

How Do Heterogeneous Wage Expectations Affect Unemployment?

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June 3, 2006

Abstract

A strand of survey studies indicates that wage expectations are widely dispersed, even among people with similar background. This paper considers a job search model with heterogeneous wage expectations. It shows that aggregate unemployment increases when expectations become more dispersed. This happens because search duration of pessimists is bounded by accepting the next wage offer, whereas that of optimists has no upper bound. Moreover, when calibrated the model suggests that welfare gains from improving the dissemination of wage information may be considerable. Finally, we present the first empirical material suggestive of a link between optimism and search duration.

Keywords: Search, Wage information, Heterogeneous expectations, Unemployment
JEL Classification: D83, D84, J30, J64

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1 Introduction

Theoretical studies that consider the behaviour of job searchers generally start from the assumption that these searchers know the distribution of wage offers that they can expect. But a growing literature of survey studies, particularly surveys among students, finds that although the median searcher may have a fairly correct expectation, the variance of these expectations is large. In his survey, Betts (1996), for example, compares students' estimates of national average salaries in different fields with the actual salaries. The median student has roughly zero error, but, ranked by their estimate of (national average) salary, the 90th percentile of respondents foresees wages twice as high as the 10th percentile. Some overestimate wages, others underestimate them. Betts' approach has the disadvantage that it does not directly elicit expectations about own wages, although by asking students about averages it avoids issues of unobserved individual heterogeneity. Dominitz and Manski (1996) have the same result as Betts for national averages, but also ask students about their own wage expectations, controlling for factors such as age, gender, education, etc. They find a close correspondence between overestimating national average wages and high personal wage expectations. In a similar survey, Brunello et al. (2001) find that for most European countries wage expectations are even more widely dispersed than in the US.¹

How is an economy's unemployment rate affected by heterogeneous wage expectations? Our aim in this paper is to analyse this question by introducing subjective wage distributions in a job search model. We show that aggregate unemployment increases when wage expectations become more dispersed. Quite intuitively, this effect arises because search duration of those who underestimate is bounded by accepting the very next offer, but search duration of those who overestimate can tend to infinity.

This paper is not the first to consider job searchers who do not know the true wage offer distribution. But the existing literature, starting with Rothschild (1974), has looked at a single searcher who learns by making wage draws. Rothschild (1974) was first to investigate whether the reservation wage property also holds under Bayesian learning. He proved that it does, but only under particular assumptions about the prior (Dirichlet distribution). Bikhchandani and Sharma (1996) generalise the result of Rothschild (1974). They show that if the posterior distribution - the searcher's prior next period - is a convex combination of the initial prior distribution and the empirical distribution, there exists an optimal stopping rule which has the reservation wage property. They also consider comparative statics under learning, based on (an extended) definition of Kohn and Shavell (1974) where one searcher is referred to as being more optimistic than another if his wage distribution yields a larger expected utility from searching. The more optimistic searcher sets a higher reservation wage

¹Botelho and Pinto (2004) provide a useful overview of this survey literature about wage expectations.

and searches longer. Other studies of interest in this field include Burdett and Viswanath (1988), who derive conditions under which reservation wages are strictly decreasing over time, and Dubra (2004), who discusses the welfare implications of overconfidence among searchers: when the true wage distribution is unknown, overconfident individuals may be better off than unbiased ones, because of downward updating.

Contrary to the previous papers, we consider the effect of aggregation. We start from a job search model which includes job separation, and derive the equilibrium unemployment rate. We bring in subjective wage distributions, where overconfidence, unbiasedness and underconfidence are defined according to Kohn and Shavell (1974). Subsequently, we impose the assumption that searchers' priors are distributed symmetrically in over/underconfidence around the truth, from which a symmetric distribution of reservation wages is derived. This assumption is not necessarily empirically plausible. But the assumption of symmetry distills the main point of the paper, since it is quite obvious that an overconfidence (underconfidence) bias leads to larger (smaller) unemployment. In fact, a large literature in both experimental economics and psychology documents that on average people tend to be overconfident. For an overview of this literature see Kőszegi (2006, forthcoming), Hoelzl and Rustichini (2005) and Camerer and Lovallo (1999). If, as we find, even under symmetry heterogeneous expectations lead to higher unemployment, then an overconfidence bias would merely strengthen this effect. We are able to show that when the symmetric distribution of beliefs becomes wider the average unemployment rate rises.

Unlike the previous studies, however, we abstract from learning, in order to focus on the effect of aggregation.² This keeps the analysis simple, but it violates the result that rational agents who learn should eventually converge to a common prior, as argued by Aumann (1976) and Geneakoplos and Polemarchakis (1982). In reality, however, there is new inflow into the pool of unemployed, so that heterogeneity of wage expectations could be sustained even if searchers learn. Computing a solution for Bayesian (or non-Bayesian) updating in our model may be feasible, but in the current paper we choose to focus simply on the main point of aggregation.

But aside from identifying this theoretical effect running from heterogeneous wage expectations to unemployment, we would also like to have some idea as to its quantitative relevance. We start out by calibrating a completely standard search model without heterogeneous wage expectations on the current unemployment rate in the United States and Germany. We use a standard lognormal distribution, which we parameterise according to figures from the US BLS and the German Statistisches Bundesamt. The shape parameter of the wage distribution is left open and imputed by matching to the actual unemployment rate.

²There have, in fact, been several studies in search theory that abstract from learning in order to focus on a different aspect, such as distinguishable search alternatives. See Adam (2001) for an overview.

We then apply the same parameters to our model with heterogeneous wage expectations, and check "how much" heterogeneity is required for a significant impact on the unemployment rate. The results from survey studies provide us with an upper bound on the dispersion of wage expectations in the economy. They give an upper bound, because the surveys were conducted among students and more experienced labour market participants likely possess better wage information. We find that for degrees of dispersion far below this upper bound unemployment reacts strongly to heterogeneity of expectations. Furthermore, to be able to say something about potential unemployment reduction due to better wage information, we also conduct a slightly different exercise. Here we match the model with heterogeneity on the current unemployment rate for different degrees of dispersion, and calculate how much unemployment decreases as expectations become homogeneous. The results suggest that the welfare gains from improving the dissemination of wage information may be considerable.

