College Majors and Skill Mismatch in Labour Markets: A General Equilibrium Approach*

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Abstract

This paper studies the aggregate and distributional consequences of college major–occupation mismatch. While most existing research focuses on individual-level wage losses in partial equilibrium, we develop a general-equilibrium framework to quantify the aggregate inefficiencies. We define mismatch as the deviation from the optimal allocation of college majors to occupations, given observed wage returns, and estimate these returns using a Roy model applied to unique Australian administrative tax panel data linking university degrees to the longitudinal earnings and employment histories. Consistent with prior work, we find that mismatch leads to substantial individual wage losses—up to 28 percent in a partial equilibrium. However, the corresponding general-equilibrium output losses are more limited, peaking at 10 percent. Importantly, mismatch declines over the life cycle and largely vanishes by age 35 in a general equilibrium. The findings underscore how micro-level misallocation in human capital may not always aggregate to output inefficiencies.

Keywords: Skill Mismatch, College Major, Occupation, Roy Model, Output Losses, Administrative Tax Record

JEL Classification: E24, J24, J31.

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1 Introduction

Tertiary education plays a central role in a country's economic development by equipping individuals with skills that are expected to meet labor market needs. In most systems, students freely choose their fields of study, often guided by preferences and beliefs about future labor demand. However, due to rapid technological change and evolving industry needs, these expectations can be misaligned with actual labor market outcomes. As a result, many graduates find themselves in occupations that do not fully utilize their acquired skills—a phenomenon known as skill mismatch.

Skill mismatch is increasingly a concern for economists and policymakers. At the individual level, mismatch can reduce wages and hinder career progression; at the aggregate level, it may distort labor allocation, exacerbate inequality, and generate inefficiencies in production. Existing empirical research has focused largely on partial equilibrium measures of mismatch—typically estimating wage penalties for individuals working outside their field of training. Yet the policy stakes of mismatch are inherently macroeconomic: education systems are designed and funded with the goal of improving overall productivity and welfare. In addition, large-scale labor reallocations can lead to price adjustments, causing individual gains from reallocation to rise or fall depending on general equilibrium effects. This creates a disconnect between individual-level estimates and the aggregate outcomes that education and labor market policies ultimately target.

This paper develops a structural framework to bridge that gap. We quantify college major–occupation mismatch both at the individual level and in general equilibrium. Our framework builds on the Roy model of occupational choice to estimate the returns to each major-occupation pairing. Individuals select into occupations based on both observed and unobserved factors, allowing us to identify the wage penalties associated with not working in the occupation that offers the highest return for a given major. This yields a partial equilibrium mismatch measure, reflecting individual-level losses conditional on current labor market prices.

To assess the aggregate efficiency consequences, we embed these estimates in a general equilibrium model where occupational output is produced using a nested CES technology that aggregates workers by major within occupations. Using regional and temporal variation in labor markets, we estimate the elasticities of substitution of college major by occupation and the elasticity of substitution between occupations for an aggregate production function. We then compute the optimal allocation of workers across occupations—one in which marginal products are equalized within each major—and compare it to the observed allocation to quantify output losses from mismatch. This approach is conceptually similar to the factor misallocation literature, such as Hsieh and Klenow (2009), but applying micro-level data to measure the human capital allocation across occupations instead of relying on the estimation of wedges through matching group-specific outcomes.

We apply this framework to the Australian labor market using the ALife dataset (Carter et al., 2021), a unique administrative panel dataset that allows us to link individuals' tax records with their university degrees. We find substantial individual-level mismatch, with large wage penalties from working outside one's top-return occupation. After accounting for selection, these penalties are large, average 28 percent and are particularly pronounced for STEM, Management and Commerce, and Arts and Humanities graduates.

However, when labor market prices adjust in general equilibrium, the aggregate output losses from mismatch are far smaller—averaging about 10 percent over the period 2003–2019. These losses further represent an upper bound of mismatch-induced inefficiencies, assuming no role for preferences. Similar to individual mismatch, most of the aggregate loss is concentrated in a few major groups: Management and Commerce (3.5%), STEM (2.5%), and Society and Culture (2.4%). Importantly, mismatch declines significantly over the life cycle. In general equilibrium, mismatch largely disappears by age 35, suggesting that labor market experience and reallocation help mitigate initial misalignments.

By quantifying both individual and aggregate mismatch in a unified framework, our paper contributes to the growing literature on human capital misallocation. More broadly, it provides policymakers with tools to evaluate the economic costs of educational misalignment—not just in terms of wages, but also in terms of macro-level efficiency. In doing so, we offer a new way to assess whether education systems are meeting their broader development goals.

Literature Review

A growing literature measures skill mismatch at a micro-level by comparing workers' qualifications with the requirements of their jobs, often using detailed occupational data from ONET and similar sources.[1] Early contributions, such as Pellizzari and Fichen (2013) and McGowan and Andrews (2015), laid the groundwork for widely used mismatch indices, including those adopted by the OECD. Recent work estimates models of occupational choice using multidimensional skill measures and sorting behavior, often combining longitudinal survey data with occupation-level skill profiles from ONET (Guvenen et al., 2020; Lise and Postel-Vinay, 2020). These approaches rely on rich data linking individual worker attributes to job requirements, which can limit their applicability in other contexts. Other studies de-

[1] See for example Autor, Levy, and Murnane (2003); Ingram and Neumann (2006); Poletaev and Robinson (2008); Gathmann and Schönberg (2010); Bacolod and Blum (2010); Rendall (2025); Yamaguchi (2012); Autor and Handel (2013); Deming (2017); Deming and Noray (2020); Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2020); Edmond and Mongey (2021).

fine mismatch empirically as gaps between entrants and incumbents (Fredriksson, Hensvik, and Skans, 2018), or between workers and their peers (Groes, Kircher, and Manovskii, 2015). Our paper offers an alternative framework that defines mismatch through the observed wage returns to major–occupation pairs, allowing us to estimate the efficiency loss from deviation from optimal sorting, even in the absence of fine-grained task data. This approach is analogous to the misallocation literature that infers wedges from observed group trends/outcomes (Hsieh and Klenow, 2009; Hsieh, Hurst, Jones, and Klenow, 2019).

A second related strand of literature focuses on the estimation of occupational returns using structural models of occupational choice, particularly the Roy model (Roy, 1951). This literature emphasizes the role of self-selection and comparative advantage in shaping observed wage outcomes (French, Taber, et al., 2011), and has developed methods to address high-dimensional selection problems using control function approaches (Lee, 1983; Dahl, 2002). More recently, Eckardt (2019) extends the Roy framework to analyze training–occupation mismatch in the German apprenticeship system. Our paper builds on this tradition by estimating a Roy model of occupational choice based on college major, and using it to construct a mismatch measure that adjusts for selection. We then extend this analysis into general equilibrium, embedding our estimates into a nested CES production framework to evaluate the aggregate implications of observed mismatch. In this sense, our paper bridges micro-level structural modeling with macro-level general equilibrium evaluation—an approach that remains rare in the mismatch literature.

Finally, our work contributes to a growing literature on the returns to college major. Much of this research focuses on estimating the causal effect of major choice on wages (Arcidiacono, 2004; Altonji, Kahn, and Speer, 2014; Kirkeboen, Leuven, and Mogstad, 2016), often emphasizing heterogeneity across majors and over time (Altonji, Blom, and Meghir, 2012; Altonji, Arcidiacono, and Maurel, 2016). A smaller subset of papers has examined how returns vary depending on whether individuals work in fields related to their training (Lemieux, 2014; Kinsler and Pavan, 2015). Liu, Salvanes, and Sørensen (2016), for instance, estimates returns to majors by industry and proposes an index-based mismatch measure for Norway.

Our paper differs in three key respects to the existing literature. First, we estimate returns to major–occupation combinations directly rather than ranking them by average earnings or matching task with skills. Second, our mismatch measure accounts for selection using a structural model. Third, we evaluate the general equilibrium consequences of mismatch, an aspect absent from existing studies of major-level returns. In doing so, we show how focusing solely on individual-level outcomes may overemphasize the need for policy intervention to correct mismatch in the economy. Instead our results suggest target policies towards recent graduates in specific fields may be most appropriate to balance both individual and aggregate welfare concerns.

The remainder of the paper is organized as follows. Section 2 outlines the framework used to study mismatch. Section 3 describes the specific ALife dataset. Section 4 discusses the estimation. Section 5 discusses the results. Finally, Section 6 concludes.

2 Skill Mismatch Framework

The economy consists of K intermediate firms, which are each defined by a unique occupation. Intermediate firms operate competitively using a CES production function and hire workers with different skills (from different college majors). Occupations produce a differentiated good that is aggregated to a final good with a CES production function. There is no capital in the economy. Workers choose the occupation that maximizes their utility based on the Roy model. Workers differ in their acquired skills - college majors. We take these skills as given and fixed. In this setting, we compare two allocation scenarios, (i) the optimal allocation under perfect mobility of labor across occupations and (ii) the allocation under imperfect mobility.

2.1 Model Components

Individual Wages Suppose that, after graduating from college, a worker enters the labor market and provides college-major-specific human capital $\tilde{h}^j_{i,t} = h^j a_i$, where h^j is a college-major-specific skill for which we assume $h^j = 1$ if the worker studied major j at college, and a_i is general labor efficiency units.[2] Let $\mathcal{J} = (1, \ldots, j, \ldots, J)$ represent the set of college majors. In any period t the individual chooses one occupation from the set $\mathcal{K} = (1, \ldots, k, \ldots, K)$. Income for an individual i with college major j, who works in occupation k is,

$$w_{i,j,k} = p^k_j \tilde{h}_i = p^k_j h^j a_i \tag{1}$$

where p^k_j is the price for major-j specific human capital in occupation k which equals the marginal product of labor. Taking the logarithm on both sides of Equation (1), we have an empirical specification to estimate returns to college majors:

$$\ln w_{i,j,k,t} = \sum_{j'}^{J} \sum_{k'}^{K} \underbrace{\beta^{k'}_{j'}}_{\ln p^{k'}_{j'}} D_{j',k'} + \ln(a_{i,t}) + \epsilon_{i,j,k,t} \tag{2}$$

[2]We also consider a robustness exercise where the efficiency unit, a_i depends on college-major a^j_i.

where $w_{i,j,k,t}$ is annual earnings, $\beta_{j'}^{k'}$ is the rate of return to major-j'-specific human capital in occupation k' (or logarithm of the price ($p_{j'}^{k'}$) of major j' in occupation k'), $D_{j',k'}$ is a dummy variable that takes 1 if $k' = k$ and $j' = j$, and $\epsilon_{i,j,k,t}$ is the error term.

Firms To determine the marginal product of labor, assume the economy's production function is a nested CES of major-occupation pairs.[3] We start with the intermediate production functions—the occupation-specific production functions. For each occupation k, we assume a CES production function that takes workers' skills, which are summarized by his/her major j, as inputs,

$$\begin{aligned} Y_t^k &= F^k(H_{1,t}^k, ..., H_{j,t}^k, ..., H_{J,t}^k) \\ &= A_{k,t}\left(\alpha_{1,t}^k\left(H_{1,t}^k\right)^{\sigma_k} + ... + \alpha_{j,t}^k\left(H_{j,t}^k\right)^{\sigma_k} + ... + \alpha_{J,t}^k\left(H_{J,t}^k\right)^{\sigma_k}\right)^{\frac{1}{\sigma_k}}, \end{aligned} \tag{3}$$

where $H_{j,t}^k = \sum_{i \in I^{j,k}} \tilde{h}_{i,t}$ is the supply of labor efficiency units of individuals with college major j to occupation k in year t, with $I^{j,k}$ the set of indexes for the individuals with major j in occupation k. Note that majors summarize different bundles of skills, where $\left(\alpha_1^k, \alpha_2^k, ..., \alpha_J^k\right)$ are the weights for all majors and σ^k is the substitution parameter across majors, all of which are occupation-specific.

The competitive final good producer then aggregates occupational outputs Y^k with a CES production function,

$$\begin{aligned} Y_t &= F\left(Y_t^1, \ldots, Y_t^k, \ldots, Y_t^K\right) \\ &= A_t\left(\alpha_{1,t}\left(Y_t^1\right)^{\sigma} + ... + \alpha_{k,t}\left(Y_t^k\right)^{\sigma} + ... + \alpha_{K,t}\left(Y_t^K\right)^{\sigma}\right)^{\frac{1}{\sigma}}, \end{aligned} \tag{4}$$

where $\left(\alpha_1, \alpha_2, ..., \alpha_J\right)$ are the weights for all occupations and σ is the substitution parameter across occupations.

The marginal product of labor in occupation k for college major j is,

$$p_j^k = \frac{\partial Y_t}{\partial Y_t^k}\frac{\partial Y_t^k}{\partial H_{j,t}^k} = \alpha_{k,t} A_t Y_t^{1-\sigma}\left(\sum_{j=1}^{J}\alpha_{j,t}^k\left(H_{j,t}^k\right)^{\sigma_k}\right)^{\frac{\sigma}{\sigma_k}-1}\alpha_{j,t}^k\left(H_{j,t}^k\right)^{\sigma_k - 1}, \tag{5}$$

Optimal Allocation under Perfect Mobility We first discuss an economy with perfect mobility across occupations and no tastes of individual workers for occupations. In this case,

[3] We focus only on the production function of college graduates. We could further assume a final goods sector aggregating university and non-university labor. This, however, will not affect the results of the analysis as long as university and non-university labor is separable and aggregated in the final CES goods sector only.

workers move across occupations to maximize their wages, which equalizes prices for major-specific human capital. Therefore, conditional on college majors, workers' earnings only differ in their efficiency units of labor which are common across occupations.

Individual i, who graduates in major j, chooses occupation k in calendar year t to maximize utility, $U_{i,j,t}$, or equivalently maximizes income,

$$U_{i,j,t} = \max\left\{w_{i,j,1,t}, \ldots, w_{i,j,k,t}, \ldots, w_{i,j,K,t}\right\} \tag{6}$$

Thus, the labor supply to an occupation is infinitely elastic. Workers will relocate to the occupation with the highest marginal product until marginal products conditional on college major equalize across occupations,

$$\frac{\frac{\partial Y_t}{\partial Y_t^{k'}} \frac{\partial Y_t^{k'}}{\partial H_{j,t}^{k'}}}{\frac{\partial Y_t}{\partial Y_t^{k}} \frac{\partial Y_t^{k}}{\partial H_{j,t}^{k}}} = \frac{\alpha_{k',t}\left(\sum_{j=1}^{J} \alpha_{j,t}^{k'} \left(H_{j,t}^{k'}\right)^{\sigma_{k'}}\right)^{\frac{\sigma}{\sigma_{k'}}-1} \alpha_{j,t}^{k'} \left(H_{j,t}^{k'}\right)^{\sigma_{k'}-1}}{\alpha_{k,t}\left(\sum_{j=1}^{J} \alpha_{j,t}^{k} \left(H_{j,t}^{k}\right)^{\sigma_{k}}\right)^{\frac{\sigma}{\sigma_{k}}-1} \alpha_{j,t}^{k} \left(H_{j,t}^{k}\right)^{\sigma_{k}-1}} = 1. \tag{7}$$

Optimal Allocation under Imperfect Labor Mobility Relaxing the assumption of perfect mobility, we now assume that workers experience non-pecuniary utility shocks across occupations. These shocks capture factors such as search or informational frictions, occupational licensing barriers, non-pecuniary occupational amenities, and individual-specific preferences for certain occupations. The utility, $U_{i,(k|j),t}$ of choosing occupation k given major j is now determined by earnings $w_{i,j,k,t}$ and non-pecuniary utility shock $\eta_{i,(k|j),t}$ received from unobserved occupational characteristics,

$$U_{i,(k|j),c,r,t} = \underbrace{w_{i,j,k,t}}_{\text{Earnings}} + \underbrace{\eta_{i,(k|j),t}}_{\text{Non-Pecuniary Utility}} \qquad \text{for each } j \in \{1,...,J\}. \tag{8}$$

A larger $\eta_{i,(k|j),t}$ means that a worker has a particular taste for occupation k. Alternatively, $\eta_{i,(k|j),t}$ could also represent labor market frictions faced by the individual or alternatively a combination of the two – tastes and frictions. Irrespective of the origin of η, workers pick the occupation where their utility $U_{i,j,t}$ is maximized,

$$U_{i,j,t} = \max\left\{U_{i,(1|j),t}, \ldots, U_{i,(k|j),t}, \ldots, U_{i,(K|j),t}\right\}. \tag{9}$$

The key difference now is that the marginal products of labor, conditional on a college major, do not necessarily equalize any longer, as only the *marginal* worker will be indifferent between different occupation choices,

$$\frac{\frac{\partial Y_t}{\partial Y_t^{k'}}\frac{\partial Y_t^{k'}}{\partial H_{j,t}^{k'}}}{\frac{\partial Y_t}{\partial Y_t^{k}}\frac{\partial Y_t^{k}}{\partial H_{j,t}^{k}}} = \frac{\alpha_{k',t}\left(\sum_{j=1}^{J}\alpha_{j,t}^{k'}\left(H_{j,t}^{k'}\right)^{\sigma_{k'}}\right)^{\frac{\sigma}{\sigma_{k'}}-1}\alpha_{j,t}^{k'}\left(H_{j,t}^{k'}\right)^{\sigma_{k'}-1}}{\alpha_{k,t}\left(\sum_{j=1}^{J}\alpha_{j,t}^{k}\left(H_{j,t}^{k}\right)^{\sigma_{k}}\right)^{\frac{\sigma}{\sigma_{k}}-1}\alpha_{j,t}^{k}\left(H_{j,t}^{k}\right)^{\sigma_{k}-1}} = \frac{p_j^{k'}}{p_j^{k}}. \tag{10}$$

2.2 Skill Mismatch Measures

We define skill mismatch both at the individual level and the aggregate economy. We measure individual (partial-equilibrium) mismatch as wage gains by reallocating workers across occupations while keeping returns fixed. Second, we measure aggregate mismatch as output gains in a general equilibrium set-up where prices adjust when workers relocate across occupations.

