Schooling Investment, Mismatch, and Wage Inequality*

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Abstract

This paper examines how policies, aimed at increasing the supply of education in the economy, affect the matching between workers and firms, and the wages of various skill groups. We build an equilibrium model where workers endogenously invest in education, while firms direct their technology toward skill intensive production activities. Search frictions induce mismatch on both extensive (unemployment) and intensive (over-education) margins, with ensuing wage consequences. We estimate the model using NLSY and O*NET data, and propose an ex-ante evaluation of prominent educational policies. We find that higher education cost subsidies boost college attainment, produce substantial welfare gains in general equilibrium, but increase wage inequality. These changes are associated with a substantial upward shift in the distribution of job complexity, which leads to worse allocations for high-school graduates who end up under-educated in less productive firms, while highly-educated workers match with more productive firms and experience less over-education during their careers.

Keywords: Human capital, education policy, wage inequality, job search, technology choice, equilibrium.

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1 Introduction

Wage inequality has increased substantially in the United States over the past 40 years.[1] Many public policy-makers and economists have expressed concerns, and in 2013 President Obama declared that "growing income inequality and a lack of upward mobility is the defining challenge of our time".[2] Policy initiatives as varied as "investing in early childhood" to a "more progressive tax code" have been proposed. However, in recent years educational policies (such as grants and financial aid programs) have gained considerable prominence among the set of measures, and several proposals have been floated including Senator Bernie Sanders plan to "make [public] college tuition free and debt free".[3] Yet, while the importance of education in improving individual labor market outcomes is well-recognized, relatively little is known about the interplay between an expansion in the supply of education and wage inequality.

The existing literature on the impact of tuition subsidies has largely focused on the enrollment effects associated with changes in aid policy admission criteria, and concludes that college take-up increases between 3 and 5 percentage points when an additional \$1,000 of grant is provided.[4] However, one limitation of the approach taken in these studies is that they neglect the possible displacement effects associated with large scale policy interventions in the education and labor markets.[5] Indeed, Heckman et al. (1998b) find that once allowing for equilibrium considerations, the impact of tuition subsidies on college enrollment is one order of magnitude smaller than previously reported estimates. A key feature of the models used to examine the equilibrium effect of educational policies, such as in Heckman et al. (1998b), Lee (2005), and Abbott et al. (2018), is that they are cast in a competitive equilibrium setting, with the impact on wages resulting from the diminishing rate of return to labor in an aggregate production. In this paper we focus on a different channel, whereby an expansion in the supply of skills in the economy may have a non-neutral effect on the distribution of jobs, leading firms to direct their production

[1] See, for example, Katz and Autor (1999) and Acemoglu (2002) and references therein.

[2] Obama, B. (2013). Retrieved from `https://obamawhitehouse.archives.gov/the-press-office/2013/12/04/remarks-president-economic-mobility`.

[3] For example, the Excelsior Scholarship Program, which provides tuition awards to eligible students attending New York State's public colleges and universities, has materialized recently.

[4] For an overview, see Deming and Dynarski (2009). Findings in this literature are based on programs such as the Georgia Hope Scholarship program, the Social Security Student Benefit program, the Washington DC Tuition Assistance Grant program, and the Swedish Knowledge Lift program (Albrecht et al., 2009).

[5] More unintended consequences, which are beyond the scope of this paper, include effects on the general level of tuition, student effort, and social interactions in college enrollment. See Heckman et al. (1998b), Blundell et al. (2004), and Acemoglu (2010), for examples of equilibrium effects in policy evaluation.

technology towards more skill-intensive activities.

We propose an empirical framework for evaluating the impact of a large scale implementation of educational policies, such as higher education tuition subsidies, when both workers and firms make pre-market investment decisions (education choices for workers, and job complexity decision by firms).[6] We consider an environment where matching is subject to search frictions and may therefore generates sub-optimality in the allocation of workers to jobs, both on the extensive margin (resulting in unemployment or a vacancy) and the intensive margin (over-education or under-staffed).[7] We use our model to predict how policy-induced shifts in the supply of education affects the assignment of workers to jobs, and the absolute and relative wages of different workers. Importantly, we let firms direct their technology choices in response to changes in education choices.[8]

The interplay between endogenous education choices and job complexity decisions allows us to study the distributional consequences of policies that affect the supply of education. We estimate the parameters of the model using data from the National Longitudinal Survey of Youth 1979 (NLSY79) and the Occupational Information Network (O*NET). Data from NLSY allows us to recover education outcomes along with wages and job transitions in the labor market, while O*NET defines the education required for each job. In our empirical application, the education decision is not a binary choice between high school graduation and college education. Indeed, we also account for the decision not to complete high school, as well as the acquisition of advanced degrees, whose role in explaining rising wage inequality, has been analyzed recently (Altonji et al., 2014 and Lindley and McIntosh, 2015).

The estimates are then used to evaluate the effects of educational policies on earnings

[6]As such, our framework relates to Acemoglu (1996), which presents a two-period theoretical framework with ex-ante worker and firm investment and bilateral search in the labor market, and shows that the rate of return to human capital is increasing in the average level of human capital in the economy. See also Acemoglu (1997).

[7]Our work is also related to the literature that argues that incentives to invest in education are generally too weak in the presence of frictions (for example, Masters, 1998 and Burdett and Smith, 2002), and the empirical search literature that incorporates human capital accumulation over life-cycle (for theoretical and empirical applications see, e.g., Yamaguchi, 2010, Burdett et al., 2011, Bagger et al., 2013, and Lise and Postel-Vinay, 2015). Most related is Albrecht and Vroman (2002), which proposes a model where firms make endogenous skill requirement decisions prior to meeting heterogenous workers, and Flinn and Mullins (2015), which introduces education choice in a standard search and matching framework, and investigates the impact of bargaining power on investment in both partial and general equilibrium.

[8]There is a substantial literature in the assignment literature on this question with given exogenous worker and firm types. See, for example, Teulings and Gautier (2004) and Teulings (2005). The main difference is that this literature does not consider the role of imperfect information on the matching between workers and jobs.

and wage inequality. In particular, we simulate the effect of the introduction of two prominent educational policies: a college cost subsidy and compulsory high school graduation. In the competitive frictionless labor market setting, an increase in the relative supply of more highly educated workers depresses the wage premium in general equilibrium and may decrease inequality. In our setting, the effect on wages hinges on the prevalence of mismatch, which depends on both the entry and job complexity decisions of firms. As a consequence, the structure of wages and unemployment are both altered.[9]

Using our estimated model, we show that while higher education (college) subsidies do not have a quantitatively important impact on high-school drop-out rates, they promote skill acquisition in higher education. Consistent with the recent empirical evidence surveyed in Deming and Dynarski (2009), where the estimated impacts are based on variation in tuition subsidies, we find that a \$1,000 subsidy generates a 2 percentage point increase in higher education graduation. We also consider alternative education cost subsidies that vary in their generosity and demonstrate that general equilibrium considerations are key to understanding how endogenous shifts in the distribution of education affects earnings. Under a large (\$10,000) education cost subsidy, the resulting 14.6% increase in college enrollment leads to a 15% increase in demand for that category of workers. These endogenous changes do not, however, alleviate the mismatch problem as individuals spend a larger portion of their working-life in mismatched states (unemployment, over-education and under-education).

The educational policies considered generate substantial welfare gains, which are almost entirely captured by individuals who complete a college degree. The welfare gains originate from a better matching between highly educated workers and more complex jobs, and a more efficient allocation between high-productivity firms and workers. Our experiments also show that wage inequality increases after the introduction of a college tuition subsidy, which is driven by the combination of two elements. First, the increasing college enrollment leads to additional wage inequality among college graduates, resulting from the selection of lower ability workers into college education, and the inflow of lower productivity firms into the set of firms that posts college-required positions. Second, individuals with a high-school degree are subject to additional mismatch, and ultimately end-up matched to less productive firms. This conclusion illustrates the importance of both within- and between-group variances in generating wage inequality. Given the take-up rate of college education under subsidies, our results suggest that the component of the

[9] This mechanism is highlighted in a simple theoretical framework by Teulings (2005).

variance that can be attributed to differences between education groups decreases. However, the within-group component of the variance increases substantially among college graduates, leading to an overall increase in wage inequality.[10] As a consequence, wage inequality is intrinsically related not only to the assignment of workers to jobs, but also to the increasing productivity heterogeneity of firms who offer high job complexity positions. Our model provides a framework to understand the specifics of these mechanisms.[11]

The remainder of the paper proceeds as follows. In Section 2, we present the theoretical model used for our quantitative analysis and discuss the equilibrium properties. In Section 3, we describe our data, identification, and estimation strategy, and present our estimation results. The impact of educational policies on earnings and inequality is then described in Section 4. Finally, Section 5 concludes.

2 Model

In this section, we describe our model economy. Risk-neutral workers and firms make irreversible technology choices (education and job complexity) and then join a decentralized labor market in the spirit of Mortensen and Pissarides (1994). Search is random. We consider the steady-state equilibrium of a continuous-time economy, where all agents discount the future at the common rate ρ.

Environment

Consider an economy populated by infinitely lived workers and firms. The measure of workers is normalized to L. Workers are ex-ante heterogeneous in their permanent innate ability $\alpha \in \mathcal{A}$, and endogenously decide to acquire human capital $h \in \mathcal{H}$ at some cost, with the support of both ability and human capital taken to be discrete and finite.[12] The

[10] This is in contrast with Acemoglu (1997), which suggests that the components within and between of the earning dispersion should move in the same direction.

[11] While our analysis does not exploit exogenous policy variation, our main findings are consistent with a number of empirical regularities. First, the counterfactual experiments that induce substantial shifts in the education choices of workers are also associated with additional wage dispersion, a finding that is reminiscent of the current period (see, for example, Goldin and Katz, 2001). Second, under college cost subsidies we find that the within-group component of wage dispersion increases substantially, an empirical regularity that aligns very well with observed patterns of wage dispersion among the younger generations of workers in the NLSY97 where college attainment is significantly higher.

[12] In principle, both ability and human capital may be continuous. We consider a discrete version here as these measures will be discrete in our empirical application, and because it will simplify our exposition regarding the respective education and technological choice problem of workers and firms.

decision to obtain education reflects the prospect that higher education levels are associated with better labor market outcomes. Throughout this paper, we do not take a stand on the origin or determinants of ability. Still, we assume that ability directly affects both human capital acquisition and labor productivity. We denote by $\ell(\alpha, h)$ the endogenous measure of type-$\langle \alpha, h \rangle$ individuals (or workers) in the population, with total population $L = \sum_{\alpha'} \sum_{h'} \ell(\alpha', h')$.

Individual agents enter the labor market as unemployed but switch endogenously to employment upon receiving and accepting job offers. Hereafter, once in the labor market, agents may be either employed, or unemployed, and these states are respectively indexed by e and u. The endogenous measure of type-$\langle \alpha, h \rangle$ unemployed workers is given by $u(\alpha, h)$, while the total stock of unemployed workers is given by $U = \sum_{\alpha'} \sum_{h'} u(\alpha', h')$.

We assume that matches occur between individuals and jobs.[13] In contrast to the majority of the job search literature, we assume that a job is a bundle of a permanent firm productivity p, and a job complexity q.[14] The productivity component p is continuously distributed on the support $[\underline{p}, \overline{p}]$ with the density function $\phi(p) > 0$, while the job complexity component q is endogenously determined prior to job creation and with the same support as human capital.

The measure of type-$\langle p, q \rangle$ jobs in the economy is given by $n(p, q)$ with the total measure of jobs $N = \sum_{q'} \int n(p', q') \, \mathrm{d}p'$. Similarly, the measure of vacant type-$\langle p, q \rangle$ jobs is given by $v(p, q)$, with $V = \sum_{q'} \int v(p', q') \, \mathrm{d}p'$ describing the aggregate stock of vacancies. Workers and jobs are brought together through a random matching process that produces an equilibrium measure of matches $\mathcal{M}(\alpha, h, q, p)$ mapping workers to jobs. The following equalities holds in equilibrium

$$L - U = N - V = \sum_{q'} \sum_{h'} \sum_{\alpha'} \int \mathcal{M}(\alpha', h', p', q') \, \mathrm{d}p'. \tag{1}$$

Equation (1) states that the number of employed workers $(L - U)$ is equal to the number

[13] A firm can therefore be considered as a collection of jobs with similar productivity. This approach is not unreasonable in the absence of matched employer-employee data, as in our empirical application.

[14] See also Lise and Postel-Vinay (2015), which develops a rich model of on-the-job search where heterogeneous workers accumulate skills in various dimensions (cognitive, manual, and interpersonal skills) and match with multi-dimensional jobs.

of filled jobs $(N - V)$ and the total number of matches.[15]

Preferences and Technology

Agents have linear preferences over income and discount the future at rate ρ. The flow utility of an agent consists of the wage w if he is employed, or $f_u(\alpha, h)$ if unemployed. The latter function should be thought of as capturing unemployment benefits, together with home production activities and the value of leisure. In our empirical application, home production is specified as a multiplicative factor of the scalar parameter b and the ability-specific efficiency units of time, $g(\alpha)$.

