Review and Replication of: The Career Decisions of Young Men

Replication Notes for Keane and Wolpin (1997) *

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Abstract

This study seeks to adopt the structural model and framework from Keane and Wolpin (1997) with three goals: 1) gain knowledge and understanding of the model solution and estimation, 2) replicate selected results, and 3) employ the KW model for counter-factual policy simulation. I adopted the KW baseline model and used the original parameters from the paper. The respy package for python, developed by Open Source Economics is used to solve, estimate, simulate, and calibrate the baseline model. After solving the model, I then simulate predicted outcomes for 500 simulated individuals over 15 periods and compare my simulated results to the same NLSY 79 cohort observations used by KW. After evaluating model fit, I apply a calibration regiment to update the model parameters and again predict simulated outcomes. Calibration is carried out via the method of simulated moments. As a counterfactual exercise, educational benefits are fixed across occupation classes. The model is resolved and used to predict simulated outcomes to compare to the observed data sample. White-collar occupation experience and schooling investments significantly decrease due to this environment change and blue-collar occupation experience dramatically increase. Much of the observed change in predicted outcomes is due to schooling investments no longer being optimal when educational investment benefits are equalized.

Key words: Education, Human capital, Occupational Choice

JEL Codes: I21, J31, J45, O15

*This is a document containing replication notes for Keane and Wolpin (1997). The model implimented with the respy package in python from Open Source Economics, see `https://github.com/OpenSourceEconomics/respy` or the Website.

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1 Introduction

Keane and Wolpin's (1997) (KW henceforth) paper "The Career Decisions of Young Men" is a hallmark in the field of applied microeconomics. While the structural econometric approach has a long history in microeconomics (Galiani & Pantano, 2021), KW was one the first to take "seriously" a fully structural approach to explaining observed patterns in the data. A key contribution of KW was explaining patterns for not just one complex decision process such as school attendance or labor supply, but a bundle of highly complex decision processes over the life cycle, including school attendance, employment, occupational choice, home production, and college education starting from adolescence into retirement. Each of these individual decisions is difficult in and of itself to understand. Both the economic impacts and implications on behavior and economic outcomes such as wages are important. Thus, KW utilization of a structural approach to study this phenomenon not just for qualitative prediction, but to obtain detailed quantitative parameter estimates was a true validity test of this methodology in the era of modern economic research.

At present, the state of economic research is in the midst of two revolutions. First, the credibility revolution – a heightened focus on the reproducibility and transparency of research, see Angrist and Pischke (2010) for a detailed discussion. Second, the data revolution. In the years since Keane and Wolpin dictated their original model there has been an exponential increase in both the amount of data generated as well as computing power available to analyze such data Einav and Levin (2014). These trends have ostensibly ambiguous effects on the structural methodological approach advocated in KW. In a forthcoming handbook of economic research chapter, Galiani and Pantano (2021) articulate three key advantages of structural models: 1) counter factual evaluation or the study of new environments with the study sample, 2) mechanism evaluation – a detailed analysis of mechanism that would otherwise be unidentifiable, and 3) welfare evaluation – a quantifiable analysis of welfare implications under new policy regimes (2021). These contributions are distinguishing features of economic research relative to other disciplines and are essential to the viability of the discipline in the future.

Armed with the above-mentioned knowledge, it is apparent why an understanding of KW is relevant 26 years since its inception. This study seeks to adopt the structural model and framework from KW with three goals: 1) gain knowledge and understanding of the model solution and estimation, 2) replicate selected results, and 3) employ the KW model for counter-factual policy simulation. I adopted the KW baseline model and use the original parameters from the paper. Using the respy python package from Open Source Economics, I solve, estimate, simulation, and calibrate the KW baseline model. After solving the model, I then simulate predicted outcomes for 500 simulated individuals over 15 periods and compare my simulated results to the same National Longitudinal Surveys of Labor Market Experience (NLSY) 79 cohort observations used by KW. After evaluating model fit, I apply a calibration regiment to update the model parameters and again predict simulated outcomes. Calibration is carried out via the method of simulated moments and new simulation results are accessed, evaluating the model's predictive power.

Finally, in the KW baseline model education benefits from additional years of schooling are heterogeneous across occupation types and agents are heterogeneous in their skill endowments. I fix educational benefits to be homogeneous across occupation classes while keeping heterogeneous skill or ability the same as in the baseline model. I then resolve the model and predict simulated outcomes to compare to the observed data sample. White-collar occupation experience and schooling investments significantly decrease due to this environment change and blue-collar occupation experience dramatically increases. Much of the observed change in predicted outcomes is due to schooling investments no longer being optimal when educational investment benefits are equalized. This simulation has implications for related literature on human capital investment theory and signaling theory.

The remainder of the paper is organized as follows. Section 2.1 describes the model and solution method. Section 3 introduces data set and main variables. Section 4 and 5 present parameter values estimated and calibration. Section 6 discusses counterfactual exercises.