As it is impossible to disentangle taste from labor market frictions, we consider the extreme cases where imperfect mobility is driven exclusively by frictions. From an individual and social welfare perspective if imperfect mobility is entirely driven by frictions, removing these frictions will be welfare improving. Thus, it suffices to compare the effect of relocating workers across occupations to achieve the perfect mobility outcome (see Equation (7)). This bounds our skill mismatch results from above. In contrast, if imperfect mobility is entirely driven by taste relocating workers across occupations will not lead to any Pareto improvement when considering individuals' welfare - the lower bound on the cost of skill mismatch is zero.

Individual Mismatch If skills acquired in college major j earn the highest wage reward in occupation $k^*(j)$, we refer to this as the *top*-occupation for major j. The wage return to the combination of college major j and occupation k is captured by p_j^k. Thus, $p^* \equiv p_j^{k^*(j)}$ is the return to a top-match, while all remaining p_j^ks are wage returns to other matches. Suppressing time subscripts, we define average individual *within* major-occupation mismatch for major j as,

$$m_j = \frac{\sum_{i\in I^j} p^*\tilde{h}_i - \sum_{i\in I^j} p_j^k\tilde{h}_i}{\sum_{i\in I^j} p_j^k\tilde{h}_i}, \tag{11}$$

where I^j and I are the set of indexes for the individuals with major j and the set of all the individuals in the economy, respectively. Equation (11) calculates major-specific mismatch with fixed returns as average individual wage gains by allocating workers with major j to their top-occupation $k^*(j)$, relative to the total wages of workers with the same major j in the economy.

Having defined major-specific mismatch measure, the economy-wide individual mismatch can be defined as,

$$\mathcal{M} = \frac{\sum_{i\in I} p^* \tilde{h}_i - \sum_{i\in I} p_j^k \tilde{h}_i}{\sum_{i\in I} p_j^k \tilde{h}_i}, \tag{12}$$

average individual wage gains by allocating all workers to their top-occupation $k^*(j)$, relative to the total wages of all workers in the economy. This rate represents the average potential gains for all individuals if they were to *switch* to their top-occupation conditional on majors. By assumption returns $\{p_j^k\}$ are fixed even after the reallocation of workers. In reality, the reallocation of talent across occupations will result in a change in returns.

General-Equilibrium Mismatch In general equilibrium, with frictions, the social planner will maximize societal income conditional on college major j for all individuals i,

$$\sum_i^I \max\{w_{i,k|j,t}\}_k \tag{13}$$

subject to the production functions (3) and (4). Thus workers will be relocated until Equation (7) is satisfied. Firstly, define the frictionless allocation of workers to occupations in year t as $\hat{\mathbf{H}}_t^k = \left(\hat{H}_{1,t}^k, ..., \hat{H}_{j,t}^k, ...\hat{H}_{J,t}^k\right)$ for all $k \in \mathcal{K}$. Obtaining the frictionless allocation $\hat{\mathbf{H}}_t^k$ for all occupations jointly requires solving $K\times J$ unknowns or the solution of the following $(K-1)\times J + J = K\times J$ equations,

$$\frac{\frac{\partial Y_t}{\partial Y_t^{k'}} \frac{\partial Y_t^{k'}}{\partial \hat{H}_{j,t}^{k'}}}{\frac{\partial Y_t}{\partial Y_t^{k}} \frac{\partial Y_t^{k}}{\partial \hat{H}_{j,t}^{k}}} = \frac{\alpha_{k',t}\left(\sum_{j=1}^J \alpha_{j,t}^{k'}\left(\hat{H}_{j,t}^{k'}\right)^{\sigma_{k'}}\right)^{\frac{\sigma}{\sigma_{k'}}-1} \alpha_{j,t}^{k'}\left(\hat{H}_{j,t}^{k'}\right)^{\sigma_{k'}-1}}{\alpha_{k,t}\left(\sum_{j=1}^J \alpha_{j,t}^{k}\left(\hat{H}_{j,t}^{k}\right)^{\sigma_{k}}\right)^{\frac{\sigma}{\sigma_{k}}-1} \alpha_{j,t}^{k}\left(\hat{H}_{j,t}^{k}\right)^{\sigma_{k}-1}} = 1, \tag{14}$$

and

$$\hat{H}_{j,t}^1 + ... + \hat{H}_{j,t}^k + ... + \hat{H}_{j,t}^K = \bar{H}_{j,t}, \quad \forall j \in \mathcal{J}, \quad \forall k \in \mathcal{K}, \tag{15}$$

where relative returns within major j across all occupations equal in equilibrium (see Equation (14)); and a market clearing condition that the optimal amount of labor across occupations within each major j equals the total supply of labor in major j, $\bar{H}_{j,t}$ (see Equation (15)). Equation (14) implicitly assumes that in a world without frictions or asymmetric information, all occupations should pay the same conditional on major. Denote the price in the optimal allocation in the general equilibrium as

$$\hat{p}_j^k = \frac{\partial Y_t}{\partial H_{j,t}^{k'}}\left(\hat{\mathbf{H}}_t^1, ..., \hat{\mathbf{H}}_t^K\right). \tag{16}$$

In the optimal allocation, the returns to each major are the same across occupations. Thus, we can define a unique price for each major j as

$$\hat{p}_j \equiv \hat{p}_j^1 = \ldots = \hat{p}_j^K. \tag{17}$$

Then, the general equilibrium mismatch for major j is defined as

$$m_j^{GE} = \frac{\sum_{i \in I^j} \hat{p}_j \tilde{h}_i - \sum_{i \in I^j} p_j^k \tilde{h}_i}{\sum_{i \in I^j} p_j^k \tilde{h}_i}. \tag{18}$$

The aggregate general equilibrium mismatch can be defined as

$$\mathcal{M}^{GE} = \frac{\sum_{i \in I} \hat{p}_j \tilde{h}_i - \sum_{i \in I} p_j^k \tilde{h}_i}{\sum_{i \in I} p_j^k \tilde{h}_i}. \tag{19}$$

The above definition represents the potential gains by moving to the frictionless allocations.[4] The concept is equivalent to the partial equilibrium mismatch, but with endogenous prices.

3 Data

We make use of the ALife dataset, a longitudinal dataset administered by the Australian Tax Office (ATO) (Carter et al., 2021). ALife contains an extract of personal income tax records from 1991 to 2019 for a 10 percent representative sample. The data provide accurate and detailed information on variables that are required to estimate individual tax liabilities. It collates employer records, salary information, and self-reported data from taxpayers. ALife, given Australian tertiary financing policies, can also be merged with details on Higher Education loan information or the study records of terminal degrees.[5]

Given the administrative nature of ALife, the data has very little attrition, with on average, 96.5 percent of tax filers who lodge in a given year also lodge in the subsequent income year (Carter et al., 2021). The dataset contains around 300 variables from individual tax records, including some constructed variables, such as the presence of a spouse. Demographic infor-

[4]The aggregate mismatch measure can be also defined as

$$\mathcal{M}_t^{GE} = \frac{F\left(F^1\left(\hat{\mathbf{H}}_t^1\right), \ldots, F^K\left(\hat{\mathbf{H}}_t^K\right)\right) - F\left(F^1\left(\mathbf{H}_t^1\right), \ldots, F^K\left(\mathbf{H}_t^K\right)\right)}{F\left(F^1\left(\mathbf{H}_t^1\right), \ldots, F^K\left(\mathbf{H}_t^K\right)\right)}, \tag{20}$$

where $\mathbf{H}_t^k = \left(H_{1,t}^k, \ldots, H_{j,t}^k, \ldots H_{J,t}^k\right)$ represents the current allocation of majors across occupations.

[5]For additional data details see Appendix A.

mation includes age at 30 June of a given year, gender, residential location, occupation, and whether the tax filer is a non-resident for tax purposes. A caveat, given that occupation information, is self-reported and prefilled in later tax years when the tax filing system moved to a predominantly online reporting basis, there is potential for misreporting and limited occupation switching (Hathorne and Breunig, 2022). To ameliorate the potential noise in occupation information, we restrict our sample to college-educated individuals aged 21 to 35.[6] We also restrict the sample to the workers who only choose one specific major in college. This implicitly assumes that each individual has only one *top*-occupation which is solely determined by his/her unique college major.[7]

Table 1: Summary Statistics of Occupation Share by Major

	Occupations by Major									
	Share			Switch-in			Stay			
2-digit ASCED Major	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	No.Occ
Natural and Physical Sciences	0.038	0.005	0.325	0.005	0.001	0.026	0.034	0.004	0.299	26
Information Technology	0.050	0.004	0.471	0.006	0.001	0.036	0.044	0.004	0.435	20
Engineering and Related Technologies	0.042	0.002	0.582	0.003	0.000	0.022	0.039	0.001	0.561	24
Architecture and Building	0.062	0.012	0.443	0.005	0.001	0.023	0.058	0.010	0.420	16
Agriculture, Environmental and Related Studies	0.043	0.008	0.349	0.005	0.001	0.024	0.038	0.006	0.325	23
Health	0.037	0.001	0.654	0.002	0.000	0.019	0.035	0.001	0.635	27
Education	0.037	0.002	0.696	0.002	0.000	0.020	0.035	0.001	0.676	27
Management and Commerce	0.037	0.003	0.397	0.004	0.001	0.029	0.033	0.002	0.368	27
Society and Culture	0.037	0.005	0.240	0.004	0.001	0.017	0.033	0.004	0.223	27
Creative Arts	0.037	0.002	0.130	0.005	0.001	0.019	0.032	0.002	0.118	27

Notes: This table shows the summary statistics of the occupational share for each field of study. Columns (2)-(4) show the mean, minimum, and maximum of the occupational share within the field in the corresponding row. Columns (5)-(7) show the mean, minimum, and maximum of the share of staying in the observed occupation from the previous period. Columns (8)-(10) show the the mean, minimum, and maximum of switching into the observed occupation from the previous period. Column (11) show the number of occupations within the field. The product of the mean occupational share and number of occupations within the field is not 1, since estimation sample removes the field-by-occupation cells that contain less than 100 observations.

Table 1 provides a snapshot of college majors in our data. We consider all 11 ASCED 2-digit college majors, while occupations are classified based on 2-digit ANZSCO codes. The last column shows the number of occupations within each field, while the second column shows the average of occupational shares within each major. We also report the share of individuals switching into occupations over time and the share that are stayers by occupation within their major.

As shown in Table 1, number of occupations has a large variance across majors. Management and Commerce, and Society and Culture majors match to 27 occupations, while Food,

[6] Hathorne and Breunig (2022) report similar findings across HILDA, a national representative sample, and ALife for the age group 25 to 38.

[7] Our results show that the proportion of workers with more than one major as classified under the 2-digit ASCED fields of study account for 19.6 percent of all workers.

Hospitality, and Personal Services majors match to only 11 occupations. The majors with the lowest switching shares are Education and Health (as seen in column 5), consistent with the notion that educational and medical occupations are highly regulated and require specialized skills.

Observing large heterogeneity across fields of study in the number of occupational matches, employment shares, and switches, we study wage penalties from working in an occupation relative to the *top*-occupation of an individual's major. There are potentially many ways of defining the *top*-occupation. In our baseline, we use both wage and share information—by ranking occupations within fields of study by their wages subject to having at least a 10 percent share of major-specific graduates under consideration. We define the *top*-occupation as the occupation with the highest average wage among this set.[8] We use the 10 percent share, as the goal is not comparing mismatch relative to a *superstar*, but relative to a typical college graduate.

Table 2: Summary Statistics of Top Occupation by Major

		Share of Occ. by Field			
2-digit ASCED Major	Top-Occupation	Total	Stay	Switch-in	Earnings
Natural and Physical Sciences	Design, Engineering, Science and Transport Professionals	0.325	0.299	0.026	76,348
Information Technology	ICT Professionals	0.471	0.435	0.036	87,449
Engineering and Related Technologies	Design, Engineering, Science and Transport Professionals	0.582	0.561	0.022	94,139
Architecture and Building	Engineering, Ict and Science Technicians	0.136	0.123	0.013	72,533
Agriculture, Environmental and Related Studies	Design, Engineering, Science and Transport Professionals	0.349	0.325	0.024	76,476
Health	Health Professionals	0.654	0.635	0.019	69,172
Education	Education Professionals	0.696	0.676	0.020	65,211
Management and Commerce	Business, Human Resource and Marketing Professionals	0.397	0.368	0.029	85,057
Society and Culture	Legal, Social and Welfare Professionals	0.240	0.223	0.017	74,620
Creative Arts	Business, Human Resource and Marketing Professionals	0.106	0.088	0.019	69,335

Notes: This table shows the summary statistics of the top occupational for each field of study. Column (3) shows the share of top occupation of the field in the corresponding row. Column (4) shows the share of staying in the top occupation from the previous period. Column (5) shows the share of switching into the top occupation from the previous period. Column (6) shows the mean earnings in the field-by-occupation combination.

Table 2 shows the top occupation by major and their employment share within a major. We also decompose the share by the share of stayers and switchers. The last column reports average yearly earnings of *top*-occupations. Comparing "Switch-in" columns between Table 2 and Table 1, the *top*-occupation is typically also the occupation that workers are most likely to switch in.

[8] We also perform robustness by: (1) ranking occupations based on the highest wage returns within majors with at least 5 percent share of graduates, and (2) based only on the highest wage returns within majors, and (3) based only on their highest share of employment within majors. *Top*-occupations remain largely unchanged in these permutations.

4 Estimation

The estimation has two parts: (1) estimating the returns to college majors by occupation, and (2) estimating the production function parameters. The second part requires us to have consistent estimates of the returns to college majors by occupation.

4.1 Returns to College Majors

To allow us to capture some of the richness in the data when estimating college returns, we introduce further characteristics to individual efficiency units of labor, a_i, in Equation (1). Suppose that, after graduating from college, a worker enters the labor market and provides college-major-specific human capital. His/her wage equation is then

$$w_{i,j,k,r,c,t} = p^k_{j,t}\tilde{h}^j_{i,t} = p^k_{j,t}h^j a_{i,t} = p^k_{j,t}h^j e^{X_{i,t}\gamma+\lambda_{r,t}+\nu_c+\epsilon_{i,j,k,c,r,t}}, \quad (21)$$

where individual abilities is defined by, $X_{i,t}$ a vector of time-varying individual characteristics in year t, $\lambda_{r,t}$ a region-by-year specific productivity, and ν_c a graduate-cohort specific productivity, and an idiosyncratic productivity shock $\epsilon_{i,j,k,c,r,t}$.

