Search Frictions and the College Premium

(Preliminary and incomplete: please do not cite)

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Abstract

I examine how important job search and job destruction are for understanding the college premium in a model of human capital investment and random job search. I find that the college premium is mainly driven by differences in the average rental rate of college and high school human capital which induces differences in human capital investment. Differences in post schooling wage growth account for about 50% of the college premium after 10 years in the labor market, and half of this is explained by differences in search. (JEL: J24, J31, J64)

1 Introduction

This paper studies the importance differences in search frictions between high school and college workers are for determining in the college wage premium. Workers of different educational levels generally differ also in terms of their unemployment rates and average job and employment durations in addition to their level of human capital. These facts are difficult to incorporate in a competitive labour market, yet they are important for determining wages. Quantifying the role and extent of these frictions in the labour market for generating differences in wages is important for understanding the nature of skill premia and the role policy can play for encouraging skill formation.

*All opinions expressed here are those of the author and do not necessarily reflect those of the Bank of Canada

For example, if differences in search frictions across education groups reflects sorting by individuals who happen to be effective at finding and keeping their jobs, part of the college premium may reflect a type of *search ability bias* and policies that subsidize college enrollment may not yield large welfare gains. However, if search frictions are market specific, and do not depend on the individual, policies to encourage college enrollment may yield large gains.

The main finding of this paper is that differences in search frictions can explain nearly half of the difference in wages between college and high school graduates 10 years out of the labor market. This effect comes from strong interactions between the human capital investment decision and the search frictions which affects the intensity of investment and the reservation wage.

Worker search leads to wage growth because over time workers sample more and more offers, always taking the best one. Human capital theory posits that wages grow because workers gain experience which is valuable on the job. Rubinstein and Weiss (2006) conclude that both worker search and human capital accumulation quantitatively important for understanding post-schooling wage growth. Subsequent empirical work (e.g. Yamaguchi (2010), Bowlus and Liu (2013), Bagger et al. (2014)) upholds this conclusion, finding that search can explain between one-third to one-half of post-schooling wage growth. However, little has been done which compares the relative contribution across different groups of workers and how these differences translate into differences in overall earnings.

Differences in the rates of job finding and job destruction affects the incentive to accumulate human capital for an individual, and affects the distribution of wages in the cross-section. The first effect will show up as differences in the relative growth rates of wages. The second effect shows up in differences in the composition of match quality. To study these two effects, I estimate an extension of simple worker search model with on-the-job search and job destruction where workers also make a decision to invest in general human capital. In a model with a competitive market, neither of these two effects are present. Instead, individual wage growth will overstate estimated productivity growth and the composition of match quality differences will overstate the return to college labor. While a competitive market model may be a good statistical description to study the determinants of the college wage premium, it will not be able to address how changes in market frictions will affect the college premium.

The intuition of the main mechanisms of the model is as follows. Let R be the rate of pay per unit of human capital paid by the firm. For a worker earning a low wage rate below the average wage rate, $\hat{R} < \bar{R}$, the presence of on-the-job search can induce greater human capital investment than without. This is because in expectation, on-the-job search promotes wage growth in the future from receiving better wage rates which induces greater human capital investment relative to a constant wage. This effect is tempered by the job destruction rate. The more likely a worker is to losing his job, the less incentive there is to invest in human capital. In the cross section, the more often a worker receives job offers relative to the probability of losing his job, the higher is the expectation of R in a randomly selected moment of time. So on average, workers who face less market frictions (high arrivals relative to destruction) will have better matches. In general, college educated workers typically face less market frictions, so we should expect this to be reflected in the college premium.

