One Says Goodbye, Another Says Hello: Turnover and Compensation in the Early Care and Education Sector

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The quality of the early environment children experience influences their human capital development. We investigate retention and compensation in the Early Care and Education workforce by merging datasets from three different government agencies in Texas. We employ non-structural methods to compare turnover and pay in Early Care and Education with those in other sectors that employ similar workers. We estimate a dynamic discrete choice occupational model to quantify the labor supply and turnover elasticities in this industry. In addition, we simulate the impact of wage supplementation programs.

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1. Introduction

The analysis of the Perry Preschool Program proves that a high-quality early childhood intervention can impact outcomes over a lifetime for the individuals who participated in it and for their descendants (García, Heckman, and Ronda 2023).[1] In 2016, two first-generation teachers shared their memories about the Program, particularly their role (Derman-Sparks et al. 2016). From their current standpoint, the Perry teachers created adequate learning opportunities that matched their developmental state and life contexts. Therefore, one could hypothesize that a significant part of Perry's impact might be due to the Program's success in recruiting expert teachers and retaining them long enough to instruct at the appropriate level and establish a strong bond with the children.

Research in Developmental Psychology provides the theoretical basis for such a conjecture. For example, Vygotsky (1978) defined the Zone of Proximal Development as "the distance between the actual developmental level as determined by independent problem solving and the level of potential development as determined through problem-solving under adult guidance or in collaboration with more capable peers." Scaffolding is one of the ways that a parent, teacher, or more experienced peer can support a student's learning (Wood, Bruner, and Ross 1976).[2] However, the successful implementation of scaffolding requires the correct assessment of the child's current level of development and the speed at which the child progresses in skill acquisition (e.g., see Palincsar and Brown 1984; Swanson and Lussier 2001; Lajoie 2005; Macrine and Sabbatino 2008; Garza 2009). Arguably, when turnover rates are high, teachers may fail to successfully implement appropriate scaffolding techniques because they don't have enough time to correctly gauge the level and rate of change of the child's human capital.

According to Bowlby (1969), attachment is an emotional connection that keeps children close to an adult figure, particularly during distressful times. Children who form a secure attachment to their caregivers develop more skills because they are more likely to explore (and create) developmental opportunities in their environment (Elicker and Fortner-Wood 1995; Moss et al. 1996). However, when turnover is high, it is challenging to develop secure

[1] Technically, the Perry Preschool Program is not a childcare program. However, it is an influential study on the significance of the early environment for human capital formation. A growing literature investigates the long-term impact of high-quality childcare programs such as the Early Head Start or Head Start (e.g., see Garces, Thomas, and Currie 2002; Deming 2009; Carneiro and Ginja 2014), and the Infant Health Development Program (e.g., see Duncan and Sojourner 2013; Chaparro, Sojourner, and Wiswall 2020; Dougan, García, and Polovnikov 2023). In addition, see Herbst (2017) for evidence from the U.S. Lanham Act of 1940.

[2] According to van de Pol, Volman, and Beishuizen (2010), scaffolding is a form of instructional support that has three characteristics. First, it is tailored according to the child's current level of performance. Second, it fades gradually as the child acquires the skills to execute the task. Third, the responsibility for the performance of a task is progressively transferred to the learner.

attachment (Cryer, Hurwicz, and Wollery 2000; Institute of Medicine 2015) because this formation requires time (e.g., see Howes 1999; Raikes 1993) and caregivers' behaviors to be responsive, consistent, and forecastable by the child (Verschueren and Koomen 2012).

Research in Labor Economics also provides a theoretical foundation for our hypothesis. Becker (1962) frames training as an investment in human capital that raises future productivity but has a present cost. In the ECE sector, greater productivity means the teacher becomes more effective in applying scaffolding techniques to build skills or interacting in responsive ways to establish a secure attachment. However, it makes little sense for firms or workers to invest in training if the turnover likelihood is high. It is perhaps for this reason that professional development in the ECE sector is scarce and inconsistent (Phillips, Austin, and Whitebook 2016).[3]

Unfortunately, few empirical studies investigate the links between turnover and child development. Nevertheless, the few studies that do so suggest that turnover affects child development negatively. For example, Tram and Winsler (2011) shows that four-year-old children who did not experience a teacher turnover during the academic year experienced greater improvement in teacher-reported attachment. Markowitz (2019) used Head Start data to show that teacher departure is negatively and meaningfully associated with children's language, literacy, social, and behavioral self-regulation skills.[4]

In addition, turnover increases the chance of exposing children to "rookie" teachers. The literature in Economics of Education finds that lack of experience is one of the few observable teacher characteristics that predict learning consistently (Staiger and Rockoff 2010). For example, Araujo et al. (2016) find that the children assigned to teachers with little experience in an "as good as random" fashion have test scores that are 0.17 standard deviation lower, thus confirming quasi-experimental evidence from studies in the United States (e.g., see Rivkin, Hanushek, and Kain 2005; Clotfelter, Ladd, and Vigdor 2006; Harris and Sass 2011).