The flow output of a type-$\langle \alpha, h \rangle$ worker when matched with a type-$\langle p, q \rangle$ firm is described by the production technology $f(\alpha, h, p, q)$. Workers may potentially be matched with jobs of any complexity level. When the human capital level of the worker exceeds the job complexity, that is $h > q$, we describe a worker as being *over-educated*, and similarly when $h < q$ the worker is *under-educated*. For lack of a better term, when $h = q$ we describe the worker as being *even-educated*.

In our empirical application we parametrize the production function to capture the productivity consequences of mismatch. We assume that the worker's education and the job complexity combine to form a composite labor input according to the following three-way CES function

$$\widetilde{h} = \left(\zeta_1 \cdot h^{\zeta_0} + \zeta_2 \cdot q^{\zeta_0} + [1 - \zeta_1 - \zeta_2] \cdot \min\{h, q\}^{\zeta_0} \right)^{\frac{1}{\zeta_0}}, \tag{2}$$

with $\zeta_1, \zeta_2 > 0$ and $\zeta_1 + \zeta_2 < 1$. Note that specification in Equation (2) implies an absolute advantage for more highly educated workers, and more complex positions. We additionally embed the notion of mismatch in our specification by assuming that the minimum between education and skill also enters as a third element in this CES formulation. As a consequence, for any given worker education level, the composite input is maximized

[15] Further identities hold

$$\ell(\alpha, h) = \sum_{q'} \int \mathcal{M}(\alpha, h, p', q')\, \mathrm{d}p' + u(\alpha, h),$$
$$n(p, q) = \sum_{\alpha'} \sum_{h'} \mathcal{M}(\alpha', h', p, q) + v(p, q),$$

which respectively define the relationship between i) workers, matches, and unemployment; and ii) jobs, matches, and vacancies.

when the worker is even-educated within a match.

Finally, we specify that the production technology depends on firm productivity p, our composite labor input $\widetilde{h}$, and worker ability α. This is given by

$$f(\alpha, \widetilde{h}, p, q) = g(\alpha) \times [a_1 + a_2 p + a_3 \widetilde{h} + a_4 \widetilde{h} p - \kappa \max\{q - h, 0\}^{a_5}], \tag{3}$$

where the function $g(\alpha)$ is an unrestricted function of worker ability, and where a_1, a_2 and a_3 are loading parameters. Note that the production function also includes an interaction term a_4 that captures potential complementary or substitution between the composite labor input and firm productivity. Finally, we assume that under-education lowers production by κ units multiplied by a function of the under-education gap, $q - h$.

Search and Matching

Heterogeneous workers and firms are brought together in a time-consuming random matching process. We defer to the next section the implications of random matching. In an effort to generate the matching patterns observed in the data, we define the aggregate market tightness as

$$\theta = \frac{V}{U + \xi(L - U)}, \tag{4}$$

where $\xi > 0$ is the relative efficiency of job search for employed workers. Let $M(U + \xi(L - U), V)$ denote a standard matching function that is increasing in both its arguments, and linearly homogeneous. Letting $m(\theta) \equiv M/V = M([U + \xi(L - U)]/V, 1)$, we define $\lambda_u = \theta m(\theta)$ as the instantaneous probability that an unemployed agent meets a vacancy, and symmetrically define $\gamma_u = m(\theta)$ as the rate that a vacancy is filled by an unemployed worker. Similarly, an employed individual meets a vacancy at rate $\lambda_e = \xi \theta m(\theta)$ and a vacancy is filled by an employed individual at rate $\gamma_e = \xi m(\theta)$. As a consequence, there is a simple correspondence between on-the-job and off-the-job meeting probabilities such that $\lambda_e = \xi \lambda_u$ and $\gamma_e = \xi \gamma_u$.

In our empirical application, we assume that the aggregate matching function technology is constant returns to scale Cobb-Douglas with an elasticity with respect to unemployment of 0.5. The function $m(\theta) \equiv M/V$ is therefore given by an inverse square function (see, e.g., Petrongolo and Pissarides, 2001).

Finally, we assume that matches are destroyed at the exogenous rate δ, which is independent of both worker and firm characteristics. The presence of frictions in the matching between workers and jobs implies that individuals may be mismatched on the extensive margin (unemployment), or on the intensive margin (over-education and under-education). Note that the model structure and parametrization do not rule-out any of these states by assumption.

Rent Sharing and Wages

This section describes how wages, which result from bargaining between a worker and a firm, are determined. The outcome of this bargaining process depends upon both worker and firm value functions. On the worker side, we let $\mathcal{V}_u(\alpha, h)$ denote the present value of an unemployed type-$\langle \alpha, h \rangle$ worker, and similarly define $\mathcal{V}_e(w, \alpha, h, p, q)$ to be the value of an employed type-$\langle \alpha, h \rangle$ worker in a type-$\langle p, q \rangle$ firm with wage w. Note that the employed value function depends upon both the current wage and the firm characteristics. As we describe below, the latter is important as it reflects the ability of the firm to respond should a worker receive a competing job offer. On the firm side, we similarly let $\mathcal{J}_v(p, q)$ denote the present value of a job vacancy for a type-$\langle p, q \rangle$ firm, while $\mathcal{J}_f(w, \alpha, h, p, q)$ is the present value to such a firm when matched with a type-$\langle \alpha, h \rangle$ worker at wage w.[16] Following Shimer and Smith (2000), we define the surplus of a type-$\langle \alpha, h, p, q \rangle$ match as

$$\mathcal{S}(\alpha, h, p, q) \equiv \mathcal{V}_e(w, \alpha, h, p, q) - \mathcal{V}_u(\alpha, h) + \mathcal{J}_f(w, \alpha, h, p, q) - \mathcal{J}_v(p, q).$$

Under linear preferences over wages, this surplus is independent of the current wage w. The surplus function is essential for describing the rent sharing between workers and firms. Any type-$\langle \alpha, h, p, q \rangle$ match yielding a positive surplus, i.e. $\mathcal{S}(\alpha, h, p, q) \geq 0$, is feasible.

When an unemployed type-$\langle \alpha, h \rangle$ worker meets a type-$\langle p, q \rangle$ firm they bargain over the wage, with $w = w_u(\alpha, h, p, q)$ denoting the outcome of this bargaining process. We adopt the perfect equilibrium bargaining framework of Rubinstein (1982) and therefore assume that wages are set according to the following rent sharing process

$$\mathcal{V}_e(w_u, \alpha, h, p, q) - \mathcal{V}_u(\alpha, h) = \beta_u^h \mathcal{S}(\alpha, h, p, q), \tag{5}$$

[16]These firm value functions are defined excluding any persistent and additive preference term that is associated with the job complexity decision of firms, and which is assumed common to both filled and vacant jobs. As we describe later, these terms will be important in generating dispersion in the behavior of firms. Given these terms are additive and common, the *difference* in the firm value functions $\mathcal{J}_f(w, \alpha, h, p, q) - \mathcal{J}_v(p, q)$ is independent of the value of this preference term. See Section 2.1 for details.

which states that workers who accept a job from non-employment receive fraction β_u^h of the match surplus.[17] Note that we allow the bargaining power parameter to be education h specific. This assumption allows education to impact not just workers' productivity, but also their position in the bargaining process.

Now consider a type-$\langle \alpha, h \rangle$ worker matched to a type-$\langle p, q \rangle$ firm, who is contacted by a type-$\langle p', q' \rangle$ challenger firm. As in Dey and Flinn (2005) and Cahuc et al. (2006), amongst others, we allow the incumbent firm to respond to outside offers from the challenger firm, which consequently makes the rent sharing process more complex. Firstly, we note that mobility is efficient as the worker moves to the challenger firm if and only if there is a greater surplus associated with the new match, i.e. whenever $\mathcal{S}(\alpha, h, p', q') > \mathcal{S}(\alpha, h, p, q)$. In this case the bargained wage $w = w_c(\alpha, h, p, q, p', q')$ is set such that the worker appropriates the surplus associated with being matched with the incumbent firm, together with fraction β_e^h of the incremental surplus generated by the challenger firm. That is

$$\mathcal{V}_e(w_c, \alpha, h, p', q') - \mathcal{V}_u(\alpha, h) = (1 - \beta_e^h)\mathcal{S}(\alpha, h, p, q) + \beta_e^h \mathcal{S}(\alpha, h, p', q'). \tag{6}$$

Note that the worker bargaining power from a position of employment β_e^h is again education specific, and also potentially different from when bargaining as a non-employed worker β_u^h. The reason for this asymmetry in bargaining parameters for employed and unemployed workers will become clear in our identification discussion in Section 3.3. In addition, it should be clear that the firm can not adjust the skill requirement associated with a position to retain a worker.

Conversely, when $\mathcal{S}(\alpha, h, p', q') \leq \mathcal{S}(\alpha, h, p, q)$ there is no mobility and the worker remains at the incumbent firm. To understand what happens to wages in this case note that the current worker surplus at wage w is $\mathcal{V}_e(w, \alpha, h, p, q) - \mathcal{V}_u(\alpha, h)$. Thus, if $\mathcal{S}(\alpha, h, p', q') \leq \mathcal{V}_e(w, \alpha, h, p, q) - \mathcal{V}_u(\alpha, h)$ the worker remains at his current firm with no change in wage, as the challenger firm can not offer greater surplus than he is currently receiving. In contrast, if $\mathcal{V}_e(w, \alpha, h, p, q) - \mathcal{V}_u(\alpha, h) < \mathcal{S}(\alpha, h, p', q') \leq \mathcal{S}(\alpha, h, p, q)$ then the worker's wage is renegotiated to a new wage $w' = w_i(\alpha, h, p, q, p', q')$ which is such that the worker receives the entire surplus from the challenger firm, together with a share of the incremental surplus as described above. That is

$$\mathcal{V}_e(w_i, \alpha, h, p, q) - \mathcal{V}_u(\alpha, h) = (1 - \beta_e^h)\mathcal{S}(\alpha, h, p', q') + \beta_e^h \mathcal{S}(\alpha, h, p, q). \tag{7}$$

[17] We may symmetrically define firm values. The value of a type-$\langle p, q \rangle$ firm matched with a type-$\langle \alpha, h \rangle$ worker is given by $\mathcal{J}_f(w_u, \alpha, h, p, q) - \mathcal{J}_v(p, q) = (1 - \beta_u^h)\mathcal{S}(\alpha, h, p, q)$.

We are now in a position to provide a recursive formulation of the agent's choice problem.

Recursive formulation

Given the matching technology, the surplus function, and the rent sharing rules, we now derive the asset values, $\mathcal{V}_u(\alpha, h)$ and $\mathcal{V}_e(w, \alpha, h, p, q)$, that drive the decisions of agents. First consider unemployed workers. The flow utility to a type-$\langle \alpha, h \rangle$ unemployed worker is given by $f_u(\alpha, h)$. In equilibrium an unemployed worker will accept any job provided that the match yields positive surplus. The set of acceptable type-$\langle p, q \rangle$ jobs to such an unemployed worker is denoted $\mathcal{R}_u(\alpha, h)$, and it is defined as

$$\mathcal{R}_u(\alpha, h) : \{p', q' : \mathcal{S}(\alpha, h, p', q') > 0\}.$$

When leaving unemployment, individuals may accept a position where they are over-educated. The prevalence of over-education ultimately depends on the properties of the production function, the relative efficiency of on-the-job search, and the joint distribution of firm productivity and skill requirement. When offers from high productivity firms are scarce, over-education may allow workers to climb the wage ladder quickly, by using high skill requirement offers in low productivity firms until a higher surplus match comes along. As a consequence, our model can generate diverse wage profiles over the life-cycle. The value function of a type-$\langle \alpha, h \rangle$ unemployed individual is recursively defined by

$$\rho \mathcal{V}_u(\alpha, h) = f_u(\alpha, h) + \lambda_u \mathop{\sum\!\!\!\!\!\!\int}_{\mathcal{R}_u(\alpha, h)} \beta_u^h \mathcal{S}(\alpha, h, p', q') v(p', q') \, \mathrm{d}p', \tag{8}$$

where for conciseness we adopt the integral-sum notation $\sum\!\!\!\!\!\!\int_{\mathcal{R}} \mathrm{d}p'$ to denote that we are integrating over the discrete q' and continuous p' over the set defined by $(p', q') \in \mathcal{R}$. The interpretation of Equation (8) is standard. The first term $f_u(\alpha, h)$ captures the opportunity cost of unemployment, while the integral-sum term captures the option value of employment. The optimal strategy of an unemployed worker therefore consists of accepting any contract that compensates the sum of its instantaneous payoff and the option value of unemployment.

