Social Networks and Labor Market Transitions

Yann Bramoullé and Gilles Saint-Paul

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Abstract: We study the influence of social networks on labor market transitions. We develop the first model where social ties and job status coevolve through time. Our key assumption is that the probability of formation of a new tie is greater between two employed individuals than between an employed and an unemployed individual. We show that this assumption generates negative duration dependence of exit rates from unemployment. Our model has a number of novel testable implications. For instance, we show that a higher connectivity among unemployed individuals reduces duration dependence and that exit rates depend positively on the duration of the last job held by the unemployed worker.

*Bramoullé: LEERNA, Université des Sciences Sociales, Toulouse. Saint-Paul: IDEI, GREMAQ, LEERNA, Université des Sciences Sociales, Toulouse; CEPR and IZA. We are grateful to participants at the CEPR/DAEUP final workshop, April 2004 and at the T2M conference, Orleans, January 2004, for helpful comments and suggestions

I. Introduction

The importance of social ties in finding a job is documented by a long tradition in sociology and labor economics.[1] However, very little work has tried to confront that literature with stylized facts about the anatomy of unemployment. An important paper by Calvó-Armengol and Jackson (2003) goes a long way into bridging that gap. They construct a model where it is shown that if social ties are important, then one should observe negative duration dependence of exit rates from unemployment.

The present paper builds on that contribution by proposing another mechanism through which social ties may affect duration dependence, which we believe is more quantitatively significant. The network of social ties in our approach is endogenous instead of fixed as in Calvó-Armengol and Jackson. We assume that a bond between an employed and an unemployed worker, which increases the unemployed's likelihood of finding a job, is less likely to arise than between two employed workers—an assumption we refer to as economic inbreeding.

We show that this simple and plausible assumption has a number of implications, one of which is negative duration dependence of exit rates. This is because the long-term unemployed then have fewer connections with employed workers than the short-term unemployed, which reduces their exit rates compared to the latter. We find that the amount of duration dependence introduced by that mechanism is far higher quantitatively than under a fixed network. Furthermore, duration dependence under a fixed network is essentially due to heterogeneity in the number of connections among workers, i.e. unemployment duration is positively correlated with having few connections. In contrast, our source of duration dependence remains operative even controlling for an individual fixed effect.

The effect we highlight is therefore that workers accumulate social capital (as defined by the stock of ties with employed workers) during employment, that this stock is depleted during unemployment, and that social capital increases the likelihood of finding a job.

We study a dynamic process where job status and social ties coevolve through time. This process allows us to investigate in detail the properties of duration dependence. We notably analyze how changes in the model's parameters affect the magnitude of duration dependence. To

[1] See e.g. Rees (1966), Montgomery (1991), Topa (2001) in economics and Granovetter (1995), Petersen et al. (2000) in sociology.

illustrate our comparative statics results, consider the likelihood of formation of a new tie between two unemployed workers. We find that an increase in the connectivity of the unemployed reduces duration dependence. Why? When this connectivity is higher, a long-term unemployed will have relatively more unemployed friends. These friends consitute a form of **latent** social capital. They are not directly helpful but they become helpful when they find a job. Thus, prospects of finding a job for the long-term unemployed are indirectly improved, which explains the reduction in duration dependence. We develop similar analysis for the other parameters of the model.

Another important prediction of our model is that exit rates positively depend on the duration of the last job held by the unemployed worker. This is again due to the greater connectivity between two employed workers as compared to between an employed and an unemployed. People who have been employed longer have more ties with employed workers than those who have been employed for a shorter time. Hence, the former will find jobs more easily than the latter if they become unemployed.

Finally, we look at the extent of **social separation** that emerges between employed and unemployed. This separation turns out to be quite low when the labor market turnover is sufficiently high. The labor market thus plays a **mixing role**, offseting the original bias in link formation.

That establishing a tie with an employed is easier when one is also employed, our key assumption, is uncontroversial and well documented. The workplace is an important locus of social interaction,[2] and residential segregation by income and economic status also makes it more likely that the employed match together rather than with the unemployed in out-of-workplace social interactions such as bars, sports clubs, school committees, and so on.[3] The mechanism we study is also consistent with descriptive accounts of social exclusion and on how long spells of unemployments progressively isolate people from the workplace.

That exit rates from unemployment tend to be be lower when the duration of the spell goes up is also a well-documented fact. However, whether it is due to unobserved heterogeneity – with workers with an intrinsically lower job finding probability being over-represented among the long-term unemployed – or to a genuine fall in exit rates as unemployment duration goes up, is a matter of controversy, which to our knowledge is not resolved. Depending on which study

[2] see e.g. Granovetter (1995, p. 152).

[3] The fact that social ties are formed preferentially among people who have similar attributes, a property often referred to as "homophily", is well established in the social network literature, see e.g. Lazarsfeld and Merton (1954).

is used, opposite conclusions are reached. A recent study by Abbring et al. (2002) controls for unobserved heterogeneity and finds evidence of true negative duration dependence at long durations. Rosholm (2000), reaches similar conclusions, as do Arulampalam et al. (2000). But Steiner (2001), using German data, does not find duration dependence, while Van den Berg and Van Ours (1996), using US data, find duration dependence for some groups but not all.

II. The model

Our model is a minimal model designed at capturing the idea that social ties are more likely to arise between people of similar labor market status ("economic inbreeding"). In particular, we abstract from phenomena like price determination in general equilibrium, or the resources needed for establishing and maintaining social ties. While introducing these considerations would be of great interest, our simplified framework allows to focus on the role of economic inbreeding, and it is likely that our results would be robust to any extension of the model that preserves the economic inbreeding property.

We consider a group of n agents with similar characteristics, looking for similar jobs. Time is discrete. At each date $t = 0, 1, ...$, an individual i is either employed or unemployed. Labor market state is described by a function $s_{i,t} = 1$ if i is employed at t and 0 if unemployed. Aggregate unemployment u_t at time t is thus $u_t = n - \sum_{i=1}^{n} s_{i,t}$. Next, we model the social network among agents. At each date t, there are links between people described by the function $g_{ij,t} = 1$ if i and j are connected and 0 if not. Links are symmetric: $g_{ij,t} = g_{ji,t}$. The resulting pattern of links at t is a social network g_t. At $t = 0$, the initial labor state s_0 and the initial social network g_0 are drawn at random. Labor state and ties then coevolve through time in the following manner.

Job destruction: The transition rate from employed to unemployed is constant and equal to d.
Job creation: This process determines who finds a new job. At any date t, a flow of hu_t jobs are created. The flow probability that an unemployed becomes employed is proportional to his number of ties with employed workers. Formally, let $n_t(i) = \sum_{j=1}^{n} s_{j,t} g_{ij,t}$ denote the number of ties that individual i has with employed workers. Then,

$$proba(s_{i,t+1} = 1 | s_{i,t} = 0) = hu_t \frac{n_t(i)}{\sum_{j:s_{j,t}=0} n_t(j)} \qquad \text{(II.1)}$$

Link destruction: Any given link is destroyed with probability λ.

Link creation: The probability of formation of a new connection between two individuals depends on their job status:

a. If i and j are employed at t and $g_{ij,t} = 0$, there is a probability p_{EE} that a link is formed between them and $g_{ij,t+1} = 1$.

b. If i and j are unemployed at t and $g_{ij,t} = 0$, there is a probability p_{UU} that a link is formed between them and $g_{ij,t+1} = 1$.

c. If i is employed and j unemployed, the probability is p_{UE}.

In our analysis, we focus on situations where people have greater chance to connect with people of their own type: $p_{EE} \geq p_{UE}$ and $p_{UU} \geq p_{UE}$.

This process is characterized by a number of features. First, it captures in a simple way the property that connections with employed have a positive impact on the likelihood to find a job. Equation (II.1) could be interpreted as follows: a total number h of jobs per unemployed worker are created during period t. Those who hear about them first are the employed; if jobs are created randomly, each employed has the same probability to hear about a position. The employed then tell about the jobs in a random and uniform fashion to their unemployed friends. The unemployed who hear about the jobs then apply to all the jobs that have been mentioned to them by their friends. Employers then hire randomly from all the applicants to a given position. If h is not too high, one can neglect cases where an unemployed gets more than one offer, and a good approximation to an unemployed's probability of finding a job is equation (II.1), which tells us that the probability of being hired is proportional to the number of ties one has with employed workers.

Second, we can study fixed social networks by simply setting $\lambda = p_{EE} = p_{UE} = p_{UU} = 0$. This allows us to compare, in the next section, the effect of fixed and endogenous networks. Third, observe that network effects affect the distribution of jobs among individuals and across time, but not the aggregate level of unemployement. This is because the average number of jobs created in period t is hu_t, hence the average level of unemployment is $d/(d+h)$.

In the remainder of the paper, we report numerical simulations of our model, use them to perform comparative statics exercises, and we provide economic interpretations of the results.

III. Fixed vs. endogenous networks

A crucial aspect of our model is the reciprocal feedback between social connections and labor market status. The results we report in this section highlight the important role played by that feedback in generating duration dependence in unemployment exit rates. To measure duration dependence we simply use the regression coefficient of the likelihood of being employed at date $t+1$ conditional on being unemployed at date t and on the duration of unemployment up to t. Table 1 compares that coefficient between a median simulation with an endogenous network and one with an exogenous one. Simulations are conducted for $n = 100$ individuals and $T = 20,000$ periods.[4] We consider the following benchmark for the parameters of the model: $h = 0.12$, $d = 0.02$ and $\lambda = 0.01$, $p_{UU} = p_{EE} = 0.02$, $p_{UE} = 10^{-5}$. This leads to an aggregate level of unemployment of 14.3%. In each period, individuals lose, on average, 1% of their connections and form 2% of the possible connections with others of their own type. Two features characterize these benchmark values. First, we set λ, p_{UU}, p_{UE}, p_{EE} at relatively low levels. This gives us confidence that our findings on the effect of link evolution are robust. Second, p_{UE} is almost equal to zero. This allows us to investigate more sharply the effect of our key assumption that ties form preferentially among people of the same labor status. Both features will be relaxed in the analysis. Finally, for each estimation, we consider three simulation runs and report the estimates from the median run. Standard errors are given in parenthesis. The intercept can be interpreted as the probability to find a new job for an individual who has just lost his previous job. The slope captures the effect of the duration of unemployment.

Table 1: Fixed vs endogenous network - pooled data

	Fixed network	Endogenous network
Intercept	0.122724 (0.001247)	0.130023 (0.001167)
Slope ($*10^{-4}$)	-2.35 (1.06)	-10.62 (0.86)

Clearly, the regression coefficient is negative in both cases, but larger with an endogenous network.

[4] The initial labor state and social network are picked at random. In the estimations, we restrict attention to values from periods 10,000 to 20,000 to remove initial effects.

Next, we control for individual fixed effects. Duration dependence with a fixed network then disappears as shown in Table 1bis. This indicates that duration dependence observed on pooled data for fixed networks is mainly caused by heterogeneity in the individual number of ties.

Table 1bis: Fixed vs endogenous network - individual fixed effects

	Fixed network	Endogenous network
Intercept	0 (0.000868)	0 (0.000858)
Slope ($*10^{-4}$)	-0.43 (1.07)	-9.81 (0.87)

In contrast, Calvó-Armengol and Jackson (2003) show that duration dependence arises at the individual level with a fixed network. In their model, a long spell of unemployement indicates that the individual's contacts are more likely to be unemployed. This, in turn, leads to a lower probability of finding a job through contacts. This effect clearly applies in our context. However, our results show that its magnitude is likely to be very low. Here, duration dependence is much stronger: unemployed workers gradually lose connections with employed ones as their spell lengthens. These connections are not replaced one for one because $p_{UE} < p_{EE}$. Consequently, the long-term unemployed have much fewer connections with the employed than the short-term unemployed. This is shown on Figure 1 and Figure 1bis which depict, for a typical run and benchmark values, the average probability to find a job and the average number of connections that an unemployed has with the employed as function of time spent unemployed. As the probability of getting a job increases with the number of connections with the employed, the exit rate from unemployment is smaller, the longer the unemployment spell. This mechanism is clearly not present under a fixed network.