2 Model

2.1 Model Setup

Keane and Wolpin's model is coupled to human capital theory. It is explicit and intuitive on how the model assumptions translate to human capital accumulation. Individual agents make investment decisions, accumulate experience, and then receive payoffs each period for a given investment. The per period payoffs contain all the benefits and costs for an associated investment decision. Codifying the baseline model into distinct segments we have the model choice-space and the model state-space.

2.1.1 Choice Space

In the choice space, agents make an investment decision each period in one of five mutually exclusive occupational decisions: work in a white-collar job, work in a blue-collar job, work in the military, attend school, or home production. This choice is not only a labor supply decision that is rewarded with wages, but also an investment that is compensated with accumulated experience that increases wages in future periods. Keane and Wolpin operationalize this discrete choice decision with choice vector $d_m(a)$ which is a (5 x 1) vector for m = 1, ..., 5 for each of the occupational choice variables in the model. $d_m(a) = 1$ if m is chosen at age a. This binary choice vector is multiplied by (1 x 5) vector of rewards in the form of wages or experience for each occupational path. The dot product of each of these vectors equates to the Reward function value for each age, a, starting at 16 until age **A**. For m=1, 2, 3 or the white collar, blue collar, and military occupation decisions are awarded with monetary benefits, m=4,5 are associated with non-monetary benefits in the current period.

2.1.2 State Space

$$s_t = \{\boldsymbol{k_t}, h_t, t, a_{t-1}, \boldsymbol{e}, \boldsymbol{\epsilon_t}\} \tag{1}$$

The state space for this model is more complex and is a function of age (t), but also skill endowment at age 16 e_{16}, education attainment $h(a)$ at age t, occupation specific work experience $k_j(a)$, and occupational path specific shocks $\epsilon_t(a)$. Both educational attainment and work experience are investments that increase wages in future periods. Occupational specific shocks introduce uncertainty into the model as well as volatility in rewards such that an occupational decision made a one age might not be maximizing in the next period at age (a_{t+1}).

$$u_a(\cdot) = \begin{cases} \zeta_a(\boldsymbol{k_t}, h_t, t, a_{t-1}) + w_a(\boldsymbol{k_t}, h_t, t, a_{t-1}, e_{j,a}, \epsilon_{a,t}) & \text{if } a \in \{1, 2, 3\} \\ \zeta_a(\boldsymbol{k_t}, h_t, t, a_{t-1}, e_{j,a}, \epsilon_{a,t}) & \text{if } a \in \{4, 5\}. \end{cases} \tag{2}$$

$$\begin{aligned} k_{a,t+1} &= k_{a,t} + \nVdash[a_t = a] \qquad \text{if } a \in \{1, 2, 3\} \\ h_{t+1} &= h_t \;\; + \nVdash[a_t = 4] \end{aligned} \tag{3}$$

Work Occupation Paths

The culmination of both the space and the choice space lies definition of the reward structure, designated by equation 4. The reward function follows the traditional Mincerian form Mincer (1958) where wages or in this case rewards are allocated based on the level of skill an agent has accumulated at the current age. These units of skill are multiplied by the rental rate to become wages or earnings for a worker. Skill units are determined by the initial skill endowment which is realized at age 16, $e_m(16)$, the number of years of schooling and experience up to the current age, and an occupational specific shock at each age.

$$\begin{aligned} \zeta_1(\boldsymbol{k_t}, h_t, a_{t-1}) = \alpha_1 &+ c_{1,1} \cdot \nVdash[a_{t-1} \neq 1] + c_{1,2} \cdot \nVdash[k_{1,t} = 0] \\ &+ \vartheta_1 \cdot \nVdash[h_t \geq 12] + \vartheta_2 \cdot \nVdash[h_t \geq 16] + \vartheta_3 \cdot \nVdash[k_{3,t} = 1] \end{aligned} \tag{4}$$

$$
\begin{aligned}
\zeta_2(\boldsymbol{k_t}, h_t, a_{t-1}) = \; & \alpha_2 + c_{2,1} \cdot \nVdash[a_{t-1} \neq 2] + c_{2,2} \cdot \nVdash[k_{2,t} = 0] \\
& + \vartheta_1 \cdot \nVdash[h_t \geq 12] + \vartheta_2 \cdot \nVdash[h_t \geq 16] + \vartheta_3 \cdot \nVdash[k_{3,t} = 1]
\end{aligned} \tag{5}
$$

$$
\zeta_3(k_{3.t}, h_t) = c_{3,2} \cdot \nVdash[k_{3,t} = 0] + \vartheta_1 \cdot \nVdash[h_t \geq 12] + \vartheta_2 \cdot \nVdash[h_t \geq 16] \tag{6}
$$