We can now turn to the value of employed workers, but before doing so, it is important to understand that wage renegotiation creates a path dependency between wages over the life-cycle. To see this, consider the value to a type-$\langle \alpha, h \rangle$ worker when matched to a type-$\langle p, q\rangle$ firm. The flow benefit is given by the wage w. Workers will accept a job at a challenger firm if and only if the new match generates a higher surplus than the current match. The set of jobs such that a worker changes employer is therefore defined as

$$\mathcal{R}_e^c(\alpha, h, p, q) : \{p', q' : \mathcal{S}(\alpha, h, p', q') > \mathcal{S}(\alpha, h, p, q)\}, \tag{9}$$

and with the value associated with such a job acceptance given by Equation (6). Conversely, the match will continue when the surplus of the current match is higher. Wages are renegotiated upwards if the current *worker* surplus, which depends on the current wage, is lower than the match surplus at the challenger firm. We denote as $\mathcal{R}_e^i(\cdot)$ the set of jobs such that the worker remains with the incumbent firm, but experiences a pay increase

$$\mathcal{R}_e^i(w, \alpha, h, p, q) : \{p', q' : \mathcal{S}(\alpha, h, p, q) > \mathcal{S}(\alpha, h, p', q') > \mathcal{V}_e(\alpha, h, w, p, q) - \mathcal{V}_u(\alpha, h)\},$$

and where the value to the worker of such a wage increase at the incumbent firm is as given by Equation (7). It then follows that the value of employment $\mathcal{V}_e(w, \alpha, h, p, q)$ is such that

$$\begin{aligned}
\rho\mathcal{V}_e(w, \alpha, h, p, q) = {} & w + \delta\left[\mathcal{V}_u(\alpha, h) - \mathcal{V}_e(w, \alpha, h, p, q)\right] \\
& + \lambda_e \sum\!\!\!\!\!\!\int_{\mathcal{R}_e^c(\alpha,h,p,q)} \left[(1-\beta_e^h)\mathcal{S}(\alpha, h, p, q) + \beta_e^h \mathcal{S}(\alpha, h, p', q')\right] v(p', q')\,\mathrm{d}p' \\
& + \lambda_e \sum\!\!\!\!\!\!\int_{\mathcal{R}_e^i(w,\alpha,h,p,q)} \left[(1-\beta_e^h)\mathcal{S}(\alpha, h, p', q') + \beta_e^h \mathcal{S}(\alpha, h, p, q)\right] v(p', q')\,\mathrm{d}p' \\
& - \lambda_e \sum\!\!\!\!\!\!\int_{\mathcal{R}_e^c(\alpha,h,p,q)\wedge\mathcal{R}_e^i(w,\alpha,h,p,q)} \left[\mathcal{V}_e(w, \alpha, h, p, q) - \mathcal{V}_u(\alpha, h)\right] v(p', q')\,\mathrm{d}p'.
\end{aligned} \tag{10}$$

The interpretation of Equation (10) is straightforward: the difference between the value of employment and wages must be compensated by the expected gains or losses resulting from job destruction, or on-the-job search opportunities.[18] Finally, we defer our exposition of firms' value functions until describing the determination of the skill requirement.

[18]Note that we do not allow workers to use unemployment at their outside option when bargaining with another firm. This is a restriction on behavior, given that the bargaining power of workers differs by employment status.

Education choice

Prior to market entry, an individual with permanent innate ability $\alpha \in \mathcal{A}$ acquires human capital $h \in \mathcal{H}$ upon paying the cost $c_w(\alpha, h) - \epsilon_{w_h}$. In our formulation, the cost function may capture both the pecuniary (monetary) and any non-pecuniary (psychic) costs to education. We do not attempt to separate these two components. Education costs depend on ability α, education h and a stochastic component ϵ_{w_h}, which varies with h and may capture parental income/wealth or non-ability education skills. This stochastic component is assumed to follow the Type-I extreme value distribution, with a zero location parameter and the scale parameter $\sigma_w > 0$. Additionally, we parametrize $c_w(\alpha, h) = \widetilde{c}_w(h)\Lambda(\alpha)$. The optimal education choice of agents can therefore be formulated as

$$\mathcal{V}(\alpha, \boldsymbol{\epsilon}_w) = \max_{h \in \mathcal{H}} \{-c_w(\alpha, h) + \epsilon_{w_h} + \rho \mathcal{V}_u(\alpha, h)\}. \tag{11}$$

Agents choose an education level to maximize their lifetime utility. In equilibrium, agents optimally choose an education level such that the marginal cost of education covers the discounted marginal expected gain attainable through search. Firstly note that whenever $\beta_u = 0$ (as considered in Postel-Vinay and Robin, 2002, and Lise and Postel-Vinay, 2015, amongst others) the education decision is driven solely by the impact that education has upon the value of home time through $f_u(\alpha, h)$. In the more general case that we consider here, a key driver of the incentives to invest in education is the value of search $\int_{\mathcal{R}_u(\alpha,h)} \beta_u^h \mathcal{S}(\alpha, h, p', q') v(p', q') \, \mathrm{d}p'$ weighted by the probability of receiving a job offer λ_u. Simple comparative statics show that the worker bargaining power directly increases the incentives to obtain education. Additionally, we can see that when $\Delta_h[\mathcal{S}](\alpha, h, p', q') > 0$, the value of education increases. The gains to education therefore accrue due to both a larger acceptance set $\mathcal{R}_u(\cdot)$, and a larger surplus when matched.[19]

Skill requirement Decision

We describe the firm entry conditions, which determine job complexity as a technology choice. We assume that in addition to productivity p, firms are endowed with a technology or skill preference parameter vector $\boldsymbol{\varepsilon}_f$. This feature breaks a potential one-to-one

[19] In the context of a search and matching model without on-the-job search, Flinn and Mullins (2015) relate the education decision of workers' to their bargaining parameter. In the partial equilibrium, where contact rates are fixed, an increase in the workers' bargaining power increases schooling. They also show that this result does not hold in the general equilibrium version of their model, where large increases in bargaining power reduce investment through the impact on vacancy creation.

mapping between productivity p and the skill requirement q. For reasons that will become clear, we assume that this preference parameter enters the flow pay-off from a vacancy additively. Moreover, the same technological preference parameter ε_{f_q} enters the pay-off for filled vacancies. As in the workers' education choice problem, we assume that these skill preference parameters are Type-I extreme value distribution (with a zero location parameter and the scale parameter σ_f). Given both the bargaining scheme, and the meeting rates, the value of creating a complexity q job for a productivity p firm with skill preference ε_{f_q} is given by

$$\rho \mathcal{J}_v(p,q) + \varepsilon_{f_q} = -c_f(q) + \varepsilon_{f_q} + \gamma_u \sum_{\alpha'} \sum_{h'} (1-\beta_u^{h'})[\mathcal{S}(\alpha',h',p,q)]^+ u(\alpha',h')$$
$$+ \gamma_e \sum_{\alpha'} \sum_{h'} \sum_{q'} \int (1-\beta_e^{h'}) \left[\mathcal{S}(\alpha',h',p,q) - \mathcal{S}(\alpha',h',p',q')\right]^+ \mathcal{M}(\alpha',h',p',q')\,\mathrm{d}p', \quad (12)$$

where $c_f(q)$ is the flow cost of maintaining a vacancy, and which does not depend upon p. The technology decision of the firm therefore solves

$$q(p,\boldsymbol{\varepsilon}_f) = \underset{q' \in \mathcal{H}}{\arg\max} \left[\rho \mathcal{J}_v(p,q') + \varepsilon_{f_{q'}}\right], \quad (13)$$

such that the fraction of firms that make a given technological choice (conditional on p and prior to the realization of $\boldsymbol{\varepsilon}_f$) takes the usual conditional Logit form. The firm skill requirement choice entails a trade-off between static and dynamic components of the value of production. On the static side, the firm maximizes production, while minimizing the cost of posting vacancies. On the dynamic side, the job minimizes the likelihood of getting poached with the understanding that higher q decreases the probability of being poached but increases the frequency of wage increases through external bargaining, while lower q has exactly the opposite effect. These different motives lead to heterogeneity in the distribution of skill requirements.

2.1 Equilibrium

This section derives the equilibrium properties of the model. Individuals optimally choose an education level while the number of jobs, as well as the distribution of skill requirements, are determined by zero profit conditions. Unemployment and the distribution of matches are determined by the steady state flow conditions.

Free-entry condition

Firms make their one-time entry decision prior to the realization of $\boldsymbol{\varepsilon}_f$, so the free-entry condition may be stated as

$$\rho\widetilde{\mathcal{J}}_v(\underline{p}) = \mathbb{E}[\rho\mathcal{J}_v(\underline{p}, q(\underline{p}, \boldsymbol{\varepsilon}_f)) + \varepsilon_{f_q})] = \sigma_f \log\left[\sum_{q'} \exp(\rho\mathcal{J}_v(\underline{p}, q')/\sigma_f)\right] = 0, \tag{14}$$

where the expectation is taken over the realization of the vector $\boldsymbol{\varepsilon}_f$, and with the resulting expression taking the usual log-sum form (McFadden, 1978). Equation (14) states that the least productive firm $\underline{p}$ will make zero expected profits, given that it will make the technology choice q optimally once $\boldsymbol{\varepsilon}_f$ is realized.

Unemployment

In steady-state, the unemployed population is constant such that the inflow into unemployment of type-$\langle\alpha, h\rangle$ workers, which consists of exogenous match destructions, exactly balances the outflow from the unemployment pool of such workers. The equilibrium unemployment rate for type-$\langle\alpha, h\rangle$ agents is therefore given by

$$u(\alpha, h) = \delta \sum_{q'} \int \mathcal{M}(\alpha, h, p', q')\,\mathrm{d}p' \times \left[\lambda_u \mathop{\sum\!\!\!\!\!\!\int}_{\mathcal{R}_u(\alpha,h)} v(p', q')\,\mathrm{d}p'\right]^{-1}. \tag{15}$$

Match distribution

Here we characterize the measure of type-$\langle\alpha, h, p, q\rangle$ matches. In steady-state for any match such that $\mathcal{S}(\alpha, h, p, q) \geq 0$ we require that

$$v(p, q) \times \left[\lambda_u u(\alpha, h) + \lambda_e \mathop{\sum\!\!\!\!\!\!\int}_{\{p', q'\}\setminus\mathcal{R}_e^c(\alpha,h,p,q)} \mathcal{M}(\alpha, h, p', q')\,\mathrm{d}p'\right] = \mathcal{M}(\alpha, h, p, q) \times \left[\delta + \lambda_e \mathop{\sum\!\!\!\!\!\!\int}_{\mathcal{R}_e^c(\alpha,h,p,q)} v(p', q')\,\mathrm{d}p'\right], \tag{16}$$

and where we recall that $\mathcal{R}_e^c(\alpha, h, p, q)$ is defined as the set of jobs that are associated with greater surplus for type-$\langle\alpha, h\rangle$ workers (see Equation (9)). The left-hand side of this equation states that inflows into an $\mathcal{M}(\alpha, h, p, q)$ match may occur from the non-employment pool, or from lower surplus matches. Outflows from this position, which are given on the right-hand side of this equation, may result from either an exogenous match destruction at rate δ, or from an individual accepting a job at a higher surplus firm. Finally, we note that matches will not be formed for all $\langle \alpha, h, p, q \rangle$ such that $\mathcal{S}(\alpha, h, p, q) < 0$, and so we necessarily have $\mathcal{M}(\alpha, h, p, q) = 0$ in these cases. We proceed to define the stationary equilibrium of our model economy.

Definition 1 (Equilibrium)**.** *A stationary equilibrium for this economy is a collection of value functions, $\mathcal{V}_u(\cdot)$, $\mathcal{V}_e(\cdot)$, $\mathcal{J}_v(\cdot)$, and $\mathcal{J}_f(\cdot)$, such that:*

1. *Individuals make optimal education choices given their ability.*
2. *The last firm entrant makes zero expected profits and the job skill requirements are optimally chosen.*
3. *The unemployment rate is stationary.*
4. *The joint distribution of matches is stationary.*

In our model economy, workers select into different education levels on the basis of their private costs and returns to schooling. Only workers with a sufficiently high return or low cost, will attain higher education levels. There are a number of reasons why the education choices of workers, and similarly the skill requirement decision of firms, will be inefficient.[20] Given the complexity of our environment, we do not attempt to analytically characterize the efficiency of the allocation. Nonetheless, we do know that there are several sources of inefficiencies. First, as in Acemoglu (1996) the worker/firm rent sharing results in a hold-up problem. This emerges in markets with frictions due to the inability of agents to write ex-ante (prior to matching) contracts. Second, the education decision of workers is made to improve both their employment prospects (through the enlargement of the acceptance set), and also their position in the wage negotiation process. As the latter effect reflects a private and not social gain, workers may over-invest in their education (Charlot and Decreuse, 2005). Third, and in a mechanism highlighted by Charlot and Decreuse (2010), the presence of heterogeneity in worker ability also generates an externality. As the average ability level within education increases, there is an increase

[20] Under the efficient benchmark economy, the planner, through choice of both education and skill requirement, maximizes the total output in the economy net of the education cost for workers and the job vacancy/complexity costs for firms. This maximization is subject to the search frictions in economy, as reflected in the steady state flow equations. Note that there are inefficiencies that are directly related to the existence of search frictions and which do not result in a frictionless (Walrasian) economy. These include the loss of production due to unemployment, the cost of maintaining vacancies, and the cost of sub-optimal worker/job assignment.

in the intensity of job creation for the associated skill requirement. Thus, the return to a given education level depends upon the schooling-specific ability composition.[21]

3 Estimation

This section presents our data and then lays out an estimation strategy. In the first part, we provide a description of the data. We keep this presentation succinct as several other papers in the literature have used similar data.[22] Second, we propose an estimation strategy based on the method of simulated moments. Finally, we discuss the assumptions required for identifying the parameters of the model.