The closest work to this paper is Bowlus and Liu (2013) and Adda et al. (2013). Bowlus and Liu (2013) estimates a very similar model to mine to study the interaction between human capital investment and endogenous search effort. However, he estimates his model only on high school graduates from the NLSY79. While I abstract from search effort, I focus on the differences in search and human capital production parameters across education groups. Adda et al. (2013) on the other hand, studies how differences in the search environment between two education groups affects the choice to become educated. They are interested in estimating the return to apprenticeship in Germany and abstract from human capital investment on-the-job and search effort. Interestingly, they find that introducing policies in the labor market that may not at first seem connected to education, such as an EITC program or an unemployment insurance system, feed back into the worker's decision to acquire education. In this paper, I am not interested in the return to education *per se*, but instead how much of the differences between groups is due to search frictions after selection has already occurred. Finally, Flinn and Mullins (2015) study a general equilibrium search and matching model of the labour market where individuals can invest in education before entering the labour market. However, they do not consider the role of on-the-job training in the post-schooling period.

As I mentioned above, there is a growing literature on studying the relative importance of search and human capital accumulation in explaining wage growth. Two papers related to mine are Yamaguchi (2010) and Bagger et al. (2014) in that they consider multiple education groups in their empirical work. Yamaguchi (2010) compares how the contribution of search and experience differs across college and high school students, however experience accumulation is exogenous in his model and he studies a different search environment where wages are set through bargaining. Bagger et al. (2014) also present a job search model with exogenous experience accumulation to study the relative importance of search. They find that the relative importance of search varies with education, however they do not discuss the implications of this with respect to the wage premiums. Also, they estimate their model on Danish data.

The paper proceeds as follows. In section 2 I present a model of job search and human capital investment. In section 3 I present the estimation methodology and in section 4 I present the data. In section 5 I present the results along with some discussion.

2 A Model of Job Search

I consider a labor market with a large number of firms and workers. Workers can either be employed in which they choose to supply a fraction of their human capital to the firm, or unemployed. I abstract from the firm's problem and assume that firm's post piece rates for human capital exogenously according to the distribution F. Workers face an information friction such that they can only sample randomly at most one additional piece rate per period over their current one, while only knowing the distribution of wage offers across other firms and without recall in the spirit of Burdett and Mortensen (1998). When matched with a firm, workers receive a constant piece rate R for the duration of the match. Wages therefore are simply the product of human capital supplied and the piece rate. Time is discrete and continues forever.

A labor market is characterized by five parameters. There are three search parameters which govern the job arrival and destruction rates and two wage parameters which characterize the distribution of wage offers. I assume in the estimation that $F \sim logN(\mu, \sigma)$ for tractability. With probability δ an employed worker loses his or her job and enters unemployment. While unemployed, workers receive a job offer with probability λ_0 from a random firm offering piece rate R from distribution F. Conditional on surviving the job destruction shock, an employed worker receives a job offer with probability λ_1 again drawing piece rates from F. In both cases workers employ a up and out decision rule, in which movement only occurs when the value of the offer is greater than the value of staying. As a simplifying assumption, I also assume that workers do not quit to unemployment.

While employed, workers have access to a Ben-Porath (1967) technology for accumulating human capital specified below.

$$h' = A(hl)^{\gamma} + h \tag{2.1}$$

where h' denotes next period's human capital stock, h is the current stock and l is proportion of human capital devoted to production. While unemployed, workers cannot invest in additional training. I specify the model with investment for two reasons. First, the prospect of future piece rate growth due to on-the-job search incentivizes workers to invest in human capital. Shutting down this margin may miss important interactions between search and human capital investment that affects wage growth. Also, including human capital investment generates a reservation wage which is increasing in experience which helps fit the declining unemployment to employment transition rates with respect to age found in the data.

For tractability, I assume that workers are infinitely lived but face a constant death risk ρ. This assumption implicitly assumes away effects due to a finite lifespan. Since I am interested in differences in early career wage growth, this assumption is innocuous. I define β as the sum of the discount factor and ρ. Finally, I assume that workers are risk neutral income maximizers.

The labor market is education specific. A worker of a particular education type is endowed with h_0^s education specific human capital when born, and enters the labor market as unemployed. All the parameters $\{\lambda_0, \lambda_1, \delta, \mu, \sigma, A, \gamma\}$ are specific to the particular labor market. Finally, workers cannot search outside of their market and the actions and outcomes of one market has no bearing on the other. For notational convenience, I suppress the sector notation, noting that markets are identical up to their parameters.