Therefore, the negative impacts of turnover on children's development provide the rationale for researchers and policymakers to study this issue more closely than turnover in other sectors of the economy. However, the lack of data makes it challenging to investigate

[3]Investment in professional development is further discouraged because the set of skills that raise educational productivity is general to the sector and not specific to a firm in that sector. Therefore, in such cases, Becker (1962) predicts that workers should bear the cost of these investments. However, this theoretical prediction holds if the labor market is perfectly competitive. If there are frictions, then firms might find it optimal to bear the costs of general training (e.g., see Katz and Ziderman 1990; Stevens 1994; Acemoglu and Pischke 1999).

[4]See also Bryk and Schneider (2002) and Guin (2004) for the association between teacher turnover and children learning in the K-12 educational sector. To our knowledge, the only study that implements a quasi-experimental approach to study the impact of turnover on learning is Ronfeldt, Loeb, and Wyckoff (2013). These authors found that turnover negatively impacted scores in English Language Arts and Math.

this issue. Some influential articles in this literature, such as Whitebook, Phillips, and Howes (2014), Bassok et al. (2013), and Brown and Herbst (2022) explore (repeated) cross-sectional data such as the National Study of Early Care and Education (NSECE, 2012, 2019), the Current Population Studies (CPS), or the Quarterly Workforce Indicators (QWI). In NSECE, the childcare program's director reports teacher turnover rates. In the CPS, one can measure turnover by comparing the main job in the previous calendar year with that in the March supplement of the current year. In the QWI, the turnover rate is calculated as an average of hires in one quarter and separations in the next quarter.

More recently, Bassok et al. (2021b) used longitudinal administrative data from the Louisiana Department of Education to study teacher retention. Their rich dataset, from Fall 2016 to Fall 2019, is a census of the 5,900 lead teachers in toddler or preschool-aged classrooms in all publicly funded center-based ECE programs. Therefore, their sample includes individuals teaching in school-based sites, Head Start locations, and childcare programs. They find that turnover is higher for workers in the childcare industry, new teachers, and teachers of younger children (i.e., toddlers). Interestingly, this dataset records teachers' scores in the Classroom Assessment Scoring System (CLASS). They find that teachers with lower scores in the CLASS are more likely to leave the sector.[5]

However, none of these datasets have information about these individuals before they join the labor force and simultaneously follow them if they leave the ECE sector. Thus, researchers cannot use these datasets to construct the workers' educational and labor force participation history or identify other individuals with similar academic and work trajectories who have never joined the ECE sector. As a result, researchers cannot use these datasets to investigate labor market outcomes in industries that employ similar individuals and compare them to the same statistics in the ECE sector. Alternatively, these datasets do not have information about the ECE workers' earnings and turnover rates when they are not working in the ECE sector. This information helps separate how much of the turnover rates are due to the sector's employment characteristics from the workers' unobserved heterogeneity. This decomposition is critical to designing personnel policies to improve employment duration, which is necessary to implement meaningful professional development programs that will enhance classroom performance and benefit children.

We study retention in the Early Care and Education sector. We contribute to this literature in two ways. First, we attempt to answer the call from Whitebook et al. (2018), who argued that the lack of data on the ECE workforce limits the search for data-driven policy

[5]Recent papers find that the CLASS does not predict gains in developmental assessments (e.g., see Burchinal 2018; Guerrero-Rosada et al. 2021; Weiland et al. 2013). Unfortunately, none of these papers account for teachers not being randomly matched to students. One exception is Araujo et al. (2016). This study finds that CLASS predicts teacher value-added.

solutions. Specifically, we construct a unique dataset by merging the Texas Education Research Center (ERC) information. The ERC houses high-quality, administrative student and worker-level data of all individuals residing in Texas.

We identify all individuals born between 1980 and 1989 who enrolled in a public school from the Texas Education Agency (TEA) dataset. Then, we link the TEA dataset with information from the Texas Higher Education Coordinating Board (THECB) and the Texas Workforce Commission (TWC). Our data can trace the academic histories from high school to post-secondary education and into the labor market of nearly three million individuals. We tag as "ECE workers" all individuals who have worked in the early care and education sector for at least one quarter.