3.1 Data

This paper uses two data sets, which characterize the layers of heterogeneity between workers and jobs. On the worker side, we use data from the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79), which allows us to derive precise information about individual ability (as measured by an AFQT score) along with education and a longitudinal characterization of individual labor market status. Our initial sample consists of working-age male individuals. The education of an agent is the highest education recorded in the sample, and we only consider labor market transitions that occur once the highest education has been achieved. We discard observations when an individual is recorded as being unemployed for more than 36 months, as we view such individuals as losing their labor market attachment. For both data and computational reasons, we consider discrete levels of educational attainment. We use four (4) levels of education which correspond to "Less than a High School Diploma", "High School Diploma", "Bachelor's Degree" and "Advanced Degree".[23] Similarly, ability is measured using the AFQT score. For simplicity,

[21]The results about inefficiency do not necessarily carry over when search is not random. For example, Acemoglu and Shimer (1999) shows that when firms post wages and workers are allowed to direct their search, efficiency could be restored. These findings raise a question about whether a model with random search, that essentially has mismatch as a built-in feature, is compelling to study wage inequality. First, we should note that modern theories of directed search with heterogeneous agents produce misallocation as individuals tend to focus on high paying jobs, thereby creating long queues for those positions. Second, such mismatch does not necessarily imply additional wage inequality. The intuition for this is that mismatch essentially acts as an equalization force, which prevents perfect assortative matching between workers and firms, and therefore restricts the extent of wage inequality.

[22]See, for example, Sanders (2012) and Lise and Postel-Vinay (2015).

[23]For this purpose, individuals who report completing some college, but less than a Bachelor's degree, are categorized together with "High School Diploma".

we discretize this variable into 3 categories: low, medium and high ability.[24] Importantly, using weekly arrays, we can construct a detailed history of individual transitions in the labor market as well as the corresponding wage dynamics. Although the NLSY79 data now provides more than 30 years of observations, there is considerable attrition. As Lise and Postel-Vinay (2015) note, while the attrition in the NLSY79 is initially gradual, it does become much more severe as the survey progresses. As we start following individuals from the point their education is completed, this attrition is associated with a compositional shift in our initial sample. In order to mitigate the impact of this, we restrict our observation window to no more than 16 years of labor market transitions. Associated wages are deflated both by regional prices indices and aggregate wage growth.

Data on the skill requirements over jobs comes from O*NET. The O*NET database provides a detailed occupation-level data set covering over 900 occupations, and includes categories such as skills, abilities, and work styles, of which we use the education and training modules. Occupation codes in the NLSY79 are based on three generations of Census codes, whereas O*NET uses 2009 SOC Codes. We follow the literature and use crosswalks to match across the different nomenclatures.[25] Since the O*NET dataset is a survey of jobs, it does not provide a level of skill requirement for each occupation, but rather a distribution of skill requirements. Theoretically, it is possible to observe such a distribution at the occupation level because of substitution between education and experience, or potential sectoral heterogeneity in skill requirements across tasks. As pointed out by Leuven and Oosterbeek (2011), there are various ways to determine the skill requirement of a job, but no approach is immune to classification errors and a-priori assumptions. After extensive testing, we use the *mode* of the required education to capture the skill requirement within each occupation.

Table 1 presents summary statistics on mismatch and how wages vary with mismatch status over the life-cycle. The table indicates that there is considerable mismatch at all stages of workers' careers. First, on the intensive margin there exists significant over-education especially for workers with college and advanced degrees. While present, under-education is much less prevalent (with the exception of high-school drop-outs). Second, the degree of mismatch typically declines over the life-cycle. The incidence of non-employment (extensive margin mismatch) is lower in later career, while individuals are less likely to be over-educated (measured relative to size of employed population). Third,

[24]Low ability corresponds to $0 \leq AFQT < 33.3$, medium ability corresponds to $33.3 \leq AFQT < 66.7$, and high ability corresponds to $66.7 \leq AFQT \leq 100$.

[25]We thank Carl Sanders for providing us with this crosswalk.

Table 1: Mismatch

	Drop-Out	High School	College	Advanced
(a). Mismatch states, early career				
Over-educated	–	0.14	0.54	0.67
Even-educated	0.12	0.59	0.25	0.14
Under-educated	0.47	0.03	0.03	–
Non-employed	0.40	0.23	0.18	0.18
(b). Mismatch wages, early career				
Over-educated	–	13.06	18.32	22.40
Even-educated	11.58	15.52	21.88	22.76
Under-educated	13.53	16.47	18.79	–
(c). Mismatch states, later career				
Over-educated	–	0.19	0.54	0.72
Even-educated	0.16	0.63	0.36	0.22
Under-educated	0.65	0.08	0.04	–
Non-employed	0.17	0.09	0.06	0.04
(d). Mismatch wages, later career				
Over-educated	–	23.13	34.76	38.62
Even-educated	14.73	20.79	37.08	39.98
Under-educated	15.79	25.85	33.26	–

Notes: The table shows the prevalence of mismatch, and the wages associated with different mismatch states, at different stages of an individuals career. “Early” career is measured to 2 years after graduation, while “later” career captures the last two years of our panel sample (14–16 years after graduation).

we see that there is growth in wages over the career, with the well-documented tendency for wage profiles to be much flatter for individuals with lower education levels. Further, wages vary by the degree of mismatch, with wages typically highest when workers are even-educated.

3.2 Estimation

We estimate our model by the method of simulated moments (MSM). The goal is to choose a set of parameters to minimize the weighted distance between relevant moments from the data and the model. Letting $\mathbf{\Theta}$ denote the parameter vector, our estimation problem may be formally described as

$$\widehat{\mathbf{\Theta}} = \arg\min_{\mathbf{\Theta}} \left[\mathbf{m_{sim}}(\mathbf{\Theta}) - \mathbf{m_{data}}\right]^{\intercal} \mathbf{W} \left[\mathbf{m_{sim}}(\mathbf{\Theta}) - \mathbf{m_{data}}\right],$$

where $\mathbf{m_{data}}$ represents the vector of moments computed on the observed data, $\mathbf{m_{sim}}(\mathbf{\Theta})$ is the model moment vector given $\mathbf{\Theta}$, and $\mathbf{W}$ is a positive definite weighting matrix.[26]

In practice we calculate $\mathbf{m_{sim}}(\mathbf{\Theta})$ by first solving for the model equilibrium given the parameter vector $\mathbf{\Theta}$ and then simulating life-cycle histories for a large number of artificial individuals. We then find the parameter values that provide the best match the simulated and observed profiles given our weighting scheme. The moments that we use to identify our model are described in the following section.

3.3 Identification

The identification problem consists of recovering the unique mapping between our moments and the parameters. This mapping operates through the model, and especially the surplus function. While theoretical information on the surplus function $\mathcal{S}(\cdot)$ is scarce, we do know that it is non-additive, and non-separable in its arguments, which include an

[26]We use a diagonal weighting matrix, with the elements set equal to the inverse of the diagonal variance-covariance matrix of the empirical moments. The covariance matrix of our estimator is

$$\left[\mathbf{D_m^{\intercal} W D_m}\right]^{-1} \mathbf{D_m^{\intercal} W \Sigma W^{\intercal} D_m} \left[\mathbf{D_m^{\intercal} W D_m}\right]^{-1},$$

where $\mathbf{\Sigma}$ is the covariance matrix of the empirical moments, and $\mathbf{D_m} = \partial \mathbf{m_{sim}}(\mathbf{\Theta})/\partial \mathbf{\Theta}$ is the derivative matrix of the moment conditions with respect to the model parameters at $\mathbf{\Theta} = \widehat{\mathbf{\Theta}}$. Since we have discrete dependents, any attempt to approximate the derivative vector $\mathbf{D_m}$ by finite differences may be sensitive to the chosen step size. We therefore calculate the derivative by first approximating the function by a low-order polynomial function as we vary each parameter locally. See Lise and Robin (2017) for a similar strategy.

univariate unobserved latent variable (firm productivity). In addition, the latent variable p is correlated with the other characteristics of the match. As a consequence, identifying $\mathcal{S}(\cdot)$ non-parametrically would be hopeless if one did not have a model. In this section, we explain how one can tailor the model to provide identification.

We do not attempt to identify the subjective interest rate ρ, which is set to 0.01 at a monthly frequency. We assume that firm productivity p follows a beta distribution with shape parameters $\alpha_p, \beta_p > 0$. We focus our discussion on parametric identification using the functional forms summarized throughout the model section.

Given these functional assumptions, our goal is to separately identify the parameters of the education and technology cost functions, the production function, the bargaining power coefficients, and the transitional parameters (that is, δ, η, and ξ). Since firm productivity is latent, and we do not have access to a matched employer-employee dataset, we can not provide a formal identification proof. Instead, we provide the following heuristic arguments for identification.

First, the identification of the transitional parameters follows standard arguments based on duration analysis. While the job destruction rate is clearly identified from the transitions into unemployment, the main challenge in establishing identification of the job arrival rates is that not all jobs are acceptable. That is, the surplus may be negative for some matches. Yet, assuming that there exists a worker type (α, h) for whom the surplus is always non-negative allows identification of $\lambda_u V$ by the associated non-employment to employment transitions. Similarly, a worker of such a type with the lowest surplus job would be willing to accept any other job and therefore we can identify $\lambda_e V$ by similar arguments. Since the form of the matching function is assumed known, given θ we may identify V using the definition of the market tightness given in equation 4. Finally, the rates at which vacancies are filled by unemployed (γ_u) and employed (γ_e) workers can be recovered following the same arguments.

Second, consider the identification of the surplus function. The argument here is based on a key property of the model: at the maximum wage, there is no room for bargaining. As a consequence, at that point, there is a clear mapping between wages and the surplus function. Following a worker who attains the maximum wage throughout his career allows us to recover the sequence of surplus associated with each of these positions. Yet, this identification argument works only if the wage of a worker reflect the surplus of a single firm. To ensure that this condition is satisfied, we assume that the bargaining power of employed workers is zero ($\beta_e^h = 0$), which implies that when a type-$\langle \alpha, h \rangle$ worker matched to a type-$\langle p,q \rangle$ firm is contacted by a $\langle p',q' \rangle$ firm, the wage is set such that he receives $\min\{\mathcal{S}(\alpha,h,p,q),\mathcal{S}(\alpha,h,p',q')\}$ and ends up working in the job that generates the highest surplus. An identical assumption is made in Lamadon et al. (2013). While intuitive, we can not establish the identification more formally, since the surplus function depends on firm productivity, which is latent.

Next, given the surplus function, we can tackle the identification of the bargaining parameters. Recall that we are interested only in the bargaining parameters for unemployed workers. Consider a worker who is initially unemployed, and who is observed finding a job, and then making a transition on-the-job. According to the bargaining rules, the wage gain associated with such a transition is given by $\Delta w \approx (1-\beta_u^h)\mathcal{S}(\cdot)$, which then establishes identification of the bargaining parameter β_u^h.[27]

Finally, we consider the identification of the education and job complexity cost functions. The decision to acquire education depends both upon the value of unemployment and the cost function (see Equation 11). To understand the identification of the value of unemployment, consider the type-$\langle p',q' \rangle$ job such that $\mathcal{S}(\alpha,h,p',q')=0$. The bargaining rule guarantees that $\mathcal{V}_e(w_u,\alpha,h,p',q')=\mathcal{V}_u(\alpha,h)$. It follows that $\rho\mathcal{V}_u(\alpha,h)=\rho\mathcal{V}_e(w_u,\alpha,h,p',q')=w_u$. Thus, the lowest wage accepted out of unemployment given worker type $\langle \alpha,h \rangle$ identifies $\rho\mathcal{V}_u(\alpha,h)$. Then, since the education conditional choice probabilities (the probability of a given education choice conditional on ability) are observed, well-known results from the discrete choice literature allow us to then recover the unknown cost function $c_h(\cdot)$ and the scale of the education cost shock σ_h.[28] Similar argument can be used to recover the vacancy cost function.