Finally, we report several empirical correlations between optimism and search duration that go in the direction predicted by the search model. Specifically, we use the Survey of Economic Expectations, that has been compiled by Jeff Dominitz and Charles Manski for the US. We find negative correlations between respondents' sadness and their search duration. Sad job searchers spend, on average, 2.5 weeks per year less looking for a job. Without thinking in terms of the search model, if anything, one would expect that sad people have a harder time getting a job. Similarly, spending more time looking for a job should normally make people more sad. Both of these channels would point to a *positive* correlation. Like for sadness, we also find a negative relationship between respondents' perceived probability of rain tomorrow and their search duration. If we interpret sadness and the subjective probability of rain as measures of optimism, the results are suggestive of a positive link between optimism and search duration.

The outline of the paper is as follows. The next section presents the model. It first derives the theoretical result and then explains the result in terms of economic intuition. Section 3 presents the calibration exercise. Section 4 discusses empirical correlations of optimism and search duration. And section 5 concludes.

2 The model

Here we write down the basic equations of the job search model which includes quitting and firing, and extend it to include subjective wage distributions. Our exposition follows that in Sargent and Ljungqvist (2004) up till equation (2). An infinitely-lived, risk-neutral, unemployed worker gets a wage offer, w , each period, which is drawn from a time-invariant cumulative density function on the support $[0, \infty)$: $F(W) = \text{prob}\{w \leq W\}$, with $F(0) = 0$ and $\lim_{w \rightarrow \infty} F(w) = 1$. The worker can reject the offer, in which case he is allowed to draw

another offer, w' , next period. Alternatively, he can accept the offer and work at wage w until he quits or is fired. On every job he faces the same fixed probability, $\lambda \in (0, 1)$, each period of being fired.

The worker maximises the expected present value of his income stream, where income at t , y_t , equals 0 if the worker is unemployed, and w if he is working. Define $V(w)$ as the expected value of $\sum_{t=0}^{\infty} \beta^t y_t$ if the worker has offer w in hand. Here, $\beta \in (0, 1)$ is the discount factor. If the searcher rejects the current wage offer w , he gets the option to make a new draw next period, which has value $V(w) = \beta \int_0^{\infty} V(w') f(w') dw'$. But if he accepts the current offer he gets

$$V(w) = w + \beta \left[\lambda \beta \int_0^{\infty} V(w') f(w') dw' + (1 - \lambda) V(w) \right] \iff V(w) = \frac{w + \beta \left[\lambda \beta \int_0^{\infty} V(w') f(w') dw' \right]}{1 - \beta(1 - \lambda)}$$

That is, he receives the wage one period, and next period either he gets fired and has the right to make another draw a period later, or he remains on the job and is back with the same $V(w)$ as in the first period. Hence, the searcher's maximisation problem becomes:

$$V(w) = \max \left\{ \frac{w + \beta \left[\lambda \beta \int_0^{\infty} V(w') f(w') dw' \right]}{1 - \beta(1 - \lambda)}, \beta \int_0^{\infty} V(w') f(w') dw' \right\} \quad (1)$$

The reservation wage, \bar{w} , is the wage offer for which the searcher is exactly indifferent between accepting and rejecting. Equating both sides in the max operator and simplifying gives

$$\frac{\bar{w}}{1 - \beta} = \beta \int_0^{\infty} V(w') f(w') dw' \quad (2)$$

From this point on the derivation is our own. Utilising the fact that a wage offer above \bar{w} will be accepted, whereas below \bar{w} it will be rejected, we can split up the value function into $\int_0^{\bar{w}} \frac{\bar{w}}{1 - \beta} f(w') dw'$ and $\int_{\bar{w}}^{\infty} \left[\frac{w' + \beta \lambda \left[\beta \int_0^{\infty} V(w'') f(w'') dw'' \right]}{1 - \beta(1 - \lambda)} \right] f(w') dw'$. But, by the time-invariance of $F(w)$ and $V(w)$, $\beta \int_0^{\infty} V(w'') f(w'') dw'' = \beta \int_0^{\infty} V(w') f(w') dw' = \frac{\bar{w}}{1 - \beta}$. Then equation (2) can be rewritten to:

$$\bar{w} = \frac{\beta}{1 - \beta + \beta \lambda} \int_{\bar{w}}^{\infty} (w' - \bar{w}) f(w') dw' \quad (3)$$

When the distribution F is determined and λ and β are parameterised, this equation can be solved numerically for \bar{w} . We do this in section 3. Note that uniqueness of the solution for \bar{w} is immediately apparent here: \bar{w} always increases the left hand side, but always decreases the right hand side. What about quitting? Once a searcher finds a job that pays him more than his reservation wage, he will never choose to quit that job, as has been shown formally by Sargent and Ljungqvist (2004, pp. 149-150).

Next, let us derive the unemployment rate. Here, we use the equilibrium unemployment formulation as in Pissarides (2000). The change from one period to another in the number of unemployed is:

$$\lambda M_t - qU_t \tag{4}$$

where M_t is the number of employed, U_t is the number of unemployed, and q is the rate of job creation. We are dealing with a representative searcher of measure 1 who can only be unemployed or employed: $M_t + U_t = 1$. The probability that a job is created is simply the probability that a job offer exceeds the reservation wage: $q = \int_{\bar{w}}^{\infty} f(w')dw' = 1 - F(\bar{w})$. In equilibrium we have $\lambda M_t - qU_t = 0$, so that the equilibrium unemployment rate can be expressed as

$$\bar{U} = \frac{\lambda}{\lambda + q} = \frac{\lambda}{\lambda + [1 - F(\bar{w})]} \tag{5}$$

We are now ready to introduce agents who do not know the shape of F . They all have their own subjective wage distributions, G_i .

Assumption 1 *The subjective wage distributions G_i on support $[0, \infty)$ can have any shape, but are all continuous and twice differentiable: $G_i \in \mathbb{C}^2$.*

G_i can differ from F in mean, variance or other moments of the distribution. How then, can we compare the different wage distributions G_i and F ? Following Kohn and Shavell (1974) and the subsequent literature on search with learning, we use first-order stochastic dominance to rank the distributions.