Then, we use the information on race, ethnicity, eligibility for free or reduced-price lunch, and scores in standardized tests to match "ECE workers" to individuals with the same probability of ever working in the ECE sector but who never did, and we tag them as "(Matched) Non-ECE workers." We do so to identify a group of individuals who are at the margin of entering the ECE sector under counterfactual compensation policies. Our approach partially resembles that of Blau (1993), who used CPS data to study the labor supply of the ECE sector thirty years ago. Like Blau (1993), we retain all individuals who worked in the ECE sector for at least one quarter. However, unlike Blau (1993), our comparison group does not include a random sample of all other individuals in our data. Instead, we retain only the individuals who, at the end of high school, had the same probability of working in the ECE sector for at least one quarter but never did during our analysis period. We do so because, as we document below, the ECE workers constitute a highly selected group.

Second, we use our rich administrative data to investigate both groups' educational attainment, participation in the labor force, and labor market outcomes, such as quarterly earnings and movements across industries. Therefore, we capture entry into, exit out of, and the duration of each employment spell of both groups. We explore two complementary methodological approaches with our data.

In our first approach, we estimate models with time, sector, and individual fixed effects to quantify the impact of working in the ECE sector on earnings and turnover rates. Our estimates indicate that the turnover rates are 12 percentage points (or 37%) higher, and wages are nearly 20% lower in the ECE sector. We also find evidence that the ECE Sector's turnover rates increase with educational attainment. The gradient is steep for African-American and Caucasian workers but not Hispanic workers.

We estimate an earnings "penalty" of approximately 20% in the ECE Sector. Our earnings analysis shows that the ECE sector penalty decreases steeply with educational attainment. For example, the penalty for an African American worker with a high school diploma (the worker with the lowest turnover rate) is nearly 31%. In contrast, the penalty is 13% for a worker of the same race but with a four-year college degree (and whose turnover rate is roughly 40% greater).

In our second approach, we formulate and estimate a canonical dynamic discrete choice model of schooling and work decisions to account for selection driven by unobservable heterogeneity in the ECE sector. Our analysis follows the seminal work by Keane and Wolpin (1997). Recently, researchers have estimated equilibrium models of childcare to evaluate the costs and benefits of interventions that increase families' access to high-quality programs (e.g., see Berlinski et al. 2020; Borowsky et al. 2022; Bodere 2022). A crucial parameter for such an analysis is the elasticity of labor supply in the ECE sector because the higher the elasticity, the lower the costs of expanding the supply of high-quality programs. However, high-quality care also requires low turnover rates to invest in professional development and give time for teachers to form a secure attachment with the pupils and gauge children's development appropriately. We use the structural model to estimate the elasticity of labor supply in the ECE sector, and we find that it is equal to two. Therefore, the labor supply is highly elastic in this sector. In contrast, the elasticity of turnover is approximately -0.5, so it is somewhat inelastic.

Finally, we use our structural model to estimate the impact of ongoing compensation policies on turnover in the ECE sector. For example, in 2021, the Virginia Department of Education implemented the Teacher Recognition Program. In this program, eligible teachers received a wage supplementation of $1,500 if they remained in the same site for the full eight-month program (Bassok et al. 2021a). In Texas, the Texas Workforce Commission is the government agency responsible for the childcare subsidy program, which, in turn, is funded by the Child Care and Development Fund (CCDF). In recent years, several TWC's Regional Boards have implemented wage supplementation programs for the workforce in the ECE sector. In Texas, the amount of the wage supplementation varies across regions and ranges from $120 to $3,900 per year. In common, these interventions represent incremental changes in compensation for workers in the ECE sector. Our model shows that these compensation policies have small (but positive) impacts on retention in the ECE sector. Given the low retention rates in this industry, our results indicate that these incremental changes in compensation will not be sufficient to attract, retain, and develop a workforce that can nurture the next generation.

We organize the rest of the paper into five sections. Section 2 introduces the data and how we construct the sample of ECE workers and matched Non-ECE workers. Section 3 presents the estimates of the fixed effect models. Section 4 outlines the model, discusses identification and estimation, and reports the estimates of key parameters of the structural model. Section 5 discusses the results of the counterfactual compensation policies. The last section takes stock of our paper's main lessons and highlights areas where additional research is necessary.

2. Data

2.1. The Education Research Center

The Texas Education Research Center (ERC) is a data clearinghouse that provides access to longitudinal, student-level data for scientific inquiry and policymaking purposes from 1994 to the present day. The ERC centralizes data from several different Texas agencies. By merging different datasets, researchers can follow Texas students from their first day at school to their last day on the job.[6]

The Texas Education Agency (TEA) and the Texas Higher Education Coordinating Board's (THECB) datasets provide detailed academic information at the level of the student. The TEA's dataset stores educational records from the public PK-12 system. It contains information about a student's demographic characteristics, grades, class attendance, courses taken, grade point average, standardized test scores, and graduation status. The THECB's database centralizes all data from degree-granting higher education institutions in Texas, and researchers observe, among other variables, admissions, enrollment, and graduation.