While our choice of estimation moments does not strictly follow the identification arguments, they are selected to capture important quantitative and qualitative features of the data. They consist of educational choices by ability, transition rates, and matching characteristics (including the share of matches that are under-educated and over-education over the life-cycle) together with the wages associated to these states. Additionally, we include the coefficients from a reduced-form regression, which relates log-wages to education, ability, and labor market experience. Finally, we target the vacancy to unemployment rate based on the estimate reported in Hagedorn and Manovskii (2008). The fit of the model

[27] The approximation sign follows from the fact that wages include the capitalized value of a job in case the match is endogenously destroyed.

[28] More precisely, with $c_h(\alpha,h)=\tilde{c}_h(\alpha,h)\Lambda(\alpha)$ and imposing the location normalization $\tilde{c}_h(\underline{h})=0$, our distributional assumptions imply a system of equations with $\log[\mathbb{P}(h|\alpha)/\mathbb{P}(\underline{h}|\alpha)]=[\rho\mathcal{V}_u(\alpha,h)-\rho\mathcal{V}_u(\alpha,\underline{h})-\tilde{c}_h(h)\Lambda(\alpha)]/\sigma_h$ for all ability levels α and education choices h.

is presented and discussed in Appendix C.

3.4 Estimated parameters

In this section, we discuss the result of our estimation exercise. Our discussion here focuses upon a subset of parameters that are particularly relevant for understanding mismatch. The complete set of parameter estimates, together with the accompanying standard errors, is presented in Appendix A.

The loading parameters of the production function (a_2 and a_3) are sizable, and indicate important absolute advantages for more productive workers and firms. The interaction parameter $a_4 = \partial^2 f(h, p)/\partial h \partial p$, which provides a measure of the complementarity or substitution in the production technology, is estimated at 0.07. A positive value indicates that the production function is supermodular and implies assortative matching between highly educated workers and high productivity firms. However, the small magnitude of the parameter implies that the gains associated to assortative matching may not be quantitatively important. Next, we study the properties of the surplus function, which provides a dynamic counterpart to the static production function, and guides both the creation of matches and the determination of wages. As a consequence, the surplus function is informative about the quantitative importance of such complementarities.

Figure 1 presents the surplus function on a productivity grid and for different mismatch status. The figure shows that the most important factor of differentiation for the surplus function is worker ability, which outweighs both education and job complexity. That is, the surplus function is decreasing in productivity for low-ability workers, relatively flat for medium ability workers, and more strongly increasing for high ability workers. There is no obvious systematic pattern for education types. Positions filled by a worker satisfying the skill requirement always generate a higher surplus, while the surplus is decreasing the more under- or over-educated is the worker. As the cost of a maintaining a vacancy is estimated to be relatively flat across job complexity levels, one could suspect that the explanation lies with the lower productivity of under-educated workers on the one hand, and a lower future value of the match (higher poaching probability) for over-educated workers on the other hand. Expressed differently, mismatched agents are unattractive to firms: under-educated workers are less productive and over-educated workers are easier to poach.

While the complementarity component in the production technology (a_4) may appear small, the surplus function shows that there are, in fact, potentially large gains from sort-

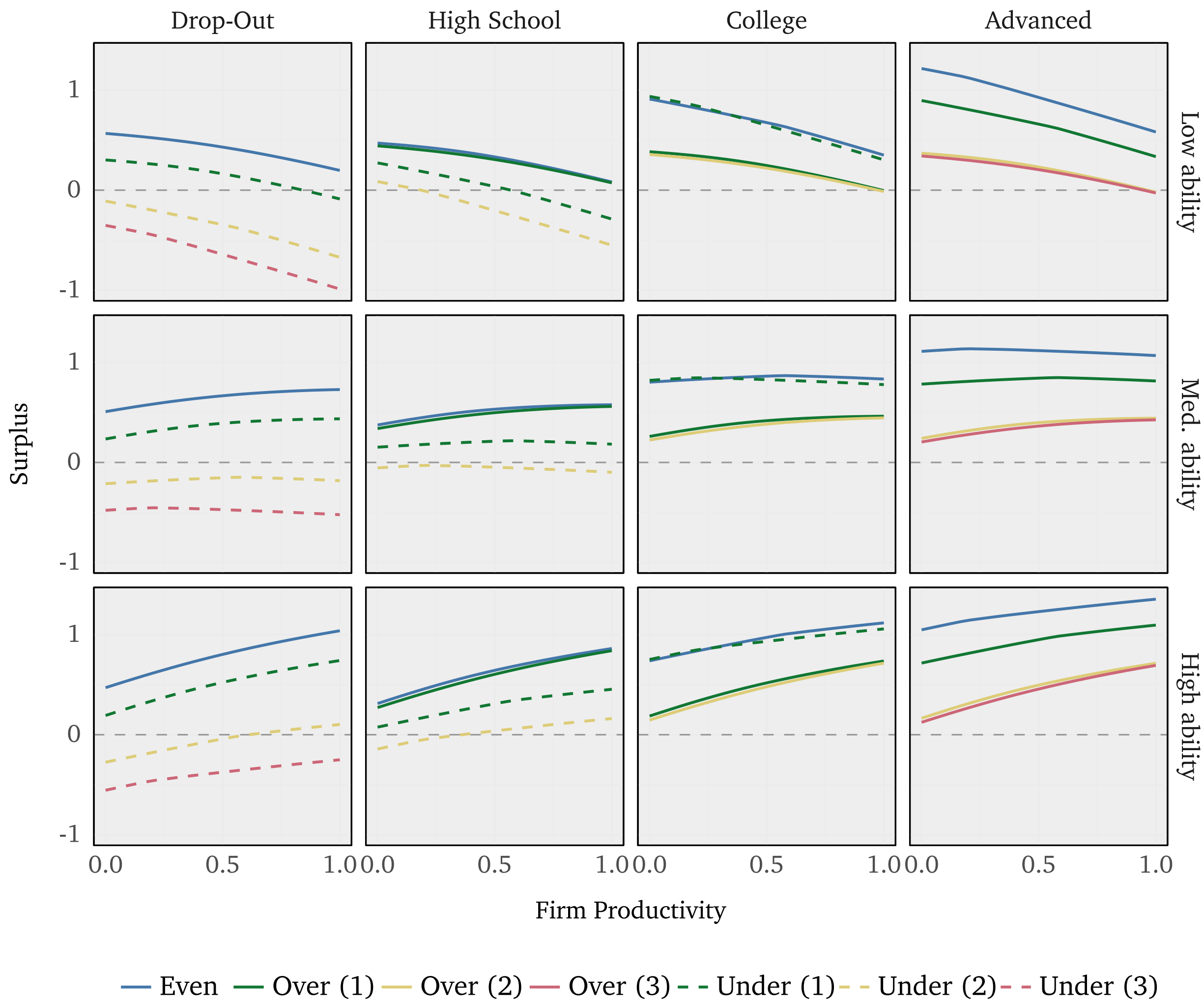

Figure 1: The figure shows surplus function $\mathcal{S}(\alpha, h, p, q)$. *Even* refers to workers who are even educated; *Under (k)* refers to workers who are under-educated by k categories; *Over (k)* refers to workers who are over-educated by k categories. Surplus is measured in thousands of dollars.

ing. The underlying reason is related to the match creation condition. A large fraction of matches that involves low ability and low education (high school diploma and below) workers yields negative surplus, and as a consequence are not created. Hence, the surplus function shows that the sizable premium associated to working for high productive firms will accrue only to high ability/education workers.

Note that the shape of the surplus function indicates considerable wage inequalities. First, the decreasing relationship between the surplus function and firm productivity for lower educated workers implies that these workers are less likely to work for high productive firms. On top of the obvious result that low educated workers are not given the opportunity to work for high productivity firms, the surplus function also implies that high productivity firms do not always serve as credible threats in the bargaining process, which limits the scope of wage mobility through the job ladder. Second, even if low productivity workers were to match with high productivity firms, the relative low surplus will yield depressed earnings.

We now turn to the estimates of the bargaining power β_u^h. Our parameter estimates reveal that unemployed workers have a somewhat low bargaining power coefficient. This coefficient is increasing in education from 0.07 (high school drop-outs) to 0.13 (advanced degree). Thus, not only does education increase workers productivity, it also improves their position in the bargaining process, with more highly educated workers able to extract a larger share of the match surplus.[29]

Finally, we discuss our matching parameters, which are summarized in Table 2. On average, exogenous job layoffs occur once every six years. On-the-job search opportunities accrue to workers every 22 months in expectation, and only half of those meetings result in matches being formed. Note that our model does not assume that matching probabilities are heterogeneous across education groups. Heterogeneity in the matching formation probabilities comes from the viability of prospective matches since low ability/education workers are more likely to meet a firm where the match surplus is negative. We show that high ability workers with an advanced degree are 36% more likely to successfully form a match than a low ability drop-out worker. This heterogeneity in acceptance rates results in substantial differences in unemployment durations across education and ability groups. On average, low ability workers have unemployment spells that are two months longer than high ability workers.

[29]While comparing estimates obtained under different models is very difficult, they are in line with those reported in Cahuc et al. (2006) on French data, and somewhat lower than other studies have obtained using NLSY data (e.g., Flinn, 2006 and Lise et al., 2016).

Table 2: Job Finding Rates

Job destruction probability	0.014
Probability of contact when employed	0.045
AR: Low ability/Drop-Out	0.019
AR: High ability/Advanced	0.021
Probability of contact when unemployed	0.188
AR: Low ability/Drop-Out	0.138
AR: High ability/Advanced	0.188

Notes: The table shows the rate that jobs are destroyed, the rate at which employed (respectively unemployed) workers meet a potential employer, and the rate at which these are associated with a higher surplus and therefore acceptable. *AR* refers to acceptance rate. All objects are measured at a monthly frequency.

4 Educational policies, welfare and inequality

This section examines the effects of policies aimed at increasing the supply of skills in the economy.[30] Since our model is a steady-state equilibrium model, we focus on the long-run outcomes. We study the effect of two relevant policies: mandatory high school graduation, and a college cost subsidy.[31]

There are several sources of inefficiencies, which may lead to under-investment in education and less complex jobs in the economy. Essentially, the inefficiencies are related to the impossibilities of writing complete contracts that would solve the coordination problem between workers and firms. The coordination failures, which arise because workers can realize the full benefit associated to education only if firms create more complex jobs, and vice versa. As a consequence, educate subsidies may alleviate that coordination problem.

First, we consider the economic effects of compulsory education, which consists of mandatory high school graduation. Such a proposal was made in President Obama's 2012 State of the Union Address.[32] Second, we analyze the impact of financial aid policies on college and advanced degree graduation rates. Specifically, we consider \$1,000, \$5,000

[30] Alternative, we can consider employer based subsidies in place of education subsidies. In general equilibrium, both policies lead to qualitatively similar outcomes.

[31] See Belzil et al. (2017) for the effect of these policies in a competitive equilibrium setting.

[32] "I am proposing that every state requires that all students stay in high school until they graduate or turn 18". Obama, B. (2012). Remarks by the President in State of the Union Address [Transcript]. Retrieved from `https://obamawhitehouse.archives.gov/the-press-office/2012/01/24/remarks-president-state-union-address`.

and \$10,000 cost subsidies.[33] We focus on the broadest application of the education subsidy abstracting from the need of the students. As a consequence, our findings can be seen as evaluating the effect of a counterfactual decrease in the tuition cost of higher education. Using these counterfactuals, we investigate whether and how policy-induced shifts in the distribution of worker education affect both the assignment of workers to jobs and relative wages. This question is motivated by the observation that most education policies alter the supply and demand of skills and as such may have potentially important general equilibrium effects. The existence of potential general equilibrium effects has been investigated in Heckman et al. (1998a), Lee and Wolpin (2006), and Abbott et al. (2018), among others. While these papers address an important set of issues (including immigration and wage inequality, the growth of the sector industry, financial aid and intergenerational transfers), they are cast in a competitive equilibrium, which is associated with an aggregate production technology with a diminishing marginal product of labor. As a consequence, an outward shift in the supply of skills leads to lower relative wages. Such an outcome is not inevitable if firms can adjust their production technology to better match the characteristics of the changing workforce. As such, our setting is appropriate to study the interplay between the schooling investment of workers and the job complexity decision of firms, which gives rise to mismatch and is therefore a potentially important determinant of wage inequality.