Non-work Occupation Paths

Keane and Wolpin model the remaining choices of schooling and home production distinctly from a pure human capital investment model. They explicitly model the unintended costs of schooling, in other words schooling requires effort which imposes a cost on the agent. Additionally, the cost of schooling has two components, costs for each additional year of college, and a cost for each additional year of graduate school. Keane and Wolpin implement these costs with the use of an indicator function such that if years of schooling at a particular age are above 12 but less than 16 then the college costs are occurred. Whereas, if years of schooling at age,a, are greater than 16 the graduate school costs start to incur.

$$
\begin{aligned}
\zeta_4(k_{3,t}, h_t, t, a_{t-1}, e_{j,4}, \epsilon_{4,t}) = e_{j,4} & + \beta_{tc_1} \cdot \nVdash[h_t \geq 12] + \beta_{tc_2} \cdot \nVdash[h_t \geq 16] \\
& + \beta_{rc_1} \cdot \nVdash[a_{t-1} \neq 4, h_t < 12] + \beta_{rc_2} \cdot \nVdash[a_{t-1} \neq 4, h_t \geq 12] \\
& + \gamma_{4,4} \cdot t + \gamma_{4,5} \cdot \nVdash[t < 18] \\
& + \vartheta_1 \cdot \nVdash[h_t \geq 12] + \vartheta_2 \cdot \nVdash[h_t \geq 16] + \vartheta_3 \cdot \nVdash[k_{3,t} = 1] \\
& + \epsilon_{4,t}
\end{aligned}
$$

Finally, home production is solely a function of the skill endowment at age 16 and the occupation specific shock variable, $\epsilon_t(a)$. As individuals in this data sample are highly unlikely to have children and subsequently high home production demands, the most typical structure in which to interpret home production would be that of leisure time. But this model remains highly generalizable to many diverse applications.

$$\zeta_5(k_{3,t}, h_t, t, e_{j,5}, \epsilon_{5,1}) = e_{j,5} + \gamma_{5,4} \cdot \mathbb{1}[18 \leq t \leq 20] + \gamma_{5,5} \cdot \mathbb{1}[t \geq 21] \\ + \vartheta_1 \cdot \mathbb{1}[h_t \geq 12] + \vartheta_2 \cdot \mathbb{1}[h_t \geq 16] + \vartheta_3 \cdot \mathbb{1}[k_{3,t} = 1] \\ + \epsilon_{5,t}$$

Value Function

$$v_t^\pi(s_t) \equiv \mathbb{E}_{p^\pi}\left[\sum_{j=0}^{T} \delta^j u_{t+j}(s_{t+j}), a_{t+j}^\pi(s_{t+j}) \,\middle|\, s_t\right] \tag{7}$$

$$v_t^\pi(s_t) = u(s_t, a_t^\pi(s_t)) + \delta\, \mathbb{E}_{p^\pi}\left[v_{t+1}^\pi(s_{t+1}) \mid s_t\right]. \tag{8}$$

The previous equations can be summarized into a representative value function as the discrete choice that agents face is the same at each age. The value function is the expected discounted per-period utility condition on a given state. In order to solve the value function I employ the following algorithm from Gabler and Raabe (2020). The value function is solved via backwards induction, starting at the terminal age **A** and determining the optimal choice and then repeating the process at the second to last age period. Figure 11 details the solution algorithm.

3 Data

The National Longitudinal Surveys of Labor Market Experience survey (NLSY) is a rich data set with many detailed questions allowing precision in documenting variables necessary for a comprehensive analysis of key questions in human capital theory and labor economics. Keane and Wolpin's study though written over 20 years ago is extremely relevant for the current debate at the frontier of microeconomics research today. Economics has been evolving through the so called data revolution, where large detailed data sets are becoming better, more accessible, and even more detailed. Thus, how much value added are models when there exists so an abundance of data?

One of the key contributions of Keane and Wolpin's work was their ability to build a fairly simple model with conservative behavioral assumptions that could accurately make predictions to match a data set as complex as the NLSY. Keane and Wolpin (1997) build a model that can explain labor market outcomes for a substantial proportion of the United States labor market. This model has predictive power of key outcomes such as education and occupation decisions, decisions which are typically fraught with endogeneity concerns. The authors' work is a testament that even in the age of 'big data' economic models are still vital to our understanding of the human behavior and critical for estimation when standard reduced form techniques are limited.

This model was built to replicate and have significant predictive power over the wealth of educational and labor market outcomes in the NLSY. The authors focus on men who were age 14-21 years old in 1979, consisting of about half of the total sample. Keane and Wolpin then restrict to the sample further to specifically focus on White males age 16 or younger. Utilizing the data structure of the NLSY the authors follow individuals with data from annual interviews. Approximately 1,373 young men comprise the final sample. School enrollment and attendance data as well as employment history are documented in the annual interviews. Thus, this data source allowed the authors to build a panel data set following the young men from the end of secondary schooling years well into their career and working lives.