The ERC also stores worker-level Unemployment Insurance (UI) records from the Texas Workforce Commission (TWC). Although UI records contain the identity of employers and employees, the ERC does not release an employer identification number to minimize identification risks. However, employers also submit their business's North American Industry Classification System (NAICS) code. The childcare services sector's NAICS code is 664210. Therefore, we study turnover at the industry level.[7]

[6] A limitation of the Texas ERC data is that it does not track individuals who move out of Texas at any point in their life. This attrition is potentially nonrandom, which can bias the results of our analysis. However, Texas has the lowest outmigration rate of any U.S. state, with 82% staying in-state as of 2012 (Mountjoy 2021).

[7] Unfortunately, UI records have two weaknesses. First, employers do not report hours worked. For this reason, we focus on quarterly earnings instead. Second, we do not observe the workers' occupations. Therefore, we do not know if the worker is a director or other non-classroom (e.g., cook) or classroom staff (e.g., lead teacher, teacher assistant). We will refer to a worker employed in the ECE sector as an "ECE worker" for short, but they are not necessarily working in the classroom. Finally, we note that self-employed individuals (e.g., babysitters) and firms in the informal sector do not submit their records to the TWC.

2.2. Target Population

Our study follows individuals born between 1980 and 1989 who enrolled in Texas public schools starting from 1996. We use data from this cohort to capture essential periods of their academic years, any post-secondary coursework, plus nearly ten years of labor market outcomes. We also use a ten-year cohort to guarantee that we will have enough workers passing through the childcare sector, as we recognize that this is a tiny industry in the country and the state. In our final data of 2,768,093 unique individuals from this cohort, only about 4% ever worked in the childcare sector.

2.3. Measures

In this subsection, we define how we measure each variable that we use in our analyses.

- *Demographics*: The TEA data informs an individual's gender, race, ethnicity, and free or reduced lunch eligibility.
- *Academic Year*: The academic year starts in the third quarter of each year and finishes in the second quarter of the following year. We align the TEA and THECB with the TWC datasets.
- *School enrollment*: TEA and THECB data inform the individuals who enroll in school each academic year. If we observe an individual in the TEA or THECB data for that academic year, we set that school attendance as the main activity for that student in all quarters of that academic year.
- *Employment and home production*: If the individual is not enrolled in school, we search for that individual in the TWC dataset in each quarter of the academic year. The search produces one of the three mutually exclusive outcomes in each quarter. First, the individual is not in the TWC dataset in a particular quarter, and we record that the individual is engaged in home production. Second, the individual is in only one job in that quarter. Third, we observe multiple jobs for the individual in that quarter. This situation arises if the person held simultaneous jobs or moved jobs within that quarter, and it is impossible to differentiate between these situations. In these cases, we choose the job with the highest observed labor income as the main job in that quarter. Finally, in the second and third cases, we investigate if the individual passes the labor income test (see below). If the individual does not pass the labor income test, we register home production as the main activity in that quarter. If the individual passes the income test,

we record that the individual is working and save the labor income and the NAICS code for the employer.

- *Main activity in a quarter*: In about 35% of quarters, we observed a person working and enrolled in school. We drop the TWC information and consider the main activity as school attendance in these cases.

- *Labor income*: We follow Keane and Wolpin (1997) and consider a valid working quarter one in which the individual earned at least the equivalent of working 20 hours per week during at least 2/3 of the quarter (8 weeks) at minimum wage.[8] Appendix Table A1 contains the labor income thresholds we used for each quarter and year. We adopt this labor income test to exclude job spells that reflect temporary work because they mechanically increase the turnover rates across all sectors. After we have performed the income test, we use the Consumer Price Index to adjust for inflation.[9]

- *Industry*: We use the NAICS codes to determine the industry for an individual who is working. For example, we register that a worker is employed in childcare if the employer's NAICS code is 624410.

- *Turnover*: We define turnover by proceeding in two steps. In the first step, we identify the employer's industry in the third quarter of the year. In the second step, we identify if the worker is still employed in the same industry in the second quarter of the following academic year. If not, then it is a turnover. Note that we do not have any information about the employer's identity, so we cannot investigate turnover at the firm level.

  Our definition reflects turnovers that may influence children's development because they occur during an academic year. Note that our turnover definition does not consider the turnover that occurs between the second and the third quarters of the calendar year because a change of teachers takes place at this time because of the natural progression in classrooms (e.g., from infant to toddler). Therefore, there is no turnover if the worker stays in the same sector from the beginning of the third quarter of year t and the end of the second quarter of year $t + 1$.