IV. Comparative statics: duration dependence

In this section, we study more thoroughly how network evolution produces duration dependence. We perform a number of comparative statics exercise, measuring duration dependence both with curves giving the average probability to find a job as a function of time spent unemployed and with the regression coefficient of the probability of finding a job on spell length. We show that the effect of a parameter's change on duration dependence can be understood through its differential effect on the average number of connections with employed workers of long-term unemployed and short-term unemployed. To make our case more clearly, we will define the latter as a worker who just lost his job. His social capital is therefore chiefly determined by the ties he made while employed.

A. Effect of p_{UE}

The most straightforward determinant of duration dependence is p_{UE}, the connectivity between the employed and the unemployed. As Table 2 makes clear, an increase in p_{UE} unambiguously reduces duration dependence (see also Figure 2). The mechanism is simple: the gross inflow of ties between an unemployed person and employed workers is greater when p_{UE} goes up, so that the stock of such ties goes down more slowly during the unemployment spell. Therefore, the difference between the number of connections with an employed worker, of a long-term unemployed and a short-term unemployed, is smaller, and so is the difference between their exit rates (Figure 2bis).

Table 2: Effect of connectivity between employed and unemployed

	$p_{UE} = 10^{-5}$	$p_{UE} = 0.005$	$p_{UE} = 0.01$
Intercept	0.130023 (0.001167)	0.124825 (0.001225)	0.122285 (0.001220)
Slope ($*10^{-4}$)	-10.62 (0.86)	-6.38 (1.00)	-4.70 (1.01)

One may also view it as follows: p_{UE} is the key determinant of the number of ties between a long-term unemployed and an employed person. In contrast, it has a weaker and indirect effect on the ties of a short-term unemployed, which only goes through the "echo" of the ties he was making during his previous, if any, unemployment spell. Because of the attrition of these ties during his last job, a short-term unemployed's stock of ties with an employed worker is less sensitive to p_{UE} than for a long-term unemployed.

B. Effect of p_{EE}

What about the effect of p_{EE}, connectivity between the employed? Table 3 and Figure 3 show that duration dependence is larger, the larger p_{EE}. This is because p_{EE} has a strong direct effect on a short-term unemployed's number of ties with the employed, while the effect on the long-term unemployed's ties is weaker and more indirect. The most recent ties of a short-term unemployed have been made during his last job, and chiefly depend on p_{EE}. In contrast, p_{EE} affects a long-term unemployed's stock of ties only through the echo effect of the ties made during his last job. Again, attrition of that stock during the unemployment spell reduces the effect of p_{EE} on the long-term unemployed's stock of ties. Consequently, p_{EE} increases the stock of ties with the employed more for the short-term than for the long-term unemployed (Figure 3bis), and the same is true for exit rates.

Table 3: Effect of connectivity between employed ($p_{UE} = 0.01$)

	$p_{EE} = 0.02$	$p_{EE} = 0.08$
Intercept	0.122285 (0.001220)	0.126806 (0.001214)
Slope ($*10^{-4}$)	-4.70 (1.01)	-7.52 (0.98)

C. Effect of p_{UU}

How does, now, p_{UU} affect duration dependence? Table 4 reports how our regression coefficients vary with that parameter (see also Figure 4). Clearly, an increase in the connectivity between the unemployed reduces duration dependence. This is because that parameter has a positive, indirect effect, on a long-term unemployed's number of ties with the employed. During any time interval, a fraction of my unemployed friends will find jobs, and these connections are valuable for me in order to find jobs. Being better connected with other unemployed workers therefore increases my exit rate. In contrast, the effect is much weaker for the short-term unemployed, since the stock of ties between an unemployed worker and other unemployed workers gradually builds up during the unemployment spell. Again, p_{UU} affects the short-term unemployed's connections with employed people only through a very weak echo effect from their previous unemployment spell. Figure 4bis shows the effect of p_{UU} on the number of ties.

Table 4: Effect of connectivity between unemployed

	$p_{UU} = 0.02$	$p_{UU} = 0.08$
Intercept	0.130023 (0.001167)	0.126284 (0.001239)
Slope ($*10^{-4}$)	-10.62 (0.86)	-5.82 (1.03)

D. Effect of total tie turnover

Finally, we look at a proportional increase in all parameters related to social links. This represents a situation where, keeping the job turnover constant, social links evolve relatively more rapidly. Results are reported in Table 5 and Figure 5. We see an increase in duration dependence. This effect is confirmed by looking at the number of connections with employed in Figure 5bis. A proportional increase in all link parameters leads to a strong decrease in the number of links with employed of the long-term unemployed, but leaves the connections of the short-term unemployed almost unaffected.

These results are due to the interactions between social and labor market transitions. For an unemployed worker, there are two sources of establishing a bond with an employed worker: creating a new bond with an employed person (which happens with probability p_{UE}), and having an unemployed fellow finding a job (which happens with probability h). Similarly, there are two sources of destruction of bonds with the employed: the bond destruction process (λ) and the job destruction process (d). Therefore, a proportional increase in λ and p_{UE} does not affect the bond creation and bond destruction rates proportionally. Because p_{UE} is small, an increase in p_{UE} has a smaller proportional effect on the rate at which bonds with the employed are created than the effect of the associated, proportional increase in λ on the total rate of destruction of such bonds. Consequently, the total number of ties of the long-term unemployed with employed workers falls, which explains the rise in duration dependence.

Table 5: Effect of total tie turnover

	$benchmark$	$benchmark * 5$	$benchmark * 10$
Intercept	0.130023 (0.001167)	0.145337 (0.001049)	0.153961 (0.001032)
Slope ($*10^{-4}$)	-10.62 (0.86)	-17.31 (0.43)	-17.95 (0.31)

Two other interesting features appear in Figure 5. First, the longest unemployement spells last longer when the tie turnover is higher. For the same average probabilities of job creation and job destruction, more people suffer from very long durations of unemployment. This arises because they have less links with employed workers: When the tie turnover is higher, the probability to find a job of a long-term unemployed is lower. Second, we see that unemployed lose much of their connections to the workplace in the beginning of their unemployment spells. The situation then reaches a positive limit after which the number of connections with employed is stable and does not decrease further. This properties are confirmed by approximate computations derived in the Appendix.

E. Effect of job creation h

Turning now to h, the gross flow of job creation, we see that it increases duration dependence, as measured by both regression results (Table 6) and the evolution of the average probability to find a job (Figure 6). Notice that changing h strongly affects the initial probability to find a job, hence the intercept of the estimation. In order to compare the magnitude of duration dependence across different values of h, we thus divide the probability to find a job by the initial probability (in Figure 6) and the slope of the estimation by the intercept (in the Table 6). This gives us relative measures of duration dependence.

An increase in h increases the total number of employed workers, and thus the opportunities to establish ties with them. Consequently, all workers will have more ties with the employed. However, that effect is stronger for the employed, and thus for the short-term unemployed, than for the long-term unemployed, because $p_{EE} > p_{UE}$. Consequently, the number of ties with the employed increases relatively more for the short-term than for the long-term unemployed, which accentuates duration dependence.

That is mitigated by another effect: when h is larger, establishing ties with unemployed workers is more valuable, because these workers will become employed more quickly. This tends to reduce the rate at which the number of ties with employed workers fall during an unemployment spell, thus dampening duration dependence. However, that effect is not strong enough to overcome the preceding one.

Finally, unemployement spells are longer when h is lower. Since the average probability to find a job becomes relatively flat when unemployment duration is high, this tends to lower the estimated slopes in algebraic values, thus decreasing estimated duration dependence.

Table 6. Effect of the probability of job creation

	h = 0.04	h = 0.12	h = 0.24
Intercept	0.044889 (0.000460)	0.130023 (0.001167)	0.249241 (0.002241)
Slope ($*10^{-4}$)	-1.60 (0.11)	-10.62 (0.86)	-25.14 (3.76)
Slope / intercept ($*10^{-4}$)	35.6	81.7	100.9

F. Effect of job destruction d

Table 7 and Figure 7 report the effect of the job destruction rate d. Given h, a greater d has either little effect on duration dependence (from $d = 0.01$ to $d = 0.02$), or reduces its magnitude (from $d = 0.02$ to $d = 0.06$).

The effects are basically the opposite of those of h. An increase in d reduces the total number of opportunities to have a link with employed workers, since it reduces employment. But the effect is proportionally larger for the employed (and thus the short-term unemployed) than for the long-term unemployed, because p_{EE} is larger than p_{UE}. There is also another effect: a higher d makes connections with the employed less valuable (because they are more short-lived), which tends to compress the gap between the stock of employed workers known by a short-term unemployed and that known by a long-term unemployed. This also tends to reduce duration dependence.

Table 7. Effect of the probability of job destruction.

	d = 0.01	d = 0.02	d = 0.06
Intercept	0.128658 (0.001521)	0.130023 (0.001167)	0.126191 0.000799
Slope ($*10^{-4}$)	-9.41 (1.04)	-10.62 (0.86)	-7.47 (0.64)

G. Effect of total labor turnover

It is also interesting to study the impact of an employment neutral increase of h and d, i.e. a proportional increase in h and d. Table 8 and Figure 8 report the results[5]. We see that the relative average probability to find a job is virtually not affected by the turnover although the estimated measure of duration dependence goes up. The main reason for this difference is that unemployment spells are shorter when labor turnover is higher. Since the average probability to

[5]Here, the number of ties with the employed and its evolution as a function of unemployment duration are also not affected by the turnover (Figure 8bis).

find a job is convex and relatively flat when unemployment duration is high, estimated slopes will be higher (in absolute value) when labor turnover is higher. In other words, if duration dependence is measured by the slope/intercept ratio, greater labor market turnover increases it only because it affects the underlying distribution of durations and because the true relationship between duration and exit probabilities is nonlinear.

Table 8. Effect of total labor turnover.

	$benchmark * 0.5$	$benchmark$	$benchmark * 2$
Intercept	0.066950 (0.000830)	0.130023 (0.001167)	0.251049 (0.001675)
Slope ($*10^{-4}$)	-3.60 (0.27)	-10.62 (0.86)	-24.75 (2.86)
Slope / intercept ($*10^{-4}$)	-53.8	-81.7	-98.6

Neutrality of exit rates with respect to an equiporportional increase in h and d is essentially due to the fact that transition rates in the labor market are large relative to transition rates in the formation and dissolution of social ties (as suggested by the approximation to the model developed in the Appendix). Intuitively, in such a situation, the labor market status of a particular connection at date t is irrelevant, because my friends will move often between employment and unemployment (relative to the characteristic time of bond formation and dissolution). During an unemployment spell, the evolution of the number of ties with employed workers is then largely driven by the process of tie destruction (λ) and tie formation (p_{UE}), so that we do not find a noticeable effect of labor turnover. In other words, the positive effects of h on duration dependence and the the negative effects of d roughly cancel each other.

V. Duration dependence in employment spells

Our model contributes to explain the well-documented phenomenon of negative dependence of exit rates on the duration of unemployment spells. However, it has another, more novel implication, which is that exit rates should also positively depend on the duration of the last job. As long as $p_{EE} > p_{UE}$, the unemployed workers who have been employed for a longer time also have relatively more links with employed workers, and we therefore expect their exit rate to be larger. This is confirmed by our regressions in Table 9 estimated for benchmark parameter values and by looking directly at probabilities (Figure 9).

Table 9. Duration dependence in employment spells

Intercept	0.126378 (0.001490)
Duration unemployed ($*10^{-4}$)	-9.58 (0.90)
Duration of last job ($*10^{-4}$)	0.75 (0.18)

VI. Social organization

In the previous sections, we studied how social ties affect the labor market dynamics. Our model can also be used in a complementary way to understand how society organizes itself along labor status lines. Especially, given that new bonds form preferentially among people with the same labor status, we would expect some form of social separation to emerge between unemployed and employed. To look at this issue, we simply consider for each individual i and at each time t the proportion of neighbors of i who are unemployed at t. We then aggregate these proportions across all unemployed individuals and across all employed individuals. The comparison of both quantities tells us whether, in fact, unemployed end up preferentially connected with other unemployed. Table 10 reports these values and (their standard deviations in parenthesis) for a typical simulation run at different values of labor and tie turnover. Recall that the average proportion of unemployed in the population is $d/(d+h) \simeq 0.143$.