Definition 1 *A wage distribution G_i first-order stochastically dominates another wage distribution G_j , denoted $G_i \triangleright G_j$, if and only if $\int_0^{\infty} u(w')g_i(w')dw' > \int_0^{\infty} u(w')g_j(w')dw'$ for all non-decreasing utility functions u (Dubins and Savage, 1965). That is, G_i yields a higher expected utility than G_j .*

Note that this does not necessarily imply that the expected wage is higher under G_i than under G_j . Hence, $G_i \triangleright G_j \not\Rightarrow \int_0^{\infty} w'g_i(w')dw' > \int_0^{\infty} w'g_j(w')dw'$. Under stochastic dominance the subjective distributions are ordered according to the "optimism" of the searchers. To rank by "optimism" it is not sufficient to consider only expected wages, as the following example demonstrates.

Example 1 *Imagine there are two searchers. Searcher 1 has subjective wage distribution G_1 which is uniform on $[5, 15]$, while searcher 2 has G_2 which is uniform on $[8.1, 12.5]$. Let us take parameter values, $\beta = 0.95$ and $\lambda = 0.025$. Then $E[w | G_1] = 10 < E[w | G_2] = 10.3$ but by equation (3), $\bar{w}_1 = 10.9 > \bar{w}_2 = 9.9$, which means that $G_1 \triangleright G_2$. This is due to the larger variance of G_1 .*

If $G_i \triangleright G_j$, then searcher i expects a higher utility from looking for a job than searcher j does. Kohn and Shavell (1974) were first to show that when $G_i \triangleright G_j$ then searcher i has a higher reservation wage and a longer expected search duration than searcher j . Optimists search longer.

Definition 2 *Searcher i is called more optimistic than searcher j if $G_i \triangleright G_j$. Searcher i is called overconfident if $G_i \triangleright F$ and underconfident if $F \triangleright G_i$ and unbiased if $G_i \not\triangleright F \wedge F \not\triangleright G_i$.*

Note that unbiasedness does not necessarily imply that F and G_i are the same, only that they yield an equal expected utility. Hence, by the result of Kohn and Shavell, the overconfident search too long and the underconfident too short. But our aim is to show that when there is a continuum of searchers, that is "symmetric" around an unbiased searcher, overall unemployment increases. As a first step we know that

$$\int_0^\infty u(w')g_i(w')dw' = \int_0^\infty u(w')f(w')dw' + \tilde{\varepsilon}_i \quad (6)$$

where $\tilde{\varepsilon}_i > 0$ implies overconfidence, $\tilde{\varepsilon}_i < 0$ underconfidence, and $\tilde{\varepsilon}_i = 0$ unbiasedness of searcher i . Moreover, for $\tilde{\varepsilon}_i > \tilde{\varepsilon}_j > 0$ we have $G_i \triangleright G_j \triangleright F$. In fact, we let $\tilde{\varepsilon}_i$ indicate the Euclidean distance between the expected utility derived under the subjective distribution G_i and under the true distribution F . We thus impose additional structure, beyond ordinal comparison based on stochastic dominance. We do this so that we can describe a complete distribution of searchers that is symmetric in overconfidence and underconfidence. We can derive

$$\implies \max \left\{ \int_0^\infty u(w')g_i(w')dw' \right\} = \max \left\{ \int_0^\infty u(w')f(w')dw' \right\} + \tilde{\varepsilon}_i$$

because $\tilde{\varepsilon}_i$ is a constant. Recall that $V(w')$ represents the expected utility of wage offer w' given the searcher's maximising policy, so that

$$\iff \int_0^\infty V(w')g_i(w')dw' = \int_0^\infty V(w')f(w')dw' + \tilde{\varepsilon}_i \quad (7)$$

We can now write by equation (2)

$$\bar{w}(G_i) = (1-\beta)\beta \int_0^\infty V(w')g_i(w')dw' = (1-\beta)\beta \left(\int_0^\infty V(w')f(w')dw' + \tilde{\varepsilon}_i \right) = \bar{w} + [(1-\beta)\beta] \tilde{\varepsilon}_i \quad (8)$$

Notice that $\bar{w}(G_i) = \bar{w}(F, \tilde{\varepsilon}_i) = \bar{w}(\tilde{\varepsilon}_i)$, because $F(w)$ is given, and let $\varepsilon_i = [(1-\beta)\beta] \tilde{\varepsilon}_i$, which gets us to

$$\bar{w}(\varepsilon_i) = \bar{w} + \varepsilon_i \quad (9)$$

where the case $\varepsilon_i = 0$ brings about the case equivalent to that of a searcher who knows $F(w)$. To clarify equations (6) through (9), we provide another example.

Example 2 Consider once more the two searchers from Example 1. What is the expected utility of searcher 1? It is, in fact, given by equation (1). If he accepts a job offer, his expected utility is given by the left side in the max operator, while if he rejects it is given by the right side. Therefore, the expected utility of searcher 1 is simply given through the solution in equation (2): $\int_0^\infty V(w')g_1(w')dw' = \frac{10.9}{(0.05)(0.95)} = 229.5$. Furthermore, let us say that searcher 2 is unbiased. Then, by the same computation his expected utility is equal to $\int_0^\infty V(w')g_2(w')dw' = \int_0^\infty V(w')f(w')dw' = \frac{9.9}{(0.05)(0.95)} = 208.5$. Hence, for searcher 1, $\tilde{\varepsilon}_1 = 229.5 - 208.5 = 21$, which translates into $\varepsilon_1 = [(1 - \beta)\beta]\tilde{\varepsilon}_1 = 1$

$$\bar{w}(\varepsilon_1) = \bar{w} + \varepsilon_1 = 9.9 + 1$$

Now imagine a third searcher, with G_3 uniform on $[5, 12]$. By the same computation as above $\tilde{\varepsilon}_3 = -21$, $\varepsilon_3 = -1$ and searchers 1 and 3 are equidistant from the unbiased searcher 2, in terms of both expected utility and reservation wages.

We can now formalise the notion of symmetry:

Assumption 2 ε_i are distributed symmetrically around 0, with maximum distance δ . That is, $\varepsilon_i \in [-\delta, \delta]$. Here distance is defined by the Euclidean norm.

This simply means that there is a symmetric distribution of underconfident and overconfident searchers in the economy. Why do we care to impose this type of symmetry? The reason is that it distills the central effect that we consider. It may be rather obvious that, for instance, a distribution which is biased towards overconfidence increases unemployment relative to perfect information. An overconfidence bias would be modeled here as a distribution of ε_i which puts most of its weight on positive values of ε_i . For instance, a symmetric distribution where the median searcher is overconfident. The question is not whether overconfidence leads to higher unemployment and underconfidence to lower unemployment, which we know already since Kohn and Shavell (1974), but whether the effects cancel each other out.