4.1.1 Occupational Choice Model conditional on College Major

Expanding on the occupation choice model from Equation (8), individual i, who graduates in major j of cohort c, chooses occupation k in calendar year t. The overall utility of choosing occupation k given major j is determined by log earnings $w_{i,j,k,c,r,t}$ and non-pecuniary utility $\eta_{i,(k|j),c,r,t}$ received from unobserved occupational characteristics (i.e., working conditions, taste, etc.). The utility from Equation (8) can be rewritten in terms of a conditional mean $\tilde{U}_{i,(k|j),c,r,t}$ and an individual-specific shock $e_{i,(k|j),c,r,t}$ such that,

$$\begin{aligned} U_{i,(k|j),c,r,t} &= \underbrace{w_{i,j,k,c,r,t}}_{\text{Log Earnings}} + \underbrace{\eta_{i,(k|j),c,r,t}}_{\text{Non-pecuniary Utility}} \qquad \text{for each } j \in \{1,\dots,J\} \quad (22)\\ &= \underbrace{\tilde{U}_{i,(k|j),c,r,t}}_{\text{Conditional Mean}} + \underbrace{e_{i,(k|j),c,r,t}}_{\text{Shock}} \\ &= \underbrace{E[w_{i,j,k,c,r,t}|W_{i,t}] + E(\eta_{i,(k|j),c,r,t}|W_{i,t})}_{\text{Conditional Mean: } \tilde{U}_{i,(k|j),c,r,t}} + \overbrace{\underbrace{\epsilon_{i,j,k,c,r,t}}_{\substack{\text{Errors in}\\ \text{Earnings Equation}}} + \underbrace{\kappa_{i,(k|j),c,r,t}}_{\substack{\text{Non-pecuniary Utility}\\ \text{Shock}}}}^{\text{Shock: } e_{i,(k|j),c,r,t}}, \end{aligned}$$

where $\tilde{U}_{i,(k|j),c,r,t}$ is the utility conditional on $W_{i,t}$, which includes a vector of individual observed characteristics by calendar year t and any exclusion restrictions for identifying the occupation preference from earnings. Utility shock of occupational choice $e_{i,(k|j),c,r,t}$ consists of earnings shock $\epsilon_{i,j,k,c,r,t}$ and non-pecuniary utility shock $\kappa_{i,(k|j),c,r,t}$. For maximizing the utility, individual i chooses occupation k in year t if and only if $U_{i,(k|j),c,r,t} \geqslant U_{i,(k'|j),c,r,t}$; $\forall\, k' \neq k$. We use indicator $M_{i,(k|j),c,r,t}$ to denote the event that we observe an individual who chooses occupation k given major j so that,

$$M_{i,(k|j),c,r,t} = 1 \text{ iff } e_{i,(k'|j),c,r,t} - e_{i,(k|j),c,r,t} \leqslant \tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(k'|j),c,r,t};\ \forall\, k' \neq k. \tag{23}$$

4.1.2 Correct Selection Bias: Parametric Correction Function

Specifically, individuals are observed in an j,k cell if and only if the rule (23), conditional on major j, is satisfied. There is potential selection bias—$E[\epsilon_{i,j,k,c,r,t}|M_{i,(k|j),c,r,t} = 1] \neq 0$, as the unexplained factor $\epsilon_{i,j,k,c,r,t}$ can be correlated with unobserved factors that are deterministic for the observations to appear in (j,k) cell. Directly using condition (23) to pin down the selectivity bias is infeasible because a complete specification of the joint distribution of error terms in the wage equation and error terms in K selection equations for each major j would be necessary, where K is the number of occupations for major j to choose. We follow the approach by Lee (1983) and Dahl (2002) to correct for the sample selection bias for observations in j,k cell by controlling for the correction function of selection probability—$g(\hat{p}_{i,j,k,c,r,t})$, where $\hat{p}_{i,j,k,c,r,t}$ is the estimated probability of choosing the observed occupation k conditional on graduating from major j, and $g(x)$ has a known inverse Mills ratio of the form: $\frac{-\phi(\Phi^{-1}(x))}{x}$. Details of the derivation of the selectivity bias can be found in Appendix B.1.

To this end, the expectation of log earnings after correcting for the selectivity bias becomes,

$$\begin{aligned} E[\ln w_{i,j,k,c,r,t}|M_{i,(k|j),c,r,t} = 1] \\ &= \sum_{j'}^{J}\sum_{k'}^{K}\beta_{j'}^{k'}D_{j',k'} + X_{i,t}\gamma + \lambda_{r',t'} + \nu_{c'} + \iota_{i'} + E[\epsilon_{i,j,k,c,r,t}|M_{i,(k|j),c,r,t} = 1] \\ &= \sum_{j'}^{J}\sum_{k'}^{K}\beta_{j'}^{k'}D_{j',k'} + X_{i,t}\gamma + \lambda_{r',t'} + \nu_{c'} + \iota_{i'} + \sum_{j'}^{J}\sum_{k'}^{K}\rho_{j'}^{k'} \cdot g(\hat{p}_{i,j,k,c,r,t}), \end{aligned} \tag{24}$$

where $w_{i,j,k,r,t}$ is annual earnings, $\beta_{j'}^{k'}$ is the rate of return to major-j'-specific human capital in occupation k' (or logarithm of the price ($p_{j'}^{k'}$) of major j' in occupation k'), $D_{j',k'}$ is a dummy variable that takes 1 if $k' = k$ and $j' = j$, and $\epsilon_{i,j,k,c,r,t}$ is the error term. Depending on the specification we allow returns to vary by region and/or year.

The earnings model that is corrected for selection bias becomes,

$$\ln w_{i,j,k,c,r,t} = \sum_{j'}^{J} \sum_{k'}^{K} \beta_{j'}^{k'} D_{j',k'} + X_{i,t}\gamma + \lambda_{r',t'} + \nu_{c'} + \iota_{i'} + \sum_{j'}^{J} \sum_{k'}^{K} \rho_{j'}^{k'} \cdot g(\hat{p}_{i,j,k,c,r,t}) + \xi_{i,j,k,c,r,t}$$
$$\text{where } E[\xi_{i,j,k,c,r,t} | M_{i,(k|j),c,r,t} = 1] = 0, \quad (25)$$

where $g(\hat{p}_{i,j,k,c,r,t})$ is the selection correction function for individuals appearing in cell j,k, with a known functional form of the single estimator $\hat{p}_{i,j,k,c,r,t}$. In total, we use $J \times K$ correction functions, with the effect of each one on log earnings captured by the j,k specific parameter, $\rho_{j,k}$.

As the occupation choice set varies considerably across majors (see Table 1), to make estimation feasible, we reduce the number of correction functions into $J \times 10$. Specifically, for all individuals with major j, we partition the entire observed (major-specific) occupational set into ordered 10 sets based on the descending order of occupational share within the major: with (1) the first set comprising the *top*-occupation for major j (i.e., the occupation with the highest wage conditional on a 10 percent share of the major j); and (2) the remaining nine even sets of occupations for major j, ordered with a decrease of the occupational share to major j.[9] We estimate the individual's occupational choice probabilities conditional on the field of study j with the individual characteristics and an exclusion restriction—a one period lagged of local market demand shock—by a random forest algorithm (see Appendix B.2 for more detail).[10]

4.2 Estimating Production Function Parameters

To solve for the frictionless allocation through Equations (14) and (15), and to define the mismatch measures through Equation (19), we need to know the parameter values of the production function. We first derive the reduced-form expressions from the first-order conditions of

[9]Occupations are approximately evenly placed in each set based on the descending order of occupational share within the major, so that the second occupation set is more major-related than the third set, so on so forth. We also perform robustness exercises with 8 and 12 occupation groups, respectively. For the major of 'Food, Hospitality and Personal Services', there are in total 11 occupations in the sample, and thus there are 11 sets in total in robustness check, in which a 12-occupation-group partition is conducted. Results are similar across the three versions.

[10]In a robustness exercise we also consider a version with individual fixed effects, ι_i, such that human capital equals, $\tilde{h}_{i,t}^{j} = h^j e^{X_{i,t}\gamma + \lambda_{r,t} + \nu_c + \iota_i}$. in Equation (1). When estimating Equation (25) with individual fixed effects, major-occupation returns are identified from individuals that switch occupations at least once in their life (roughly one-third of our sample, and smaller for skill-specific majors such as Education and Health). To recover all returns, β_j^ks, and individual fixed effects, ιs, we estimate relative returns by college major and then recover absolute returns, such that $\beta_j^1 = \sum_i \frac{\iota_i}{N_j}$, where N_j are all individuals who studied major j and $\beta_j^k = \sum_i \frac{\iota_i}{N_j} + \beta_j^k$ for all $k > 1$.Individual fixed effects that feed into $\tilde{h}_{i,t}$ (see Equation (1)) are thus demeaned, $\hat{\iota}_i = \iota_i - \sum_i \frac{\iota_i}{N_j}$.

the representative firm profit maximization problem. We then exploit the region-time variations to estimate the production function parameters.

4.2.1 Deriving the Reduced Form Expressions

We take the first-order condition for Equation (3) that yields,

$$\frac{p^k_{j',r,t}}{p^k_{j,r,t}} = \frac{\partial F^k/\partial H^k_{j',r,t}}{\partial F^k/\partial H^k_{j,r,t}} = \frac{\alpha^k_{j',t}}{\alpha^k_{j,t}}\left(\frac{H^k_{j',r,t}}{H^k_{j,r,t}}\right)^{\sigma^k-1}. \tag{26}$$

Taking the logarithm on both sides yields,

$$\underbrace{\ln\left(p^k_{j',r,t}/p^k_{j,r,t}\right)}_{\beta^k_{j',r,t}-\beta^k_{j,r,t}} = \ln\left(\alpha^k_{j',t}/\alpha^k_{j,t}\right) + \left(\sigma^k-1\right)\ln\left(H^k_{j',r,t}/H^k_{j,r,t}\right). \tag{27}$$

Equation (27) is the first equation we estimate with the data.

Next, the first-order condition for Equation (4) is,

$$\frac{p_{k',r,t}}{p_{k,r,t}} = \frac{\partial F/\partial Y_{k'}}{\partial F/\partial Y_k} = \frac{\alpha_{k'}}{\alpha_k}\left(\frac{Y_{k',r,t}}{Y_{k,r,t}}\right)^{\sigma-1}. \tag{28}$$

By taking the logarithm of Equation (28), we obtain,

$$\ln\left(\frac{p_{k',r,t}}{p_{k,r,t}}\right) = \ln\left(\frac{\alpha_{k',t}}{\alpha_{k,t}}\right) + (\sigma-1)\ln\left(\frac{Y_{k',r,t}}{Y_{k,r,t}}\right), \tag{29}$$

where Y_k is given by Equation (3). Using the equilibrium profit condition, $p_{k,r,t}Y_{k,r,t} = \sum_j p^k_{j,r,t}H^k_{j,r,t}$, we solve for the price of occupation k in region r at time t,

$$p_{k,r,t} = \frac{1}{A_{k,t}}\left(\sum_j \left(\alpha^k_{j,t}\right)^{-\frac{1}{\sigma_k-1}}\left(p^k_{j,r,t}\right)^{\frac{\sigma_k}{\sigma_k-1}}\right)^{(1-\frac{1}{\sigma_k})}. \tag{30}$$

Substituting Equation (30) for Equation (29) yields,

$$\ln\left(\frac{\left(\sum_j \left(\alpha^{k'}_{j,t}\right)^{-\frac{1}{\sigma_{k'}-1}}\left(p^{k'}_{j,r,t}\right)^{\frac{\sigma_{k'}}{\sigma_{k'}-1}}\right)^{(1-\frac{1}{\sigma_{k'}})}}{\left(\sum_j \left(\alpha^{k}_{j,t}\right)^{-\frac{1}{\sigma_{k}-1}}\left(p^{k}_{j,r,t}\right)^{\frac{\sigma_{k}}{\sigma_{k}-1}}\right)^{(1-\frac{1}{\sigma_{k}})}}\right) = \ln\left(\frac{\alpha_{k',t}}{\alpha_{k,t}}\right) + \ln\left(\frac{A_{k',t}}{A_{k,t}}\right) + (\sigma-1)\ln\left(\frac{Y_{k',r,t}}{Y_{k,r,t}}\right). \tag{31}$$

This is the second equation we estimate.

Note technology parameters, $\ln\left(\frac{\alpha_{k',t}}{\alpha_{k,t}}\right)+\ln\left(\frac{A_{k',t}}{A_{k,t}}\right)$ are not separately identifiable, but this is not crucial for our exercise. A typical assumption in the literature (see Katz and Murphy (1992)) is to assume a linear time trend in technological change, e.g., the expression can be approximated by,

$$\ln\left(\frac{\alpha_{k',t}}{\alpha_{k,t}}\right)+\ln\left(\frac{A_{k,t}}{A_{k',t}}\right)=\gamma_{0,kk'}+\gamma_{1,kk'}t,$$

when using time-series data or simply $\gamma_{0,kk'}$ if using only cross-sectional variation. Note, throughout the analysis we assume that the production technologies are the same across all regions in Australia, but potentially vary over time.

4.2.2 Exploiting Time and Regional Variations

For the occupational-specific production functions, estimating parameters $\{\alpha_j^k\}$ and σ_k from Equation (29), we exploit variations in $p_{j'}^k$ and $H_{j'}^k$. For the aggregate production function, estimating $\{\alpha_k\}$ and σ from Equation (31), we again require variations in $Y^{k'}$ and $p^{k'}$. For the baseline estimation of the production function parameters, we assume $\{\alpha_j^k\}$, $\{\sigma_k\}$, $\{\alpha_k\}$, and σ are fixed across time and regions and exploit the region and year variations.

Due to the sampling limitations, we group years into 7 year groups to estimate Equations (29) and (31). Therefore, both general and partial equilibrium evolution in mismatches are computed by Equations (12) and (19) over 7 year groups for comparison purposes. We leave further detail of parameters estimation to Appendix C. Table D1 in Appendix C shows the estimation results for occupation-specific production function parameters. Our results on the elasticity of substitution between occupations, $\frac{1}{1-\sigma}=1.830$, are comparable to Burstein et al. (2019) and Caunedo et al. (2021), who estimate a model with capital.[11]

5 Results

We illustrate the results from our framework using Australian data. We mainly focus on individual life-cycle profiles to discuss and contrast findings from the literature so far, both with fixed returns and under our newly developed general equilibrium framework. We additionally show the aggregate evolution of mismatch over time and discuss what drives the observed trends within the context of Australia. These results together provide a broad picture of the usability of our measure and skill mismatch in the economy. They especially contrast the large difference between the general equilibrium and typical fixed-return framework, highlighting

[11] We conduct further robustness check by using the estimated elasticity of Caunedo et al. (2021), $\frac{1}{1-\sigma}=1.34$.

Table 3: Individual Major-Specific Mismatch

ASCED 2-digit	Major	OLS	S.E	Correction	S.E	GE
1	Natural and Physical Sciences	0.150	0.004	0.219	0.019	0.033
2	Information Technology	0.133	0.003	0.293	0.016	0.099
3	Engineering and Related Technologies	0.107	0.001	0.306	0.010	0.083
4	Architecture and Building	0.071	0.010	0.044	0.020	-0.009
5	Agriculture, Environmental and Related Studies	0.152	0.005	0.175	0.022	0.115
6	Health	0.056	0.001	0.054	0.004	0.055
7	Education	0.076	0.001	0.120	0.005	0.070
8	Management and Commerce	0.151	0.001	0.433	0.009	0.228
9	Society and Culture	0.199	0.003	0.397	0.019	0.119
10	Creative Arts	0.237	0.007	0.372	0.018	0.167
	Aggregate	0.127	0.003	0.270	0.012	0.125

Notes: This table shows the individual mismatch for each major. Column (3)-(4) show the mismatch estimates generated by OLS estimation approach and corresponding standard error. Column (5)-(6) show mismatch estimates generated by correction function estimation approach and corresponding standard error. Standard errors are computed using delta method. The last rows show the aggregated individual-level mismatch.

potential pitfalls in applying policies based on individual micro estimation.

5.1 Base Estimates

Table 3 shows average major-specific mismatch based on Equation (11) and overall mismatch in the aggregate economy based on Equation (12) for the average worker from 2003 to 2019, with standard errors calculated using the delta method.[12] Results shown are of both OLS and selection corrected returns, estimates of β_j^k, from Equation (25).[13] Comparing column 3 with column 5, we find that correcting for selection increases the average mismatch for typical STEM-related majors (in particular, Natural and Physical Sciences, Information Technology, and Engineering and related Technologies), Management and Commerce, Society and Culture, and Creative Arts. These are also the majors with large average mismatch. The estimated baseline mismatch in the aggregate economy, calculated using Equation (12), is 28.3 percent.

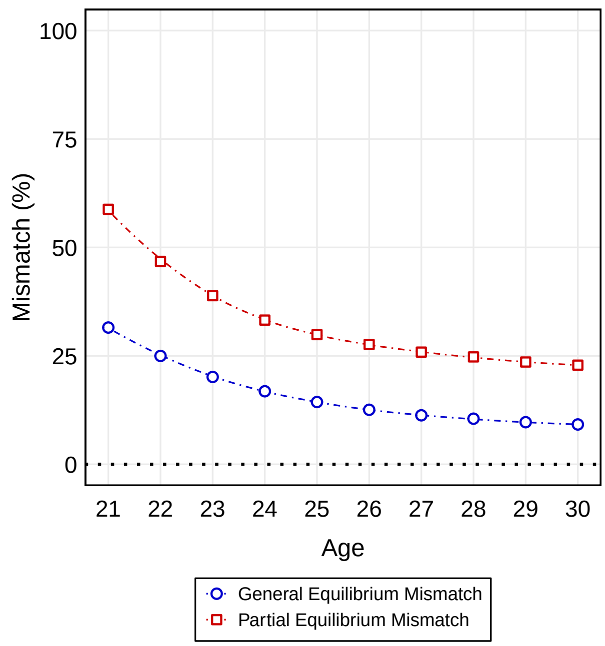
[12]Specifically, mismatch estimates in Equations (11) and (12) are functions of vector $\boldsymbol{\beta}$—i.e., $h(\boldsymbol{\beta})$, where $\boldsymbol{\beta} = (\beta_j^1, ..., \beta_j^{k^*}, ..., \beta_j^k)$. Based on the multivariate delta method, we compute the variance of $h(\boldsymbol{\beta})$ using, $Var(h(\boldsymbol{\beta})) = \nabla h(\boldsymbol{\beta})^T Cov(\boldsymbol{\beta}) \nabla h(\boldsymbol{\beta})$. To reduce the computational burden, we consider $\tilde{h}_i$ to be constant.

[13]In Appendix E we report all wage differences βs relative to the top-match occupation across college majors (see Figure F1). Based on these major-occupation returns, Section C, details the estimation procedure for the production parameters and Table D1 provides the estimated parameters.