The main data variables fall into two categories, School attendance and Work. Regarding school attendance the data-set contains information and allows for the construction of variables including the highest grade completed annually, monthly attendance, school withdrawal dates, and year of diploma and degree completion. Related to work, employment data is recorded for each individual such as job start and end dates, average working hours, average job wages as well as the three-digit occupation code. Occupation codes are then categorized into three sectors: white-collar, blue-collar, or the military. Occupation sector status is defined by which occupation class received the most number of working weeks in that calendar year. Wages are annualized and standardized to a typical 50-week full-time status work year. Presently, individuals in the NLSY data are seen in one of four categories, three occupation types, or attending school. Individuals not enrolled in school or employed are categorized as home production status.

3.1 Descriptive Statistics

Figure 1 replicates some of the key patterns and trends in the observed NLSY 79 cohort sample. These occupational choice frequencies will be what I will compare simulated model predictions with to access model fit.

Both blue-collar and white-collar occupational choices are highly unlikely at age 16 with a small fraction of individuals engaging in home production or leisure during that age category.The majority of observations are participating in school attendence. School attendance declines steeply as age progresses. While blue and white-collar occupations steadily increase with age. Military experience has a unique hump shaped distribution with only a very small proportion of individuals continuing a military career after the age of 25.

4 Estimation

I begin my replication of Keane and Wolpin's baseline human capital model by using the parameter values exactly from their paper as reported in Appendix B Table B1. I implement the model and operationalize the authors' solution algorithm by using the respy package for python 3. Respy was developed and is maintained by the Open-Source Economics collaboration, a cross disciplinary research group funded in part by the German Federal Ministry of Education and Research as well as the German Reproducibility Network. Respy is "an open-source framework for the simulation and estimation of finite-horizon discrete choice dynamic programming models" Gabler and Raabe (2020).

My implementation of Keane and Wolpin (1997) takes the model solution and simulates model outcomes on 500 observations for 15 periods. KW baseline model simulated outcomes for 5,0000 obs and 50 time periods. My simulation parameters were chosen strictly for computational convenience. While there are many possible ways to simulate model predictions I utilize n-step-ahead simulation with sampling. Respy package authors describe this technique as the following: "the first observation of an individual is sampled from the distribution implied by the initial conditions, i.e., the distribution of observed variables or initial experiences, etc. in the first period. Then, the individuals are guided for n periods by the decision rules from the solution of the model" Gabler and Raabe (2020). Given the simulated model predictions I turn to analysis of model sample fit.

Initial model predictions are sizably different than the observed data. I analyze model fit on two dimensions namely: occupational choice frequencies and experience-wage profiles. The only occupational choice profile that matches the data well is the years of school frequency. On this dimension model error is very minimal. Additionally, the proportion of white-collar workers, or simulated individuals with predominantly white-collar occupational histories, are extremely inflated relative to the observed data patterns. Figures 2 and 3 illustrate these results.

Figure 4 illustrates experience wage profiles for blue and white-collar workers with 10 years of schooling and then again in Figure 5 with 16 years of schooling. From the results notated in the preceding figures it is apparent under the baseline model specifications that the model does not fit the observed data well and parameter adjustments are needed.

5 Calibration

Both a theoretical and empirical exercise estimation is an essential part of structural modeling. Theoretically, a model is calibrated using observed individual outcomes assuming individual behave in accordance with the discrete choice model. In other words, we must assume our model has predictive power over individual outcomes conditional on the observed data. This type of exercise is plausible under the paradigm of revealed preferences, where we can make use of individual decisions and generalize them to individual 'policy rules'. These so called 'policy rules' which determine individual decision making most often come in the form of utility functions, preference parameters, and transition probabilities. In the most general form we have information about individuals at different periods of time, in the case of this model different ages. Additionally, for an individual at a specific age an action is observed, some part of the utility function, and the observable state space. Thus, one way to visualize these elements would be with the following function:

$$\mathcal{D} = \left\{ a_{it}, \bar{s}_{it}, \bar{u}_{it} : i = 1, \ldots, N; t = 1, \ldots, T_i \right\}. \tag{9}$$

Finally, there is one more data structure element vital to our theoretical understanding of structural modeling, the stochastic component $epsilon_t$. These shocks are only observed by the individual and are responsible for the unobserved heterogeneity in our model structure. The revealed preference paradigm is theoretical justification for taking the data structure (10) and using it in a calibration procedure to build a model with predictive power.