This symmetry is probably not an empirically plausible assumption. In fact, there is a large literature in both experimental economics and psychology which documents that on average people tend to be overconfident. For an overview of this literature see Kőszegi (2006, forthcoming), Hoelzl and Rustichini (2005) and Camerer and Lovallo (1999). But if, as we find, even under symmetry heterogeneous wage expectations lead to higher unemployment, then an overconfidence bias would merely strengthen this effect.

Beyond imposing symmetry, we do not restrict the shape of the distribution of ε_i . The meaning of the maximum distance δ , moreover, is directly related to the central point of our paper. When all searchers have the same wage expectations, $\delta = 0$. But when wage expectations are heterogeneous, $\delta > 0$ and increasing in the degree of heterogeneity.

Now from equations (5) and (9), unemployment of a searcher with subjective distribution G_i is

$$\bar{U}_i = \frac{\lambda}{\lambda + q_i} = \frac{\lambda}{\lambda + [1 - F(\bar{w}(\varepsilon_i))]} = \frac{\lambda}{\lambda + 1 - F(\bar{w} + \varepsilon_i)} \quad (10)$$

The economy's unemployment rate is the weighted average of the individual unemployment rates.

$$Average [\bar{U}_i] = \int_{-\delta}^{\delta} \bar{U}_i h(\varepsilon_i) d\varepsilon_i = \int_{-\delta}^{\delta} \frac{\lambda}{\lambda + 1 - F(\bar{w} + \varepsilon_i)} h(\varepsilon_i) d\varepsilon_i \quad (11)$$

where $h(\varepsilon_i)$ is the probability density function of the errors, which we assumed to be symmetric. What we care to see is what happens when δ increases. That is, when wage expectations diverge.

Proposition 1 *The average unemployment rate, $Average [\bar{U}_i]$, is strictly increasing in δ .*

Proof of Proposition 1. We simply need to show that $\frac{dAverage[\bar{U}_i]}{d\delta} > 0$. To take this derivative we use Leibniz's formula. First rewrite

$$Average [\bar{U}_i] = \int_{a(\delta)}^{b(\delta)} \frac{\lambda}{\lambda + 1 - F(\bar{w} + \varepsilon_i)} h(\varepsilon_i) d\varepsilon_i$$

where $a(\delta) = -\delta$ and $b(\delta) = \delta$. Then

$$\frac{dAverage [\bar{U}_i]}{d\delta} = \left[\frac{\lambda}{\lambda + 1 - F(\bar{w} + \delta)} h(\delta) \right] b'(\delta) - \left[\frac{\lambda}{\lambda + 1 - F(\bar{w} - \delta)} h(-\delta) \right] a'(\delta)$$

where, by Assumption 2, $h(\delta) = -h(-\delta)$ so that

$$\frac{dAverage [\bar{U}_i]}{d\delta} = \lambda h(\delta) \left[\frac{1}{\lambda + 1 - F(\bar{w} + \delta)} - \frac{1}{\lambda + 1 - F(\bar{w} - \delta)} \right]$$

and

$$\frac{dAverage [\bar{U}_i]}{d\delta} > 0 \iff F(\bar{w} + \delta) > F(\bar{w} - \delta)$$

which is true for any $\delta > 0$. ■

Let us now devote some time to think about the economic intuition of this effect. How come unemployment increases more for the optimist than it decreases for the pessimist?

The reason is actually quite intuitive. Underestimation leads searchers to search less time. For a very low reservation wage, the next wage offer is almost certainly accepted. Search duration goes to one period. But for those who overestimate there is no limit to how much longer they may keep searching. For strongly overconfident searchers, search duration can tend to infinity, as the probability of actually receiving an offer above the reservation wage becomes very small. Average search duration then obviously rises. Thinking in extremes where duration goes to infinity or to one makes the intuition simple, but the effect also holds for a marginal dispersion of expectations, as the above proof demonstrates. Let us consider one more example, in which we compute the search durations of the searchers in the previous examples.

Example 3 *Once more, consider searchers 1, 2 and 3 from the previous two examples, where searcher 2 is unbiased and searchers 1 and 3 are symmetric with respect to searcher 2 in their overconfidence and underconfidence, respectively. Let us compute their search durations. First, consider the unbiased searcher 2, for who the probability that he rejects an offer is $F(\bar{w}(\varepsilon_2)) = F(\bar{w})$. His expected search duration is $\sum_{N=1}^{\infty} N(1 - F(\bar{w})) [F(\bar{w})]^{N-1} = \frac{1}{1-F(\bar{w})}$, which for F uniform on $[8.1, 12.5]$, $\beta = 0.95$ and $\lambda = 0.025$ yields an expected search duration of 1.69 periods. But, for searcher 1 with $\bar{w}(\varepsilon_1) = 10.9$ by the same computation the expected search duration is 2.75 periods. And for searcher 3 with $\bar{w}(\varepsilon_3) = 8.9$ the expected search duration is 1.22 periods. Now, the average search duration of searchers 1 and 3 is 1.99 periods, more than the search duration of the unbiased searcher.*

3 Calibration

So far the theoretical result we have derived is purely qualitative. In this section we calibrate the model in order to understand more about the quantitative significance of the result. Specifically, we propose the following numerical exercise. First, we calibrate a completely standard homogeneous-expectations search model on the current unemployment rate in the United States and Germany. Next, we introduce heterogeneous wage expectations and we check "how much" heterogeneity is required for a significant impact on the unemployment rate. We can have some indication of realistic levels of heterogeneity through the results from survey studies for the US and Germany. As we discuss below, these results provide an upper bound on the possible dispersion of wage expectations in the economy. If, even for levels of dispersion close to the upper bound the effect on unemployment remains marginal, we can conclude that the theoretical effect we identified makes little difference in quantitative terms. If, on the other hand, a relatively small degree of dispersion has a real impact on unemployment, then the quantitative importance of heterogeneous wage expectations may

be non-negligible.