We present our results as follows. First, we report how policies alter the supply of education and the distribution of skills required by firms. Second, we analyze how different policies affect absolute and relative wages. Third, we explore the mechanism that generates wage inequality and the importance of mismatch. In presenting these results, we distinguish between the *partial equilibrium* (PE) and the *general equilibrium* (GE) effects. In PE, changes in outcomes are computed holding the firm entry and skill requirement choices constant, while in GE, firms re-optimize these decisions. Formally, in PE, the joint distribution of firm productivity, skill requirement and the aggregate market tightness θ are fixed at their values from the estimated model, which implies that meeting rates are fixed also. However, as changes in the composition of workers affects the surplus function, there are still implications for job mobility and wages even conditional upon education and ability. We should note that our definition of PE effects are therefore broadly comparable to the general equilibrium effects in the literature (e.g., Heckman et al., 1998a and Abbott

[33]In 2010, the average annual tuition at public 4-year colleges was \$7,600 according to Bureau of Labor Statistics (Spotlight on Statistics: Back to College, 2013).

Table 3: Demand, Supply and Mismatch

	Bench-mark	Compulsory High-School		Education cost subsidy					
				$1,000		$5,000		$10,000	
		GE	PE	GE	PE	GE	PE	GE	PE
(a). Supply of Education (Individual Education Choice)									
Drop-Out	0.07	–	–	0.07	0.07	0.07	0.07	0.07	0.07
High-School	0.65	0.69	0.70	0.63	0.64	0.57	0.63	0.51	0.61
College	0.16	0.17	0.16	0.17	0.16	0.19	0.17	0.22	0.18
Advanced	0.13	0.14	0.13	0.14	0.13	0.17	0.14	0.20	0.14
(b). Demand of Education (Firm Job Complexity Choice)									
Drop-Out	0.16	0.12	–	0.15	–	0.14	–	0.13	–
High-School	0.68	0.70	–	0.66	–	0.60	–	0.55	–
College	0.14	0.15	–	0.15	–	0.19	–	0.22	–
Advanced	0.03	0.03	–	0.04	–	0.06	–	0.10	–
(c). Mismatch									
Even	0.54	0.57	0.55	0.53	0.54	0.52	0.53	0.50	0.53
Over	0.28	0.27	0.30	0.28	0.28	0.28	0.28	0.28	0.29
Under	0.09	0.06	0.06	0.09	0.09	0.11	0.09	0.12	0.08
Unemp.	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10

Notes: The table reports outcomes for the benchmark economy and two alternative policies experiments (compulsory high-school graduation and college cost subsidies) on worker's education choice, firm job complexity, and the resulting mismatch. PE and GE respectively denote partial equilibrium and general equilibrium. Mismatch is measured as the share of working-life spent in each state. All results are calculated by simulating a population of 60,000 individuals over a period of 48 years.

et al., 2018).

4.1 Supply and demand of skills

In this section, we analyze counterfactual changes to the supply and demand of education under the different policies. Key results are presented in Table 3.

Compulsory High-School Graduation. We first consider the effect of mandatory high school graduation on the supply of education in Table 3(a). Under PE, a compulsory high school law primarily leads to a simple transfer from drop-out to high-school graduation. In contrast, in GE, there is an across board expansion in educational attainment: graduation rates for both college and advanced degrees rise by 1%, and high-school graduation increases by 5%. The GE effect here is in line with Lang and Kropp (1986), which presents empirical evidence that state compulsory education laws also affect workers who were not directly targeted by the policy change.

We now examine the effect of compulsory high-school graduation on the job complexity decisions of firms. Table 3(b) shows that the share of jobs requiring less than high school graduation decreases by 4%. We note that even when all workers graduate from high school, there is still a non-negligible fraction of jobs (11.6%) that requires less than high-school graduation. This finding speaks to stickiness in the production technology, and the difficulty to eliminate low-skill jobs.

Finally, we study how the shifts in the supply and demand for skills induced by this compulsory schooling policy affects the overall level of mismatch. In an effort to produce numbers that are comparable across experiments, in Table 3(c) we report the fraction of time spent in different labor market states: even-education, over-education, under-education, and unemployment. We focus here on the GE effects. Our results show that the prevalence of even-education jobs increased, while the time spent in under-education notably decreases. There is a small decrease in the prevalence of over education as well. These findings suggest that compulsory high-school graduation may improve efficiency in the assignment of workers to jobs, and induce important wage gains.

Education Cost Subsidy. Next, we turn to the experiments that subsidize the cost of higher education (i.e. individuals obtaining college and advanced degrees). Under all experiments considered, the college graduation rate increases both in PE and GE. As expected, larger subsidies produce more consequential shifts in the distribution of education. Quantitatively, subsidies of $1,000, $5,000 and $10,000 increase higher education attainment by 2%, 8% and 13% respectively in *general equilibrium*. These effects are very much in line with finding from the quasi-experimental literature that suggests that an additional $1,000 in subsidy typically leads to additional enrollment between 3–6% (see, for example, the recent survey in Deming and Dynarski, 2009).

We note that our estimates in GE are substantially larger than those under PE, which highlights the importance of expectations of both workers and firms in shaping labor market outcomes. Importantly, our estimates also imply that the subsidy to higher education have a negligible effect on the drop-out rates, and the increase in the college take-up rate comes from workers who were formerly high-school graduates.

Our results show that a higher education cost subsidy induces an upward shift in the distribution of job complexity. In GE, the largest education subsidy ($10,000) produces only a 2.5% decrease in the relative share of jobs requiring less than a high-school diploma, to be compared to more than 12% decrease for positions requiring a high school degree. These losses are offset by gains in higher complexity positions (college and advanced degrees).

Finally, we consider the implications in terms of mismatch. We focus on the GE effects, since higher education attainment leads mechanically to additional over-education in PE. In contrast to the effect of mandatory high school graduation, college cost subsidies lead to additional mismatch. Individuals spend a larger share of their working-life in under-education (11.8% under a $10,000 subsidy to be compared to 8.7% in the benchmark economy). While the importance of unemployment and over-education is relatively constant across policy alternatives, individuals spend a smaller share of their working-life in even-education positions.

To summarize, compulsory education laws have a mild effect on education choices, and induce a more efficient assignment of workers to jobs. In contrast, higher education subsidies have large effects on college attainment and lead to additional mismatch. Of course, these aggregate responses may conceal important compositional effects by education group. We discuss these below.

4.2 Welfare and wages

In this section, we quantify the welfare effect of the aforementioned policies. We focus on long run welfare, which is defined as the sum of individuals of discounted lifetime earnings net of any potential education cost subsidy. We also analyze how the new policy environment changes the absolute and relative wages of different education groups.[34] To provide an easier interpretation, we calculate average annual earnings over the life-cycle (expressed in thousands of dollars in 2012 prices). Key results are presented in Table 4.

[34] The effect of such a change is theoretically analyzed in a competitive setting by Teulings (2005), which shows that the equilibrium effect can be decomposed between changes in the composition of the labor supply and total productivity. In our setting, the existence of frictions implies that wages do not reflect only productivity, but also matching constraints. As such, the increased productivity may only be partially observed in wages.

Table 4: Effect of education policies on absolute and relative wages

	Bench-mark	Compulsory High-School		Education cost subsidy					
				\$1,000		\$5,000		\$10,000	
		GE	PE	GE	PE	GE	PE	GE	PE
Welfare (%)	0.00	1.85	1.31	0.88	0.44	2.44	0.43	4.13	0.68
Earnings (mean)	44.25	45.06	44.82	44.64	44.44	45.34	44.44	46.10	44.57
Drop-Out	29.10	32.38	32.01	28.97	29.13	28.12	29.04	27.65	29.04
High-School	40.41	39.92	40.14	40.20	40.56	38.96	40.26	37.63	40.07
College	55.71	56.43	56.02	56.43	55.88	57.48	55.70	57.84	55.74
Advanced	57.56	57.81	57.57	58.11	57.65	59.59	57.67	60.93	57.31
Earnings (s.d.)	15.58	15.62	15.40	15.95	15.75	16.96	15.76	17.89	15.85
Drop-Out	9.00	-	-	9.17	9.12	8.78	8.90	8.73	9.04
High-School	12.64	12.53	12.60	12.61	12.85	12.23	12.67	11.68	12.59
College	15.20	15.49	15.34	15.35	15.32	15.75	15.17	16.05	15.22
Advanced	15.04	15.05	14.99	15.30	15.15	15.81	15.23	16.33	15.30

Notes: The table presents the effect of compulsory high-school graduation and college cost subsidies on earnings by education groups, and wage inequality. Results from the benchmark economy is provided for comparison purposes. PE and GE respectively denote partial equilibrium and general equilibrium. Wages correspond to average annual earnings expressed in thousands of dollars in 2012 prices. All results are obtained using a simulated population of 60,000 individuals over a period of 48 years.

Compulsory High-School Graduation. Compulsory education produces modest welfare gains: average earnings increase by 1.85% in GE to be compared to 1.31% in PE under compulsory education. Although the overall effect on earnings appears limited in both partial and general equilibrium, the policy has a heterogeneous impact on workers: the average earnings of high-school graduates decreases, while the opposite occurs for college graduates. A potential interpretation may be related to role of ability in compliance to the policy. That is, individuals with low return to education (low ability) are driven into high-school graduation, while the subset of former high-school graduates with high return to education (high ability) are driven into college education. Another explanation is related to changes in the distribution of job complexity, that restrict the set of jobs available to high-school graduates, while expanding the opportunities for college graduates. We investigate these mechanisms in Section 4.3.

The model also has implications for wage inequalities: compulsory education has a mild effect on overall wage dispersion. Specifically, the level of wage dispersion decreases slightly among high-school graduates and increases among college graduates. Overall, compulsory education decreases wage inequality.

Education Cost Subsidy. Our model suggests that there are potentially large welfare gains associated to introducing a higher education cost subsidy. Since we focus on long run outcomes, the cost of the program is small compared to lifetime earnings, a fact that is well illustrated by the close alignment between welfare and absolute earnings.

When individuals are offered a \$1,000 education cost subsidy, average earnings increase by 0.88% in GE, to be compared to 0.44% in PE. When the level of subsidy increases to \$10,000, the average gains in GE and PE respectively increase to 4.18% and 0.73%. With the GE effect 2 to 6 times larger than the PE effect, taking into account changes in the structure of jobs is key to measure the impact of schooling subsidies. Furthermore, these policies also have implications for relative wages, which we now describe, again focusing our discussion on the GE effects.

The earnings of high-school dropouts decrease in both absolute and relative terms despite the constant supply. High school graduates also experience a decrease in earnings, despite the growth in supply. In contrast, the earnings of college and advanced graduates both increase. The divergent path of workers with different education levels illustrates the complexity of the relationship between the supply of skills and relative prices in markets with mismatch. Still, the model offers an explanation for these differential paths across education groups, which is related to the sharp decline in the demand for high school graduates, which depresses lifetime wages. In contrast, the demand for more highly educated workers (college and advanced) increases substantially, which leads to increases in lifetime earnings for both college and advanced graduates. The combination of these elements increases wage dispersion in the population.

Finally, one should note that the mechanism that generates increased wage inequality in the model is more complex than that produced under skill-biased technological change. That is, wage inequality in our framework is not confined to growing differential between college and high school graduates, but also increasing wage dispersion among college graduates.[35]

4.3 The Mechanism of Wage Inequality

In the previous section, we showed that increasing the supply of higher educated workers in the economy generates higher wage inequality in the total population. We now explore how education and job complexity decisions create differential exposure to the risk of mismatch for college and high graduates, and lead to wage inequality. More specifically, we consider two potential mechanisms that may generate this outcome.

The first mechanism is related to the shift in the job complexity decisions of firms, which may lead to better assignments for high-educated workers, and either under-education or unemployment for less-educated workers. Because of the lower static production but also the higher poaching probabilities, under-educated positions generate lower surplus and wages. This channel, which we refer to as the *extensive margin*, is associated with differential exposure to the risk of mismatch.

Second, wage inequality may be explained by changes in the distribution of firms who are willing to post low-skill requirement positions. A shift in the supply of skills may lead to a compositional shift in the type of firms who post low-skill requirement jobs. If there is a downward shift in the productivity of these firms, then wages in these job positions may fall as a consequence. This channel, which we refer to as the *intensive margin*, is related to differential exposure to the high-quality matches.

Exposure to Mismatch. We study the prevalence of mismatch by education status. Table 5 reports the time spent in each mismatch state for each education level. We focus our

[35] See Hoxby and Terry (1999) for a recent analysis of the rising wage inequality among the college educated.

discussion on the GE results.