Broadly speaking there are two common types of calibration techniques: likelihood based calibration and simulation-based calibration (Davidson & MacKinnon, 2003). Likelihood based calibration finds the vector of structural parameters theta that maximizes the likelihood function conditional on the observed data structure. Assuming, we know the distribution of the individual stochastic components $epsilon_t$. We can determine the probability of individuals taking specific actions during specific time periods. Generally, likelihood based calibration takes the following form Gabler and Raabe (2020):

$$\hat{\theta} \equiv \underset{\theta \in \Theta}{\arg\max} \underbrace{\prod_{i=1}^{N} \prod_{t=1}^{T_i} p_{it}(a_{it}, \bar{u}_{it} \mid \bar{s}_{it}, \theta)}_{\mathcal{L}(\theta \mid \mathcal{D})}. \tag{10}$$

As shown in the estimation and simulation section our model predictions are far from consistent with the data. Thus, we will implement the method of simulated moments calibration routine. The empirical moments that we will seek to match are the distribution of occupational choice frequencies at each period as well as the wage mean and standard error. Armed with these elements we can build the objective function notated by equation (12). There are a number of different ways to specify the optimal weighting matrix, a discussion of such properties is beyond the scope of this work. Using the respy package developed by authors Gabler and Raabe, they use a diagonal weighting matrix with weights equal to the inverse bootstrapped variances of the observed sample moments Gabler and Raabe (2020).

$$\hat{\theta} \equiv \underset{\theta \in \Theta}{\arg\min} \big(M_{\mathcal{D}} - M_{\mathcal{S}}(\theta)\big)' W \left(M_{\mathcal{D}} - M_{\mathcal{S}}(\theta)\right). \tag{11}$$

The calibration routine first computes the empirical moments, then using the original KW97 parameters estimate the simulated sample moments. The method of simulated moments seeks to minimize the distance between the empirical and simulated moments. Each time the difference between the moments is above the tolerance threshold the parameters are updated and the process is repeated. This continues until the model error is below a threshold or in other words the routine has converged to a set of new parameters. With the new parameter set, I again use the respy package to resolve the model and simulate model predictions for 500 individuals and 15 periods.

6 Counterfactual

With more confidence in our model parameterization and predictions we can proceed to counterfactual analysis. In Keane and Wolpin (1997) the returns to schooling were heterogeneous across occupational types. With benefits for white-collar workers =0.094, military occupations = 0.044, and blue-collar occupations = 0.018. I seek to simulate a world where returns to schooling are homogeneous regardless of occupation type, while keeping agent skill or ability type heterogeneous. I modify the education experience parameter to be equal for all occupations with a value of 0.05.

Figures 9 and 10 exhibit the counter factual results. Blue-collar occupation frequencies make up the majority of the simulated new sample. White-collar and military occupations see substantially diminished demand. Additionally, as a consequence of equalizing educational benefits schooling participation decreases almost 3 times is original value in the observed sample going from around 87% to less than 30%. These results are anticipated due the costs of schooling. If the benefit of schooling is equalized then rational agents in the model move into blue-collar occupations as they can have higher earnings by forgoing education investment costs.

References

Angrist, Joshua D, and Jörn-Steffen Pischke. 2010. "The credibility revolution in empirical economics: How better research design is taking the con out of econometrics." *Journal of economic perspectives*, 24(2): 3–30.

Einav, Liran, and Jonathan Levin. 2014. "Economics in the age of big data." *Science*, 346(6210): 1243089.

Gabler, Janos, and Tobias Raabe. 2020. "respy - A Framework for the Simulation and Estimation of Eckstein-Keane-Wolpin Models."

Galiani, Sebastian, and Juan Pantano. 2021. "Structural models: Inception and frontier." National Bureau of Economic Research.

Keane, Michael P, and Kenneth I Wolpin. 1997. "The career decisions of young men." *Journal of political Economy*, 105(3): 473–522.

Mincer, Jacob. 1958. "Investment in human capital and personal income distribution." *Journal of political economy*, 66(4): 281–302.