- *Achievement*: During Spring, all students enrolled in High School in Texas must take an assessment exit level test in reading, writing, and mathematics, and obtain a minimum grade in each of them to receive a diploma. They can retake any number of times

[8] In the case of Keane and Wolpin (1997), the NLSY asked retrospectively for work status during the first, seventh, and thirteenth week of each quarter for a total of nine weeks during a year.

[9] Quarterly earnings is deflated using the quarterly CPI data from FRED (Federal Reserve Bank of St. Louis 2023). The base quarter is October-December of 2020.

until they achieve the minimum requirement. From 1997 to 2002, this exit test was called TAAS (Texas Assessment of Academic Skills), while from 2003 to 2006 it was called TAKS (Texas Assessment of Knowledge and Skills). We use each individual's first attempt score in reading and mathematics to compute an achievement measure. We anchor their scores to a common metric, which in our case is completed years of education by 30 years old. Therefore, we have a measure of achievement in the metric of completed years of education. See Appendix B for the full explanation of our anchoring methodology.

2.4. Panel Construction

Our analyses explore a quarterly panel from the first quarter of 1997 (1997Q1) to the first quarter of 2019 (2019Q1). To build this panel, we use: (i) enrollment, demographics, and graduation K-12 data from the TEA from 1997 to 2010; (ii) enrollment and graduation higher education data from the THECB from 1997 to 2019; and (iii) employer NAICS sector code and quarterly wage from the TWC from 1997 to 2019. The three datasets share a unique identifier, making it possible to link an individual across all three sources.

First, we select our target population. We find in the TEA data all individuals born between 1980 and 1989. We then create quarterly panel data with those unique individuals from 1997Q1 to 2019Q1 (89 quarters). Finally, we merge in, for each quarter, whether the individual was: (i) enrolled in school according to the TEA; (ii) enrolled in postsecondary education according to the THECB; and (iii) working in a sector according to the TWC. We also include demographic variables such as sex, ethnicity, free or reduced lunch eligibility, higher education institution code and major, quarterly wage, and the employer's NAICS code.

Table 1 summarizes the data assembly process.[10] Our sample consists of individuals born between 1980 and 1989. Although the TEA has rich demographic information, it does not provide data on birth year, only the student's age on September 1st of each academic year. Thus, we set this age as the individual's age at the beginning of the academic year. The individuals in the TEA dataset form the basis of our longitudinal dataset. Thus, we discard individuals that are present in the THECB (or TWC) but not in the TEA dataset. [11] After restricting the TEA, THECB, and TWC data sources to this specific set of individuals, we drop all invalid, duplicate, and inconsistent observations.[12]

After implementing the data-cleaning procedures, our analytical dataset has 2,768,093

[10]Appendix A documents our data cleaning and merging procedures.

[11]The THECB dataset has the same demographic information as TEA's. Still, it does not report the individual's test score in high school, which is a crucial variable we use to identify individuals likely to enter the

TABLE 1. Panel construction

	Data Source		
	TEA	THECB	TWC
Data Period	1997-2010	1997-2019	1997-2019
Restrict to born 1980-89 by TEA			
Total Observations	22mi	19mi	141mi
Unique Individuals	3.3mi	1.8mi	2.9mi
Drop duplicates, inconsistent, missing			
Obs. Loss (%)	11.93	0.08	.01
Drop multiple jobs, low wages			
Obs. Loss (%)	-	-	26.34
Individual Loss (%)	-	-	1.02
Final Data			
Total Observations	19mi	18mi	102mi
Unique Individuals	3.2mi	1.8mi	2.8mi
Longitudinal Data			
Unique Individuals	2,768,093		
Quarters	1997Q1-2019Q1: 89 quarters		
Total observations	246,360,277		

Note: This table summarizes the data cleaning process across all three primary data sources, the Texas Education Agency (K-12 education), the Texas Higher Education Coordinating Board (higher education), and the Texas Workforce Commission (employment and earnings). We first restrict the data to individuals born between 1980-89, then drop duplicates, missing, and inconsistent observations, followed by observations with multiple jobs and very low wages. In each of these steps, we indicate the percentage of observation loss. More details can be found in Appendix A.