2.1 Value Functions

Define $W(R, h)$ be the value of an employed worker being paid a piece rate R and has a stock of h units of human capital at his disposal. Let $U(h)$ be the value of an unemployed worker with h units of human capital.

The value function for working is

$$
\begin{aligned}
W(R,h) = \max_{l\in[0,1]}\{&Rh(1-l) \; + \; \beta(1-\delta)W(R,h') + \beta(1-\delta)\lambda_1 * \\
&* \int_R^{\bar{R}} W(S,h') - W(R,h')\, dF(S) + \; \beta\delta U(h')\} \\
&\text{s.t. } h' = A(hl)^\gamma \; + \; h
\end{aligned} \tag{2.2}
$$

In the current period, the worker decides how much human capital to supply to the firm and receives $Rh(1-l)$ in wages. In the next period, the first term represents the value of remaining at the current job. The second term is the option value of on-the-job search and the final term is the value of unemployment.
The value of unemployment is

$$
U(R,h) \;\; = \;\; bh + \beta U(h) + \beta\lambda_0 \int_{\phi(h)}^{\bar{R}} W(S,h) - U(h)\, dF(S) \tag{2.3}
$$

While unemployed, a worker collects unemployment benefits bh proportional to the stock of human capital following Bowlus and Liu (2013) and Postel-Vinay and Robin (2002). The second term represents the continuation value of remaining unemployed, and the third term is the option value of receiving a wage offer. $\phi(h)$ is the reservation wage that solves $W(\phi(h),h) = U(h)$. It depends on h because the return to human capital investment in the employment state potentially depends on h which affects its option value.

2.2 Properties

The search parameters affect the wage distribution through two mechanisms. One is they affect the speed workers climb and fall off the wage ladder, altering the distribution of the rental rate. The other is through the effect on a worker's investment decision. Below I discuss how these effects translate into differences in the value functions, which goes directly to addressing how important search is for understanding the college premium and how it relates to welfare. Note that this discussion assumes that the offer distribution is exogenous.

Proposition 2.1. *The value functions have the following properties:*

1. *The value of employment and unemployment is increasing in* λ_1 *and* λ_0

2. *The value of employment is decreasing in δ for all piece rates R such that $W(R,h) \geq U(h)$*

3. $\frac{d\phi(h)}{d\lambda_1} \leq 0$, $\frac{d\phi(h)}{d\lambda_0} \geq 0$, $\frac{d\phi(h)}{d\delta} \geq 0$

The first two properties simply reflect the fact that increasing the rate of offers increases the chances of moving up the wage ladder and increasing the probability of losing one's job makes it more likely to be unemployed. Property 3 is interesting because it illustrates the effect the search parameters affect the reservation wage. This property illustrates the trade off in the unemployment state between waiting for a better a wage offer and taking the current wage. If the probability of offers increase in the unemployment state, the cost of rejecting an offer in hand falls because part of that cost was the expected time until next offer. If the rate of on-the-job search increases, taking a low offer out of unemployment is less costly in terms of the search cost for a better job. Note that the reservation wage is increasing in the job destruction probability. Relating this to importance of search with respect to wage growth, high job destruction may induce workers to stay in unemployment longer which will be reflected in lower wages due to forgone human capital accumulation.

Proposition 2.2. *The policy function $l^*(h, R) = \operatorname{argmax} W(h, R)$ has the following properties:*

1. *Optimal investment is increasing in the job arrival rates and decreasing in the destruction rate*

2. *Optimal investment is decreasing in both the stock of human capital h and the current piece rate R*

The first property is true because workers are risk neutral income maximizers. It is essentially a statement about the utilization rate of human capital in the future. The faster jobs arrive, the higher is the expected piece rate at which human capital can be sold, increasing its future value. The rarer is job destruction, the more likely the worker will be employed using human capital. The parameters λ_1, λ_0 and δ affect the rental rate distribution by altering the flow of workers between employment and unemployment, as well as from low paying to high paying jobs. Increasing λ_1 has an unambiguous effect of increasing average rental rate of those employed because it directly affects the rate at which on-the-job search occurs. Increasing λ_0 increases the reservation wage because it reduces the cost of future search. Increasing the reservation wage increases the average rental rate because only 'good' wages are ever accepted. An increase in δ lowers the average rental rate because it lowers the average employment duration, dampening the effect of on-the-job search.