5.2 Life-Cycle Skill Mismatch

The 28.3 percent wage loss due to skill mismatch represents a significant economic cost. Understanding how this burden is distributed across individuals is essential for designing effective policies aimed at talent reallocation or worker retraining. A thorough life-cycle analysis can shed light on these issues.

Figure 1: Life-cycle Mismatch in the General and Partial Equilibrium



Notes: This figure plots mismatch in the partial and general equilibrium using the Equations (12) and (18) over the life cycle.

We compute mismatch within each college major by age in two ways: (i) using Equation (11),[14] and (ii) using Equation (18), but substituting in equilibrium prices from Equation (17) after the reallocation of workers. While the average individual mismatch is 28.3 percent, the corresponding aggregate mismatch in general equilibrium over the same period, as defined in Equation (19), is 10.0 percent.[15]

Figure 1 displays aggregate life-cycle mismatch. Figure 2 shows results disaggregated by four major groups: Panel A reports life-cycle mismatch under fixed returns, and Panel B shows general equilibrium results.[16] Several striking patterns emerge from these three figures. First,

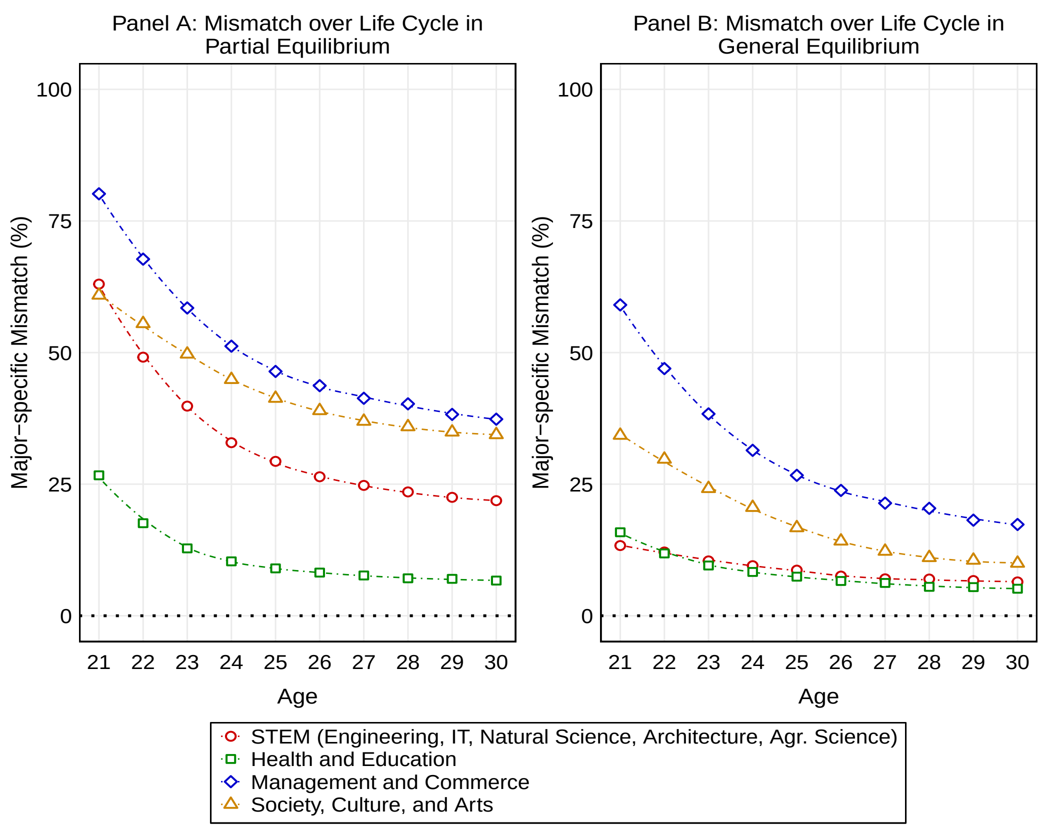
[14]Specifically, we compute mismatch for workers who studied major j and worked at age a, that is, replacing $i \in I^j$ with $i \in I_a^j$ in Equation (11).

[15]These baseline general equilibrium mismatch estimates assume a production function with linear time trends in production shares—i.e., α_j^k and α_k vary linearly over time. For details on the estimation procedure, see Appendix C.

[16]For readability of the figure, we aggregate 11 ASCED 2-digit majors into 5 major groups: (1) STEM-related

in general equilibrium, the cost of skill mismatch is substantially smaller—both in aggregate and across all majors except Health and Education. Second, skill mismatch declines below 10% by age 30 across all majors. Under fixed prices (Panel A), STEM; Management and Commerce; and Society, Culture, and Arts majors exhibit the highest mismatch at age 21 (typical graduation age), but mismatch decreases considerably with age. In contrast, Health and Education majors consistently exhibit less than half the mismatch seen in Commerce, Social Science, and Arts majors. Moreover, mismatch declines more gradually over the life cycle for Health and Education majors compared to the steeper decline observed in other fields. Comparing Panels A and B, mismatch is roughly 25 percentage points higher at most ages for STEM; Management and Commerce; and Society, Culture, and Arts majors under fixed returns.

Figure 2: The Major-Specific Mismatch in Partial and General Equilibrium over the Life-Cycle



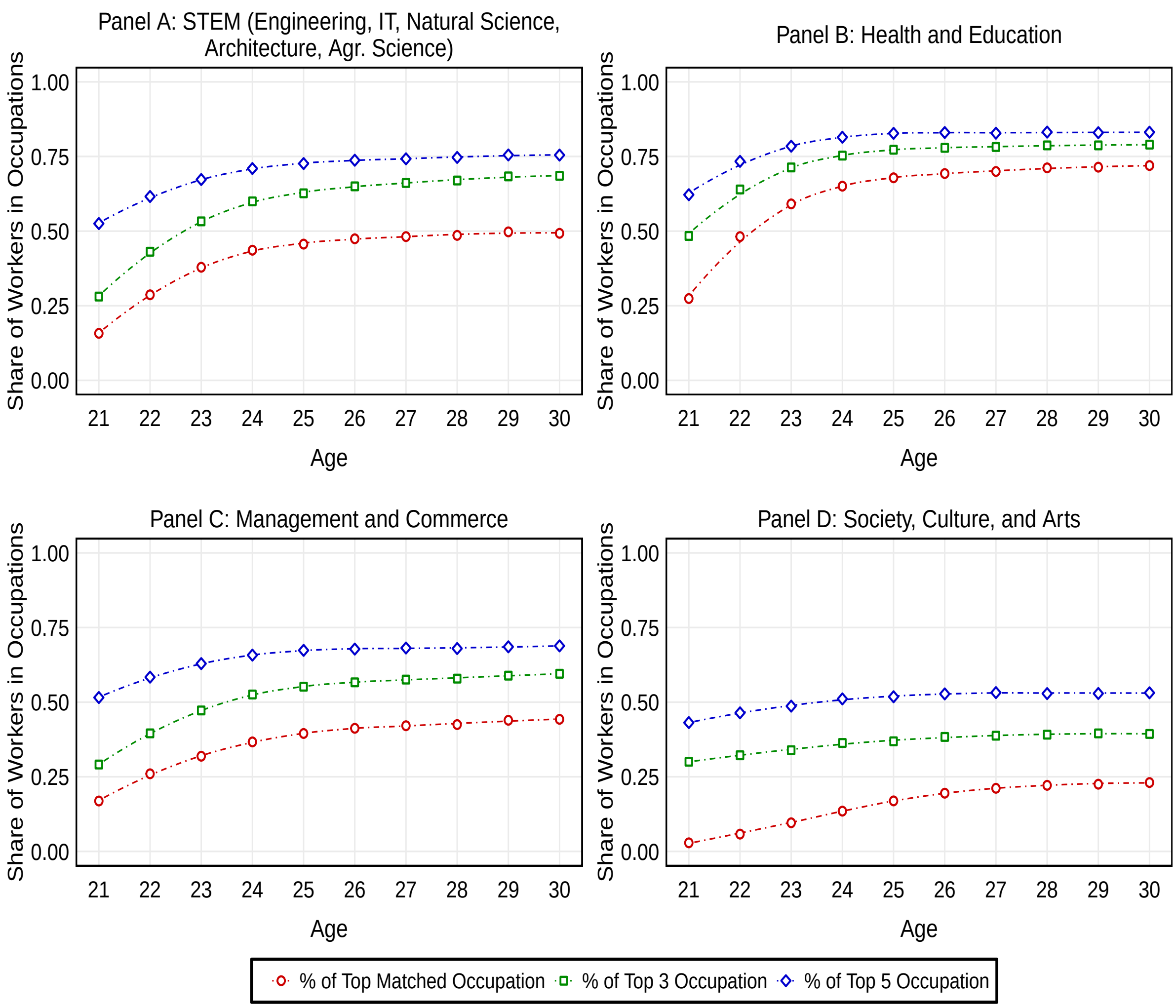
Notes: Panel A and Panel B plot the mismatch in the partial and general equilibrium for aggregate fields of study using the Equation (12) over the life-cycle.

Part of the falling mismatch with age is due to improved sorting in the labor market as seen in all Panels of Figure 3, which plots the share of individuals in the top-occupation. The finding

majors include Natural and Physical Sciences, Information Technology, Engineering and Related Technologies, Architecture and Building, and Agriculture, Environmental and Related Studies; (2) Health and Education; (3) Management and Commerce (as original); (4) Society, Culture, and Arts includes Society and Culture, and Creative Arts; and (4) Food, Hospitality, and Personal Services (as original).

is consistent with the previous literature on US data (Guvenen et al., 2020). As is evident in all majors but Hospitality, Food, and Personal Service, the share of workers in top-paying occupations increases with age. These shares are lowest in Commerce, Social Science and Arts and highest in Health and Education consistent with a concept of general versus specific skills.

Figure 3: Share of the Top Occupation within Major over the Life-Cycle



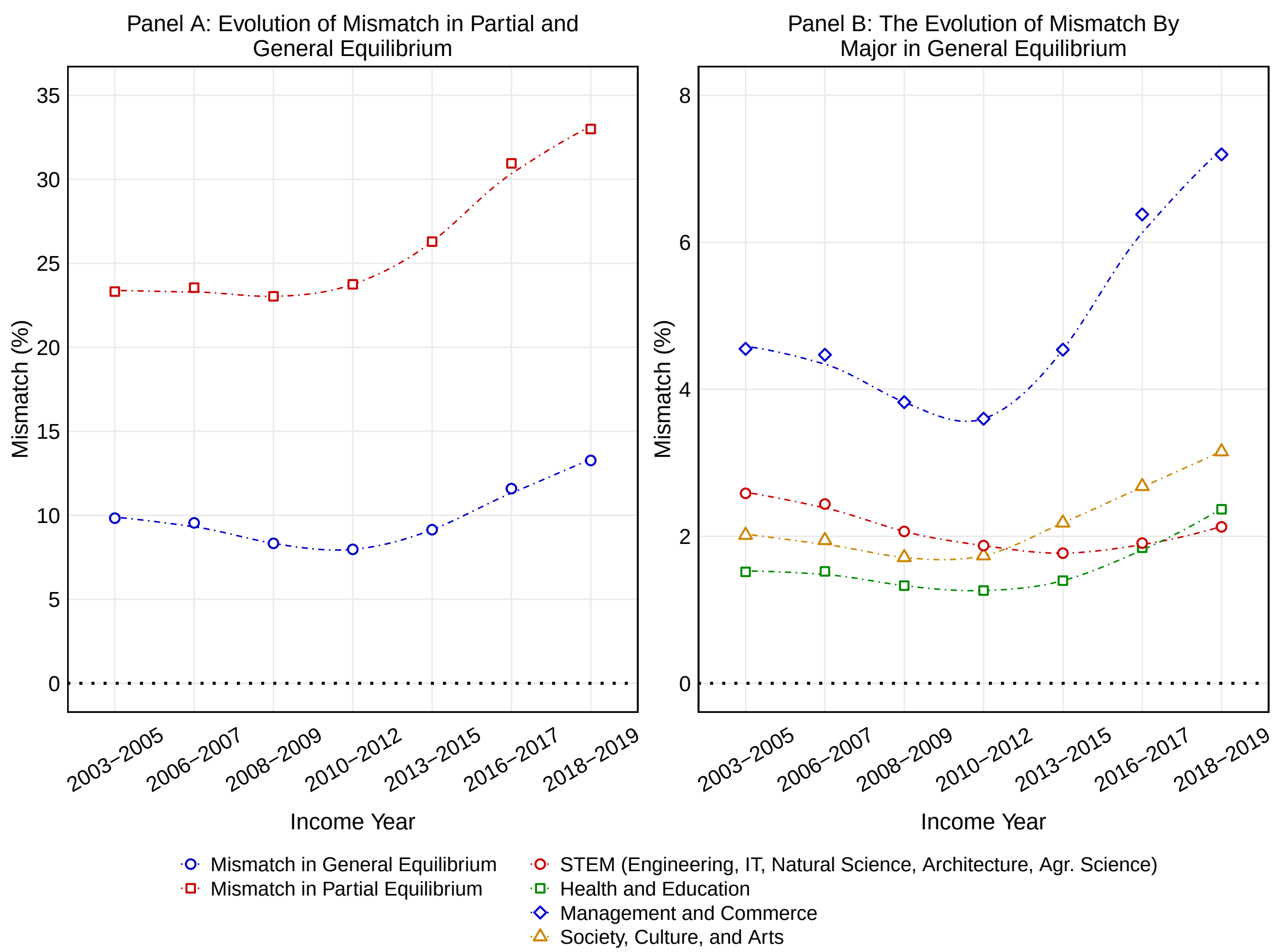
Notes: This figure plots the share of top-matched occupation, top 3 and top 5 occupations within each field of study over the life cycle.

To summarize, the results suggest estimates of skill mismatch that ignore general equilibrium reallocation effects will be overstated. This is especially true, as our baseline results represent the upper bound of the cost of skill mismatch as we attribute all mismatch to frictions and none to taste. Nonetheless, for some groups skill mismatch exists even in the general equilibrium. Policies concerned about skill mismatch should specifically target young workers, as over time, when considering general equilibrium forces, all the cost of mismatch disappears. If active policies to improve the allocation of talent are a net-positive for society and individuals' lifetime welfare is beyond the scope of this paper.

5.3 Evolution of Aggregate Mismatch

Thus far, the results have been averaged over the period from 2003 to 2019. In this section, we examine the time series of mismatch under both partial and general equilibrium frameworks. Panel A of Figure 4 illustrates the evolution of aggregate mismatch for both the average worker from Equation (12) and the general equilibrium evaluated from Equation (19) at each year (group).

Figure 4: The Evolution of Mismatch in the General Equilibrium



Notes: Panel A plots the evolution of estimated output loss in the partial and general equilibrium from year group 2003-2005 to 2018-2019 computed by Equations (12) and (19), respectively. Panel B plots the evolution of estimated output loss due to misallocation disaggregated into five major categories from year group 2003-2005 to 2018-2019. Each major group mismatch is computed by Equation (32) for each year group.

The evolution of mismatch is relatively stable until 2012, but increasing thereafter. Although the time evolution follows a similar trend with fixed returns, in the general equilibrium, the relative rise in aggregate output loss over time is roughly one-third. This suggests that although workers may demand higher wages due to a perceived shortage of talent, the forces of the general equilibrium will partially offset these pressures. In other words, as talent is reallocated within the economy to optimize output, wages will adjust accordingly.

Panel B of Figure 4 shows that further decomposing the output loss by major group shows some heterogeneity among college majors.[17] We find that all majors experience a relatively flat or slightly decreasing trend in output loss until 2012, which increases (in some cases sharply) thereafter. Management and Commerce, and STEM majors exhibit the largest mismatch pre-2012. Management and Commerce major also has the largest increase over time post-2012. STEM, and Society, Culture and Arts majors show a small decrease, which is again undone by a subsequent increase until 2019. Similarly, output loss due to the misallocation of Health and Education majors also increases markedly post-2012. Overall, aggregated mismatch in general equilibrium is mainly driven by Management and Commerce majors (3.5 percent), Society, Culture, and Arts majors (2.5 percent), and STEM majors (2.4 percent). While Health and Education has an average output loss of less than half (1.2 percent).