The wage distribution

The first thing we require is a distributional form for $F(w)$. We choose the lognormal distribution, as it is generally considered a good approximation of empirical wage distributions (see, for instance, Dominitz and Manski (1996, 1997)). In fact, we take the standard lognormal distribution, which has the following pdf:

$$f(w) = \frac{1}{w\sigma\sqrt{2\pi}} \exp\left[-\frac{[\ln w]^2}{2\sigma^2}\right] \quad (12)$$

with $w > 0$ and $\sigma > 0$. Hence the standard lognormal distribution has only a shape parameter, σ . But standardisation of empirical distributions is achieved easily by setting the 50th percentile of the cumulative wage distribution equal to 1 (standardising location) and dividing all values in the density function by that of the 50th percentile (re-scaling). The reason is that for any $\sigma > 0$ it holds that $\int_0^1 \frac{1}{w\sigma\sqrt{2\pi}} \exp\left[-\frac{[\ln w]^2}{2\sigma^2}\right] dw = 0.5$ (see also Thomopoulos and Johnson (2003)). On the other hand, we do not restrict the shape of the subjective distributions, G_i .

We first write down the equations that we can parameterise and then discuss the data we use to parameterise them. To begin with, we have equation (3), with $f(w)$ from the standard lognormal distribution.

$$\bar{w} = \frac{\beta}{1 - \beta + \beta\lambda} \int_{\bar{w}}^{\infty} \frac{w' - \bar{w}}{w'\sigma\sqrt{2\pi}} \exp\left[-\frac{[\ln w']^2}{2\sigma^2}\right] dw' \quad (13)$$

When σ , β and λ are parameterised this equation can be solved numerically for \bar{w} . Next, for the unemployment rate when all searchers know $F(w)$, we rewrite equation (10):

$$\bar{U} = \lambda \left[\lambda + 1 - \int_0^{\bar{w}} \frac{1}{w'\sigma\sqrt{2\pi}} \exp\left[-\frac{[\ln w']^2}{2\sigma^2}\right] dw' \right]^{-1} \quad (14)$$

Moreover, when searchers' expectations are heterogeneous, we know from equation (11) that:

$$\text{Average } [\bar{U}_i] = \lambda \int_{-\delta}^{\delta} \left[\lambda + 1 - \int_0^{\bar{w}+\varepsilon_i} \frac{1}{w'\sigma\sqrt{2\pi}} \exp\left[-\frac{[\ln w']^2}{2\sigma^2}\right] dw' \right]^{-1} h(\varepsilon_i) d\varepsilon_i \quad (15)$$

3.1 Standard model

The task we set ourselves is as follows. In this subsection we calibrate equation (14) so that \bar{U} matches the actual levels of unemployment in the US and Germany. In fact, we can get

realistic estimates for the parameter values of β and λ , so that only σ remains open. We do not have any good outside estimate of this σ , since there is no data on individual wage offer distributions. We therefore impute the σ that matches the actual unemployment rate. We then have everything we need in order to compute from equation (15) the unemployment rate under heterogeneous wage expectations, $Average [\bar{U}_i]$, for different values of δ . This we do in the next subsection. We describe a methodology to infer an upper bound on δ from the survey studies. Define $\Delta U = Average [\bar{U}_i] - \bar{U}$. Then we are interested in whether ΔU stays close to zero or not as δ increases towards its upper bound.

The discount rate

We start out by obtaining estimates for β and λ . First, we look at β . In a comprehensive survey on rates of time preference, Frederick et al. (2002) give an overview of the results of estimating discount rates from 42 different studies. Though the variation in results is very large, the median study finds an annual rate of time preference of around 0.90. However, we do not know how long a period is in calendar time in our model. But using data from the US BLS and the German Statistisches Bundesamt we have an indication for job arrival rates. For instance, for the US we already have $\frac{\text{unemployed}}{\text{labour force}} = 0.05$. Next, the BLS reports the ratio $\frac{\text{new job openings}}{\text{employed}}$, which for the first half of 2005 stands at around 3.5% per month. Taking these two together, plus the equation that employed + unemployed = labour force, we compute $\frac{\text{new job openings}}{\text{unemployed}} = 0.665$. We call this the monthly probability of receiving a job offer. This is of course rather rough, since job-to-job transitions and structural unemployment are implicitly assumed away: new job openings are filled only by the unemployed, and all unemployed have equal probability of receiving an offer. This is consistent with our model, however. Finally, given the monthly probability of receiving an offer, p , we can compute the average number of months until a job offer is received as follows: $Average [N] = \sum_{N=1}^{\infty} Np[1-p]^{N-1}$. For the US the average number of months till a job offer is 1.5. By similar computation it stands at 10 months for Germany. These are the periods that we have in the model: from one job offer to the next. If $\beta = 0.90$ is taken a yearly discount rate, then for Germany we mainly care to look at results for $\beta_{DE} \approx 0.915$ and for the US $\beta_{US} \approx 0.985$.

The job separation rate

As for λ , data from the German Institut für Arbeitsmarkt- und Berufsforschung (see Bachmann (2005)) indicate that in Germany the job separation rate is around 0.63% per month. It should be noted though, that the German figures are for all types of job separation, not only layoffs which is what λ essentially stands for. The US BLS reports figures by cause of separation. The layoff rate stands at about 1.2% a month in 2005. For the period lengths found above, these figures translate into $\lambda_{DE} = (1.0063)^{10} - 1 = 0.065$ and $\lambda_{US} = (1.012)^{1.5} - 1 = 0.018$. Later on, we perform sensitivity tests for both λ and β .

Imputing σ

We can now solve equations (13) and (14) such that \bar{U}_{US} is the current unemployment rate of the US: 5.0% in June 2005 according to OECD Statistics, while by the same source $\bar{U}_{DE} = 9.5\%$. For the given parameters we impute $\sigma_{US} = 0.135$ and $\sigma_{DE} = 0.235$. These values are, again, an inference about the variance of individual wage offer distributions. Unsurprisingly, this variance turns out to be much smaller than that of aggregate wage distributions. For instance, we collected data from the US Census Bureau on wage distributions (year 2000) from 504 occupational categories. The Census provides points along the cumulative wage distribution. Specifically, it provides the annual earnings of 10th, 25th, 50th, 75th and 90th percentile of employees in a certain field. Fitting lognormal wage distributions on this data, we find that nearly all good fits lie within the range $\sigma \in [\frac{1}{3}, 1]$. But it makes sense that an individual faces a wage distribution that is much less wide than that of an entire occupational category. Furthermore, it is not remarkable that the imputed σ 's differ considerably for the US and Germany, because the periods are different, i.e., it is likely that the wage offer distribution of an individual who receives an offer every 1.5 months is different from that of someone who receives an offer every 10 months.