Given $\{\lambda_0, \lambda_1, \delta\}$ and F the steady state piece rate distribution is

$$G(R) = \frac{\delta F(R)}{\delta + \lambda_1(1 - F(R))} \tag{2.4}$$

Increasing λ_1 first order stochastically shifts the distribution to the right, and increasing δ first order stochastically shifts the distribution to the right. So while an individual does not care what the distribution of piece rates in the economy, an econometrician measuring the average wage might especially if this measurement is used to identify productivity differences or a labor demand function.

3 Econometric Methodology

The model specified above does not yield closed form solutions of the evolution of the distributions of the state variables. Furthermore, the two state variables and the control variable are unobservable. Following Bowlus and Liu (2013), I estimate the structural parameters of the model via indirect inference. The basic idea is to connect the model parameters to the data via auxiliary regressions on simulated data. Given that these auxiliary regressions have sufficient identifying power to recover the structural parameters of the model, the estimator is simply the vector of parameters θ such that the regression coefficients of the simulated data minimizes the distance to the actual data moments.

For the purpose of estimation, I set the time period at three months and set β to 0.99. The model has seven parameters. However, the assumption that job destruction is exogenous in the model allows me to identify it directly from the average employment duration. The six parameters I estimate then are $\theta = \{\lambda_0, \lambda_1, \delta, \mu, \sigma, A, \gamma\}$.

3.1 Auxiliary Regressions

In the data I observe wages, cumulative experience, job duration and transitions. With this I estimate a Mincer wage equation of the form

$$log(Wage_{i,j}) = \beta_0 + \beta_1 exp_{i,j} + \beta_2 exp_{i,j}^2 + \beta_3 ten_{i,j} + \beta_4 ten_{i,j}^2 + \beta_5 Djj + \epsilon_{i,j} \qquad (3.1)$$

The dependent variable is the log of the starting quarterly earnings of job number j held by individual i. exp is cumulative experience measured as the number of weeks spent in full time employment since leaving school for good at the time of the wage observation. Tenure is the measured job duration of the job spell. Models with random search on-the-job predict a positive relationship between wages and job duration. Finally, Djj is a dummy variable that equals 1 if job j is the destination job from a job-to-job transition. Wages from jobs out of unemployment are predicted to be less than wages after a job-to-job transition. This mincer equation helps the model generate the correct wage profile in the data.

Wage growth on-the-job identifies the human capital accumulation process. Wages grow both because human capital is accumulated and investment declines over time. Furthermore, investment is inversely related to both the current stock of human capital and the piece rate R. This motivates the following regression equation

$$\Delta log(Wage_{i,j,t}) = \beta_6 + \beta_7 exp_{i,j} + \beta_8 expi, j^2 + \beta_9 ten_{i,j} + \epsilon_{i,j,t} \qquad (3.2)$$

Tenure is useful for identifying how investment varies across the different piece rates as tenure is positively correlated with the piece rate.

Next I estimate two accelerated failure time models of job duration and unemployment duration. Job duration is inversely related to the piece rate. Unemployment duration is increasing in human capital. This motivates the follow specifications

$$log(jobdur_{i,j}) = \beta_{10} + \beta_{11} first\_wage_{i,j} + \beta_{12} exp_{i,j} + \epsilon_{i,j} \qquad (3.3)$$

$$log(unempdur_{i,j}) = \beta_{13} + \beta_{14} exp_{i,j} + \epsilon_{i,j} \qquad (3.4)$$

I also include the following moments. The average and variance log wage of the first job out of schooling, μ_{logw} and σ^2_{logw}. These measures provide information about the offer distribution under the assumption that all workers are homogeneous with respect to initial human capital. Similarly, the average job tenure on the first job helps further identify the on-the-job offer arrival probability without any confounding effects of the wage distribution. Finally, the unemployment duration right out of school helps further identify the job offer probabilities from unemployment.