Table 10. Social separation between employed and unemployed

($d = 0.01$; $h = 0.06$)

% of unemployed neighbors	*tie turnover* $*1$	*tie turnover* $*5$
Among unemployed	0.1509600 (0.0561541)	0.2889542 (0.1830154)
Among employed	0.1228365 (0.0441347)	0.0764979 (0.0433909)

labor turnover $*5$

% of unemployed neighbors	*tie turnover* $*1$	*tie turnover* $*5$
Among unemployed	0.1419010 (0.0457575)	0.1455494 (0.0518359)
Among employed	0.1387108 (0.0448782)	0.1290424 (0.0445838)

We thus find that the extent of social separation is usually quite low. The exception is when the labor turnover is low and the tie turnover is high, in which case a strong social separation emerges. Also, actual preferential attachement with others of the same status tends to increase when the tie turnover increases and when the labor turnover decreases. We explain these features below.

That greater turnover of social ties increases social segregation between the employed and the unemployed may come as a surprise. It is another aspect of tie dynamics being driven by both social and labor market transitions. As already explained above, there are two sources of tie formation with employed workers for unemployed ones: establishing a new bond with an employed person (p_{UE}) and having an unemployed friend finding a job (h). Because p_{UE} is small, the first mechanism is a small component of that process, so that an increase in p_{UE} by a given factor will only have a small impact on the unemployed's ties with employed people. By contrast, an increase in p_{UU} by the same factor will have a larger impact on the unemployed's ties with other unemployed workers. Consequently, greater social turnover increases the proportion of unemployed people among an unemployed's connection. The reverse effects hold for the employed: because p_{UE} is small, job destruction (d) is the dominant source that generates ties between them and unemployed workers. The increase in p_{UE} has thus only a small impact on their links with unemployed workers, while the proportional increase in p_{EE} has a larger impact on their links with other employed workers. Therefore, the share of employed workers in their connections goes up.[6]

Conversely, an increase in labor turnover tends to reduce social segregation, because it tends to offset the bias due to the lower rate of bonding between employed and unemployed workers. When labor turnover is high, my unemployed friends quickly find jobs, and my employed friends lose their jobs often. Consequently, the fact that links are more frequent between two employed or two unemployed persons rather than between an employed and an unemployed, is of little consequences: labor turnover brings the proportion of employed workers among one's links more in line between the employed and the unemployed. This analysis highlights the important mixing role of labor markets.

[6] Also, note that if the dynamics of ties were totally independent of labor market transitions, an equiproportionate increase in p_{UU}, p_{EE}, λ, and p_{UE} would have no impact of our measure of social segregation.

VII. Discussion and Conclusion

In this paper, we studied a simple model where labor status and social ties coevolve through time. On the one hand, social ties are helpful to find a job. Connections with employed increase the unemployed's likelihood to find a job. On the other hand, labor status affects the evolution of ties. Especially, the probability of formation of a new tie is greater among two individuals who have the same job status than among individuals with different job status. We showed that this simple assumption generates negative duration dependence of exit rates from unemployment. Long-term unemployed have less connections with employed, hence a lower probability to find a job, than short-term unemployed. We provided a number of stylized facts regarding the effect of the parameters on the shape and magnitude of duration dependence.

Our model potentially has a number of testable empirical predictions that future research could test. A first range of predictions are about the link between labor market history and exit probabilities: these include the widely documented phenomenon of duration dependence, but also the positive influence of the total duration of the previous job on exit rates. However, these predictions are shared with any model where workers accumulate human capital during employment periods and gradually lose it during unemployment spells. A second range of predictions, more specific to our model, is about the coevolution of labor market status and social ties; to test them empirically, one possibility would be to compare communities with different intensities of social interactions (these differences could for example be driven by cultural customs, if one considers different ethnic groups, or by differences in urban structures, if one considers different cities), and correlate these differences with the labor market outcomes of these communities. Another approach would be to use individual data on both employment status and social ties, and examine the correlation between unemployment duration, job duration, and so on and the number of ties with employed and unemployed workers.

The model could also be enriched by introducing additional margins of economic behavior. That could include wage bargaining, price formation, a time constraint to be allocated between work, search, and socialization, and competing search methods. As stated above, we are reasonably confident that our results would be robust as long as the model exhibits economic inbreeding. However, these extensions could potentially yield many interesting insights.

Appendix.

A simple heuristic approximation to the model

The following approximation allows to compute the evolution of the number of links between an unemployed and employed and unemployed workers over time. Let us denote by $t = 0$ the date at which the worker become unemployed, let e_t his mass of ties with employed workers, let u_t his mass of ties with unemployed workers, let $E = h/(h+d)$ the steady state level of unemployment and $U = d/(h+d)$ the steady state level of employment. Then the evolution of e and u follows approximately:

$$\begin{aligned}\dot{e} &= -de + hu + p_{UE}(E - e) - \lambda e \\ \dot{u} &= -hu + de + p_{UU}(U - u) - \lambda u\end{aligned}$$

The long-term solution to that system is

$$e_\infty = h\frac{p_{UE}(\lambda + p_{UU} + h) + p_{UU}d}{(h+d)[d(p_{UU}+\lambda) + h(p_{UE}+\lambda) + (p_{UU}+\lambda)(p_{UE}+\lambda)]}$$

$$u_\infty = d\frac{p_{UE}h + p_{UU}(\lambda + d + p_{UE})}{(h+d)[d(p_{UU}+\lambda) + h(p_{UE}+\lambda) + (p_{UU}+\lambda)(p_{UE}+\lambda)]}$$

The evolution matrix $\begin{pmatrix} -(d+\lambda+p_{UE}) & h \\ d & -(h+\lambda+p_{UU}) \end{pmatrix}$ has two negative eigenvalues. When p_{UE} and p_{UU} are small compared to d and h, the evolution matrix is approximately equal to $\begin{pmatrix} -(d+\lambda) & h \\ d & -(h+\lambda) \end{pmatrix}$. In this case, the eigenvalues are $-(h+d+\lambda)$ and $-\lambda$. The corresponding eigenvectors are $\begin{pmatrix} 1 \\ -1 \end{pmatrix}$ and $\begin{pmatrix} 1 \\ d/h \end{pmatrix}$. The solution to the dynamic system is

$$\begin{pmatrix} e_t \\ u_t \end{pmatrix} = c_0 e^{-(h+d+\lambda)t}\begin{pmatrix} 1 \\ -1 \end{pmatrix} + c_1 e^{-\lambda t}\begin{pmatrix} 1 \\ d/h \end{pmatrix} + \begin{pmatrix} e_\infty \\ u_\infty \end{pmatrix}.$$

One must have $c_1 = \frac{e_0 + u_0 - (e_\infty + u_\infty)}{1 + d/h}$ and $c_0 = \frac{(e_0 - e_\infty)d/h - (u_0 - u_\infty)}{1 + d/h}$, so that

$$e_t = \frac{(e_0 - e_\infty)d/h - (u_0 - u_\infty)}{1 + d/h} e^{-(h+d+\lambda)t} + \frac{e_0 + u_0 - (e_\infty + u_\infty)}{1 + d/h} e^{-\lambda t} + e_\infty. \tag{VII.1}$$

It is interesting to see what happens when h and d become large relative to other transition rates, holding $h/d = \eta$ contant, i.e. when the temperature of the labor market is large relative to the temperature of social networks. We then have:

$$\begin{aligned} \lim e_\infty &= \frac{\eta}{(1+\eta)^2}(\eta p_{UE} + p_{UU}), \\ \lim u_\infty &= \frac{\eta p_{UE} + p_{UU}}{(1+\eta)^2} \end{aligned}$$

which does not depend on labor market temperature. In (VII.1), the first term is negligible, so that

$$e_t \approx \frac{\eta}{1+\eta}(e_0 + u_0 - \frac{\eta p_{UE} + p_{UU}}{1+\eta})e^{-\lambda t} + \frac{\eta}{(1+\eta)^2}(\eta p_{UE} + p_{UU}).$$

Clearly, the overall temperature of the labor market does not affect the evolution of links with the employed.

References.

Abbring, Jaap H. ; van den Berg, Gerard J. ; van Ours, Jan C., "The Anatomy of Unemployment Dynamics", *European Economic Review* v46, n10 (December 2002): 1785-1824

Arulampalam, Wiji ; Booth, Alison L. ; Taylor, Mark P. "Unemployment Persistence", *Oxford Economic Papers* v52, n1 (January 2000): 24-50

Calvó-Armengol, A., Jackson, M. 2003. "Social Networks in Determining Employment: Patterns, Dynamics, and Inequality," forthcoming *American Economic Review.*

Granovetter, M. 1995. *Getting a Job: A Study of Contacts and Careers.* 2nd edition, University of Chicago Press: Chicago. First edition in 1974.

Lazarsfeld, P., and Merton,R. 1954. "Friendship as a social process: A substantive and methodological analysis", in Berger, M., Abel, T., and Page, C. (eds), *Freedom and Control in Modern Society*, Princeton NJ: Van Nostrand.

Montgomery, J. 1991. "Social Networks and Labor Market Outcomes: Toward an Economic Analysis," *American Economic Review*, 81, 1408-1418.

Rees, A. 1966. "Information Networks in Labor Markets," *American Economic Review*, 56, 559-566.

Petersen, T., Saporta, I., Seidel, M. D. 2000. "Offering a Job: Meritocracy and Social Networks," *American Journal of Sociology*, 106, 763-816.

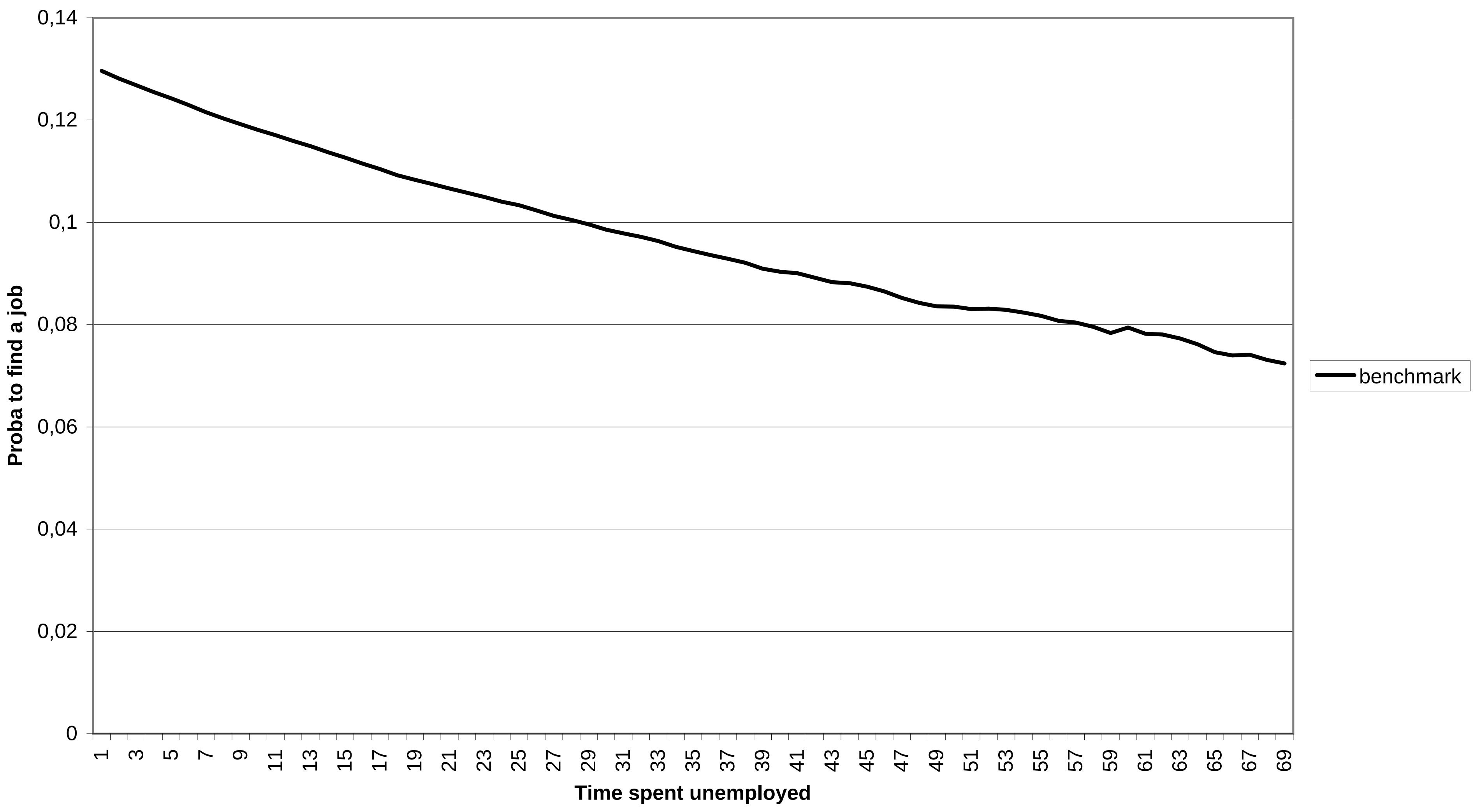
Michael Rosholm, "Observed and unobserved heterogeneity in the duration dependency parameter", *Economics Letters* ,Volume 66, Issue 3 , March 2000, Pages 347-351

Steiner, Viktor, "Unemployment Persistence in the West German Labour Market: Negative Duration Dependence or Sorting?", *Oxford Bulletin of Economics and Statistics* v63, n1 (February 2001): 91-113

Topa. G. 2001. "Social Interactions, Local Spillovers, and Unemployment," *Review of Economic Studies*, 68, 261-295.