3.2 Model with heterogeneous wage expectations

Our aim is now to derive numerical results from equation (15). We use the σ 's we imputed from the standard model. Before we can proceed, however, we need to choose a functional form for $h(\varepsilon_i)$, the distribution of the errors that heterogeneous searchers make.

The distribution of errors

We already assumed that this distribution was symmetric. Here we go one step further and set $h(\varepsilon_i) \sim N(0, \sigma_\varepsilon^2)$. The normal distribution is not only convenient to work with, but in the empirical work of Betts (1996) the errors of respondents indeed turn out to be approximately normally distributed.³ There is one problem with the normal distribution, however, which is that $\delta \rightarrow \infty$. The normal distribution has no lower bound or upper bound, after all. This would imply the possibility of negative reservation wages, even if these points get a tiny weight. To avoid this, we create an artificial "cutoff", setting $\delta = 3\sigma_\varepsilon$, which, as an empirical matter, is nearly equivalent to $\delta \rightarrow \infty$ as it includes 99.73% of the distribution.

³This is not derived in Betts's own paper, but rather in a previous version of our paper on the basis of Betts's results. This material is available upon request.

Equation (15) now becomes:

$$Average [\bar{U}_i] = \frac{\lambda}{\sigma_\varepsilon \sqrt{2\pi}} \int_{-3\sigma_\varepsilon}^{3\sigma_\varepsilon} \left[1 + \lambda - \int_0^{\bar{w} + \varepsilon_i} \frac{1}{w' \sigma \sqrt{2\pi}} \exp \left[-\frac{[\ln w']^2}{2\sigma^2} \right] dw' \right]^{-1} \exp \left[-\frac{\varepsilon_i^2}{2\sigma_\varepsilon^2} \right] d\varepsilon_i \quad (16)$$

where \bar{w} is still as given by equation (13).

An upper bound on heterogeneity

The final remaining issue is then what could be a relevant range of values for σ_ε . The lower bound is obviously $\sigma_\varepsilon = 0$, in which case equation (15) reduces to equation (14). But how do we know what constitutes "much" heterogeneity in wage expectations? We would like to have some kind of upper bound. For this we need to resort to the results that we have from the survey studies. From the papers by Betts (1996), Dominitz and Manski (1996) and Brunello et al. (2001) we have point estimates for a measure of heterogeneity of wage expectations. This measure is the ratio of the 90th against the 10th percentile of expected wages of respondents. As we mentioned before, the 50th percentile is generally found to be close to the truth. The ratio of the 90th to the 10th percentile is, therefore, an indication of how dispersed wage expectations are. Moreover, the results from the survey studies should be considered an upper bound for job searchers. The reason is that these surveys were conducted among students, questioning them about their prospective fields. But those who already have been working in a field are likely to possess more precise information about wages than the students. In fact, Betts (1996) reports that even within his sample, dispersion is smaller among students in their final year than among freshmen.

Recall, however, that σ_ε in equation (16) measures the variance of errors about reservation wages, not expected wages. We need some way to move from expected wages to reservation wages. We can do this through a measure of the elasticity of reservation wages to expected wages, which we call η . As we will discuss further on, for this measure we possess empirical estimates. First, we describe the equations that bring us from dispersion of expected wages to a value for σ_ε . We let $\varepsilon_{.th}$ refer to the $.th$ percentile, while μ refers to the mean of the wage distribution. Moreover, $\Phi = \frac{\mu(\varepsilon_{90th})}{\mu(\varepsilon_{10th})}$ denotes the ratio we have from the survey studies, which from both Betts (1996) and Dominitz and Manski (1996) is about 2 for the US, while from Brunello et al. (2001) it is around 3.2 for Germany. Then, firstly, by the definition of the elasticity:

$$\frac{\bar{w}(\varepsilon_{90th}) - \bar{w}(\varepsilon_{10th})}{\bar{w}(\varepsilon_{10th})} = \eta \frac{\mu(\varepsilon_{90th}) - \mu(\varepsilon_{10th})}{\mu(\varepsilon_{10th})} = \eta(\Phi - 1) \quad (17)$$

Note that by using a constant elasticity, we move from a symmetric distribution of expected wages (found in the survey studies), to a symmetric distribution of reservation wages, which

is consistent with our model. By $\bar{w}(\varepsilon_i) = \bar{w} + \varepsilon_i$ we can rewrite to

$$\frac{\varepsilon_{90th} - \varepsilon_{10th}}{\bar{w} + \varepsilon_{10th}} = \eta(\Phi - 1) \quad (18)$$

Secondly, in our symmetric setup

$$\varepsilon_{90th} + \varepsilon_{10th} = 0 \quad (19)$$

because the median searcher with ε_{50th} is unbiased. And since $h(\varepsilon_i) \sim N(0, \sigma_\varepsilon^2)$ then by the tables of the normal distribution

$$\varepsilon_{90th} - \varepsilon_{10th} = 2(1.28)\sigma_\varepsilon \quad (20)$$

And the three preceding equations together yield

$$\sigma_\varepsilon = \frac{1}{1.28} \bar{w} \left[\frac{\eta(\Phi - 1)}{2 + \eta(\Phi - 1)} \right] \quad (21)$$

Hence, once we have a value for η we can compute a relevant upper bound for σ_ε .

Obtaining estimates of the elasticity

A few studies have estimated the elasticity of the reservation wage to the mean of the wage distribution. There are two ways to do this. Jones' (1989) estimates an OLS equation for the UK in which he regresses the log reservation wage on, among other variables, the log past wage of the unemployed searcher. He takes the past wage as a proxy for the mean of the individual-specific wage distribution. This may seem like a rather rough procedure, but in a recent study Hogan (2004) uses a different method and has very close results to those of Jones. Hogan uses data from the British Household Panel Survey to test for the determinants of reservation wages. One of his regressors is the mean of the individual-specific distribution of wage offers. He constructs this mean by an estimation on variables that reflect a person's characteristics in terms of human capital and household composition. In the second step, the log reservation wage is regressed on, among other variables, the log mean of the individual-specific wage distribution. Both Jones and Hogan find (highly significant) elasticities in the range 0.25 – 0.29 for the UK.