In total I estimate 19 moments from the data. Let β denote the vector of these moments estimated from the data. Let $\beta(\theta)$ denote the vector of these moments estimated from simulated data given the parameters θ. The method finds an estimate $\hat{\theta}$ such that the distance between β and an average of n moments from the simulated data is minimized. For the estimation I choose $n = 250$.

3.2 Monte Carlo Exercise

In this section I test if the proposed auxiliary regressions are able to recover the correct parameters from a simulated sample. I set the parameters and generate a random sample of 1000 individuals and simulate each of their lives for 120 quarters. From the simulation, I construct a dataset similar to the one available in the NLSY79. I sample a wage for each new job as well as an annual sample of jobs that continue for more than 4 quarters. Also, I construct quarterly job, employment and unemployment duration. From this data, I estimate the above auxiliary regressions, and begin the estimation routine. The results are summarized in Table 1. The estimation does reasonably well at hitting the true parameters, however it seems to consistently underestimate the piece rate parameters and over estimate the arrival rates. The differences between the estimates and the true values are small compared to the differences of the estimates across the two education groups.

Table 1: Monte Carlo Estimates

Parameter	True Value	Estimate
μ	1.5	1.3961
σ	.5	.4561
λ_0	.4	.4474
λ_1	.2	.2207
A	.07	.0413
α	.5	.6174
δ	.1	.1132

4 Data

I use data from the NLSY79 to estimate the model above. I restrict the sample to white males who have made the transition to full time post-schooling work. I further restrict the sample to workers who have completed either 12 years or 16 years of schooling. I define all those with 12 years of schooling as belonging to the high school market, and all those with 16 years belonging to the college market. The full sample has 815 high school workers and 364 college workers. In total there are 4802 individual-job observations of the high school labor market and 1373 observations of the college market.

At a particular interview date, the NLSY79 contains detailed information of up to 5 jobs held since the last interview. This includes the start and end dates of the job, as well as the wage paid at the beginning of the spell. If the spell continues across interview rounds, a wage observation is observed for those rounds as well. The model does not allow for multiple jobs, nor is there an intensive margin for hours worked. I restrict attention to jobs that are full time defined as working at least 35 hours per week. If two jobs report overlapping start and end weeks, I assume that the second job does not begin until the first job's end date. If one job starts after a second job and ends before it too, it is dropped.

Once a sequence of jobs are defined for each individual, job duration, employment duration and unemployment duration is calculated. Unemployment duration is calculated as the difference between one job's start date and the immediately preceding job's end date. Job duration is calculated simply as the difference between the job's end and start date. If the unemployment duration between two jobs is less than 3 weeks, I consider that a job-to-job transition has occurred. The employment duration is calculated as the total duration of a sequence of jobs linked by job-to-job transitions.

Table 2 presents some summary statistics of the data. Wages are converted to quarterly earnings by multiplying the hourly rate by 40 times 12. Experience is defined as the number of weeks worked in full time employment since leaving school. There are a few things worth mentioning. First, unsurprisingly, wages are higher and grow faster for college educated than those with only high school. Also, employment durations are much longer for college educated workers. Also the number of job switches per employment duration is larger as well and the average wage gain per switch. These observations, viewed in the context of the model presented in section 2, suggest college worker's more favorable search environment reinforces the wage differences between them and high school graduates.

Table 2: Summary Statistics

	High school	College
Mincer Regression: log of quarterly earnings		
cons	3.156 (.0141)	3.421 (.0259)
exp	.00079	.00105
exp^2	-3.3e-7	-2.8e-7
average job duration	84 weeks	106 weeks
average duration of employment	249 weeks	356 weeks
average duration of unemployment	25.1 weeks	18.68 weeks
# of jobs total	6.2	4.8
average log quarterly wage after:		
j-to-j transition	3.402	3.741
u-to-j transition	3.240	3.461

5 Results

Table 3 presents the estimated parameters of the model. For the estimation, I set $h_0^s = 100$ for both $s \in \{college, highschool\}$, $\beta = .99$ and $b = 2$ for each group.