Table 5: Mismatch by Education Groups

	Bench-mark	Compulsory High-School		Education cost subsidy					
				$1,000		$5,000		$10,000	
		GE	PE	GE	PE	GE	PE	GE	PE
(a). Even-Education									
Drop-Out	0.31	–	–	0.32	0.31	0.30	0.32	0.29	0.32
High-School	0.70	0.72	0.68	0.70	0.70	0.68	0.70	0.66	0.71
College	0.32	0.34	0.32	0.34	0.32	0.38	0.32	0.42	0.32
Advanced	0.10	0.12	0.11	0.13	0.11	0.20	0.11	0.27	0.10
(b). Over-Education									
High-School	0.14	0.12	0.16	0.14	0.14	0.14	0.14	0.14	0.14
College	0.52	0.48	0.52	0.48	0.52	0.40	0.51	0.34	0.51
Advanced	0.81	0.79	0.80	0.78	0.80	0.71	0.81	0.64	0.81
(c). Under-Education									
Drop-Out	0.57	–	–	0.56	0.56	0.57	0.56	0.57	0.56
High-School	0.06	0.06	0.06	0.06	0.06	0.08	0.05	0.09	0.05
College	0.07	0.08	0.08	0.09	0.08	0.13	0.07	0.16	0.07
(d). Unemployment									
Drop-Out	0.12	–	–	0.12	0.12	0.13	0.12	0.14	0.12
High-School	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.11	0.10
College	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
Advanced	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09

Notes: The table presents the effect of compulsory high-school graduation and college cost subsidy on the prevalence of mismatch for different education groups. Results from the benchmark economy is provided for comparison purposes. PE and GE respectively denote partial equilibrium and general equilibrium. Mismatch is measured as the share of working-life spent in each state. All results are calculated by simulating a population of 60,000 individuals over a period of 48 years.

Our results indicate that under the college cost subsidy, high school graduates and dropouts spend a smaller share of their working-time in even-education positions, and a larger proportion in both under-educated positions and unemployment. The increase in unemployment is especially sharp for dropouts, who would spend 13.6% of their working life in unemployment under the $10,000 college cost subsidy, to be compared to 11.9% in the benchmark. The unemployment increase is a byproduct of the upward shift in the distribution of job complexity, which increases the likelihood of meeting a vacancy where the surplus is negative. The mismatch outcomes are reversed under compulsory education: high school graduates spend a larger share of their working life in positions with even-education, and a smaller fraction of their time as over-educated.

Different conclusions hold for college and advanced degree graduates, who are better matched: they spend more time in even-education positions, and a smaller share of their working life in over-education. Overall, we show that the substantial shift in supply and demand under higher education subsidies leads to additional mismatch for low-educated workers, while college and advanced graduates are less exposed to mismatch. The combination of these two effects results in increased inequalities.

Firm entry. Finally, we analyze whether the policies induce changes beyond exposure to mismatch. Specifically, we aim to understand whether low educated workers get matched to less productive firms after the policy change. Free-entry, together with the endogenous job complexity decisions, may lead to a substantial change in the composition of firms that post low skill contents jobs. To tackle this question, we associate each spell to a mismatch state and group wages by education level in Table 6.

Under compulsory education, complex positions (high-school and higher) diploma originate from more productive firms. This effect is stronger under the education cost subsidy. Interestingly, our results do not point to a substantial shift in the distribution of firms that post college required jobs. That is, the average wage of college educated workers decreases regardless of the mismatch status. Finally, only individuals with an advanced degree end-up working for more productive firms.

Since the lifetime earnings of college graduates increase when a college subsidy is in place, we can conclude that the gain stems for a better lifetime matching profiles rather than changes in the composition of firms. On the contrary, the plight of high-school graduates is explained by a combination of intensive and extensive margins.

5 Discussions and conclusions

In this paper we have studied how policies aimed at increasing the educational attainment of workers, change the assignment of workers to jobs, and have examined the consequences for wage inequality. We extend the basic sequential job search model to simultaneously allow for productivity enhancing education choices for workers, and job complexity decisions for firms. Frictional matching leads to unemployment, over-education, and

Table 6: Wages by Mismatch and Education Groups

	Bench-mark	Compulsory High-School		Education cost subsidy					
				$1,000		$5,000		$10,000	
		GE	PE	GE	PE	GE	PE	GE	PE
(a). Drop-Out									
Even-Educated	15.60	-	-	15.51	15.46	15.36	15.60	15.13	15.54
Under-Educated	12.30	-	-	12.25	12.31	12.19	12.31	12.12	12.26
(b). High-School									
Even-Educated	18.34	17.82	17.93	18.23	18.32	17.80	18.20	17.42	18.10
Over-Educated	16.46	17.41	17.44	16.45	16.49	16.07	16.44	15.83	16.26
Under-Educated	14.60	14.71	14.66	14.70	14.64	14.80	14.82	14.65	15.06
(c). College									
Even-Educated	29.02	29.05	28.81	29.00	29.05	29.00	29.00	28.89	28.94
Over-Educated	21.16	21.02	21.14	20.97	21.16	20.55	21.08	20.00	20.96
Under-Educated	27.68	27.29	27.35	27.10	27.50	26.02	27.29	25.19	26.91
(d). Advanced									
Even-Educated	31.89	32.09	32.37	32.33	31.95	32.38	32.08	32.26	31.84
Over-Educated	24.01	24.04	23.85	23.90	23.98	23.85	23.98	23.66	23.87

Notes: The table presents the effect of compulsory high-school graduation and college cost subsidy on hourly wages (expressed in 2012 prices) by education and mismatch groups. Results from the benchmark economy is provided for comparison purposes. PE and GE respectively denote partial equilibrium and general equilibrium. All results are calculated by simulating a population of 60,000 individuals over a period of 48 years.

under-education.

Designing educational policies that promote efficiency is a major concern for many policy makers, with a recent literature linking college education to rising wage inequality (Goldin and Katz, 2007). As a consequence, many proposals centering around a large scale implementation of policies that significantly reduces barriers to higher education have been made. A major concern related to such policies is that they may have large displacement effects, altering the structure of wages and employment in the economy.

The existing literature on the general equilibrium effects of educational policies are cast in competitive equilibrium, and conclude that accounting for such effects dampen possible short run outcomes following the adjustment in relative wages over the long run (for example, Heckman et al., 1998a, Lee and Wolpin, 2006, and Abbott et al., 2018). Our approach differs from this literature by explicitly considering the idea that educational policies can direct technological change toward certain education groups.

We show that educational cost subsidies lead to large welfare gains, which originates from a better matching between highly educated workers and more complex jobs, and a more efficient allocation between high-productivity firms and workers. Educational subsidies result into a structural change in the composition of jobs in the economy, with up to a 15% increase in the demand for jobs that require at least a college degree when a significant educational subsidy ($10,000) is provided. Expressed differently, our model shows that there is a welfare gain associated with large education subsidies both because there are more productive jobs in the economy, and because it becomes easier for high productivity workers to find these jobs.

In addition, we demonstrate that advanced and professional degrees (such as a MBA or masters degree) are an important component of the welfare gain, as they constitute the educational group that benefits the most from these policies. In additional experiments, we considered implementing even larger ($25,000 and $50,000) educational subsidies. We find that with a $25,000 educational cost subsidy, welfare gains are approximately 9%, with up to half of the jobs (50%) now requiring at least a college degree to be compared to around 20% in the benchmark.

Although there are substantial welfare gains, our results suggest that educational policies systematically lead to increased wage inequality. We document changes in the sorting patterns of both workers and firms, and show that wage inequalities are largely driven by inequality among college graduates, as additional lower ability workers select into college education. In addition, the policy leads to negative consequences for high school graduates who are then recruited by less productive firms, and face a scarcity of jobs that they can compete for. Quantitatively, we find that with a $25,000 educational cost subsidy, earnings dispersion increases by almost 30% compared to the benchmark.

There are important directions for future work. First, we note that our model does not include borrowing constraints, with any such constraints manifesting in our estimation of the education cost function.[36] Second, we have not incorporated any post-schooling human capital accumulation. Extending our approach to incorporate human capital accumulation, as considered recently by Lise and Postel-Vinay (2015), would allow potential substitution between education and labor market experience. The importance of this on the decision of workers to acquire education, and for firms to direct their technology, will naturally depend upon the degree of substitution. A quantitative investigation concerning the importance this and other channels, together with issues in identification, is left for future research.

[36] Empirical evidence on the importance of borrowing constraints is scarce. See Lochner and Monge-Naranjo (2012) and Heckman and Mosso (2014) for recent surveys.

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A Parameters

Table 7: Parameter estimates

	Estimate	Standard Error
Productivity Distribution:		
Shape parameter, Beta_α	1.195	0.063
Shape parameter, Beta_β	1.155	0.051
Production Technology:		
Constant, a_0	2.845	0.180
Productivity coefficient, a_1	258.264	14.081
Education coefficient, a_2	1.701	0.033
Productivity $\times$ Education coefficient, a_3	0.070	0.003
Education index share parameter, ζ_0	0.109	0.006
Education index substitution parameter, ζ_1	1.996	0.123
Under-education cost, κ_0	2.614	0.075
Under-education curvature, κ_1	1.324	0.022
Worker ability, $g(\alpha_2)$	1.055	0.000
Worker ability, $g(\alpha_3)$	1.087	0.005
Home productivity, b	9.996	0.262
Worker bargaining power, $\beta(h_1)$	0.072	0.004
Worker bargaining power, $\beta(h_2)$	0.105	0.002
Worker bargaining power, $\beta(h_3)$	0.121	0.003
Worker bargaining power, $\beta(h_4)$	0.127	0.005
Search and Matching Technology:		
Relative employed search intensity, ξ	0.181	0.006
Matching efficiency, η	9.712	0.341
Job destruction, δ	0.014	0.000
Vacancy Costs:		
Vacancy cost, $c(h_1)$	590.236	15.616
Vacancy cost, $c(h_2)$	590.688	17.677
Vacancy cost, $c(h_3)$	591.855	24.584
Vacancy cost, $c(h_4)$	599.020	25.511
Idiosyncratic vacancy cost SD, σ_v	1.891	0.085
Education Cost Function:†		
Cost ability, $\Lambda(\alpha_1)$	1.003	0.037
Cost ability, $\Lambda(\alpha_2)$	0.331	0.016
Cost ability, $\Lambda(\alpha_3)$	0.125	0.007
Cost education, $c(h_2)$	0.126	0.004
Cost education, $c(h_3)$	19.843	1.070
Cost education, $c(h_4)$	25.677	1.278
Idiosyncratic education cost SD, σ_c	1.504	0.050

Notes: The table presents the parameter estimates and associated standard errors. All parameters estimated simultaneously using a moment based estimation procedure as detailed in Section 3.

B Model solution algorithm

In this Appendix we describe the fixed point iterative algorithm used to solve the model given the set of model primitives. It is based on that described in Lise et al. (2016). Given a candidate $\mathcal{M}(\alpha,h,p,q)$, $\mathcal{S}(\alpha,h,p,q)$, $\ell(\alpha,h)$, and θ, it proceeds as follows:

1. *Arrival rates*. Calculate $\lambda_u = \theta m(\theta)$, $\lambda_e = \xi\lambda_u$, $\gamma_u = m(\theta)$, and $\gamma_e = \xi m(\theta)$.

2. *Unemployment*. Calculate $u(\alpha,h) = \ell(\alpha,h) - \sum_{q'}\int \mathcal{M}(\alpha,h,p',q')\,\mathrm{d}p'$.

3. *Aggregate stocks*. Calculate $V = \theta \times [U + \xi(L-U)]$, $U = \sum_{\alpha'}\sum_{h'} u(\alpha',h')$, and $N = V + \sum_{\alpha'}\sum_{h'}\sum_{q'}\int \mathcal{M}(\alpha',h',p',q')\,\mathrm{d}p'$.

4. *Jobs*. Calculate $\rho\mathcal{J}_v(p,q)$ using equation (12), and the conditional Logit choice probability $\Pr[q|p]$. Calculate the measure of jobs as $n(p,q) = N \times \Pr[q|p] \times \phi(p)$.

5. *Vacancies*. Calculate the vacancy measure $v(p,q) = n(p,q) - \sum_{\alpha'}\sum_{h'}\mathcal{M}(\alpha',h',p,q)$.

6. *Update matches*. Rearranging equation (16) we calculate matches as

$$\mathcal{M}(\alpha,h,p,q) = \frac{\lambda_u v(p,q)u(\alpha,h) + \lambda_e v(p,q)\oint\!\!\!\!\oint_{\{p',q'\}\setminus\mathcal{R}_e^c(\alpha,h,p,q)}\mathcal{M}(\alpha,h,p',q')\,\mathrm{d}p'}{\delta + \lambda_e\oint\!\!\!\!\oint_{\mathcal{R}_e^c(\alpha,h,p,q)} v(p',q')\,\mathrm{d}p'}.$$

7. *Update surplus function*. This is given by

$$\begin{aligned}\rho\mathcal{S}(\alpha,h,p,q) = {} & f(\alpha,h,p,q) - \rho\mathcal{V}_u(\alpha,h) - \rho\mathcal{J}_v(p,q) + \delta\times(0-\mathcal{S}(\alpha,h,p,q)) \\ & + \lambda_e\sum_{q'}\int\Big[\mathcal{V}_u(\alpha,h) + \mathcal{S}(\alpha,h,p,q) + \beta_e[\mathcal{S}(\alpha,h,p',q') - \mathcal{S}(\alpha,h,p,q)]^+ \\ & + \mathcal{J}_v(p,q) - \mathcal{V}_u(\alpha,h) - \mathcal{J}_v(p,q) - \mathcal{S}(\alpha,h,p,q)\Big]v(p',q')\,\mathrm{d}p'.\end{aligned}$$

8. *Update education*. Calculate $\rho\mathcal{V}_u(\alpha,h)$ using equation (8), and calculate $\ell(\alpha,h)$.