Table 2. Summary Statistics for Non-ECE and ECE Worker Sample

	Non-ECE Worker %	ECE Worker %	Diff
Sex			
Women	49.0	93.9	44.9***
Ethnicity			
White	48.7	48.4	-0.2*
Asian	2.5	1.0	-1.5***
Hispanic	34.7	31.0	-3.8***
African Am.	14.0	19.5	5.6***
Native Am.	0.2	0.2	0.0
Education			
Less Than High School	23.5	17.0	-6.5***
High School	20.7	24.9	3.2***
Some College	41.6	50.3	8.7***
Four-year degree or more	14.1	8.9	-5.3***
Eligible for Free or Reduced-Price Lunch	34.6	34.9	0.2*
Obs.	2,659,389	108,704	-

Note: $*: p < 0.10$, $**: p < 0.05$, $***: p < 0.01$. The first column shows summary statistics for individuals who never worked in the ECE sector (Non-ECE Workers). The second column shows statistics for those who worked in the ECE sector for at least a quarter (ECE Workers). The third column computes the difference and its statistical significance.

individuals born between 1980-1989, in which about 4.1% (108,704) ever worked in the childcare sector.[13] Table 2 shows the demographic characteristics of the individuals in our final sample. The first and second columns show demographics for all individuals who have never worked in the ECE sector (henceforth, non-ECE) and those who worked at least for at least one semester (ECE). The third column computes the difference and its p-value. Women and African-American individuals are overrepresented in the ECE sector. ECE workers are more likely to have a high school degree or some college education but less likely to have a four-year degree or more.[14] Finally, the differences in eligibility for free or reduced-price lunch are not economically significant.

The Non-ECE and ECE Workers are highly different in demographics and educational attainment. Next, we implement a matching procedure to retain Non-ECE Workers similar to those in the ECE sample. First, given that the overwhelming majority of ECE workers are women and that Asians and Native Americans are only 1.2% of the ECE workforce, we exclude all men and all Asians and Native Americans. Second, we restrict our panel to comprise individuals between the age of 18 to 29.[15] Finally, we drop individuals with educational attainment less than high school. We do so because our main focus is the teaching staff within the ECE sector. In Texas, ECE teachers must have a valid high school diploma.

Next, we implement a simple matching procedure to narrow the sample of Non-ECE workers. Let $D_i = 1$ if agent i has ever worked in the ECE sector, and $D_i = 0$ otherwise. Let Z_i be a vector of observable attributes of an individual at age 18. The vector Z_i includes race, ethnicity, a dummy for whether the individual was eligible for the free or reduced-price lunch program in their last year of high school, dummies for their school district in the last year of high school, and their achievement based on their exit test scores.[16] We estimate

ECE Sector. The TWC UI dataset has no information on demographic characteristics or test scores.

[12]Invalid identifiers are individuals with unique identifiers that we could not use to link across years or data sources. Duplicates are individuals who show up twice or more in the same year and same data source with repeated information. For example, a student enrolls in two different schools or colleges in the same quarter. For these cases, we keep the observation with the highest credit hours. An individual has inconsistent observations if we observe different values across years for variables that should not change, such as gender, race, or ethnicity.

[13]We use NAICS code 624410 - Child Day Care Services for identifying the childcare sector. This industry is described on the NAICS website as one that "comprises establishments primarily engaged in providing day care of infants or children. These establishments generally care for preschool children but may care for older children when they are not in school and may also offer pre-kindergarten or kindergarten educational programs."

[14]Note that ECE teachers must have at least a high school degree in Texas.

[15]We delimit our data to these periods because these are the ages for which we observe all choices made by all individuals from our sample.

[16]Note that Z_i does not include educational attainment. We exclude it for two reasons. First, we drop all individuals with less than a high-school degree. Second, any educational attainment after high school is an

the probability that an individual will ever work in the ECE sector, $\Pr(D_i = 1|Z_i)$, by:

$$\widehat{\Pr}(D_i = 1) = \Lambda(Z_i\hat{\beta}), \tag{1}$$

where $\Lambda(\cdot)$ is the cumulative distribution function of a Logistic distribution, and $\hat{\beta}$ is the estimated parameter vector from a logit model. We then use a k-nearest neighbor search to find, for each individual that ever worked in the ECE sector, $k = 5$ individuals that never worked in the ECE sector but with similar propensity scores.

Table 3 and Figures 1A and 1B show the results of our matching exercise.[17] We obtain a good level of similarity across observable attributes, but our sample size is now significantly smaller as we must restrict our analyses to individuals whose propensity scores overlap. Still, our analytical dataset contains nearly 330,000 observations, 16.7% in the ECE sample, and 83.3% in the Matched Non-ECE sample.