From the estimates of the piece rate distribution in each market, I find that a college worker's human capital is paid on average 27% more than high school worker's human capital, and that this price is much less variable. The human capital production function estimates indicated that college workers are on average more productive at

Table 3: Parameter Estimates

Parameter	High school	College
μ	.7698	1.26
σ	1.038	.841
λ_0	.3429	.5935
λ_1	.1086	.0806
A	.1081	.1888
α	.5420	.4716
δ	.048	.033

producing human capital than high school workers. It is worth noting that my estimates for the human capital production function for the high school students is in line with those provided by Bowlus and Liu (2013), who also uses NLSY79 data. Finally, I find that college workers receive job offers out of unemployment nearly twice as often as high school workers, but actually receive job offers on-the-job somewhat less frequently. While my model exogenously specifies the job arrival rates, these numbers may reflect that college workers are better at finding good matches earlier and subsequently job shop less.

Job destruction is estimated entirely off the employment duration in the data. The probability of job destruction in a quarter for college workers is .033 and .048 for high school workers.

Using these estimates I simulate 5000 college workers and 5000 high school workers for 40 years. Figure 1 plots the wage profiles of employed workers over this time period. Figure 2 plots the difference in wages.

The goal of this paper is to quantitatively asses the role of search in determining the college premium. Because the investment decision interacts with the level of the piece rate, the contribution of search cannot be easily assessed from the model's parameters. However, I can simulate a counterfactual world in which the search process is shut down (all workers receive a common piece rate) and a world where there is no human capital production. Finally, I study the importance of job destruction relative to on-the-job search by I simulating a world where there is still transitions to and from unemployment, but a constant piece rate is earned.

Table 4 presents the results of these experiments. The wage premium predicted by the model is 79% after 10 years in the labour force. The case with no search or human capital accumulation is where workers earn the average piece rate for their entire lives, and so the wage premium is simply the ratio of the price of college human capital versus high school human capital. I look at three cases. First I shut off the search process by setting λ_0, λ_1 and δ to 0. The wage premium falls substantially to 43%. If I only shut down on-the-job search, the wage premium still falls all the way to 49% illustrating that the difference is not solely due to differences in the amount of time spent in unemployment where human capital accumulation doesn't occur. Finally, if I shut down human capital accumulation while keeping search active, the wage premium nearly collapses. In fact, search differences are such that the wage premium is less than without search. Without human capital investment, college workers have less incentive to enter employment, raising their reservation wage. However, high school

Table 4: Contribution of human capital and search

Case	College premium at 10 years of experience
Full Model	1.79
No search	1.43
No human capital	1.24
No on-the-job search	1.496
No search or human capital	1.27

workers actually receive more offers on the job, so it is not clear what direction the wage premium should go *a priori* given the parameters.

In the full model, the search process interacts with individual's choice of investment. It is not obvious how the college premium is changed by this interaction. Figures 1 and 2 plot the reservation wage as a function of human capital for both the college and high school workers. Notice that the reservation wage of the college worker is much steeper in h than the high school reservation wage. Early in the life-cycle, the return to human capital is high. However, it is much higher for college workers than high school workers because they are so much more productive at producing it. Late in life, the value of human capital accumulation declines and the differences in job arrival probabilities begins to dominate. College workers are much better at finding job offers, so the cost of rejecting a bad offer is lower. This force pushes up the reservation wage.

6 Role of Unemployment Benefits

The decision to enter into employment at a given piece rate depends on the relative value of employment at that rate against the value of continuing in unemployment. The main two sources of this difference is the relative magnitude of the offered piece rate to the unemployment benefit b and the value of investing in human capital while employed and the frequency of job offers. Since college workers are much more productive at producing human capital, it is more costly for them to sit in unemployment. On the other hand, they are much more likely to receive a job offer out of unemployment in a given period. These two forces work in the opposite direction. This suggests that changes in unemployment benefits may have differential effects on the reservation wage of college and high school workers.