Figures and Tables

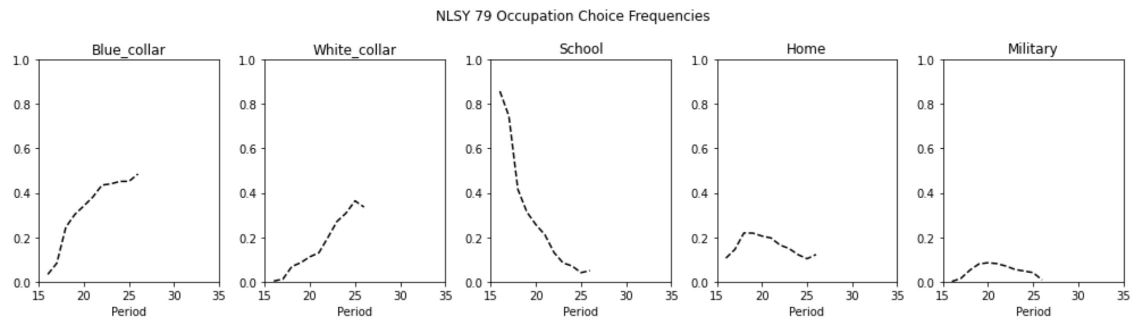

Figure 1: Descriptive Statistics: NLSY 79 Occupation Choice Frequencies

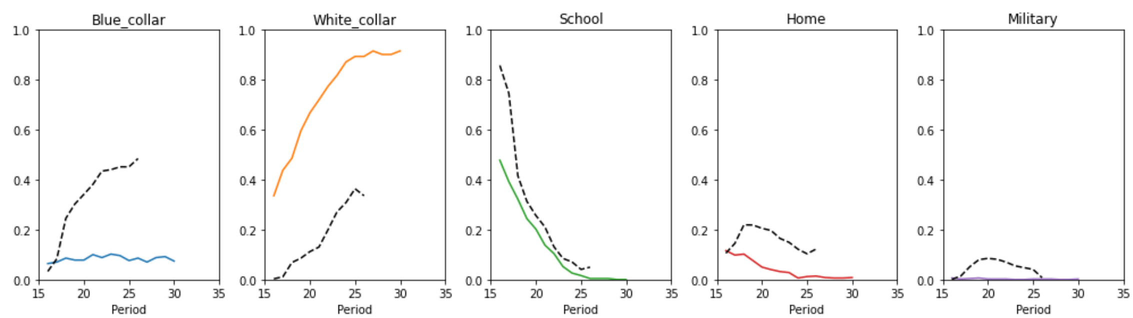

Figure 2: Simulated Baseline Model Prediction vs Obs Data

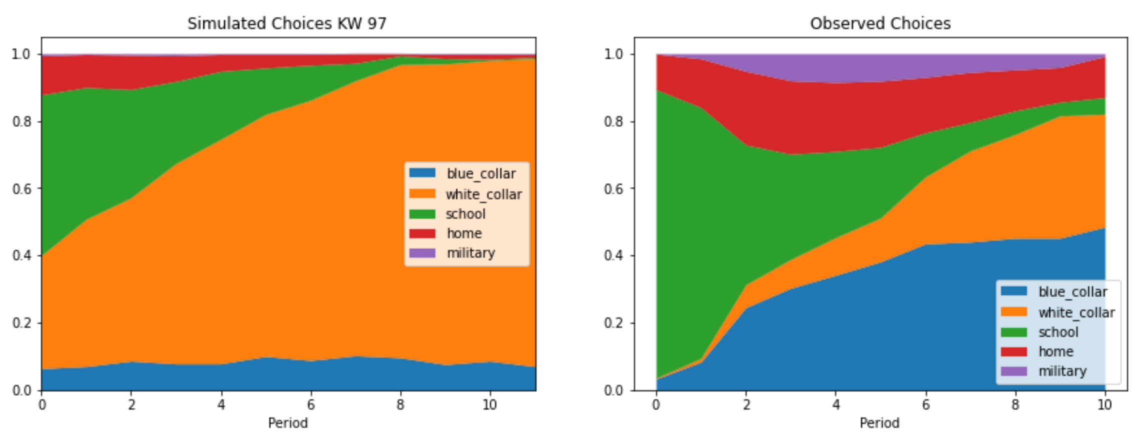

Figure 3: Simulated Baseline Model Prediction vs Obs Data

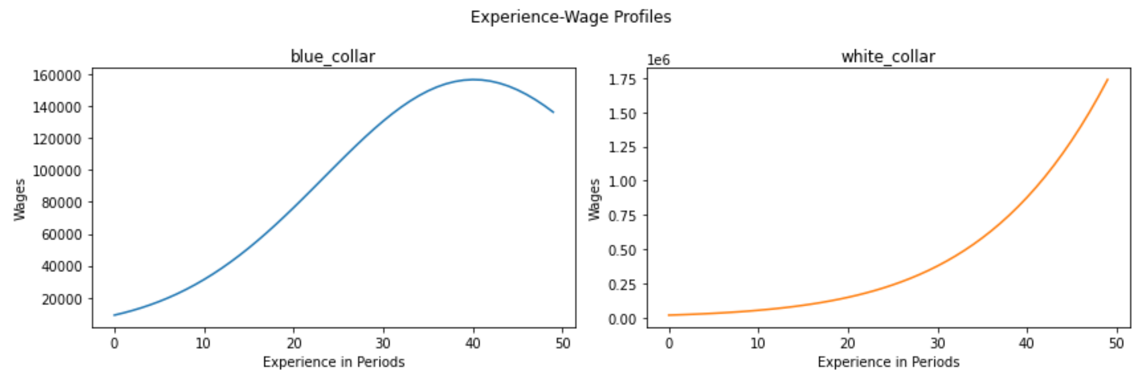

Figure 4: Experience-Wage Profile - Type 1, Years Edu 10

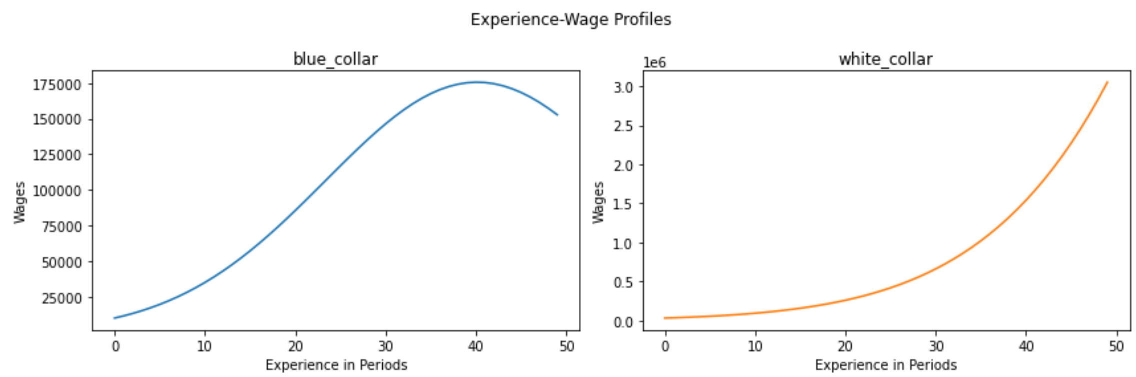

Figure 5: Experience-Wage Profile - Type 1, Years Edu 16

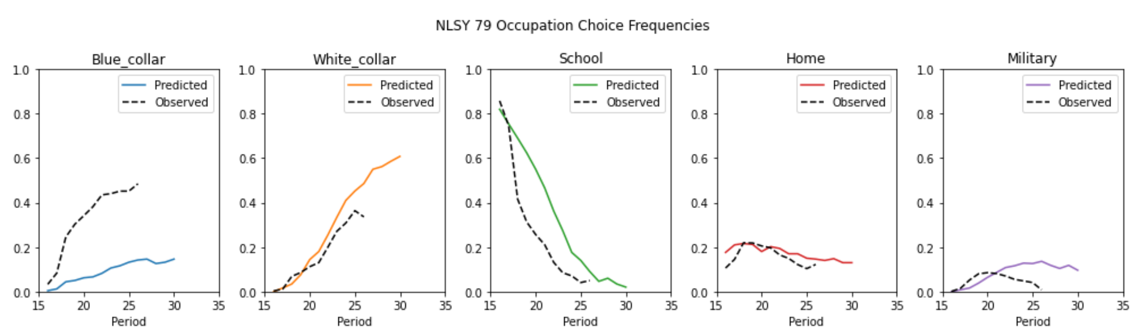

Figure 6: Simulated Updated Model Predictions vs Obs Data