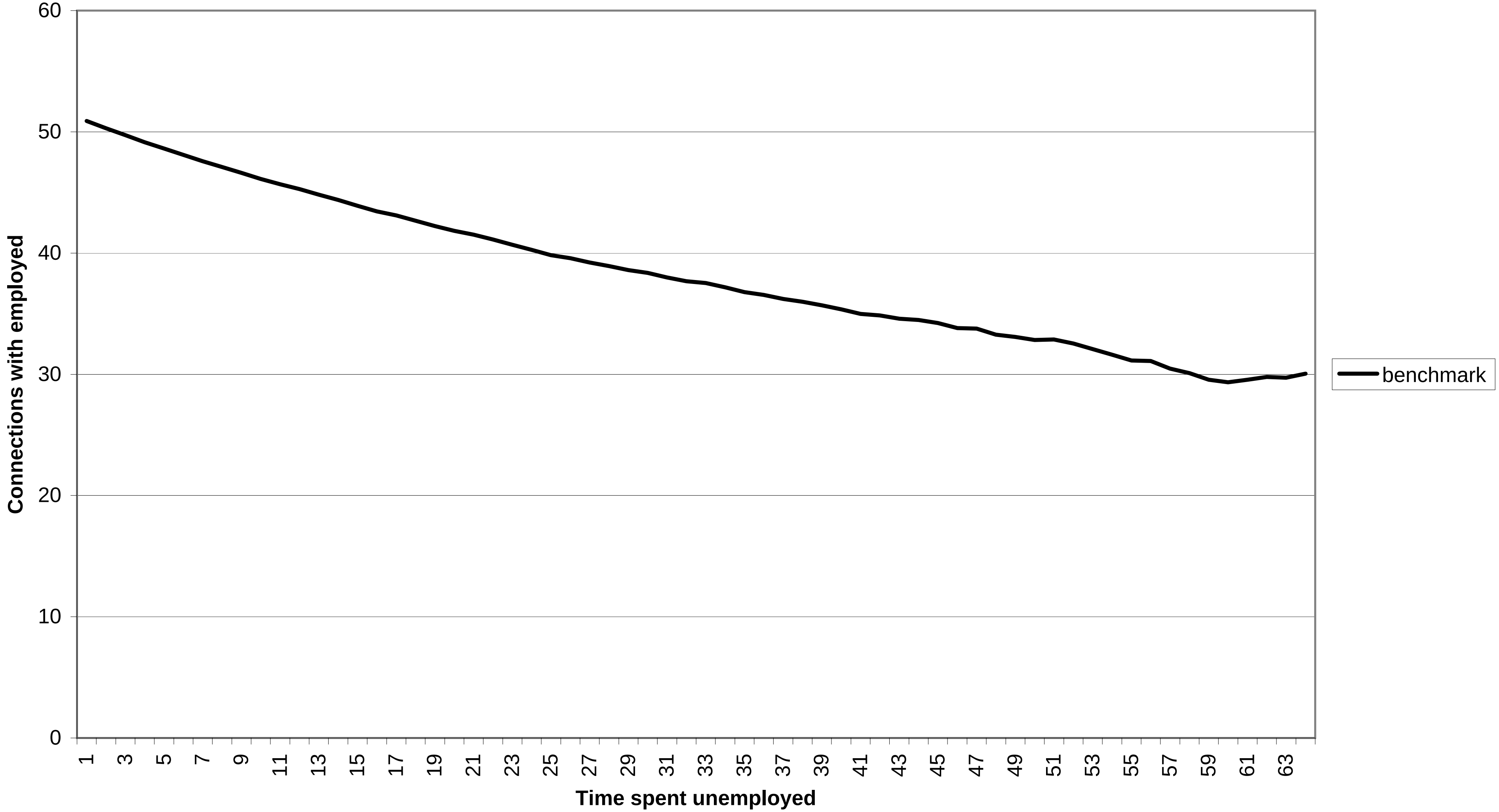
van den Berg, Gerard J. ; van Ours, Jan C. , "Unemployment Dynamics and Duration Dependence", *Journal of Labor Economics* v14, n1 (January 1996): 100-125

Figure 1.



0,14
0,12
0,1
0,08
0,06
0,04
0,02
0
Proba to find a job
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 59 61 63 65 67 69
Time spent unemployed
benchmark

Figure 1bis.



Connections with employed
0
10
20
30
40
50
60
1
3
5
7
9
11
13
15
17
19
21
23
25
27
29
31
33
35
37
39
41
43
45
47
49
51
53
55
57
59
61
63
Time spent unemployed
benchmark