5.3.1 Decomposing the Rise in Mismatch

There are two potential drivers of the rise in mismatch post-2012. A change in the relative supply of college graduates across majors (see Figure F2 for the number of new college graduate workers by major over time) or a change in the efficiency of matching of workers to top occupations post-2012 (see Figure F3 for the life-cycle of mismatch across different cohorts). For context, 2009 marked a major change to the subsidies of the Australian tertiary education system as the federal government decided to uncap the Commonwealth Supported Places (CSPs). CSPs are university places that are partly funded by the government. Until 2009, the government set the number of CSPs by discipline available each year. The uncapping was done gradually from 2010 onward, but by 2012 all domestic students had the ability to access

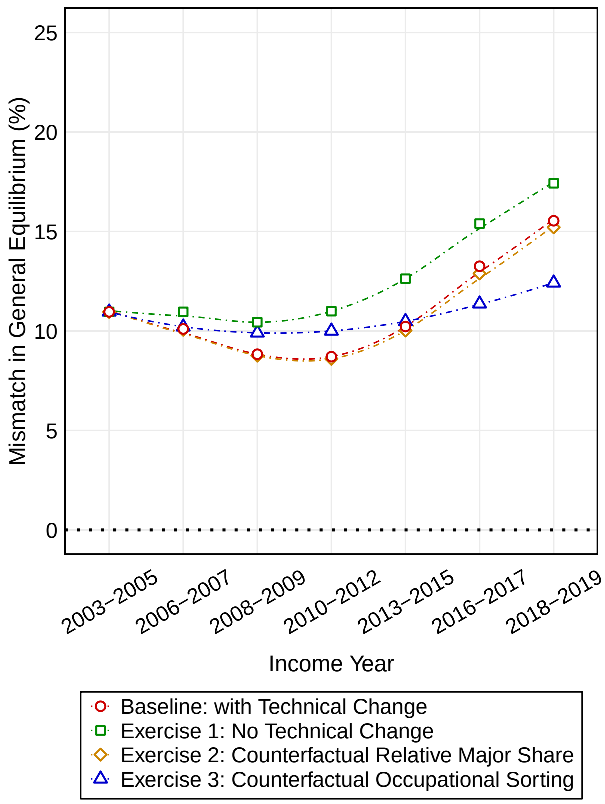
[17] We decompose the aggregate mismatch for major j in terms of GDP per capita loss by:

$$m_{j,t}^{GE} = \frac{F\left(F^1\left(\hat{\mathbf{H}}_t^1\right),\ldots,F^K\left(\hat{\mathbf{H}}_t^K\right)\right) - F\left(F^1\left(\hat{\mathbf{H}}_{-j,t}^1\right),\ldots,F^K\left(\hat{\mathbf{H}}_{-j,t}^K\right)\right)}{F\left(F^1\left(\hat{\mathbf{H}}_{-j,t}^1\right),\ldots,F^K\left(\hat{\mathbf{H}}_{-j,t}^K\right)\right)} \tag{32}$$

where $\hat{\mathbf{H}}^k_{-j,t} = \left(\hat{H}^k_{1,t},\ldots,H^k_{j,t},\ldots\hat{H}^k_{J,t}\right)$ means that all majors are at their optimal allocation across occupations, except for major j remaining at their current allocation. Summing all five major groups' mismatch evolution yields the aggregate mismatch in Panel A of Figure 4. We show major-specific mismatch in partial and general equilibrium using Equation (11) over years in the companion Figure **??**.

a subsidized university spot if they were admitted to a university. Previous studies have suggested that this policy resulted in an increase of 31.5 percent in CSPs places from 2009 to 2016 (Department of Education and Training, 2017). This subsequent increase in admissions was uneven across majors and Universities and coincided with the Financial Crisis.

Figure 5: Counterfactual Analysis



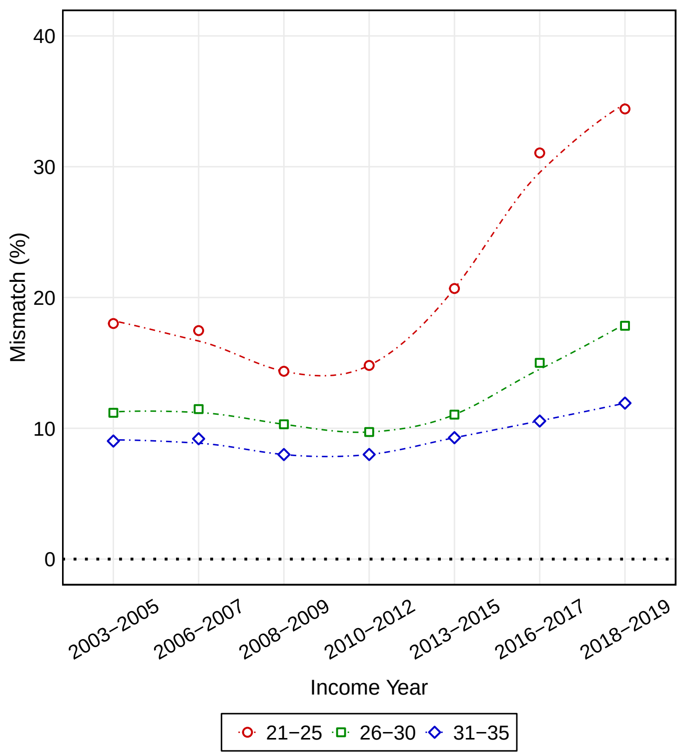
Notes: The figures shows 3 counterfactual, to study the rise in the evolution of skill mismatch in general equilibrium. The red circular line plots the baseline with technical change (changing α's) as in Figure 4. The green square lines shows the counterfactual when fixing α's to the base year, 2003-2005. The yellow diamond line fixed relative major supplies to 2003-2005 and, finally, the blue triangle line fixes the sorting of workers to occupations by major to the 2003-2005 base year.

We show through two counterfactuals, in the context of our general equilibrium framework, how to quantify a change in (i) relative supplies, and (ii) sorting. To do so we compare each year-bin post-2012 with a base period, the average of 2003-2009.

For the first counterfactual, given the production function is homogeneous of degree one, we quantify mismatch for a counterfactual labor supply, that has the same relative major shares as the actual labor supply in the base period, but sorts according to labor market conditions post-2012. The optimal reallocation of counterfactual talent $\hat{H}c^{k'}_{j,t}$ at time t satisfies Equations (14) and (15) and the counterfactual mismatch is computed through Equation (19). This counterfactual mismatch (see Figure 5 yellow-diamond line) shows how mismatch falls once relative supplies across majors are kept constant.

The second counterfactual quantifies mismatch for a counterfactual labor supply, that has the same relative occupation shares conditional on major as the actual labor supply in the base period, but graduations shares from the current time period. Thus, this counterfactual mismatch (see Figure 5 blue triangle line) shows how mismatch falls in the post-2012 period once new cohorts sort into top occupations at the same rate and timing as cohorts in the base period.

Figure 6: Decomposition by Age Group



Notes: The figure plots the decomposition of mismatch in general equilibrium by age groups of 21-25, 26-30, and 31-35 over years. Specifically, we compute the mismatch measure by using equation (20) for each age group and year-bin.

Virtually all change since 2003 can be attributed to sorting. To understand if sorting is driven by a change in technology and affects all workers equally we consider two further exercises. First, we consider if technical change, through changes in α's can explain some of the evolution in skill mismatch. However, if α's are fixed at 2003-2005 values and shutting down any time trend in technology leads to an even larger increase in skill mismatch (see Figure 5 green square line). If anything this suggests that workers have responded to technical change in matching with a different occupation set over time. Secondly, we consider if all workers' skill matches have deteriorated equally, to do so we decompose the evolution of skill mismatch by three age groups – 21-25, 26-30, and 31-35-year-old. As is evident from Figure 6, for workers aged 31-35 skill mismatch is flat during the entire period. Almost all of the increase in skill mismatch is driven by the youngest cohort (workers aged 21-25). This is consistent with life-cycle results as shown in the previous section.

6 Conclusion

This paper proposes a framework to study skill mismatch consistently at the individual level and in general equilibrium. We apply the framework to study mismatch across college major-occupation combinations. At the individual level, we measure mismatch through wage loss at fixed skill returns, in the general equilibrium, we measure mismatch through output loss. We estimate our mismatch measure with Australian administrative tax panel data using employment history and university degree information. We find that Commerce, Social Sciences, Arts, and STEM-related fields are the main drivers of mismatch in the aggregate. At the individual level, only Commerce, Social Sciences and Arts majors show that mismatch imposes costly and persistent scarring effects, as STEM majors seem to be able to leverage multiple skills across occupations in the labor market. Our results indicate that skill mismatch is overestimated when ignoring general equilibrium effects. While on average there are significant individual gains by reallocating workers to occupations best suited for their majors, the effect completely disappears as individuals age and occupation-major returns are allowed to adjust accordingly. In summary, our results highlight that the estimated general equilibrium mismatch is substantially smaller than found in previous studies. Our findings suggest that identifying the causes of mismatch and informing policy decisions is an important direction for future research.

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Appendix

A Data

A.1 HECS/HELP Data

We use Higher Education Loan Program (HELP) data to obtain an individual's post-secondary educational information. This data provides us with the worker's college course name—i.e., Bachelor of Engineering—which suggests both degree level and field of study; institutional types such as university, Technical and Further Education (TAFE)/College/Academy, or school/others; and yearly student loan debt. We design a keyword extraction algorithm to classify thousands of different course names recorded in HELP into the 4-digit level of the Australian Standard Classification of Education (ASCED) as well as into different degree levels.[18] Since degree completion indicators are not available in the administrative data, we follow the approach by Andrews, Deutscher, Hambur, and Hansell (2020) and impute the completion indicator by observing when students stop incurring new HECS/HELP debt for each degree level. As such, the graduation cohort is defined as the last year when the worker incurs the new debt.

A.2 Australian Longitudinal File on Individuals (ALife)

ALife tax record provides us with annual pre-tax salary and wage, occupational track record (classified by ANZSCO), and place of residence for 10% Australian population. We aggregate workers' occupations at ANZSCO 2-digit level. We construct an individual's work experience based on his or her years of full-time employment, which is calculated as the number of years between the first year of observed pay and the current year, provided that the annual salary is higher than the annual minimum wage.[19] We inflate wages to 2019 Australian dollars.

A.3 Estimation Sample and Restriction

We link workers' labor market outcomes from ALife to their college major and restrict observations to the period after the year of graduation. To ensure that we have sufficient samples within each major-occupation pair, we use 2-digit levels of ASCED and ANZSCO to classify

[18] Specifically, degree level is aggregated based on ASCED into three broad groups: (1) non-award degree; (2) certificate/diploma and bachelor; and (3) graduate certificate/diploma and postgraduate degree.

[19] We compute annual minimum wage as minimum annual wage = minimum wage rate/2×35hours$\times 48$weeks.

majors and occupations, respectively. We focus on the undergraduate sample, which is limited to individuals between the ages of 21-35 years old who held at least one type of academic degree, such as a diploma, certificate, or bachelor's degree, regardless of institution type. To ensure that wage reflects the skill prices and to alleviate the concern of the impact of career promotion on wage, we remove observations that are self-employed or work in managerial or government servant positions. It is not uncommon to find a worker may have studied two different majors, and/or obtained more than one degree level throughout their higher education history. To ensure that occupations are matched to only one field of study and degree level, we restrict the sample to individuals with only one major at the 2-digit classification and the most recent degree level.

B Details on Estimation Procedure

B.1 Correct Selection Bias

Individuals are observed in an j,k cell if and only if the Rule (23), conditional on major j, is satisfied,[20]

$$M_{i,(k|j),c,r,t} = 1, \text{ iff } e_{i,(k|j),c,r,t} - e_{i,(k'|j),c,r,t} \leqslant \tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(k'|j),c,r,t};\ \forall k' \neq k \tag{B.1}$$

Directly using (B.1) to pin down the selectivity bias is infeasible because we would need a complete specification of the joint distribution of error terms in the wage equation and error terms in K selection equations for each major j. To address the estimation challenge, we follow Lee (1983) to reduce the problem by only looking at the maximum order statistic. Equivalently, (B.1) can be rewritten as:

$$M_{i,(k|j),c,r,t} = 1, \text{ iff } \max_{k'}(e_{i,(k'|j),c,r,t} - e_{i,(k|j),c,r,t} - (\tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(k'|j),c,r,t})) \leqslant 0 \tag{B.2}$$

Given this, the observation in cell (j,k) is observed ($M_{i,(k|j),c,r,t} = 1$) if the maximum order statistics is less than 0. To get the probability of this event, let $F^{e}_{k|j}$ be the joint CDF of selection error terms $(e_{i,(1|j),c,r,t} - e_{i,(k|j),c,r,t}, \ldots, e_{i,(K|j),c,r,t} - e_{i,(k|j),c,r,t})$. We can derive the CDF of the maximum

[20]Note, we allow for regional variation on selection probabilities giving us additional variation in the data.

order statistics, conditional on sub-utility differences, as the following:

$$
\begin{aligned}
&H_{k|j}(t \mid \tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(1|j),c,r,t}, ..., \tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(K|j),c,r,t}) \\
=&Pr(\max_{k'}(e_{i,(k'|j),c,r,t} - e_{i,(k|j),c,r,t} - (\tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(k'|j),c,r,t})) \leqslant t \mid \\
&\quad \tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(1|j),c,r,t}, ..., \tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(K|j),c,r,t}) \\
=&Pr(e_{i,(1|j),c,r,t} - e_{i,(k|j),c,r,t} \leqslant \tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(1|j),c,r,t} + t, ..., \\
&\quad e_{i,(K|j),c,r,t} - e_{i,(k|j),c,r,t} \leqslant \tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(K|j),c,r,t} + t) \\
=&F^{e}_{j,k}(\tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(1|j),c,r,t} + t, ..., \tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(K|j),c,r,t} + t)
\end{aligned} \tag{B.3}
$$

If $t = 0$, then

$$
\begin{aligned}
&Pr(\max_{k'}(e_{i,(k'|j),c,r,t} - e_{i,(k|j),c,r,t} - (\tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(k'|j),c,r,t})) \leqslant 0 \\
&\quad |\tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(1|j),c,r,t}, ..., \tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(K|j),c,r,t}) \\
=&F^{e}_{j,k}(\tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(1|j),c,r,t}, ..., \tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(K|j),c,r,t}) \\
=&F^{e}_{j,k}(\vec{U})
\end{aligned} \tag{B.4}
$$

where the vector of sub-utility difference is $\vec{U} = (\tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(1|j),c,r,t}, ..., \tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(K|j),c,r,t})$.

To this end, above Equation (B.4) gives the probability that the maximum order statistics $\max_{k'}(e_{i,(k'|j),c,r,t} - e_{i,(k|j),c,r,t} - (\tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(k'|j),c,r,t}))$ is less than 0. That is the probability of observing an individual in occupation k conditional on major j. However, these random variables indexed over i are not identically distributed because the sub-utility differences might be systematically different.

Following Lee (1983), we propose a new random variable that can be constructed using the transformation,

$$
v^{*}_{i,j,c,k,r,t} = \Gamma^{-1}_{j,k}\{F^{e}_{j,k}(\vec{U})\}, \tag{B.5}
$$

where $\Gamma^{-1}_{j,k}$ can be any univariate continuous strictly increasing function, so that $\Gamma_{j,k}$ can be defined as a marginal distribution of the new random variable $v_{i,j,k,c,r,t}$.[21] Therefore, the probability of a random variable $v_{i,j,k,c,r,t}$ that is less or equal to the value $v^{*}_{i,j,k,c,r,t}$ can well summarize the probability of the event that the maximum order statistics is less than 0, and thereby $M_{i,(k|j),c,r,t} = 1$. To see this,

$$
Pr(v_{i,j,k,c,r,t} \leqslant v^{*}_{i,j,k,c,r,t}) = \Gamma_{j,k}(\Gamma^{-1}_{j,k}\{F^{e}_{j,k}(\vec{U})\}) = F^{e}_{j,k}(\vec{U}) \tag{B.6}
$$

[21] Lee's implicit assumption for the above transformation is that the same transformation is applied regardless of the specific values of sub-utility differences.

Hence, using (B.5), we can rewrite (B.2) as the following:

$$M_{i,(k|j),c,r,t} = 1, \text{ iff } \upsilon_{i,j,k,c,r,t} \leqslant \Gamma_{j,k}^{-1}\{F_{j,k}^{e}(\vec{U})\} \tag{B.7}$$

Following Lee (1983), we assume that the error in wage equation $\epsilon_{i,j,k,c,r,t}$ and this new transformed random variable $\upsilon_{i,j,k,c,r,t}$ are independently and identically distributed with a joint distribution function $G_{j,k}(...)$. With this assumption, we can use the two-stage Heckman estimation for correcting selectivity bias. Specifically, we assume that: (1) $\Gamma_{j,k}$ is a univariate standard normal CDF (Φ); (2) $G_{j,k}(...)$ is a bivariate standard normal CDF.