TABLE 3. Balancing of observable attributes after matching

	(1) ECE Worker	(2) Matched Non-ECE Worker	(3) Unmatched Non-ECE Worker	(4) Diff. (1)-(2)	(5) Diff. (1)-(3)
Ethnicity					
White (%)	50.53	50.58	52.73	0.05	-6.69***
Hispanic (%)	30.47	30.47	33.41	0.05	-2.94***
African American (%)	18.98	18.94	9.35	0.04	9.63***
Free/Reduced-Price Lunch Eligible (%)	32.94	32.84	25.99	0.10	6.95***
Achievement	11.95	11.95	12.75	0.00	-0.79***
Obs.	54,898	274,491	448,987		

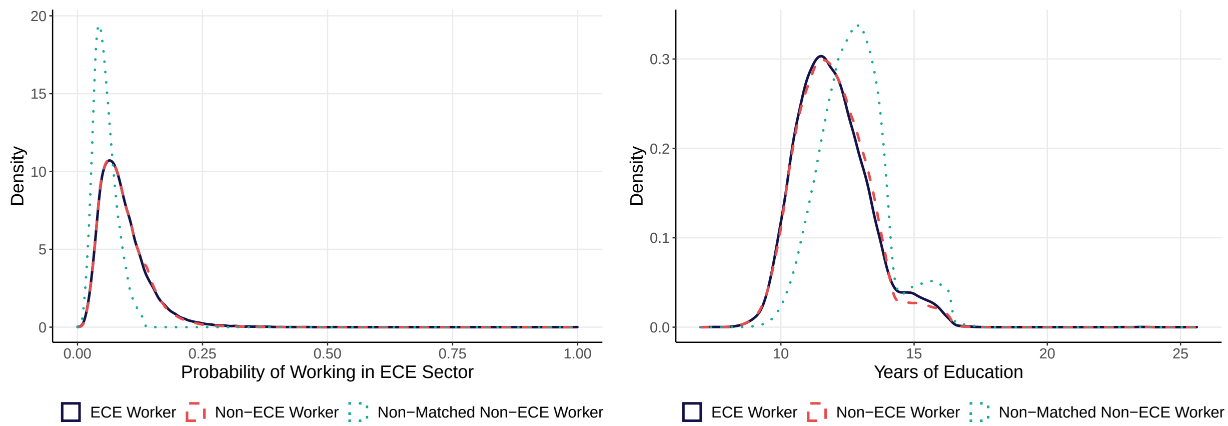
Note: $*: p < 0.10$, $**: p < 0.05$, $***: p < 0.01$. This table shows summary statistics for individuals at 18 years old. We omit school district dummies. Column (1) are individuals who at some point between 19 and 29 years old will work in the ECE sector (ECE Workers). Columns (2) and (3) are individuals who never work in the ECE sector between 19 and 29 years old (Non-ECE Workers). Column (2) are individuals who were matched to people from Column (1) by a nearest neighbor search, and Column (3) are the ones who were not matched. "Free/Reduced-Price Lunch" is a dummy variable for whether someone was in the reduced lunch price program in their last year of high school. "Achievement" is a measure of academic achievement derived from exit test scores and anchored in completed years of education by 30 years old (More details about the anchoring procedure in Appendix B). Columns (4) and (5) compute the difference and display their statistical significance.

Figures 1A and 1B show the density of working in the ECE sector and anchored test

endogenous variable we aim to use as an outcome in our analyses.

[17] We present the results from the logit regression in Table A4 in Appendix D.

FIGURE 1. Balancing of observable attributes after matching



A. Balancing of propensity score after matching

B. Empirical density of anchored test scores

scores, respectively. Non-Matched-Non-ECE workers have a much lower probability of ever working in the ECE Sector (see Figure 1A). Additionally, they tend to have higher test scores in high school (see Figure 1B). We note that our matching procedures generate two groups with identical densities of ever working in the ECE Sector and test scores. For the remainder of the paper, we use the ECE Workers and Matched Non-ECE Workers to conduct our analyses. We do so because the counterfactual economic regimes we consider in our structural analysis are incremental modifications to compensation policies for workers in the ECE sector. We argue that these policies are too small to attract a significant portion of the Non-Matched-Non-ECE Workers to the ECE Sector.

Table 4 presents summary statistics for our final sample. Socio-demographic variables have very similar values to the ones shown in Table 3 since they were used in the matching process. We also document statistics for the quarterly variables. About 43.7% of observations are working while 25.2% are in college. The remaining 31.1% of quarters are spent at home production. The average quarterly earnings, with a mean of $9,473.96 and standard deviation of $8,927.41, show significant variability in the sample. Completed credit-hours have a mean value of 6.835 and a standard deviation of 3.715.

3. Fixed Effect Analysis

Our analytical sample follows 329,389 individuals between the ages of 19 and 29. We focus on two groups of individuals, the "ECE" and the "Non-ECE".[18] These two groups are similar in observable attributes and probability of working in the ECE sector when they were 18.

[18] Henceforth, we refer to the Matched Non-ECE individuals as simply Non-ECE.