Figure 2. Effect of pue

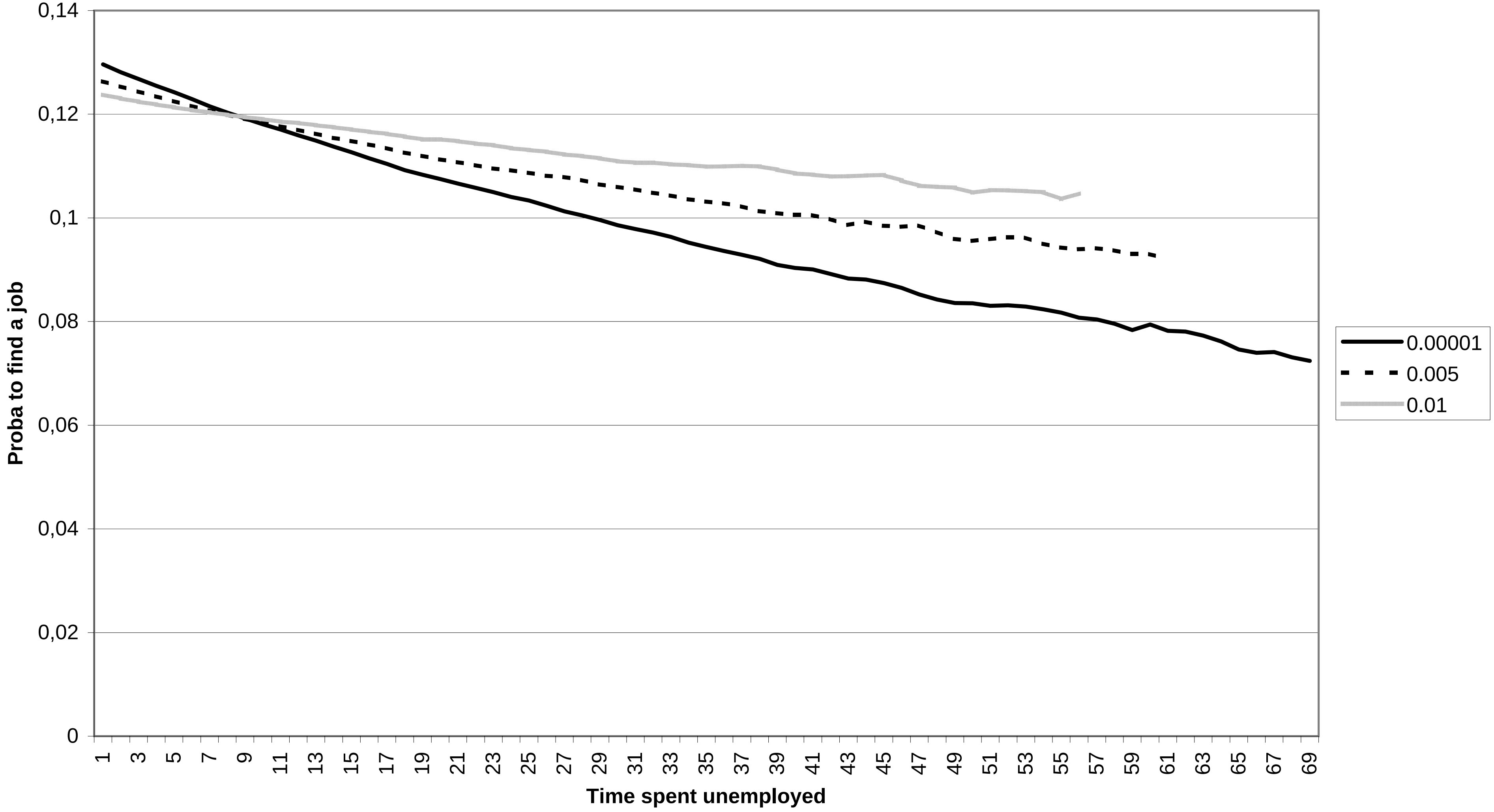


Figure 2bis. Effect of pue

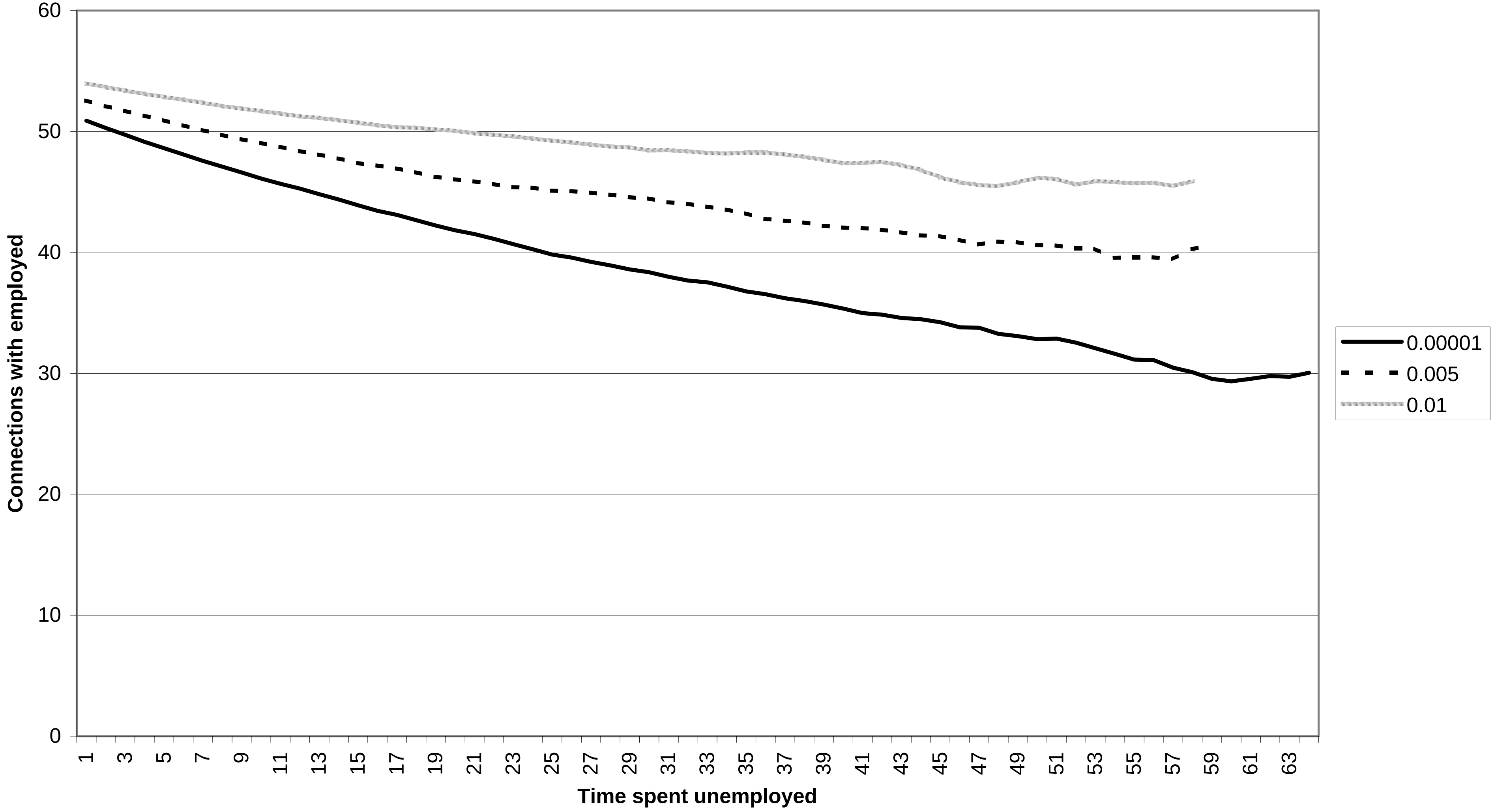


Figure 3. Effect of pee at pue=0.01

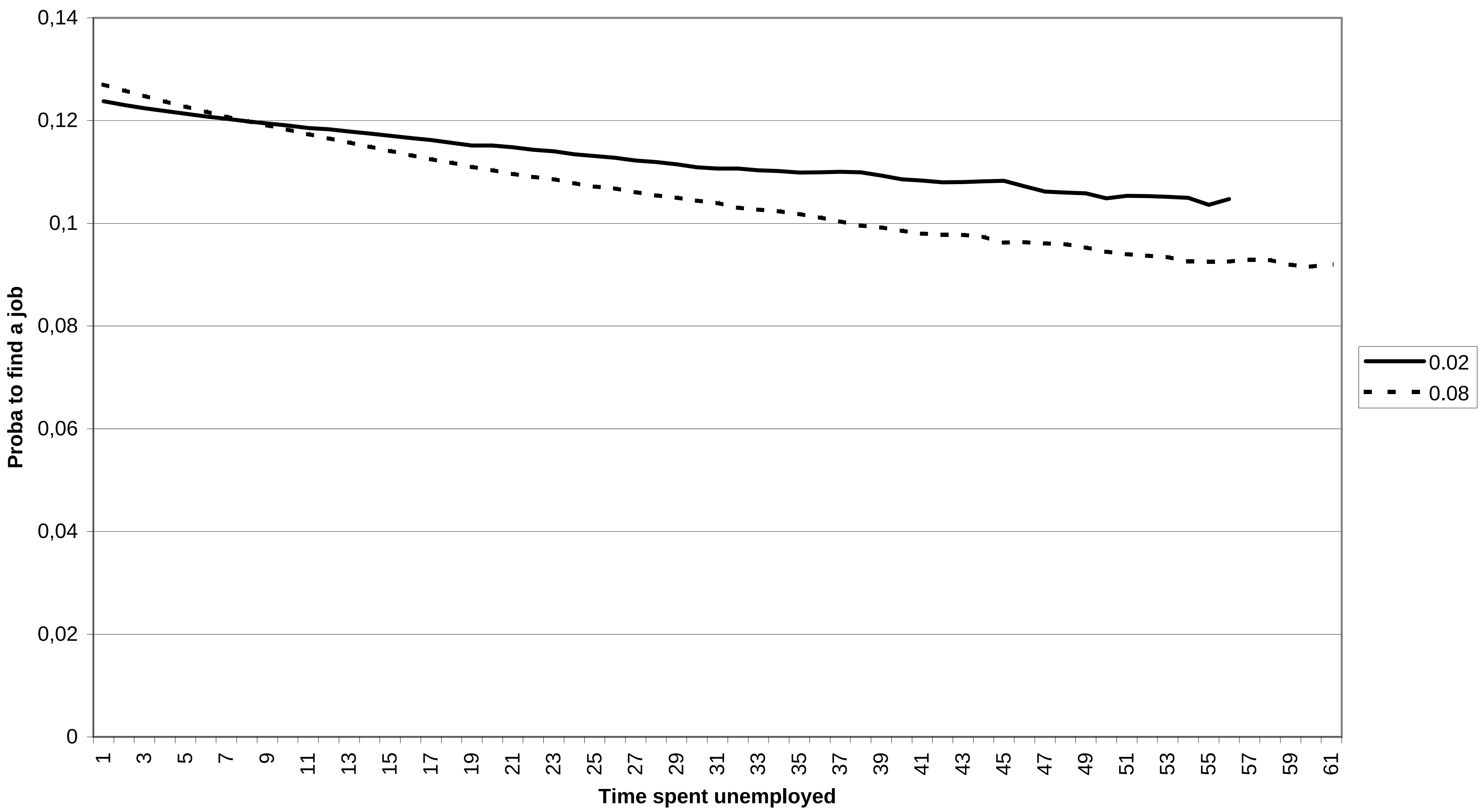


Figure 3bis. Effect of pee at pue=0.01

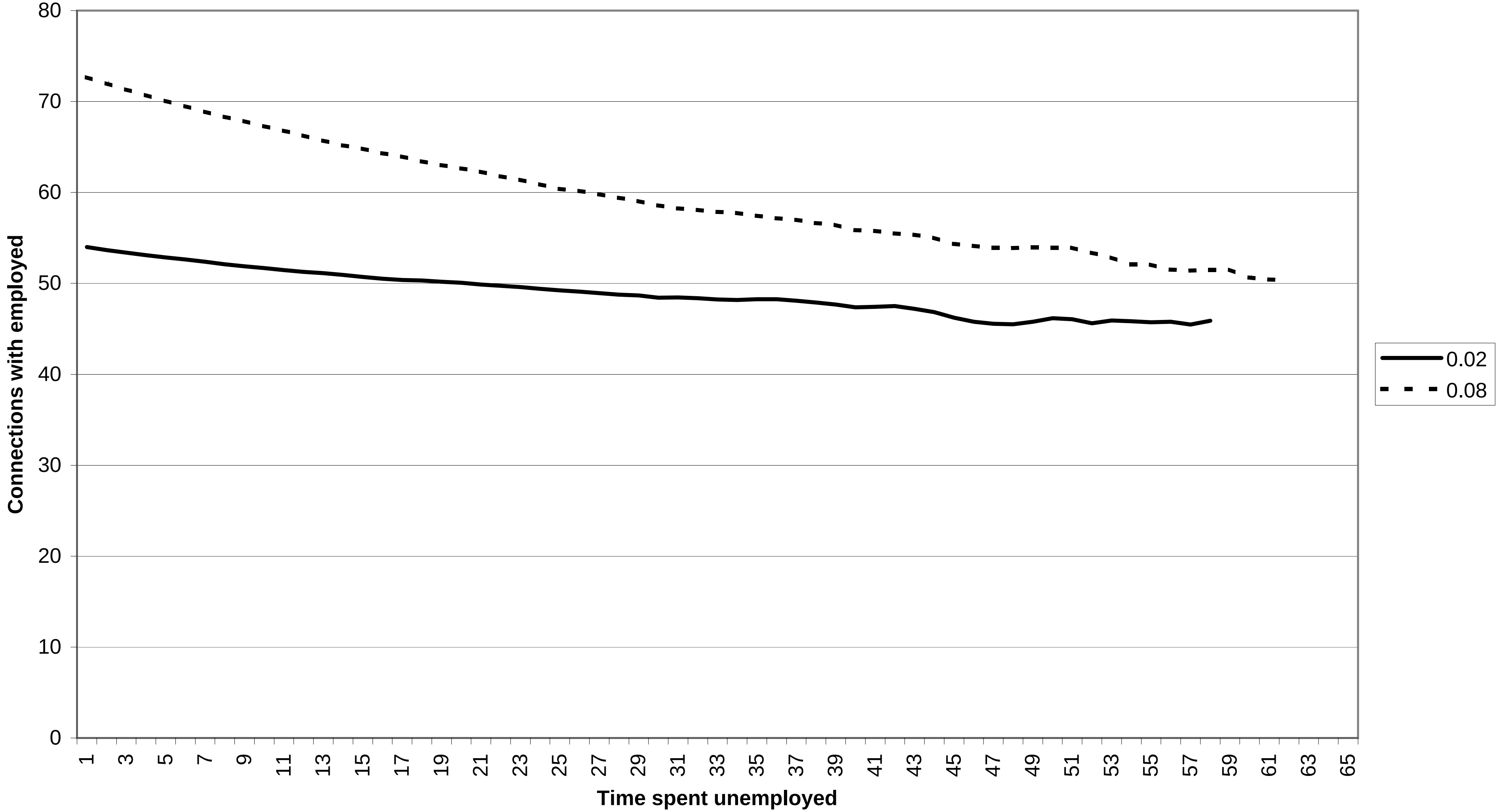
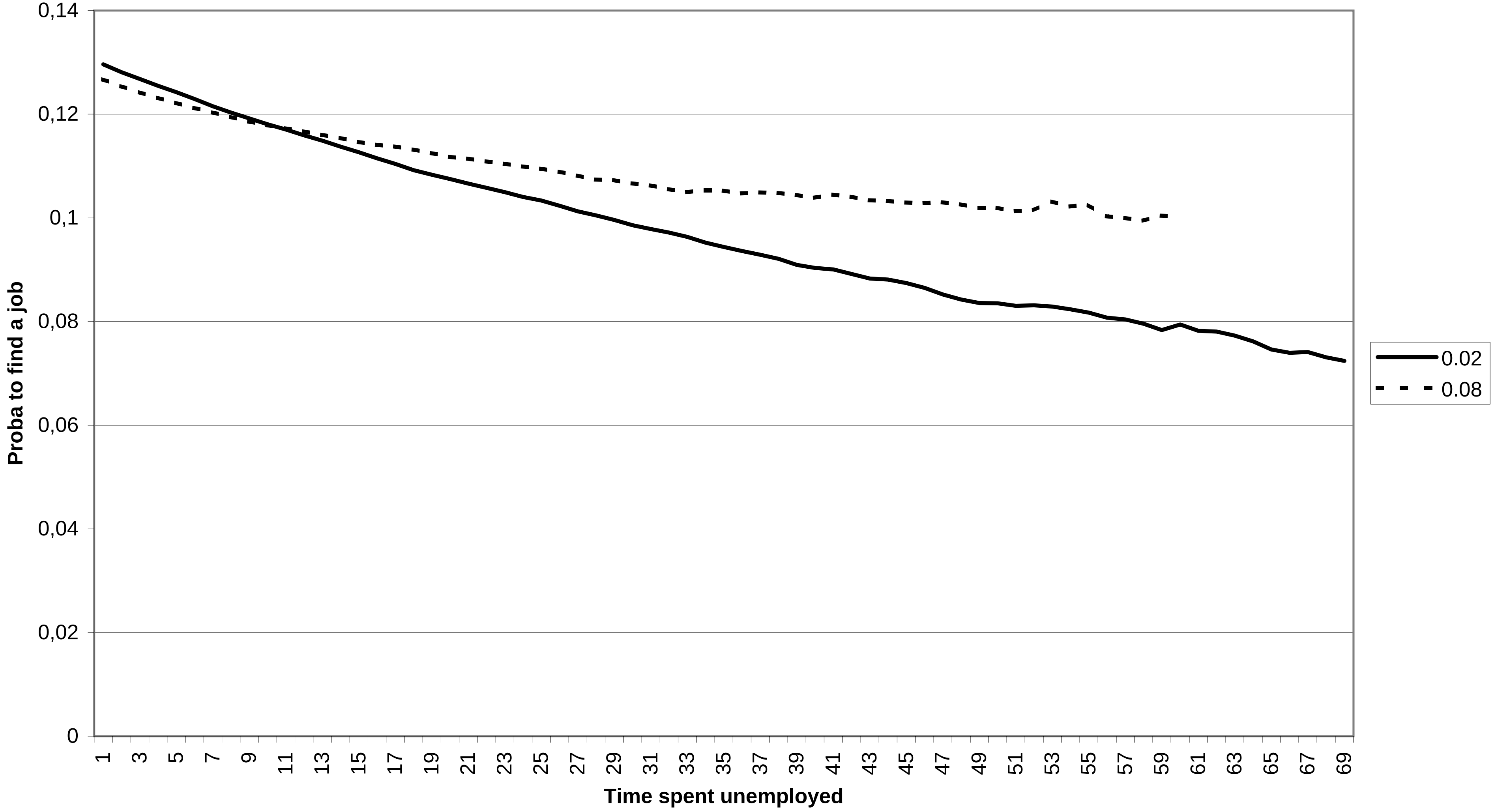


