, \iota, \epsilon))) + \beta(1 - \gamma)E(S_m(p_i, \iota, \epsilon)/\epsilon) - \beta q_j^u XS(p_i, \iota^u, \epsilon^u))$$
(105)

for j = 1, 2.

The definition of equilibrium for the stochastic version follows directly in the same way as before with additional value functions and contingent upon a vector  $(p_j, \epsilon, \iota)$ .

### References

- ANDERSON, P., AND B. MEYER (1994): "The Nature and Extent of Turnover," Brookings Papers on Economic Activity: Microeconomics, pp. 177–199.
- BLANCHARD, O., AND P. DIAMOND (1989): "The Beveridge Curve," Brookings Papers on Economic Activity, 1, 1–60.
- COLE, H., AND R. ROGERSON (1996): "Can the Mortensen-Pissarides Matching Model Match the Busines Cycle Facts?," Staff Report 224, Federal Reserve Bank of Minneapolis, Research Department.
- DAVIS, S., AND J. HALTIWANGER (1992): "Gross Job Creation, Gross Job destruction and Employment Reallocation," *Quarterly Journal of Eco*nomics, 107, 819–863.
- DAVIS, S., AND J. HALTIWANGER (1998): "Gross Job Flows," in *The Handbook of Labor Economics*, ed. by O. Ashenfelter, and D. Card. Amsterdam:North-Holland.
- FELDSTEIN, M. (1975): "The Importance of Temporary Layoffs: An Empirical analysis," *Brookings Papers on Economic Activity*, 3, 725–745.
- HALL, R. (1982): "The Importance of Lifetime Jobs in the U.S. Economy," American Economic Review, 72(4), 716–724.
- HALTIWANGER, J. (1984): "The Distinguishing Characteristics of Temporary and Permanent Layoffs," *Journal of Labor Economics*, 2, 523–538.
- KATZ, L., AND B. MEYER (1990): "Unemployment Insurance, Recall Expectations and Unemployment Outcomes," *Quarterly Journal of Eco*nomics, 105, 993–1002.
- LILIEN, D. (1980): "The Cyclical pattern of Temporary layoffs in United States Manufacturing," *Review of Economics and Statistics*, 62(1), 24–31.

- MERZ, M. (1999): "Heterogeneus Job-matches and the Cyclical Behaviour of Labor Turnover," Journal of Monetary Economics, 43, 91–124.
- MORTENSEN, D. (1994): "The Cyclical Behaviour of Job and Worker Flows," Journal of Economic Dynamics and Control, 18, 1121–1142.
- MORTENSEN, D., AND C. PISSARIDES (1994): "Job Creation and Job Destruction in the Theory of Unemployment," *Review of economic Studies*, 61, 397–415.
- PISSARIDES, C. (1986): "Unemployment and Vacancies in Britain," *Economic Policy*, pp. 499–559.