Figure 3 and Figure 4 plot the reservation wages of college and high school workers as a function of h for $b \in \{2, 2.5, 3, 3.5, 4, 4.5, 5\}$. The experiment I conduct is to vary b to see how unemployment benefits affect the college premium. Figure 3 plots the result of that experiment. I find that the college premium follows an inverted-U pattern but is relatively stable. When b is large, high school workers only selectively enter employment which raises the average wage of the employed group. But they also invest less in human capital since they spend more time in unemployment, which reduces wages in the future. When b is small, the opposite is true: they invest more and enter at a lower margin. At low levels of human capital, the reservation wage is much more sensitive for high school workers to changes in b. This may be what is leading to the inverted-U shape in Figure 5.

7 Conclusions

I estimate a simple model of random search and human capital investment on a sample of college and high school workers in the NLSY79 to study how differences in search parameters translates into differences in the college wage premium. I find that search is responsible for a sizable fraction of the wage premium, mostly through the interaction with the human capital investment decision.

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Figure 1: Wages of Employed Workers: College and High School

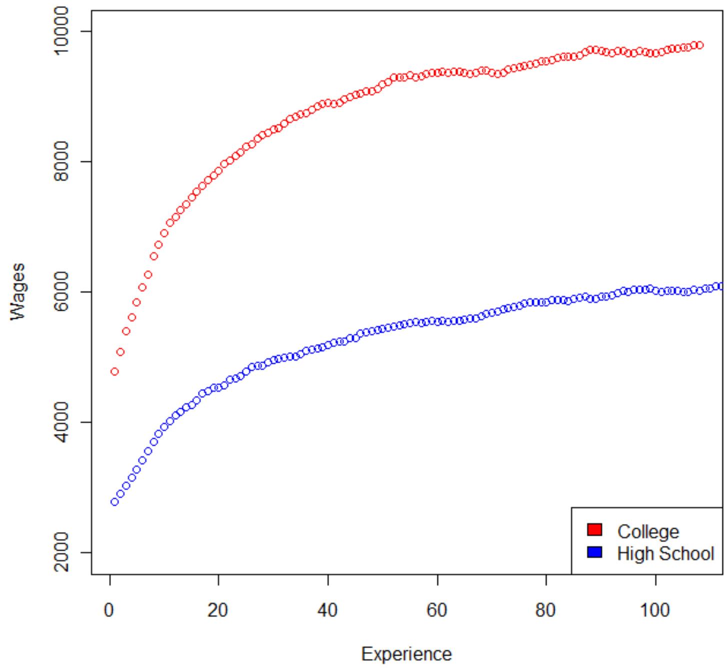

Figure 2: Rental Rates of Employed Workers: College and High School

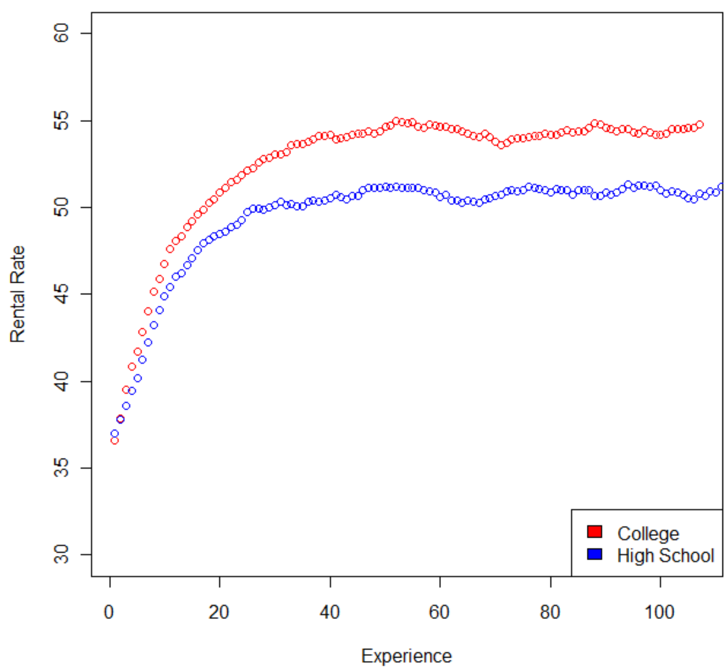

Figure 3: Reservation wage: college worker

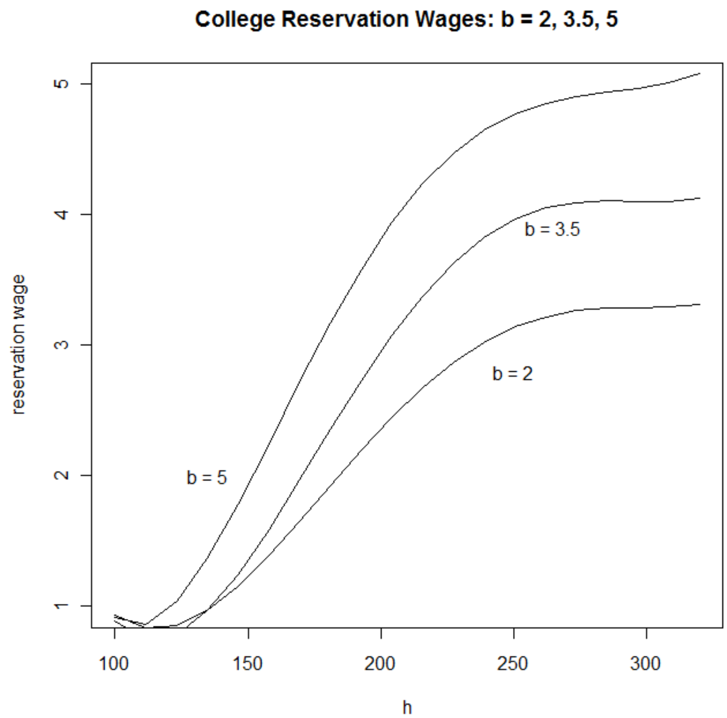

Figure 4: Reservation wage: high school worker

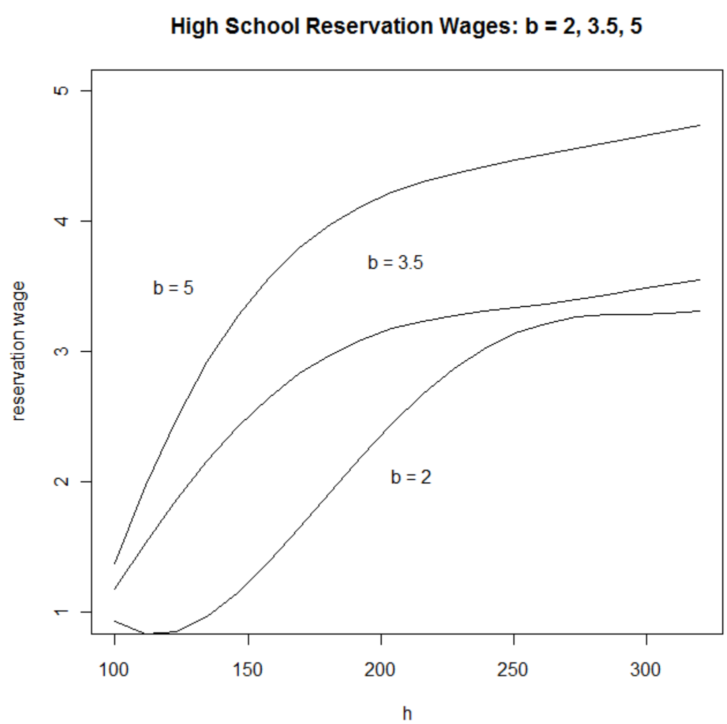

Figure 5: Unemployment benefits and wage premium