Figure 4. Effect of puu



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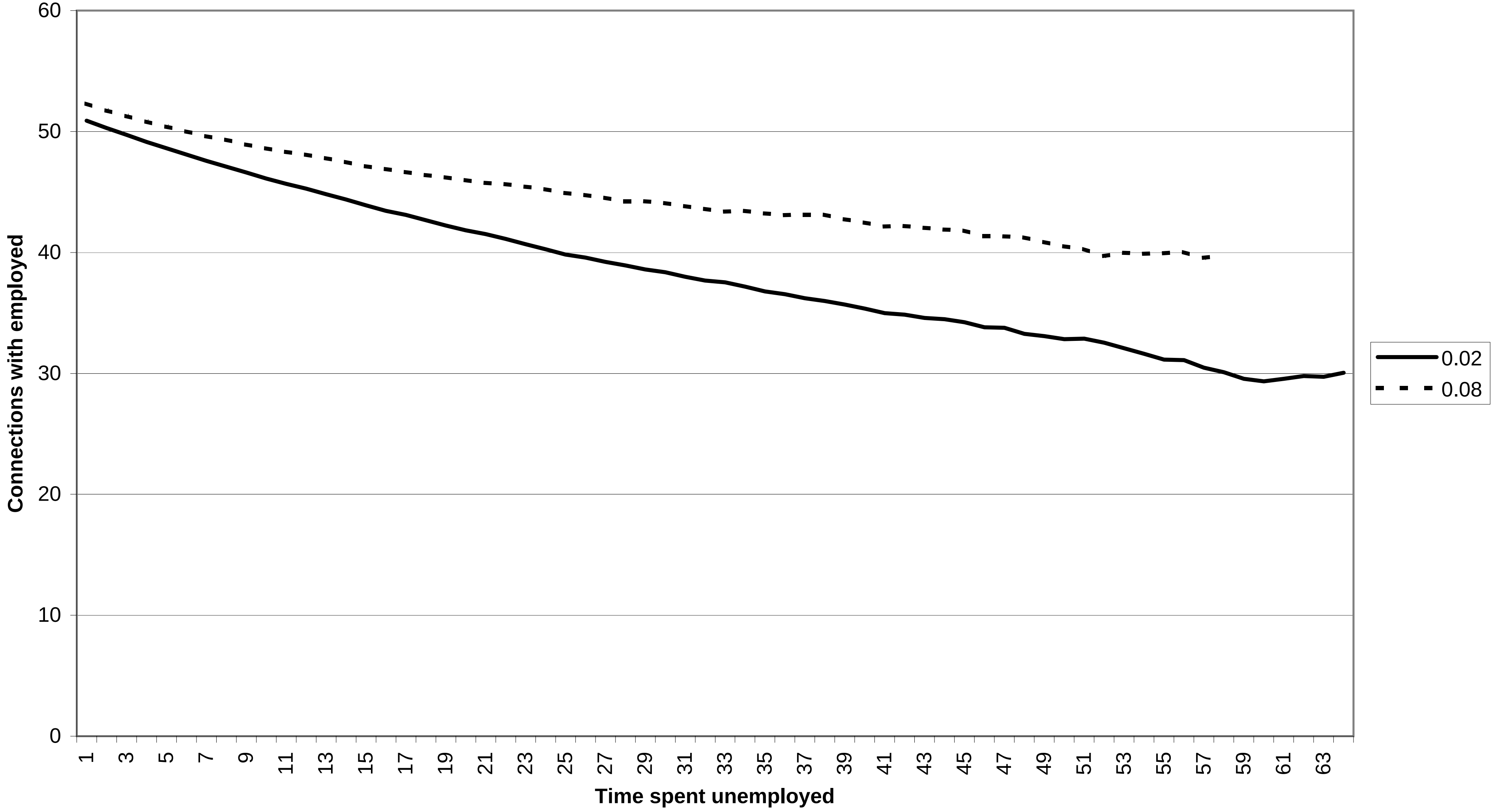