To this end, we can pin down the self-selection bias $E[\epsilon_{i,j,k,c,r,t}|M_{i,(k|j),c,r,t} = 1]$ based on the above distributional assumption in the following way:

$$\begin{aligned}
&E[\epsilon_{i,j,k,c,r,t}|M_{i,(k|j),c,r,t} = 1] \\
&\quad = E[\epsilon_{i,j,k,c,r,t}|\upsilon_{i,j,k,c,r,t} \leqslant \Phi_{j,k}^{-1}\{F_{j,k}^{e}(\vec{U})\}] \\
&\quad = \frac{Cov(\epsilon_{i,j,k,c,r,t}, \upsilon_{i,j,k,c,r,t})}{var(\upsilon_{i,j,k,c,r,t})} E(\upsilon_{i,j,k,c,r,t}|\upsilon_{i,j,k,c,r,t} \leqslant \Phi_{jk}^{-1}\{F_{j,k}^{e}(\vec{U})\}) \\
&\quad = \frac{Cov(\epsilon_{i,j,k,c,r,t}, \upsilon_{i,j,k,c,r,t})}{\sqrt{var(\epsilon_{i,j,k,c,r,t})var(\upsilon_{i,j,k,c,r,t})}} \frac{\sqrt{var(\epsilon_{i,j,k,c,r,t})}}{\sqrt{var(\upsilon_{i,j,k,c,r,t})}} E(\upsilon_{i,j,k,c,r,t}|\upsilon_{i,j,k,c,r,t} \leqslant \Phi_{j,k}^{-1}\{F_{j,k}^{e}(\vec{U})\}) \\
&\quad = \rho_{j,k} \times 1 \times E(\upsilon_{i,j,k,c,r,t}|\upsilon_{i,j,k,c,r,t} \leqslant \Phi_{j,k}^{-1}\{F_{j,k}^{e}(\vec{U})\}) \\
&\quad = \rho_{j,k} \frac{-\phi(\Phi^{-1}(F_{j,k}^{e}(\vec{U})))}{\Phi(\Phi^{-1}(F_{j,k}^{e}(\vec{U})))} \\
&\quad = \rho_{j,k} \frac{-\phi(\Phi^{-1}(F_{j,k}^{e}(\vec{U})))}{F_{j,k}^{e}(\vec{U})} \\
&\quad = \rho_{j,k}\lambda_{j,k}(F_{j,k}^{e}(\vec{U}))
\end{aligned} \tag{B.8}$$

where $\vec{U} = (\tilde{U}_{i,(k|j)c,r,t} - \tilde{U}_{i,(1|j),c,r,t}, ..., \tilde{U}_{i,(k|j),c,r,t} - \tilde{U}_{i,(k'|j),c,r,t})$, $\rho_{j,k}$ is the correlation between $\epsilon_{i,j,k,c,r,t}$ and $\upsilon_{i,j,k,c,r,t}$, and $\lambda_{j,k}(\cdot)$ is the parametric form of correction function.[22] Following Dahl (2002) with the index sufficiency assumption, we can show $F_{j,k}^{e}(\vec{U}) = p_{i,j,k,c,r,t}$.

B.2 Estimation of Selection Probability

To estimate occupational selection probability, we follow Eckardt (2019) and adopt a flexible machine learning approach—random forest—to avoid functional form assumption of the un-

[22]We assume the correlation only differs among j, k combinations.

derlying subutility function. The advantage of the random forest lies in its flexibility in incorporating a large number of predictors into the model and its prediction accuracy. Meanwhile, it avoids the usual drawbacks of the conditional logit model that suffers from the independence of irrelevant alternatives property.

We predict occupational choice conditional on each major by using a random forest algorithm. The explanatory variables for predicting occupational choice include graduation cohort dummies, age, gender, working experience, balance of debt, and a set of Bartik shift-share instruments capturing exogenous change in occupational demand in each year and region. Specifically, Bartik instrument $B_{k'|r,t}$ for each occupation k is constructed as:

$$B_{k'|r,t} = \underbrace{z_{k'|r,(t=0)}}_{\substack{\text{Share: Initial Occ. } k' \text{ share} \\ \text{in region } r}} \times \underbrace{m_{k',t}}_{\substack{\text{Shift: Growth of Occ. } k' \\ \text{at the national level}}} \tag{B.9}$$

where $z_{k'|r,(t=0)}$ is the initial share of occupation k' in region r at the base year $t = 0$ (i.e., year 1994—the first year when occupation code is observed), and $m_{k',t}$ is the yearly growth rate of occupation k' share in year t at the national level. Both initial occupation shares in the local region and yearly national-level shift in occupation shares are assumed exogenous.[23] That is, $B_{k'|r,t}$ approximates the exogenous change in the share of occupation k in region r in year t.[24]. As the exclusion restriction should affect the probability of choosing an occupation rather than directly affecting wages, we use a one-year lagged Bartik instrument, $B_{k'|r,t-1}$, as a predictor, to mitigate the issue.

C Estimation of Production Function Parameters

For baseline estimation of production function parameters, we assume no technical change and use the fixed $\{\alpha_j^k\}$ and $\{\alpha_k\}$ across time. For occupational-specific production function, estimating parameters $\{\alpha_j^k\}$ and $\{\sigma_k\}$ in specification (27) needs to exploit the region and time variation in $\ln(p^k_{j',r,t}/p^k_{j,r,t})$ and $\ln(H^k_{j',r,t}/H^k_{j,r,t})$. In order to obtain sufficient variation and to address the sampling limitations, we group 17 years into two year-bins (hereafter denoted as b) and obtain the price of major-occupation combination $p_{j',r,b}$ and efficiency labor units $H_{j',r,\mathcal{T}}$ by estimating the specification (25) conditional on each region r and year-bin $\mathcal{T}$.[25] We then

[23]Since regional occupation shares in the initial period (1994) are a decade ahead relative to the beginning of the estimation period (2003) we consider this a reasonable assumption.

[24]To precisely gauge the growth of occupational share in the economy, we only use the occupation information in the tax data, without imposing any sample restriction.

[25]We aggregate the years 2003-2019 into 7 two-year-bins, 2003-2005, 2006-2007, 2008-2009, 2010-2012, 2013-2015, 2016-2017, and 2018-2019. To obtain precise estimates of the price of major-occupation combinations, we

estimate the following specification for each occupation,

$$\underbrace{\ln\left(p^k_{j',r,\mathcal{T}}/p^k_{j,r,\mathcal{T}}\right)}_{\beta^k_{j',r,\mathcal{T}}-\beta^k_{j,r,\mathcal{T}}} = \ln\left(\alpha^k_{j'}/\alpha^k_j\right) + \left(\sigma^k - 1\right)\ln\left(H^k_{j',r,\mathcal{T}}/H^k_{j,r,\mathcal{T}}\right); \quad \text{for each } k \in K, \tag{C.1}$$

where $p^k_{j',r,\mathcal{T}}$ is the return to major-occupation combination conditional on the region r and year-bin $\mathcal{T}$; and $H^k_{j',r,\mathcal{T}} = \sum_{i\in I^k_{j',r,\mathcal{T}}} \tilde{h}_i$ is total efficiency labor units. To this end, for each occupation k, we obtain the estimates of σ_k and $\{\alpha^k_j\}$ with the constraint of $\sum_{j\in J} \alpha^k_j = 1$.

For the aggregate production function, estimating $\{\alpha_k\}$ and σ from Equation (31) needs variation in $p_{k',r,t}$ and $Y_{k',r,t}$. We continue to exploit cross-regions and year-bin variation. By Equation (3), we obtain $Y^k_{r,\mathcal{T}}$ using estimated $p^k_{j',r,\mathcal{T}}$ and $H^k_{j',r,\mathcal{T}}$. Equation (31) can then be estimated at the level of region and year-bin,

$$\ln\left(\frac{\left(\sum_j \left(\alpha^{k'}_j\right)^{-\frac{1}{\sigma_{k'}-1}} \left(p^{k'}_{j,r,\mathcal{T}}\right)^{\frac{\sigma_{k'}}{\sigma_{k'}-1}}\right)^{(1-\frac{1}{\sigma_{k'}})}}{\left(\sum_j \left(\alpha^{k}_j\right)^{-\frac{1}{\sigma_{k}-1}} \left(p^{k}_{j,r,\mathcal{T}}\right)^{\frac{\sigma_{k}}{\sigma_{k}-1}}\right)^{(1-\frac{1}{\sigma_{k}})}}\right) = \ln\left(\frac{\alpha^{k'}}{\alpha^k}\right) + (\sigma - 1)\ln\left(\frac{Y^{k'}_{r,\mathcal{T}}}{Y^k_{r,\mathcal{T}}}\right). \tag{C.2}$$

Note technology parameters, $\ln\left(\frac{\alpha_{k',t}}{\alpha_{k,t}}\right) + \ln\left(\frac{A_{k',t}}{A_{k,t}}\right)$ are not separately identifiable, but this is not crucial for our exercise. A typical assumption in the literature (see Katz and Murphy (1992)) is to assume a linear time trend in technological change, e.g., the expression can be approximated by:

$$\ln\left(\frac{\alpha_{k',t}}{\alpha_{k,t}}\right) + \ln\left(\frac{A_{k,t}}{A_{k',t}}\right) = \gamma_{0,kk'} + \gamma_{1,kk'}t$$

when using time-series data or simply $\gamma_{0,kk'}$ if using only cross-sectional variation.

To this end, we obtain the estimates σ and $\{\alpha^k\}$ by the constraint of $\sum_{k\in K} \alpha^k = 1$. Therefore, all production function parameters $\{\alpha^k_j\}$, $\{\sigma_k\}$, $\{\alpha^k\}$, and σ are estimated. Table D1 provides the estimated production function parameters.

restrict the number of observations within the cell of major-occupation-year-bin-and-region to at least five and restrict the number of majors with occupation to be at least two. In total, this leaves us 233 major-occupation combinations, the same number as the original estimation sample without restriction, while the caveat is that it loses 44 percent of the number of cells of major-occupation-region-and-year-bin.

Table D1: Estimates of Production Function Parameters

ANZSCO 2-digit	Occupation Title	$alpha_{k}$	Elas	Major Weights Within Occupation									
				1	2	3	4	5	6	7	8	9	10
21	Arts and Media Professionals	0.027	1.753	0	0	0	0	0	0.208	0.182	0.193	0.183	0.235
22	Business, Human Resource and Marketing Professionals	0.094	2.25	0.076	0.084	0.095	0.057	0.07	0.074	0.066	0.324	0.092	0.063
23	Design, Engineering, Science and Transport Professionals	0.084	1.983	0.114	0.067	0.279	0.093	0.109	0.066	0.049	0.073	0.072	0.077
24	Education Professionals	0.046	1.796	0.061	0.045	0.051	0	0.052	0.088	0.517	0.081	0.078	0.028
25	Health Professionals	0.04	1.758	0.055	0	0.039	0	0.044	0.684	0.034	0.057	0.048	0.038
26	ICT Professionals	0.067	1.984	0.072	0.239	0.162	0	0.094	0.072	0.065	0.159	0.068	0.068
27	Legal, Social and Welfare Professionals	0.034	1.877	0.079	0	0.104	0	0	0.086	0.058	0.152	0.485	0.037
31	Engineering, ICT and Science Technicians	0.044	1.878	0.115	0.107	0.125	0.123	0.089	0.086	0.065	0.111	0.095	0.083
34	Electrotechnology and Telecommunications Trades Workers	0.035	1.856	0.085	0.119	0.149	0.076	0.081	0.087	0.081	0.126	0.099	0.096
36	Skilled Animal and Horticultural Workers	0.021	1.612	0.12	0	0.083	0.102	0.156	0.118	0.097	0.131	0.107	0.085
3X	Automotive, Engineering, and Construction Trades Workers	0.03	1.768	0.08	0.096	0.152	0.111	0.088	0.091	0.096	0.132	0.1	0.054
3Y	Food Trades, Other Technicians, and Trades Workers	0.026	1.69	0.094	0.084	0.133	0.099	0.12	0.113	0.093	0.135	0.096	0.034
41	Health and Welfare Support Workers	0.019	2.303	0.068	0	0	0	0	0.283	0.143	0.167	0.223	0.115
42	Carers and Aides	0.031	1.857	0.084	0.096	0.086	0	0.082	0.151	0.174	0.123	0.155	0.049
43	Hospitality Workers	0.025	1.93	0.094	0.082	0.093	0.086	0.069	0.097	0.09	0.149	0.111	0.129
45	Sports and Personal Service Workers	0.025	1.727	0.111	0	0.12	0	0.104	0.148	0.136	0.181	0.163	0.038
52	Personal Assistants and Secretaries	0.02	1.779	0.096	0	0	0	0.117	0.121	0.125	0.261	0.176	0.103
53	General Clerical Workers	0.036	1.648	0.086	0.076	0.092	0.084	0.076	0.113	0.116	0.198	0.126	0.033
54	Inquiry Clerks and Receptionists	0.025	1.997	0.108	0.101	0.118	0	0.084	0.114	0.111	0.184	0.133	0.047
55	Numerical Clerks	0.045	1.787	0.066	0.092	0.091	0.075	0.078	0.077	0.096	0.194	0.112	0.119
56	Clerical and Office Support Workers	0.021	1.666	0.135	0.1	0.096	0	0	0.122	0.111	0.185	0.166	0.085
59	Other Clerical and Administrative Workers	0.035	1.711	0.088	0.081	0.084	0.068	0.088	0.079	0.083	0.201	0.142	0.087
61	Sales Representatives and Agents	0.041	1.85	0.07	0.088	0.092	0.075	0.082	0.106	0.084	0.231	0.11	0.06
62	Sales Assistants and Salespersons	0.033	2.056	0.087	0.099	0.095	0.093	0.077	0.102	0.105	0.153	0.125	0.063
63	Sales Support Workers	0.03	1.789	0.083	0.108	0.096	0.116	0.095	0.081	0.101	0.148	0.089	0.082
7X	Machinery Operators and Drivers	0.031	1.826	0.1	0.094	0.121	0.089	0.105	0.098	0.094	0.151	0.114	0.034
8X	Labourers	0.037	1.949	0.091	0.082	0.128	0.098	0.09	0.096	0.083	0.153	0.114	0.065
	Elasticity of Substitution of Occupational Products		2.332										

Notes: This table shows the estimated production function parameters Columns 5-15 shows the major weights within each occupation, with the number 1-11 in the top panel representing for the 2-digit ASCED major.

D Robustness

D.1 Mismatch with Occupational Tenures 1

Consider aggregate human capital for a major j and an occupation k,

$$\hat{H}_j^k = \sum_{i \in I_j^k} \tilde{h}_{i,k} e^{\tau_i} = \sum_{i \in I_j^k} \tilde{h}_{i,k} \frac{\sum_{i \in I^k} \tilde{h}_{i,k} e^{\tau_i}}{\sum_{i \in I_j^k} \tilde{h}_{i,k}} = H_j^k T_j^k \tag{D.1}$$

where $T_j^k = \frac{\sum_{i \in I_j^k} \tilde{h}_{i,k} e^{\tau_i}}{\sum_{i \in I_j^k} \tilde{h}_{i,k}} = E_{\tau_j^k}\left[e^{\tau_j^k}\right]$ is the expected value of the exponential of tenure length. Rewrite the production function as

$$\begin{aligned} Y^k &= F^k(\hat{H}_1^k, ..., \hat{H}_j^k, ..., \hat{H}_J^k) \\ &= F^k(H_1^k T_j^k, ..., H_j^k T_j^k, ..., H_J^k T_j^k). \end{aligned} \tag{D.2}$$

Now, assume that the planner CANNOT choose a type of worker when reallocating so that T_j^k doesn't change (i.e. the distribution of tenures within occupation k doesn't change). Then, the reallocation problem becomes

$$Y^k = F^k\left(\left[H_1^k - R_1^k(-)\right] T_1^k + R_1^k(+), ..., \left[H_j^k - R_j^k(-)\right] T_j^k + R_1^k(+), ..., \left[H_J^k - R_J^k(-)\right] T_J^k + R_J^k(+)\right), \tag{D.3}$$

for all occupation k, where $R_j^k(-) \geq 0$ is the number of major-j workers reallocated out of occupation k and $R_j^k(+) \geq 0$ is that into occupation k, which satisfy the resource constraints,

$$\sum_k R_j^k(-) = \sum_k R_j^k(+), \tag{D.4}$$

for all major j. In addition, if $R_j^k(-) > 0$ holds, then $R_j^k(+) = 0$, or vice versa.

D.2 Mismatch with Occupational Tenures 2

Now assume that the planner CAN choose whom to reallocate. Let G_j^k, distribution of tenure length τ_j^k for major j in occupation k. In this situation, it is optimal for the planner to choose the workers with the lowest tenure first to reallocate, because

Then, the reallocation problem becomes

$$Y^k = F^k\left(\left[H_1^k - R_1^k(-)\right]\int_{G^{-1}\left(R_1^k(-)\right)}^{\infty}\tau_1^k dG_1^k + R_1^k(+), \dots, \left[H_j^k - R_j^k(-)\right]\int_{G^{-1}\left(R_j^k(-)\right)}^{\infty}\tau_j^k dG_j^k + R_j^k(+), \dots, \left[H_J^k - R_J^k(-)\right]\int_{G^{-1}\left(R_J^k(-)\right)}^{\infty}\tau_J^k dG_J^k + R_J^k(+)\right), \tag{D.5}$$

for all occupation k, where $R_j^k(-) \geq 0$ is the number of major-j workers reallocated out of occupation k and $R_j^k(+) \geq 0$ is that into occupation k, which satisfy the resource constraints,

$$\sum_k R_j^k(-) = \sum_k R_j^k(+), \tag{D.6}$$

for all major j.

D.3 Mismatch with Self-Selection Effects

From Equation (25), we could estimate the effect of selection on workers' wages. Let k' the worker's current occupation. Define

$$\tilde{h}'_{i,k} = \begin{cases} \tilde{h}_{i,k} \times \exp\left[\hat{\rho}_{j,k} \cdot g\right] & \text{if } k = k', \\ \tilde{h}_i & \text{otherwise.} \end{cases} \tag{D.7}$$

This is major-specific human capital that includes selection effects. Note that this human capital depends on an individual's occupational choice and thus has the subscript k.