Using Jones' method, Christensen (2001) estimates this elasticity for Germany at $\eta_{DE} = 0.46$. Another estimate by Addison et al. (2004) for the EU-15 minus Sweden and Luxemburg gives a fairly similar result, with an elasticity of 0.41. For the US we are aware of only one such estimate, again following Jones (1989), by Haurin and Sridhar (2003), $\eta_{US} = 0.64$.⁴ We use the estimates by Christensen (2001) and Haurin and Sridhar (2003) for our calibration.⁵

⁴From Jones (2002) we do have an estimate of this elasticity for Canada at 0.59.

⁵One issue is, however, that these elasticities are estimated using a regression in logarithms. Hence, they

Calibration results

We now have all the elements we require in order to compute $\Delta U = Average [\bar{U}_i] - \bar{U}$ using equation (16). Our results are reported in the tables below. In these tables ΔU is expressed in terms of percentage points. So, for instance, for the United States if $\Phi = 1.2$ then $Average [\bar{U}_i]$, the unemployment rate with heterogeneous wage expectations, is 5.47%. This is 0.47% more than \bar{U} , which we matched to be the actual US unemployment rate. Hence the entry 0.47 at $\Delta U_{\Phi=1.2}$ in the first row of Table 1. From the studies of Betts (1996), Dominitz and Manski (1996) and Brunello et al. (2001), we consider $\Phi = 2$ as upper bound for the US and $\Phi = 3.2$ for Germany. The first row of each table indicates our main calibration result. The rows below give an indication of the sensitivity of the results to changes in the values of the exogenous parameters β and λ .

Table 1: US, calibration results

β	λ	imputed σ	$\Delta U_{\Phi=1.1}$	$\Delta U_{\Phi=1.2}$	$\Delta U_{\Phi=1.3}$	$\Delta U_{\Phi=1.5}$	$\Delta U_{\Phi=2}$
0.985	0.018	0.135	0.12	0.47	1.08	3.03	9.58
Sensitivity to β							
0.98	0.018	0.155	0.08	0.34	0.77	2.14	7.25
0.99	0.018	0.117	0.15	0.66	1.54	4.34	12.42
Sensitivity to λ							
0.985	0.016	0.15	0.09	0.41	0.93	2.59	8.40
0.985	0.020	0.125	0.12	0.51	1.18	3.37	10.47

Table 2: Germany, calibration results

β	λ	imputed σ	$\Delta U_{\Phi=1.1}$	$\Delta U_{\Phi=1.2}$	$\Delta U_{\Phi=1.3}$	$\Delta U_{\Phi=1.5}$	$\Delta U_{\Phi=2}$	$\Delta U_{\Phi=3.2}$
0.915	0.065	0.235	0.00	0.04	0.11	0.34	1.23	4.19
Sensitivity to β								
0.905	0.065	0.250	0.00	0.03	0.10	0.29	1.05	3.61
0.925	0.065	0.220	0.00	0.05	0.14	0.40	1.44	4.89
Sensitivity to λ								
0.915	0.06	0.256	0.00	0.03	0.10	0.31	1.11	3.76
0.915	0.07	0.213	0.00	0.05	0.13	0.38	1.37	4.71

are only a good approximation for local changes. But the data we have are on 90th versus 10th percentile, very large changes. In a computation that is available upon request, we assume that the subjective wage distributions are also lognormal and compute theoretical elasticities from the model. We find that global and local elasticities tend not to differ very much. If this would also hold for empirical elasticities then it may not make too much of a difference that we use empirical local instead of global elasticities.

The most striking thing about the results is how much of a difference heterogeneous wage expectations make. For example, $\Phi = 1.2$ in the US means, roughly speaking, that the most optimistic people have wage expectations 10% above the median, and the most pessimistic people 10% below the median. This is very moderate, compared to the findings in survey studies. Nonetheless, the estimated unemployment rate already increases by half a percentage point.

In Germany the sensitivity to Φ is smaller. This is due to the higher σ , which implies a wider distribution, and a less steep relationship between overconfidence and rising search duration: setting a reservation wage that is too high is penalised less strongly when the true wage offer distribution is more skewed, putting more weight on more extreme offers. But, at least according to Brunello et al. (2001), information about wages is less disseminated in Germany than in the US, and the upper bound on Φ is larger. For $\Phi = 1.5$ the impact on the unemployment rate is already sizeable. Admittedly, the precise impact of Φ on ΔU is quite sensitive to the values of β and λ , as can be seen in the lower rows of Tables 1 and 2. But in any case, the main quantitative result holds: for levels of wage dispersion far below the upper bound based on survey empirics, heterogeneous wage expectations have an effect on unemployment that is not marginal.

Welfare analysis

Of course, the above results do not tell us how much policymakers could potentially reduce unemployment by improving information about wages in the economy. The calibration exercise was constructed to check whether heterogeneity in wage expectations makes a difference in estimated unemployment relative to the standard model. But we can also attempt a different numerical exercise. We can match *Average* $[\overline{U}_i]$ with the actual unemployment rate, and see how much unemployment falls as $\Phi \rightarrow 1$. This provides an upper bound on unemployment reduction due to better wage information. As an example, say that in the US we set $\Phi = 1.2$, and find the σ that matches *Average* $[\overline{U}_i] = 5.0\%$. This turns out to be $\sigma = 0.133$. Then we can compute for $\Phi \rightarrow 1$ that the model predicts that unemployment goes to 4.47%, so that the maximum reduction in unemployment due to better wage information is 0.53%. Table 3 reports the maximum unemployment reduction due to better wage information for different values of Φ , given the same β and λ as before.

Table 3: Maximum unemployment reduction due to better wage information

US	$\Phi = 1.1$	$\Phi = 1.2$
maximum unemployment reduction	0.11%	0.53%
imputed σ	0.133	0.118

Germany	$\Phi = 1.1$	$\Phi = 1.2$	$\Phi = 1.3$	$\Phi = 1.5$	$\Phi = 2$
maximum unemployment reduction	0.00%	0.04%	0.11%	0.37%	1.82%
imputed σ	0.235	0.234	0.233	0.218	0.155

Unfortunately, we cannot compute beyond $\Phi = 1.2$ for the US and $\Phi = 2$ for Germany. The reason is that for high values of Φ there no longer exists a σ that matches the current unemployment rate.⁶ However, already for the relatively low values of Φ in Table 3, the model predicts that a considerable part of current unemployment is due to heterogeneous wage expectations. Hence, the calibrated model suggests that the potential for unemployment reduction due to better dissemination of wage information is rather large.