Figure 5. Effect of total tie turnover

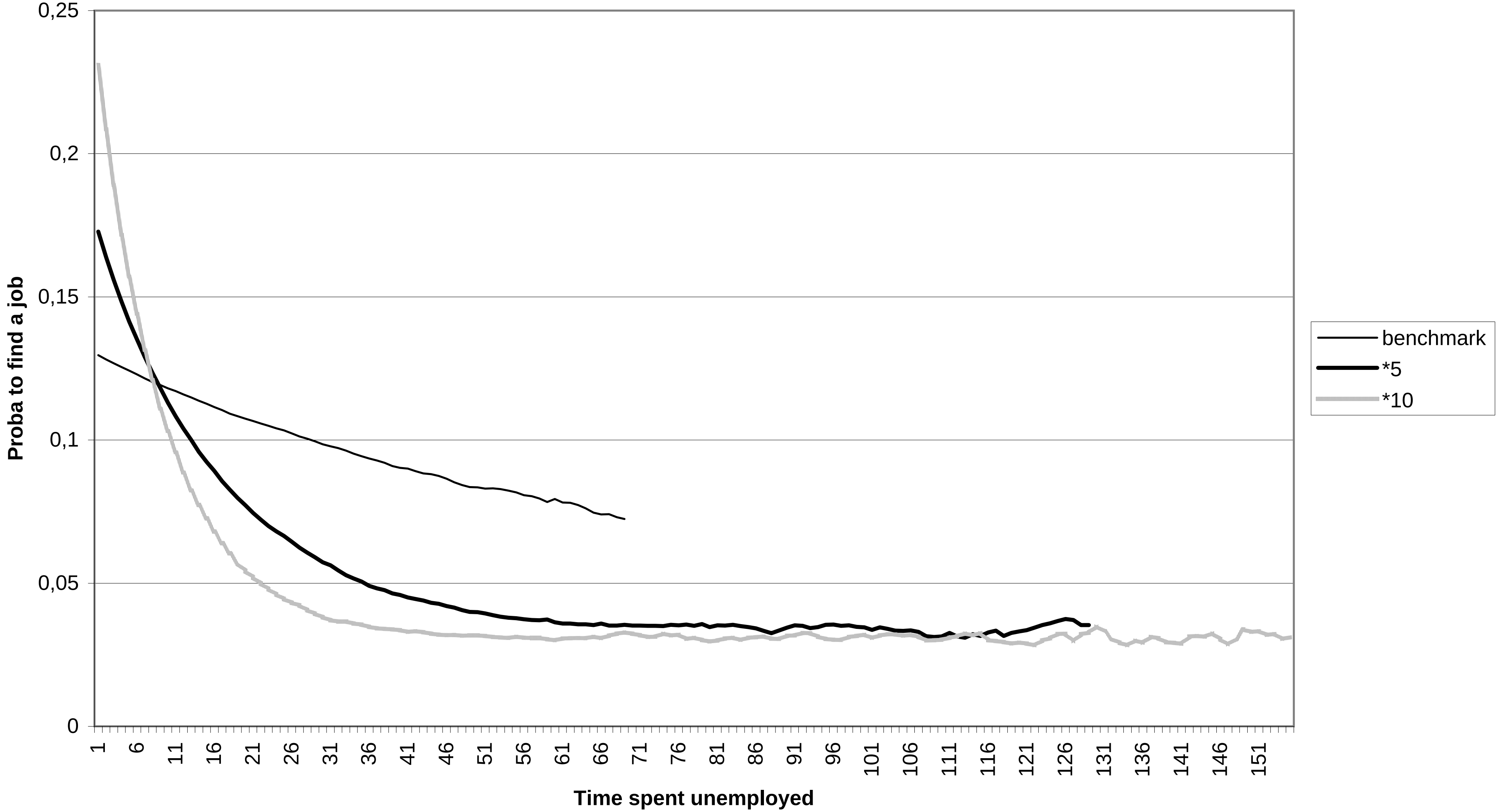

Figure 5bis. Effect of total tie turnover

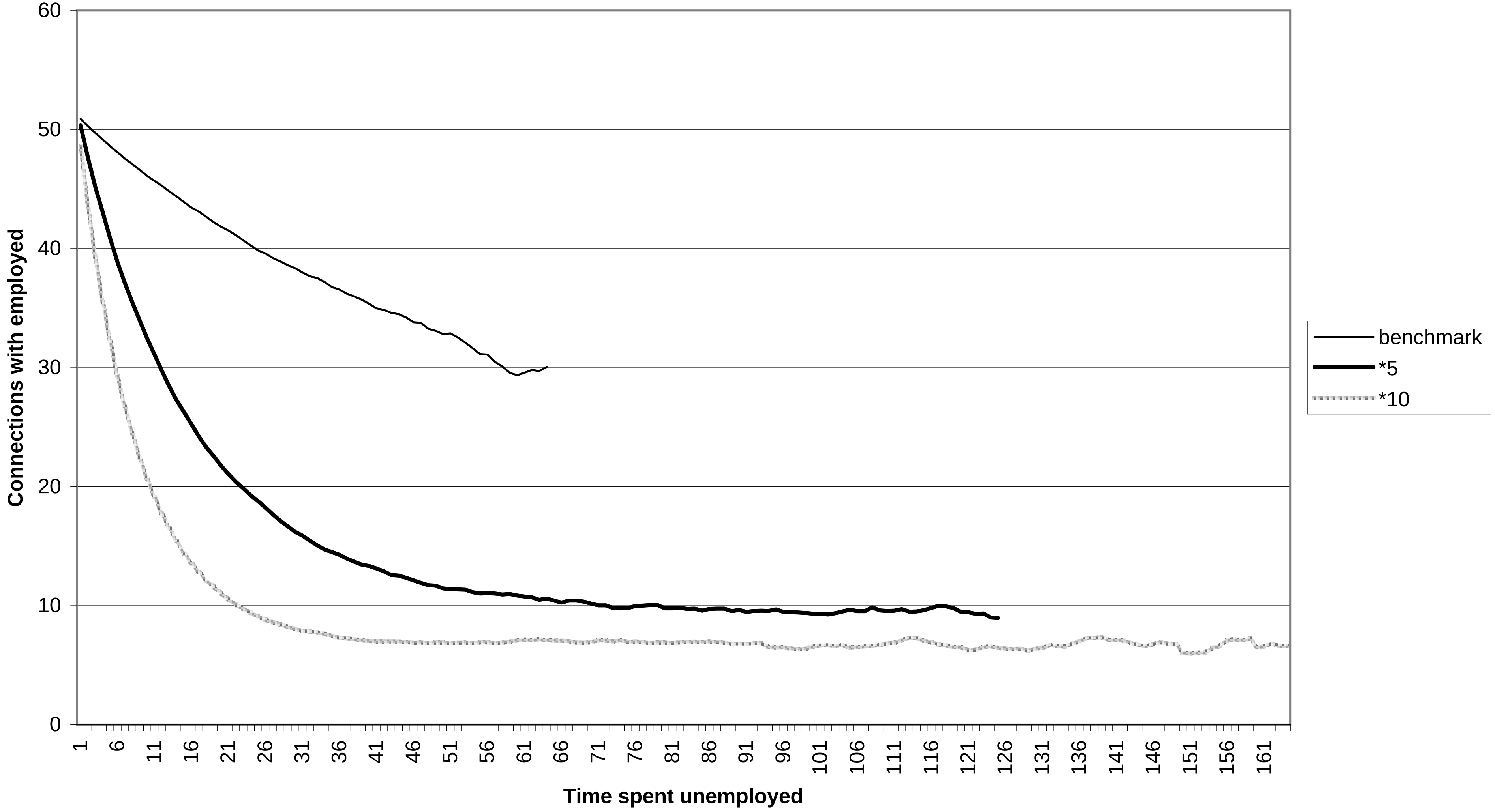

Figure 6. Effect of h

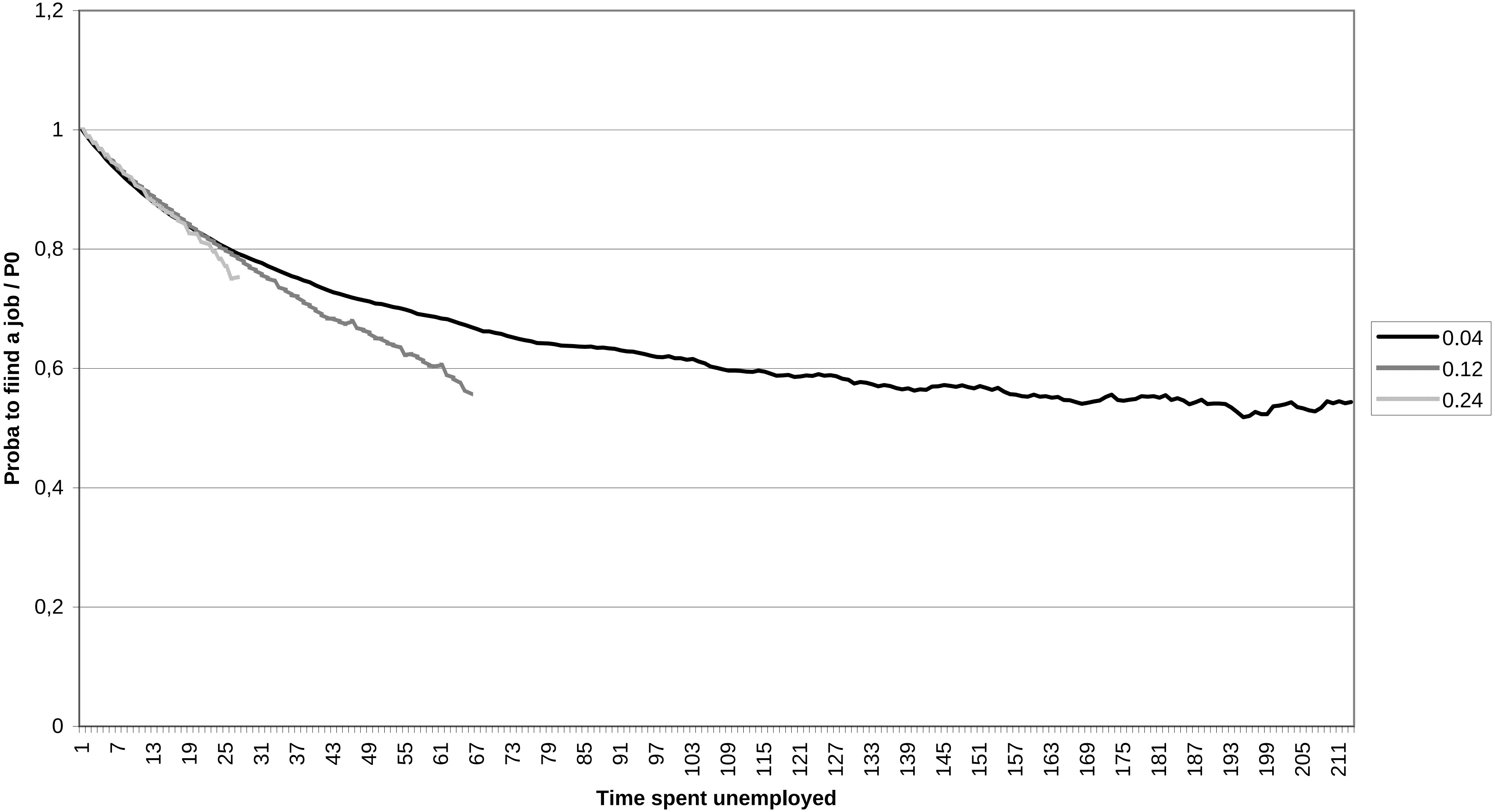

Figure 6bis. Effect of h

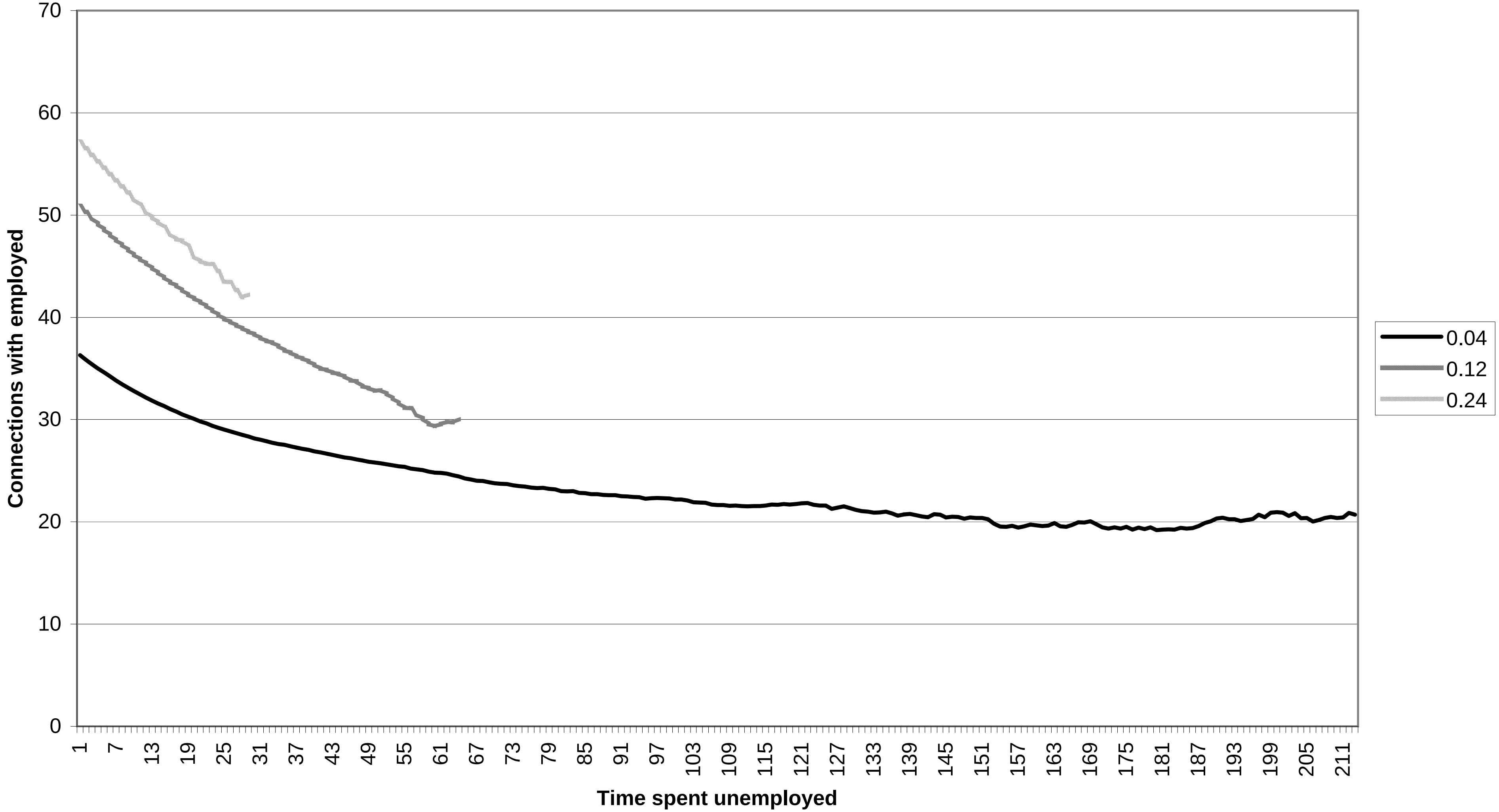

Figure 7. Effect of d