We can now define a measure of major-occupation mismatch in a partial equilibrium with selection effects. Suppressing time subscripts, our mismatch measure for major j can be defined as:

$$m_j^{PE} = \frac{\sum_{i \in I^j} p_j^{k^*(i)} \tilde{h}'_i - \sum_{i \in I^j} p_j^k \tilde{h}'_{i,k}}{\sum_{i \in I} p_j^k \tilde{h}'_{i,k}}, \tag{D.8}$$

where

$$k^*(i) = \arg\max_k \left[p_j^k \tilde{h}'_{i,k} - p_j^{k'} \tilde{h}'_{i,k'}\right]. \tag{D.9}$$

Equation (D.9) defines individuals' top occupation taking into account the selection effect. could lose their selection effect, captured by $\tilde{h}'_{i,k}$. Having defined major specific mismatch measure, the aggregate economy-wide mismatch is now defined as,

$$\mathcal{M}^{PE} = \sum_{j \in J} m_j^{PE} = \frac{\sum_{i \in I} p_j^{k^*(i)} \tilde{h}'_i - \sum_{i \in I} p_j^k \tilde{h}'_i}{\sum_{i \in I} p_j^k \tilde{h}'_i}. \tag{D.10}$$

E Figure Appendix

Figure F1: Major-Occupation Mismatch Estimates

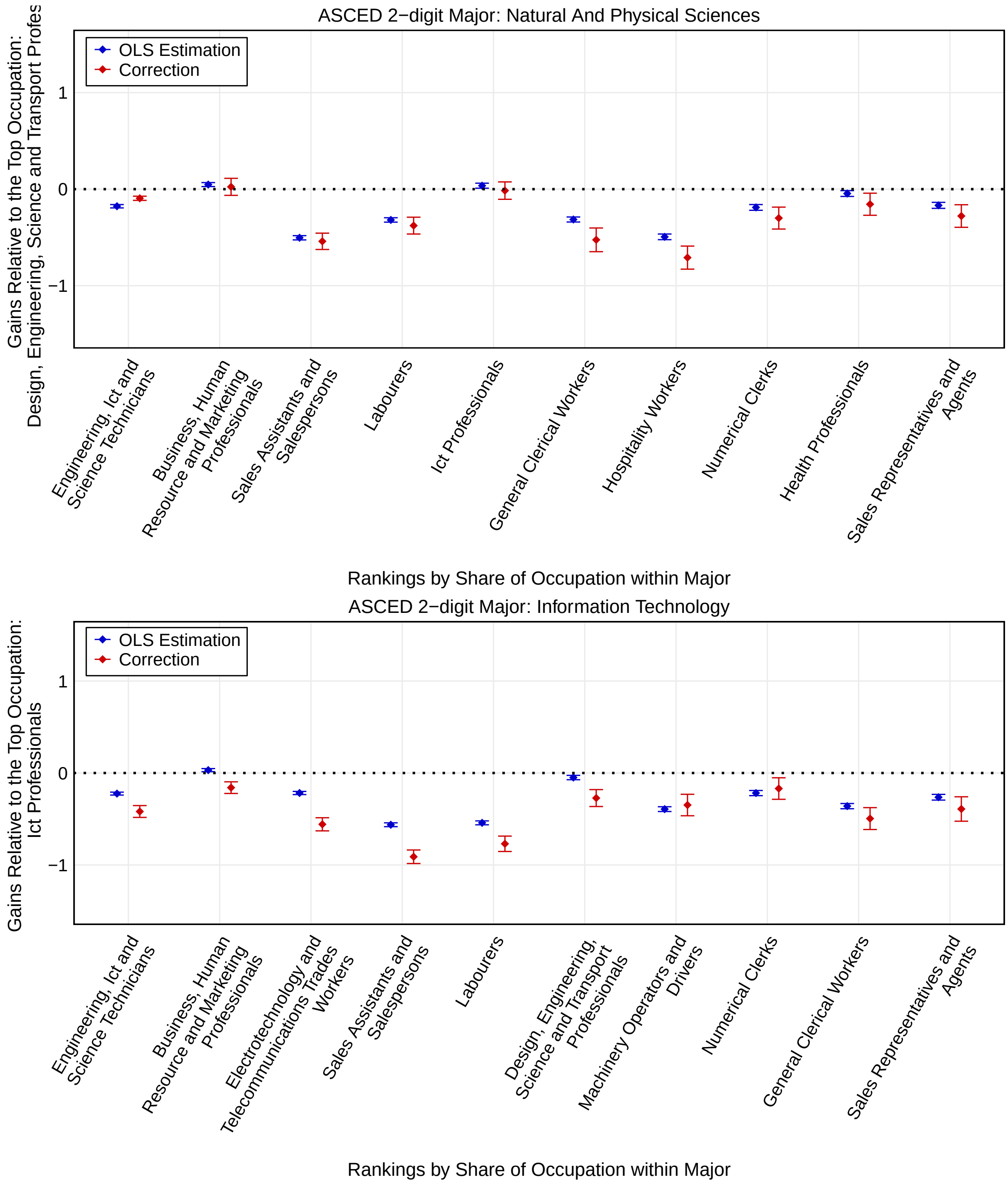
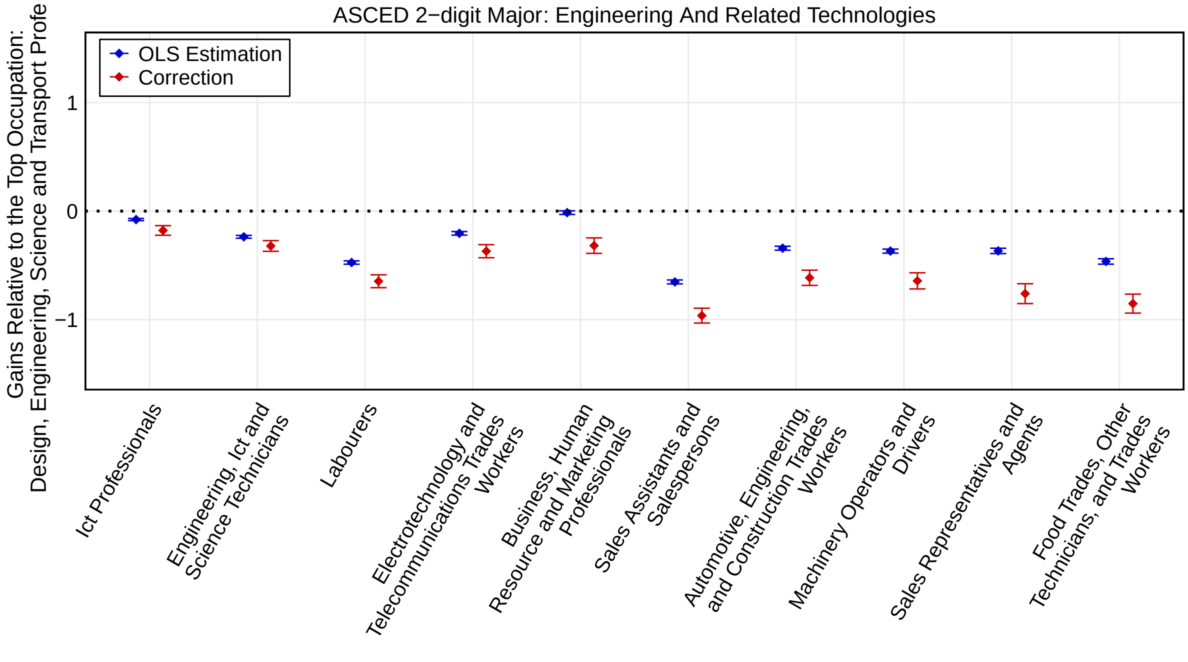
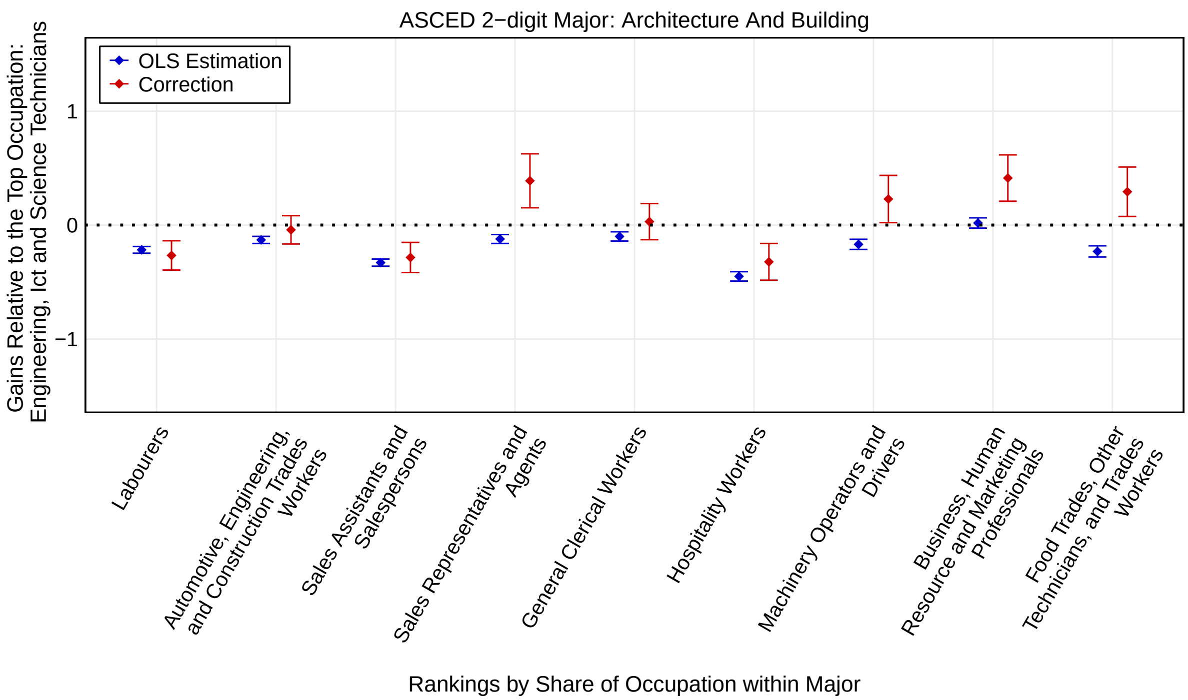


Figure Continued





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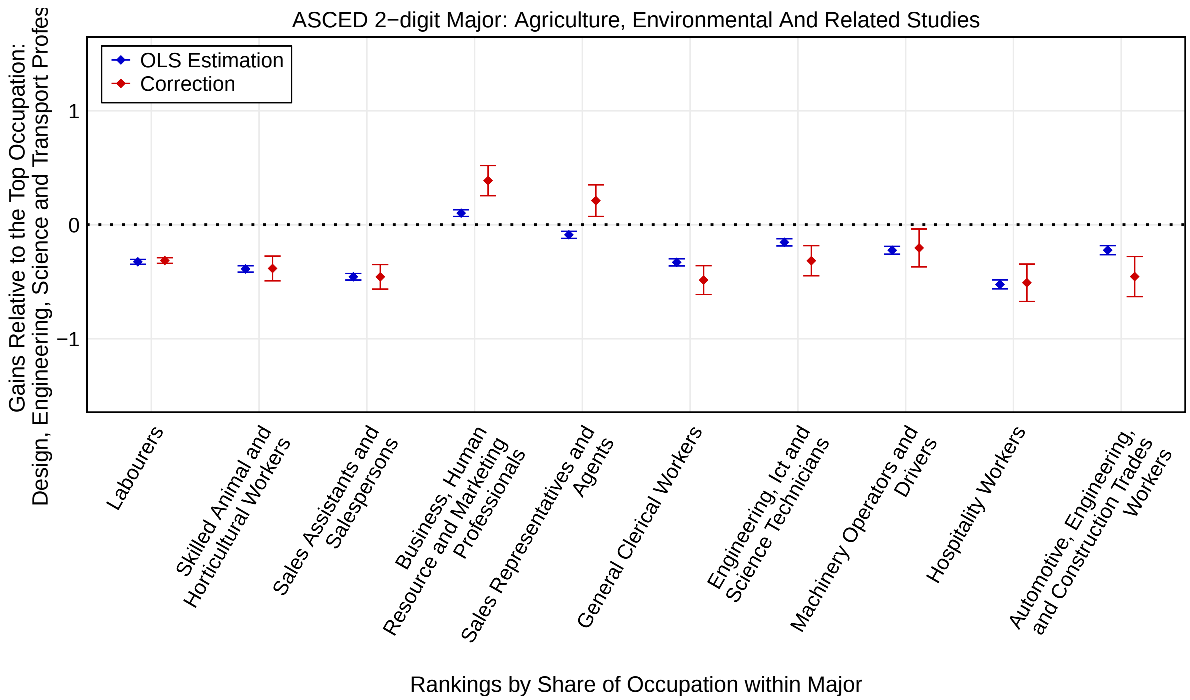


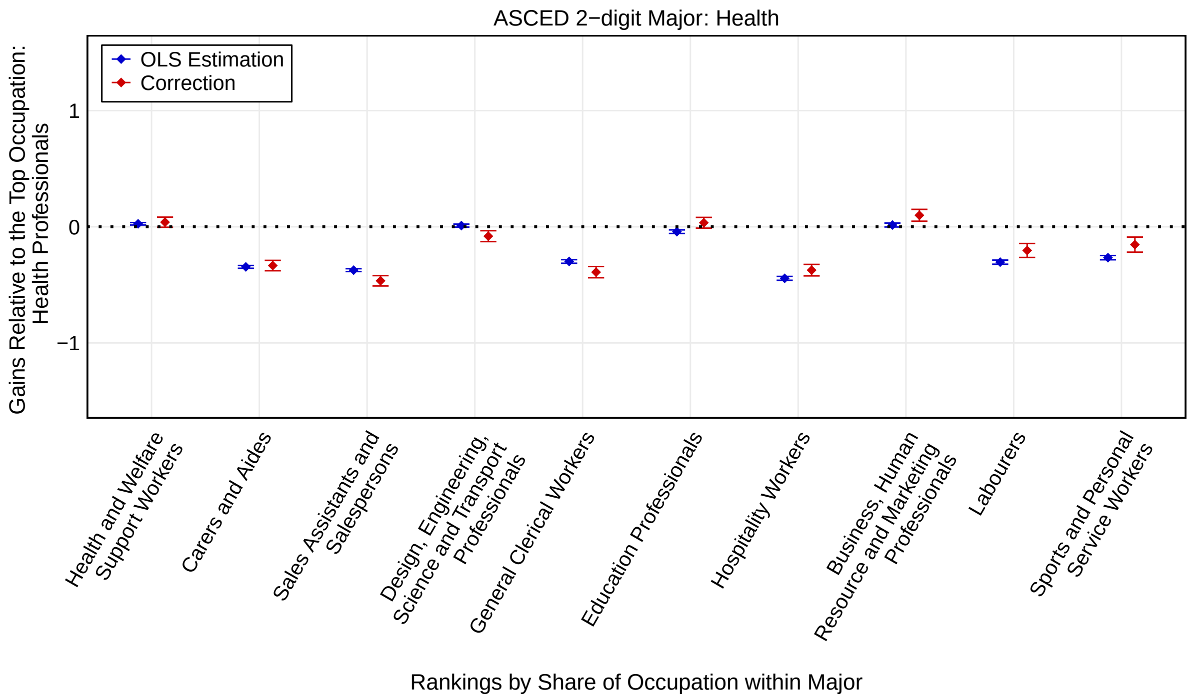
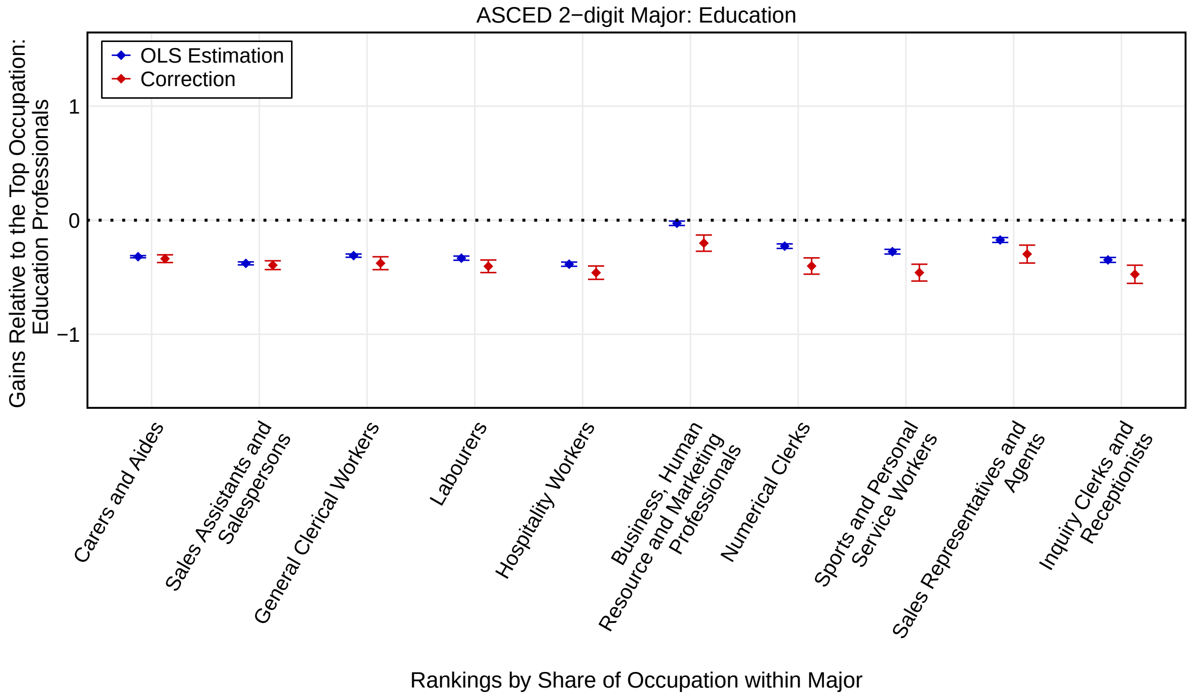