9. *Update market tightness*. Using the free entry condition solve for the value of θ such that $\rho\widetilde{\mathcal{J}}_v(\underline{p}) = \mathbb{E}[\rho\mathcal{J}_v(\underline{p},q(\underline{p},\varepsilon_f)) + \varepsilon_{f_q})] = 0$.

10. *Repeat until convergence*.

C Model fit

In this Appendix, we report the fit of the model to an important set of moments. All our simulated moments are obtained by using our model parameter estimates (see Table 7) and simulating a population of 60,000 individuals over a period of 16 years. First, in Table 8 we show that the model is successful in replicating the distribution education attainment for individuals with different ability levels. In terms of post-schooling outcomes, Figure 2 shows the fit of the model to both labor market transition rates and mismatch levels by education level. Overall, the model fits these moments well. For the job finding rate for unemployed workers (U2E), we are able to match the overall level very well, but are not able to replicate some of the variation that we observe over the life-cycle. We do note, however, that this set of empirical moments are relatively imprecisely estimated. Similarly, we can match the levels for both on-the-job transitions (J2J) and job destruction events (E2U) well, but under-predict the early career transition rates, especially for workers with lower education levels. The figure also shows that the model provides a good fit to the share of individuals who are over, under, or even educated, over the life-cycle and for the different education groups. As an alternative way of representing the degree of mismatch, in Table 9 we present the distribution of education levels within firms with different skill requirements. While generally successful, the model does predict a greater degree of under-education in jobs with the advanced skill requirement compared with what we observe in the data. In Figure 3 we then show the fit to log-wages (both the mean and the standard deviation) for different education groups and different mismatch status. The model generally does well in replicating average wages, although in some cases it does underpredict the wage growth later in careers. Similarly, the model is generally successful in explaining the variation in wages, although it does not generate enough variation in cases where a high-school graduate in under-educated, and when an advanced education worker is even-educated. Finally, in Table 10 we report the coefficients of a linear regression model that relates log-wages to education, ability, and potential labor market experience. As in the data, we obtain that wages are increasing in education, ability, and experience. Compared to the regression coefficients obtained with the actual data, we slightly underpredict the return to labor market experience.

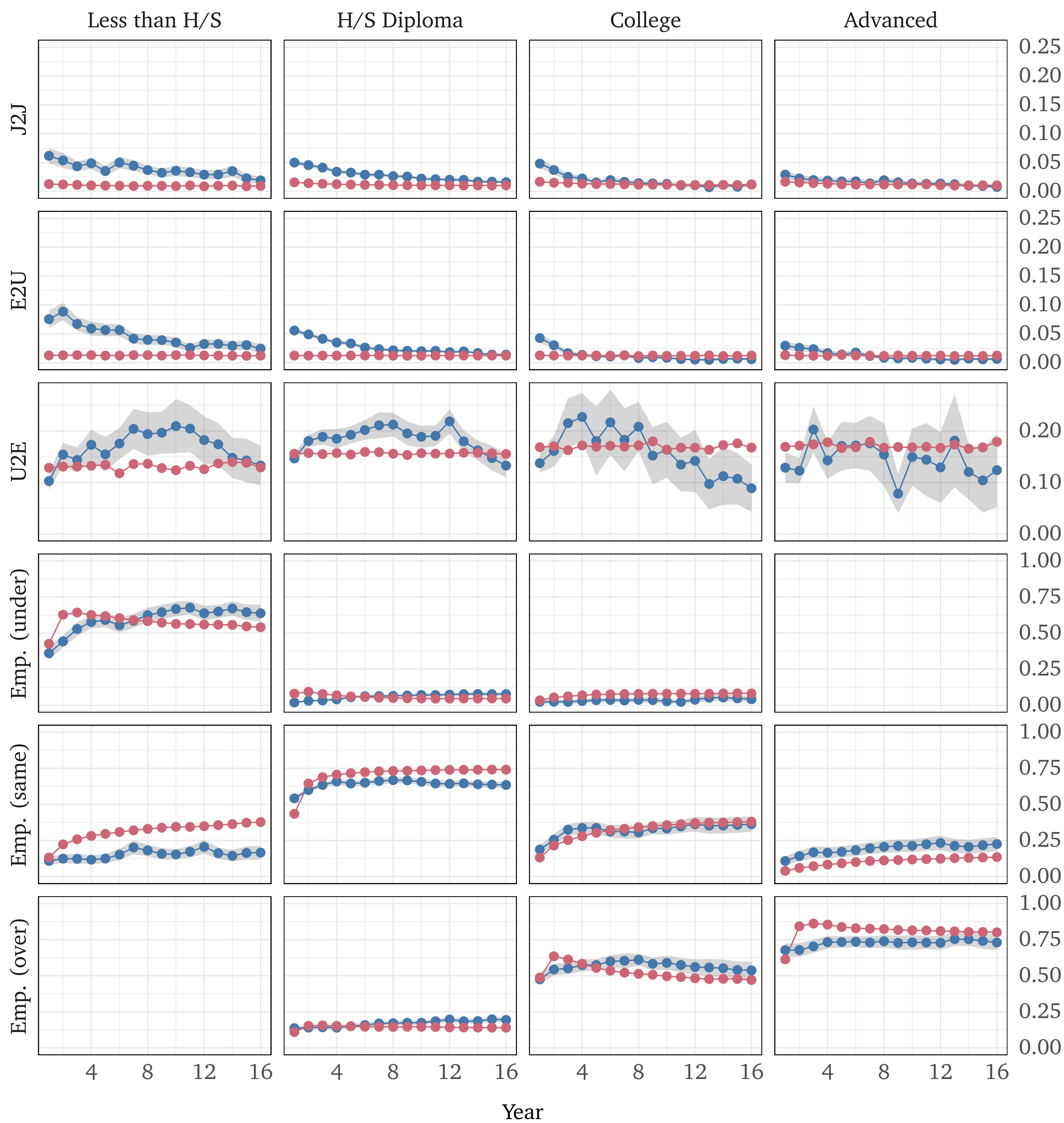

Figure 2: The figure shows the fit of the model to select employment and transition moments. The blue lines correspond to empirical moments, and the red lines correspond to simulated moments. Simulated moments are calculated using a population of 60,000 individuals over a period of 16 years. J2J, E2U, and U2E, respectively measure job-to-job, employment-to-nonemployment, and nonemployment-to-employment transitions. Each data point corresponds to a monthly statistic averaged over the period of a year. Time is measured relative to the completion of education.

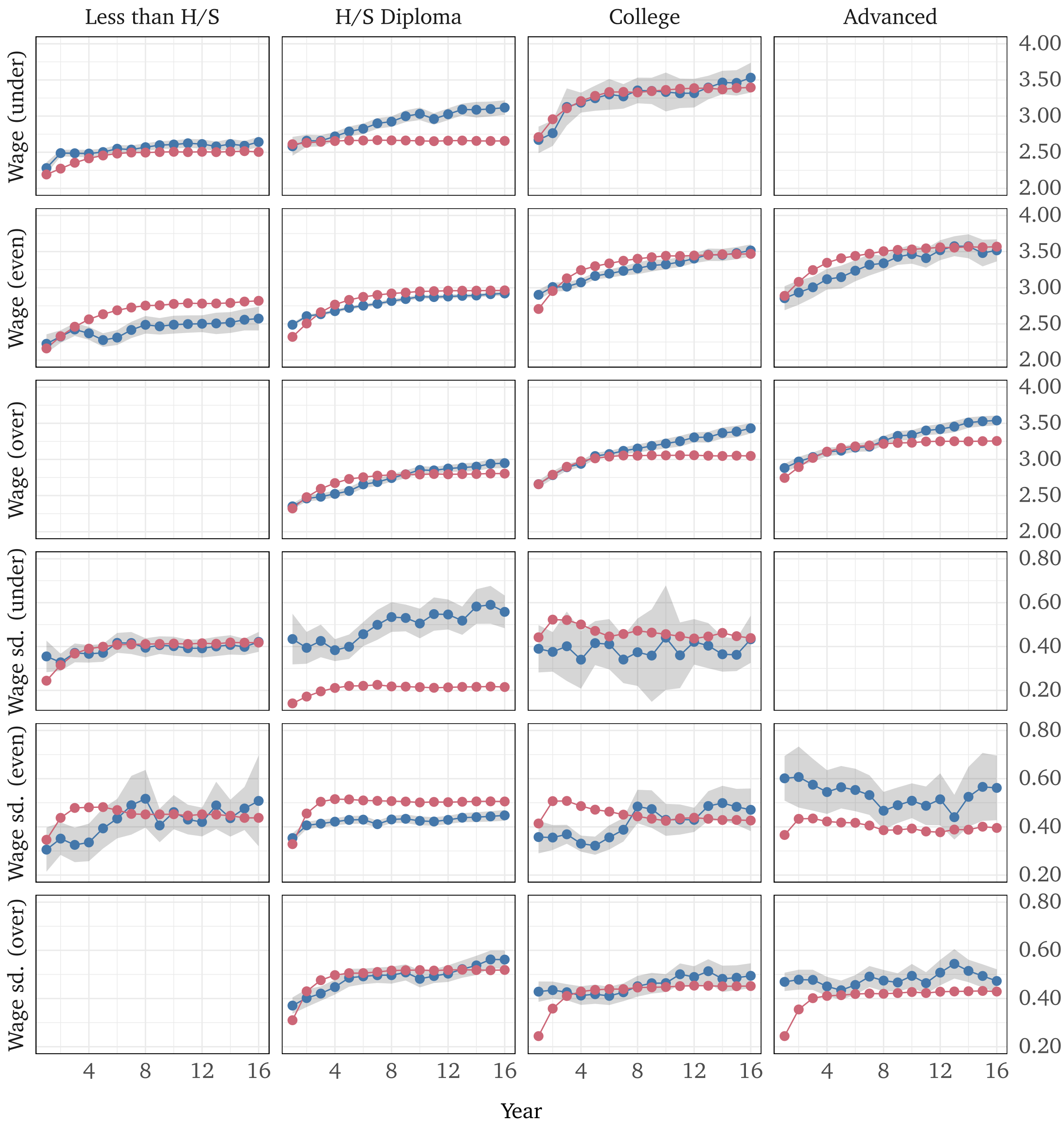

Figure 3: The figure shows the fit of the model to select wage moments. The blue lines correspond to empirical moments, and the red lines correspond to simulated moments. Simulated moments are calculated using a population of 60,000 individuals over a period of 16 years. Wages are measured as hourly log wages. Each data point corresponds to a monthly statistic averaged over the period of a year. Time is measured relative to the completion of education.

Table 8: Worker education choices

	$0 \leq AFQT \leq 33$		$33 < AFQT \leq 66$		$66 < AFQT \leq 100$	
Education	Model	Data	Model	Data	Model	Data
Less than H/S	0.133	0.251	0.062	0.050	0.012	0.006
H/S Diploma	0.848	0.725	0.847	0.774	0.276	0.424
College	0.010	0.018	0.066	0.117	0.380	0.294
Advanced	0.010	0.006	0.025	0.058	0.332	0.276

Notes: The table shows the empirical and simulated distributions of worker education choices conditional on the ability level of the worker (as measured by AFQT score).

Table 9: Education distribution within firms

	Skill Requirement							
	Less than H/S		H/S Diploma		College		Advanced	
Education	Model	Data	Model	Data	Model	Data	Model	Data
Less than H/S	0.151	0.091	0.063	0.107	0.002	0.008	0.000	0.014
H/S Diploma	0.656	0.650	0.738	0.727	0.295	0.284	0.067	0.076
College	0.104	0.164	0.110	0.107	0.404	0.398	0.439	0.174
Advanced	0.088	0.095	0.088	0.059	0.299	0.310	0.494	0.735

Notes: The table shows the empirical and simulated distributions of worker education levels conditional on the skill requirment level of the firm.

Table 10: Wage regression

	Model	Data
Constant	2.2253	2.2303
High School Diploma	0.2370	0.1577
College	0.4153	0.4578
Advanced	0.4552	0.5450
$33 < AFQT \leq 66$	0.1715	0.1816
$66 < AFQT \leq 100$	0.2807	0.2472
Potential Experience	0.0287	0.0319

Notes: The table shows the coefficients of an ordinary least squares log-wage regression (obtained from actual and simulated data) on categorical education and ability variables, and potential labor market experience.