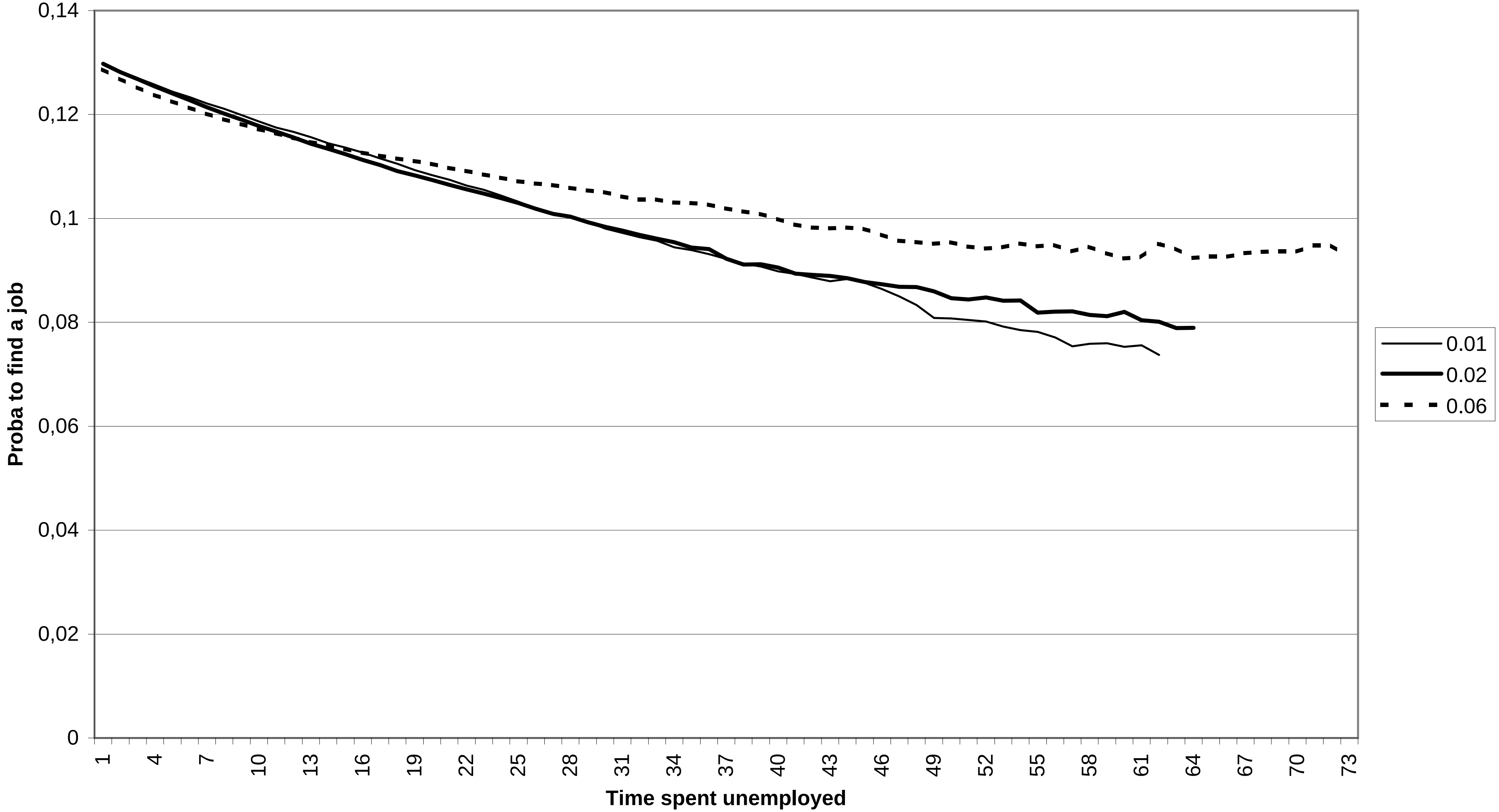

Figure 7bis. Effect of d

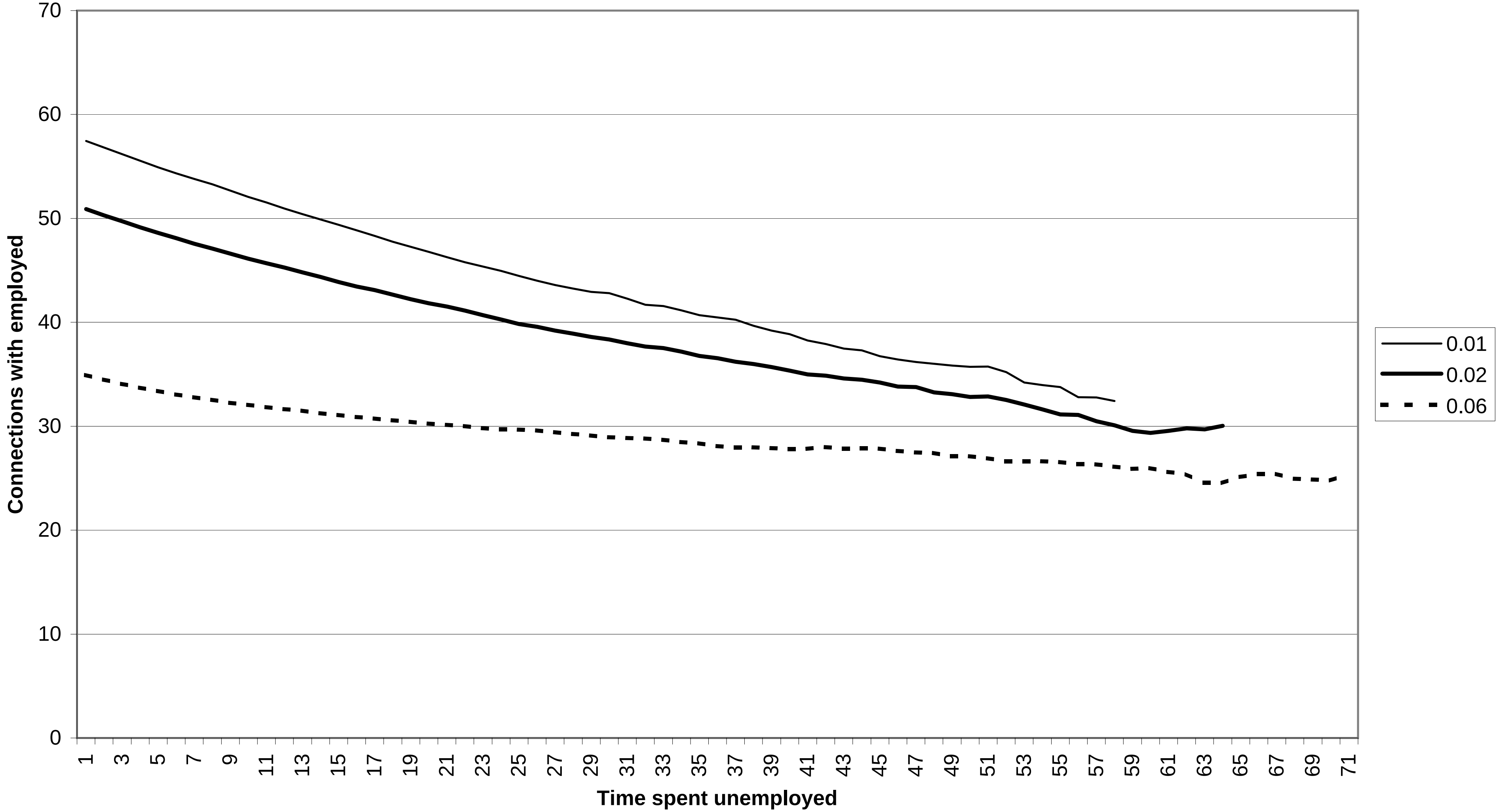

Figure 8. Effect of total labor turnover

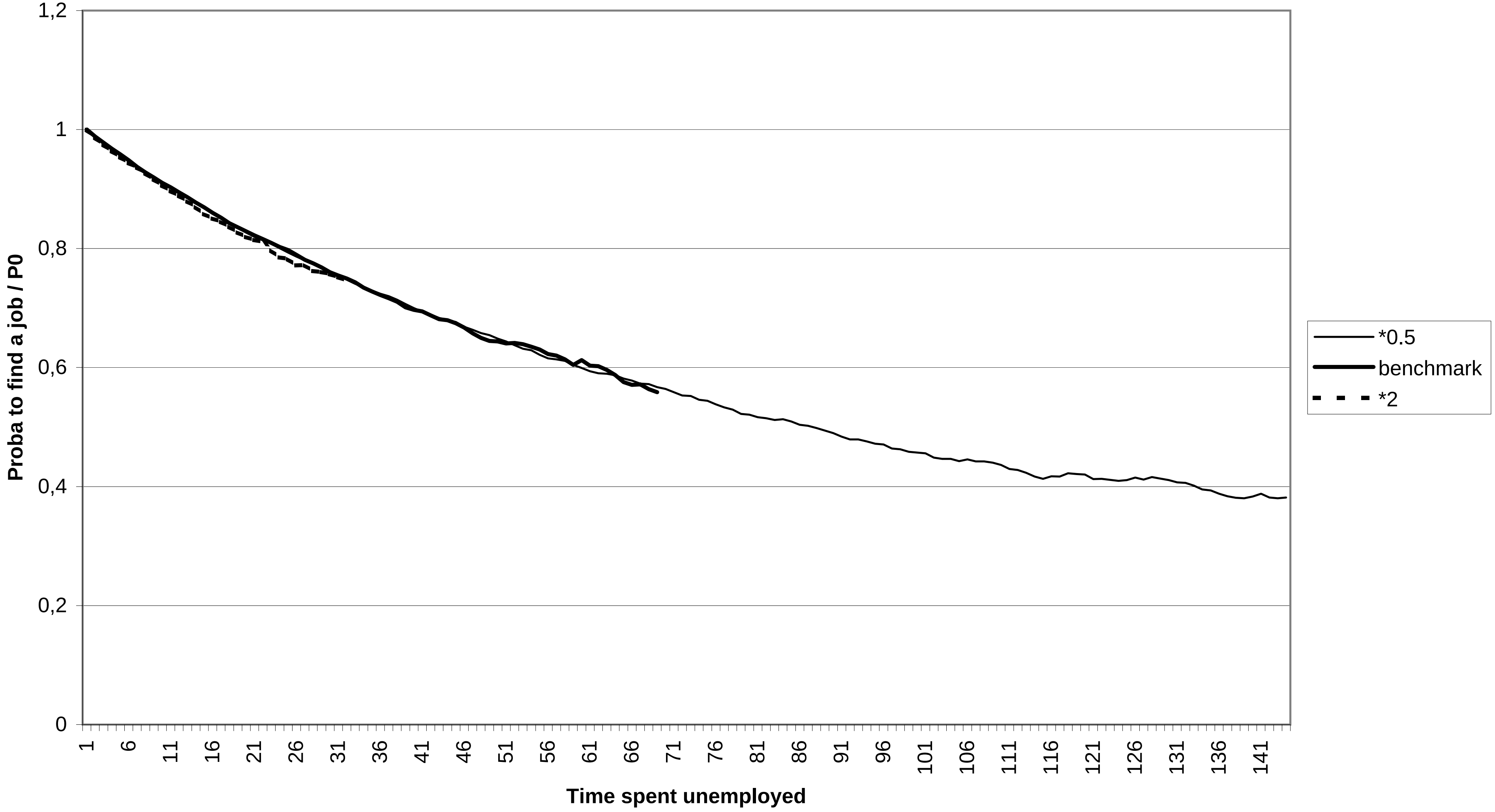

Figure 8bis. Effect of total labor turnover

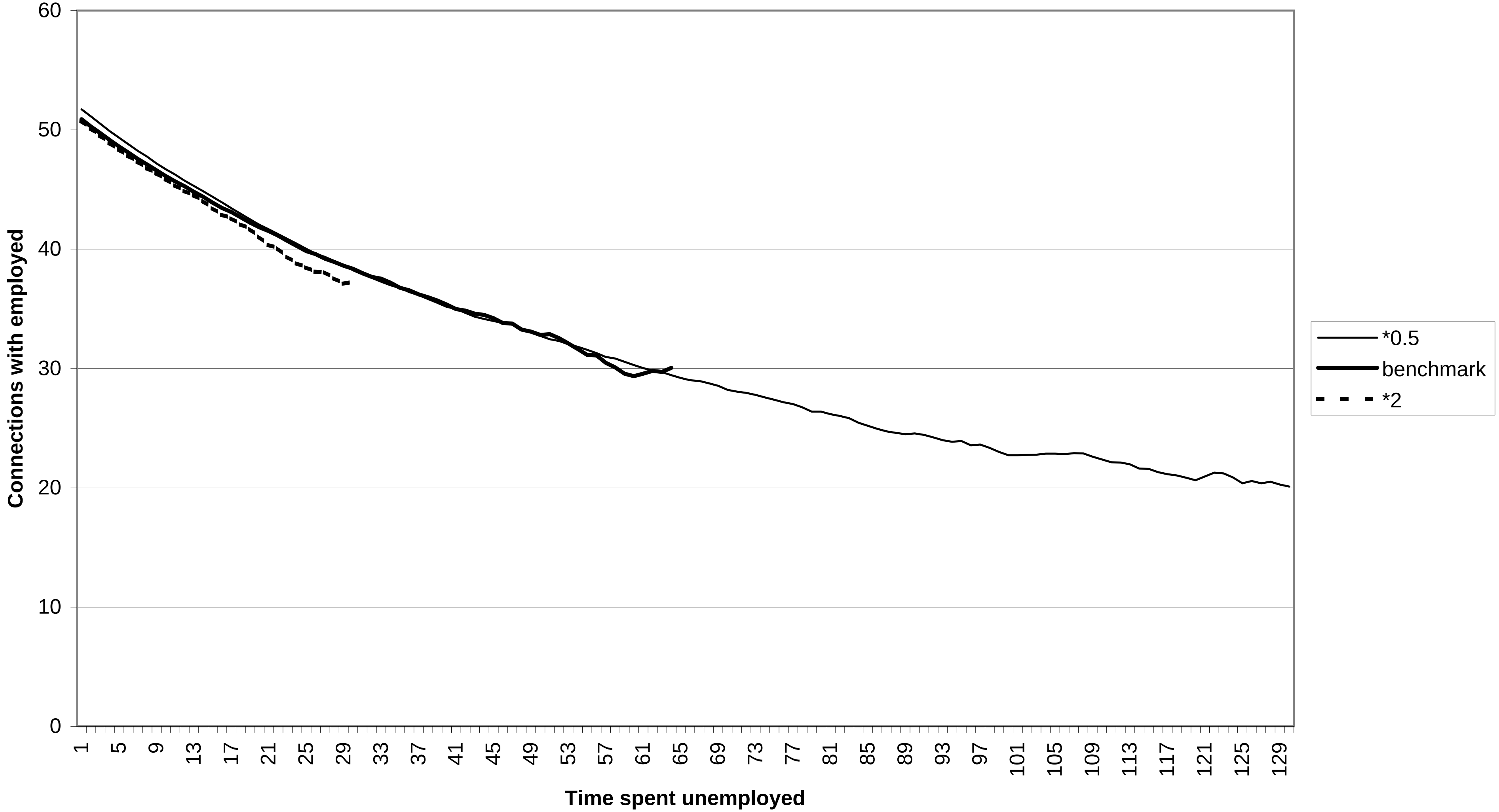

Figure 9. Effect of duration of last job