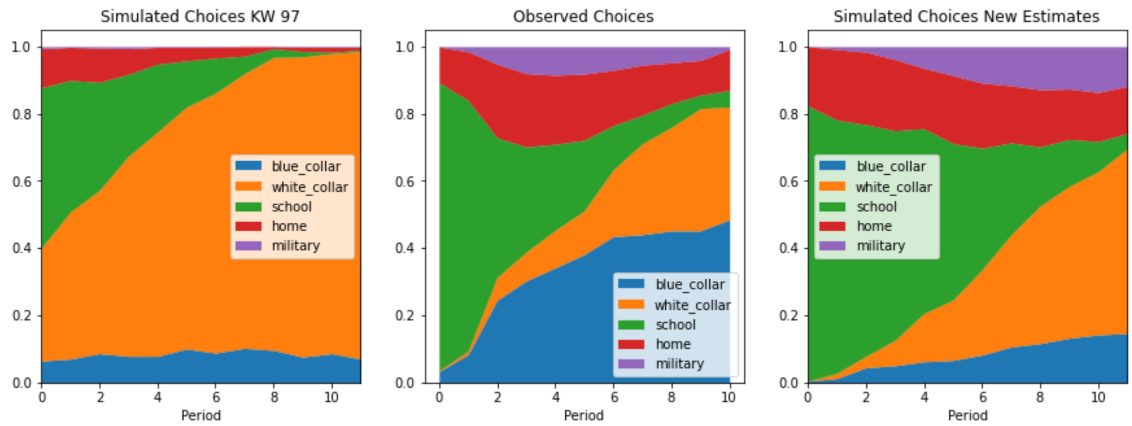

Figure 7: Simulated Updated Model Predictions vs Obs Data

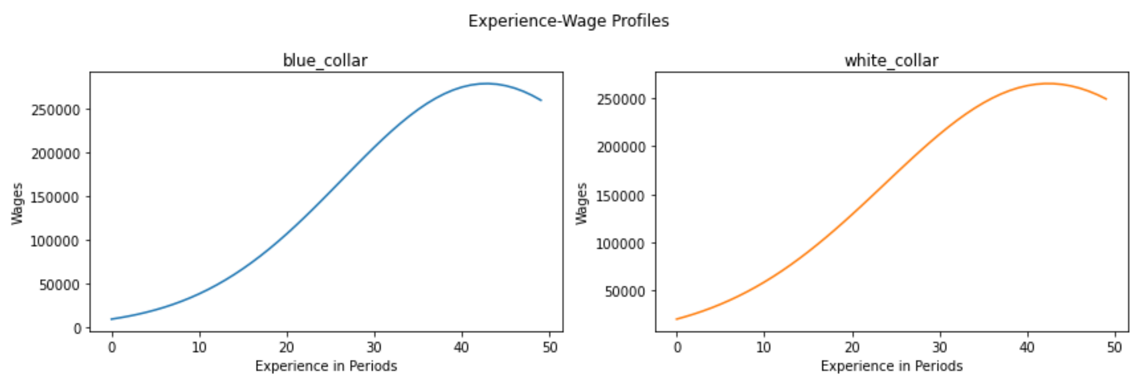

Figure 8: Experience-Wage Profile - Type 1, Years Edu 16

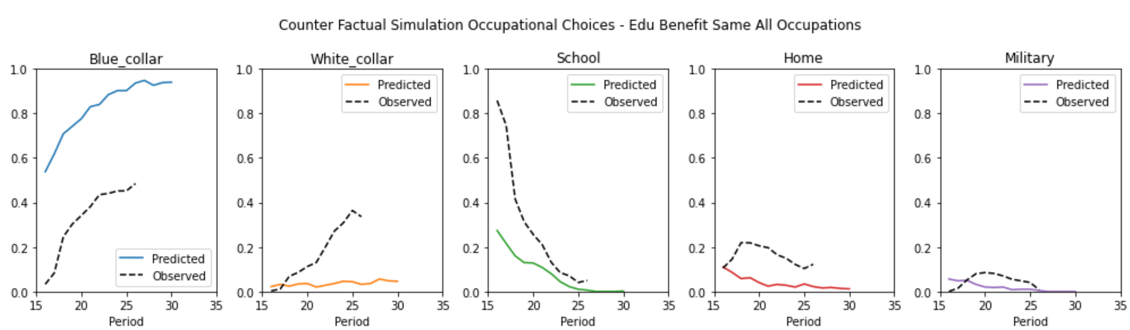

Figure 9: Counterfactual: Equalized Edu Benefits

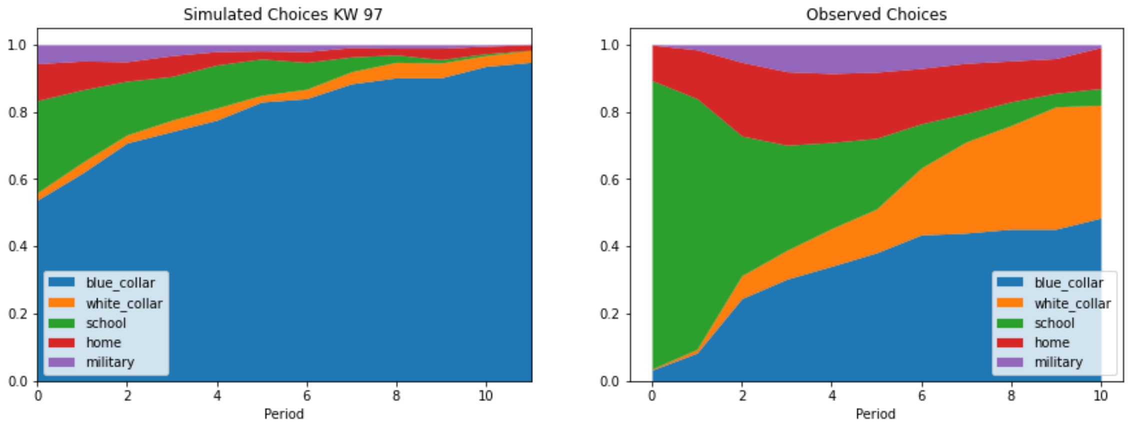

Figure 10: Counterfactual: Equalized Edu Benefits

Algorithm 1 Value function iteration – standard human capital model.

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for $t = T, \ldots, 1$ **do**
  if t == T **then**
    $v_T^{\pi^*}(s_T) = \max_{a_T \in \mathcal{A}} \left\{ u(s_T, a_T) \right\} \qquad \forall\, s_T \in \mathcal{S}_T$
  else
    Compute $v_t^{\pi^*}(s_t)$ for each $s_t \in \mathcal{S}_t$ by
      $v_t^{\pi^*}(s_t) = \max_{a_t \in \mathcal{A}} \left\{ u(s_t, a_t) + \delta\, \mathbb{E}_{p^{\pi^*}} \left[v_{t+1}^{\pi^*}(s_{t+1}) \,\middle|\, s_t \right] \right\}$
    and set
      $a_t^{\pi^*}(s_t) = \arg\max_{a_t \in \mathcal{A}} \left\{ u(s_t, a_t) + \delta\, \mathbb{E}_{p^{\pi^*}} \left[v_{t+1}^{\pi^*}(s_{t+1}) \,\middle|\, s_t \right] \right\}.$
  end if
end for

Figure 11: VFI Solution Algorithm - Source: Gabler and Raabe (2020)