4 Empirical correlations

As pointed out before, the finding that a more optimistic prior implies longer expected search duration dates back to Kohn and Shavell (1974). Yet, to our knowledge, there has never been any empirical work done to examine this feature of the search model. Although our main contribution pertains to the aggregation across searchers with heterogeneous wage expectations, the results are grounded upon the prediction of the search model that an optimist is expected to spend more time searching than a pessimist. Even though it goes beyond the scope of this paper to provide a full empirical test, this section provides several interesting empirical correlations that are hard to interpret without thinking in terms of the search model relationship between optimism and unemployment duration.

We use data from the US Survey of Economic Expectations⁷ that was compiled under management of Jeff Dominitz and Charles Manski, and which they have applied in several of their papers. The survey comprises 137 variables and a sample of 5543 respondents from all

⁶For instance, when $\Phi = 1.3$, $\beta = 0.985$ and $\lambda = 0.018$, then $Average [\bar{U}_i]_{US} > 5.0$ even as $\sigma \rightarrow 0$. This happens because for low values of σ , $Average [\bar{U}_i]$ becomes almost irresponsive to further reductions. The reservation wage then asymptotes towards a lower bound, in this case $\bar{w} \rightarrow 0.967$.

⁷Dominitz, Jeff, and Charles F. Manski. The Survey of Economic Expectations – Waves 1-8, with data from the UW Survey Center’s National Survey [computer file]. 1st ed. Madison, WI.: John D. Straub, University of Wisconsin-Madison [producer], 2000. Madison, WI: Data and Program Library Service [distributor], 2000; <<http://dpls.dacc.wisc.edu/econexpect/index.html>>.

over the US. It was collected through telephone interviews, in eight waves within the period 1994-1998. The respondents were interviewed only once, however, so the dataset is purely cross-section.

Our aim is to take variables from this dataset that relate to optimism of job searchers, and correlate it with their search duration. We look only at those respondents who are unemployed at the time of the interview, which leaves 134 observations. For each of these we have a variable representing the number of weeks over the past year that they were looking for a job. We call this variable "DURATION". We then take two variables which may be indicative of optimism. One is derived from a question which asks respondents if they felt sad during the past week. We call this variable "SAD". And the other comes from a question that asks what the respondent believes is the percentage probability of rain tomorrow. We call this variable "RAIN".

First, let us take a look at the relationship between "RAIN" and "DURATION". It turns out that the correlation between these two variables is -0.196 . Moreover, if we split the observations into two or three bins, we get the following picture

Table 3: Unemployment duration and subjective expectation of rainfall

Bin	Number of observations	Average Duration
2 Bins		
Perceived probability of rain < 50%	83	25.0 weeks
Perceived probability of rain \geq 50%	50	20.3 weeks
3 Bins		
Perceived probability of rain < 33%	56	27.4 weeks
Perceived probability of rain 33-66%	34	20.0 weeks
Perceived probability of rain > 66%	43	20.4 weeks

We can conclude that there is a strong negative relationship between the subjective probability of rain tomorrow and the time spent looking for a job. Could it be that sunnier areas have longer average unemployment duration in the United States? Casual evidence would suggest the opposite, as sunshine states are not known for more severe unemployment problems in the United States. If the subjective probability of rain tomorrow is indicative of a person's stance towards life, with a higher probability indicating a more pessimistic view, then the correlation goes in the direction predicted by the search model. But what about duration dependence? After all, the respondent is asked about the probability of rain after he has already "incurred" a search duration of given time. Yet, this would work in the opposite direction: if anything after having been searching for a longer time we would expect the person to become *more* sad or have a *higher* probability of rain. That would imply a *positive*

correlation.

As for the relationship between our measure of sadness and unemployment duration, the observed correlation is -0.07 . And putting the observations in bins we obtain

Table 4: Unemployment duration and sadness

Bin	Number of observations	Average Duration
2 Bins		
Not sad during past week	58	24.6 weeks
Sad during past week	76	22.1 weeks

As before, this negative relationship is difficult to interpret without the prediction of the search model. Not only does duration dependence work in the opposite direction, but also one would tend to think that people who are more sad have a harder time on job interviews. Although the correlations reported in this section do not constitute a complete empirical finding in favour of the search model’s prediction, they do provide the first piece of empirical material suggesting a positive relationship between optimism and search duration.

5 Conclusions

Motivated by survey studies which find that wage expectations are dispersed, we have considered the effects of heterogeneous expectations about wages on unemployment. We introduced subjective wage distributions in a standard search model. We subsequently showed that if the population of searchers is symmetric in overconfidence and underconfidence relative to the truth, unemployment increases in the dispersion of beliefs. This is due to the fact that the search duration of pessimists converges to a lower bound, whereas optimists face no upper bound on their search duration. Next, we calibrated our model based on the results from survey studies. The outcome suggests that the effect of heterogeneous wage expectations on unemployment may be quantitatively non-negligible. Finally, we presented empirical correlations of optimism and search duration.

Our model and calibration lead to several policy implications. Most obviously, they advocate efforts to improve the dissemination of information about wages. We can think of several channels through which this may be achieved in practice. Career counseling among students, for instance, which generally focusses on helping students in knowing what jobs to look for and where (reducing frictions), could also focus on improving students’ knowledge of the wages they can expect. Legislation could be designed that, for example, requires firms to always give clear indications of the salary range applicants for a job may expect. More generally, awareness of the importance of a culture that fosters greater openness about wages

may be helpful. Especially in Europe, there tends to be a culture that does not promote the exchange of knowledge about wages.

Finally, there are several avenues for further research. On the theoretical side, the model can be extended to include unemployment benefits, learning dynamics and macroeconomic shocks. Or the model can be written in a way that includes an endogenous firm side, like in the matching framework. We have abstracted from these for the purpose of simplicity of exposition. But embedding expectations dispersion in a richer structure may tell us even more. Inroads can also be made on the empirical side. One could think, for example, of a panel data estimation, which however requires a sufficiently rich dataset that reports individuals' expectations and their search durations over time. That brings us to a broader point: there is still a relative paucity of data and research about individual wage expectations. This study indicates that heterogeneous wage expectations may have consequences that are both qualitatively and quantitatively interesting. Further research efforts in this field are likely to be fruitful.

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