Figure Continued



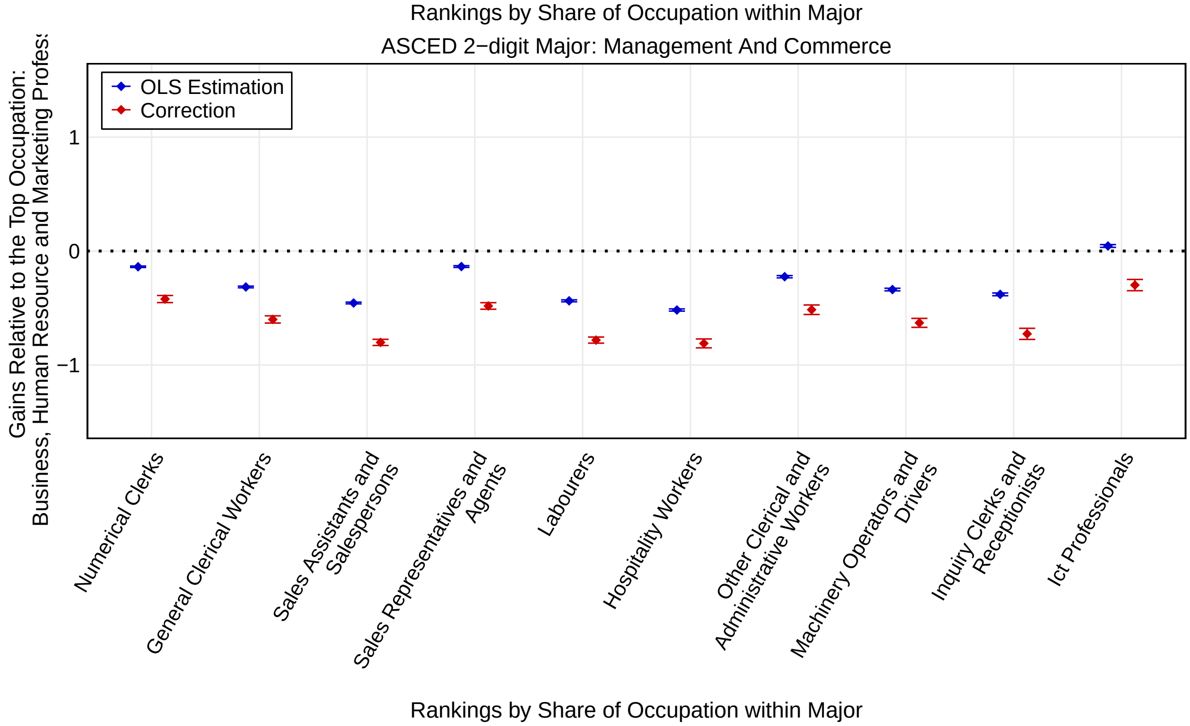
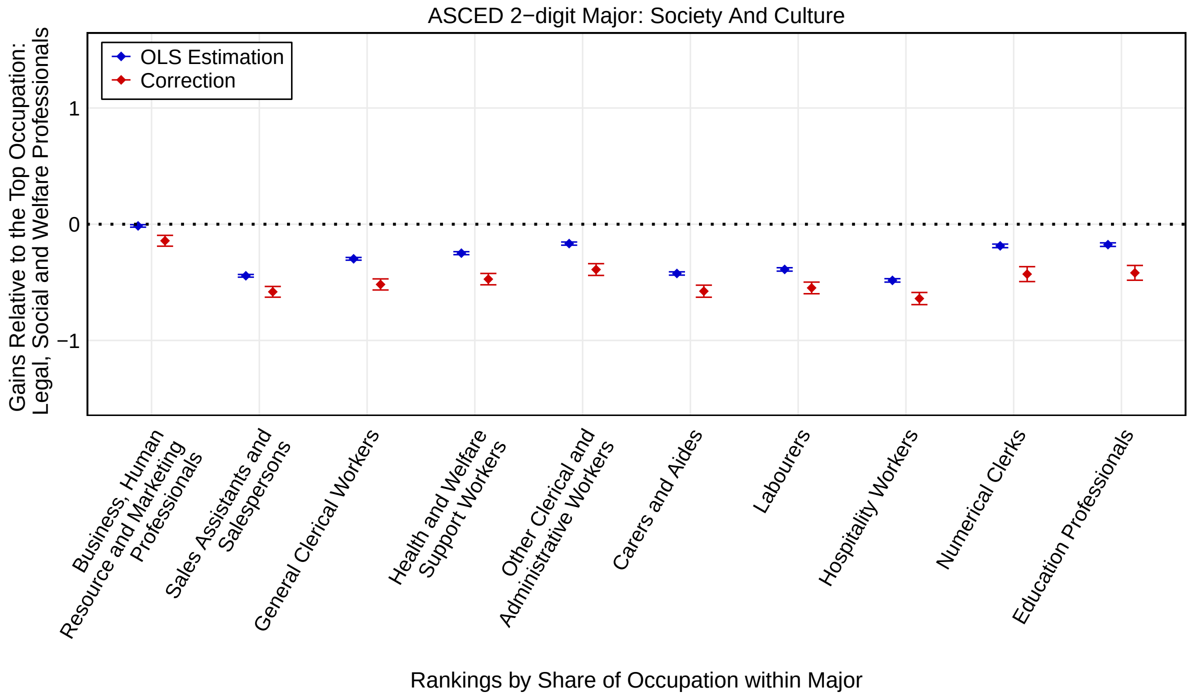
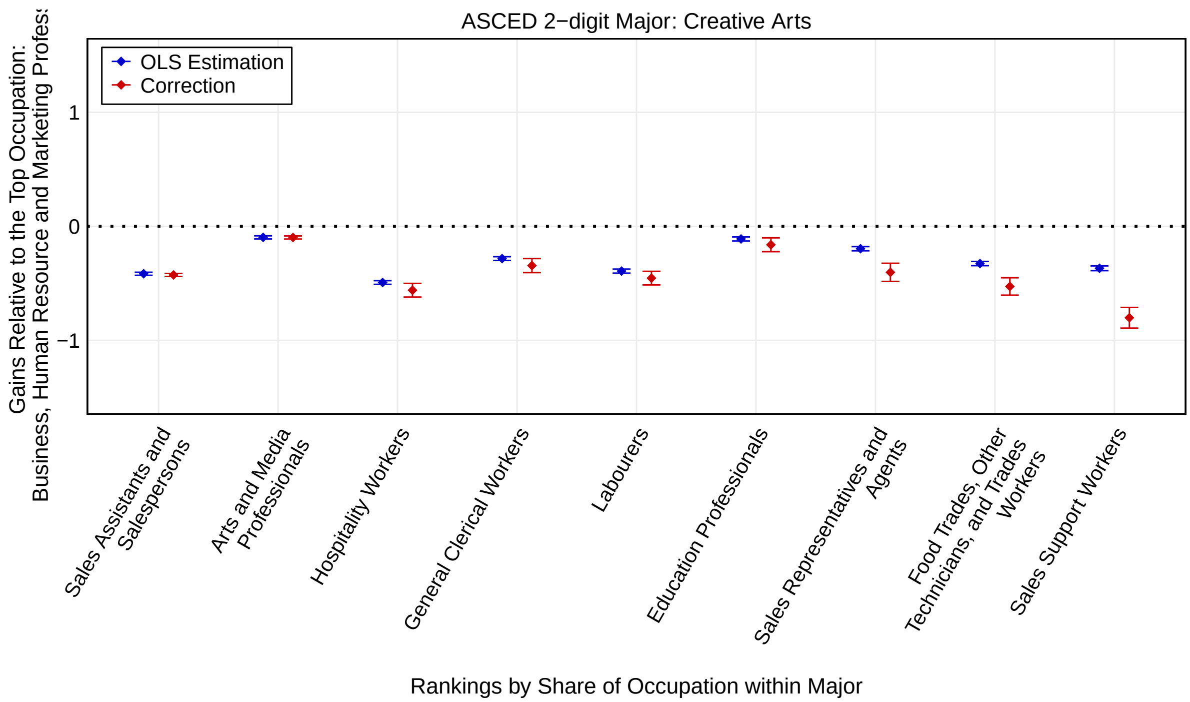


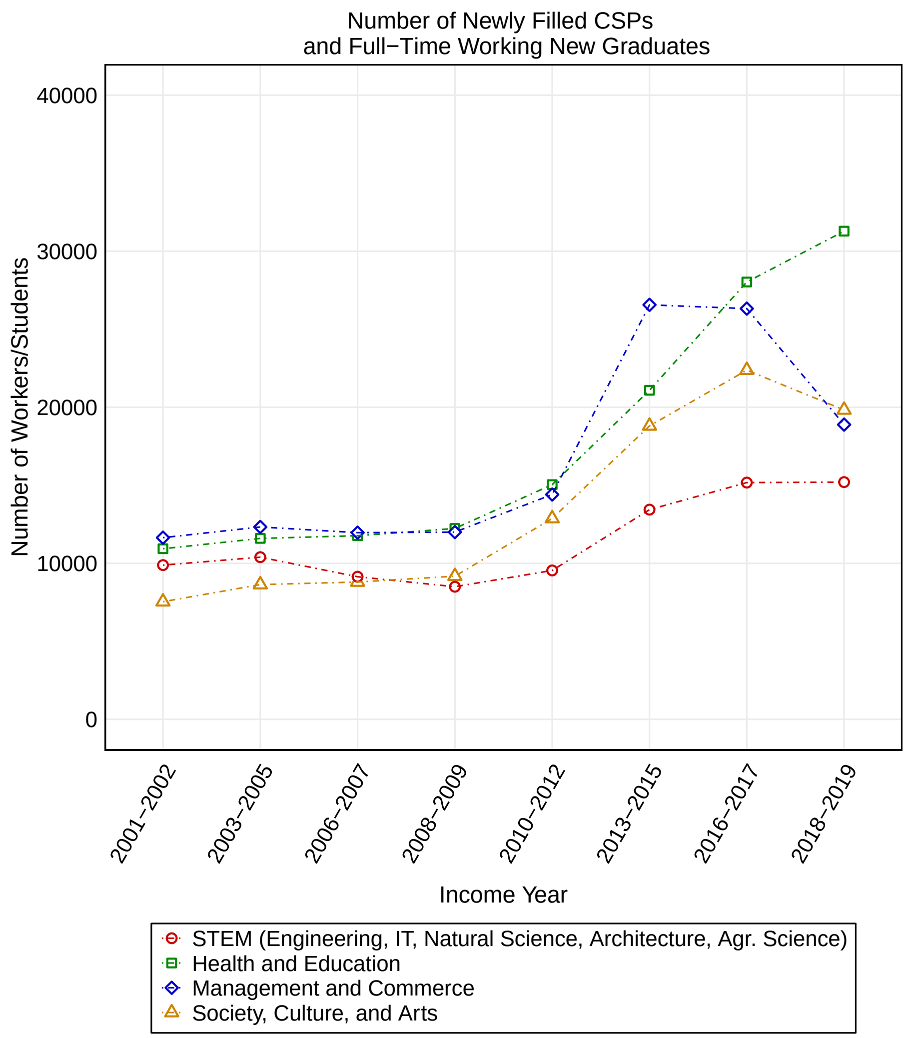
Figure Continued





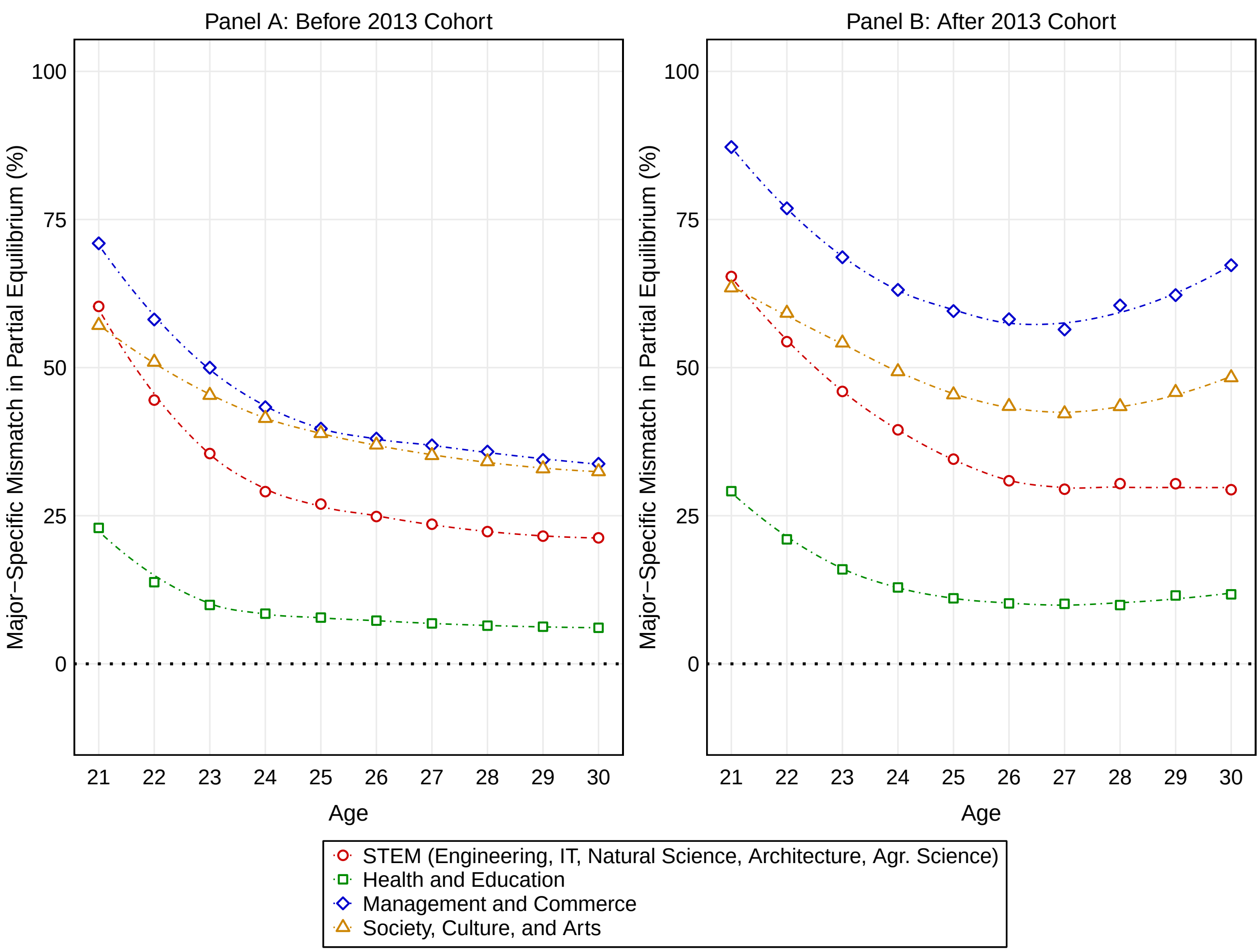
Notes: These figures plot the wage penalties from not choosing the field top-occupation (as shown in y-axis) at each observed occupational choice (as shown in x-axis) for each field of study. The order of occupations in the x-axis is based on the descending order of the share of occupations, ordered from Left to Right. The scale of y-axis represents for the relative gain (or loss) in log earnings from not choosing the top-occupation. We show both of the OLS and corrected point estimate of the wage penalties $\zeta_{(k|j)}$ from Equation (25) and 90% confidence interval. To avoid cluttering the figure, we only show the penalties of the occupations whose occupational share is among top 10 of all occupations within the major.

Figure F2: Number of New (Full-time Working) Graduates By Majors



Notes: This figure plots the number of newly full-time working graduates by each major over years.

Figure F3: The Average Mismatch in Partial Equilibrium over the Life-Cycle by Cohorts



Notes: This figure plots the evolution of occupational mismatch for aggregate fields of study over the life-cycle. Cohorts are split pre- and post-policy intervention in 2009, such that cohorts graduating from 2013 onward are assumed to have studied under an uncapped system of Commonwealth-supported places. The estimate of field-specific occupational mismatch is computed using Equation (11) for each age by each cohort group.