TABLE 4. Descriptive Statistics of Final Sample

Panel A: Overall Sample				
	Mean	Std. Dev.	Min.	Max.
Race & Ethnicity				
White (%)	0.506	0.500	0	1
African Am. (%)	0.189	0.392	0	1
Hispanic (%)	0.305	0.460	0	1
Free/Reduced-Price Lunch Eligibility (%)	0.328	0.469	0	1
Achievement	11.957	1.355	6.988	25.583
Activity (across all quarters)				
Participating in the Labor Force (%)	0.437	0.496	0	1
Enrolled in Higher Education (%)	0.252	0.434	0	1
Engaged in Home Production (%)	0.310	0.462	0	1
Edducational Attainment				
High School (%)	0.191	0.393	0	1
Some College (%)	0.533	0.499	0	1
4-year or More (%)	0.276	0.447	0	1
Credit-Hours	6.835	3.715	0.01	25.00
Quarterly Earnings ($)	9,473.96	8,927.41	1,021.20	8,118,90
Turnover Rates (%)	0.339	0.473	0	1
Ever Worked in ECE	16.7	32.3	0	1

This table shows summary statistics for the final sample of individuals after matching. Our sample consists of only women with at least a high school degree by 18 years old, and excludes Asians and Native Americans. There are 329,388 unique individuals, from ages 19 to 29 years old across 44 quarters. "Free/Reduced-Price Lunch Eligible" is a dummy variable for whether someone was in the free or reduced-price lunch price program in their last year of high school. "Achievement" is a measure of academic achievement derived from exit test scores and anchored in completed years of education by 30 years old. "High School" is a dummy for High School graduation. "Some College" is dummy for someone who accumulated college credits (or a two-year degree) but not a four-year degree. "Four-year degree or More" is a dummy for four-year or any graduate degrees. These variables are described in detail in the Data Section.

The difference is that individuals in the first group worked in the ECE sector for at least one quarter, while none of the workers in the second did.

We start our analysis by describing turnover and summarizing information about transitions into and out of the industry. Next, we investigate differences in quarterly earnings.

3.1. Transitions and Turnover

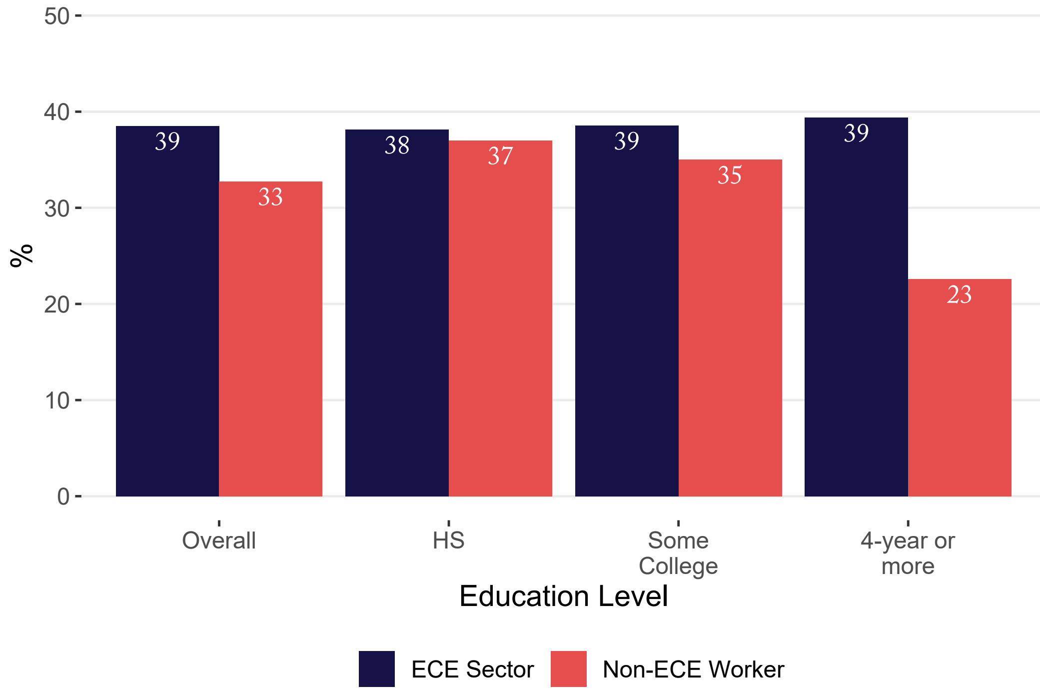
We observe labor force participation quarterly. This frequency gives us some flexibility in how to define turnover. We consider a turnover if the individual was employed in the ECE sector in the third quarter of a year but left the ECE sector before the end of the second quarter of the following year. Therefore, our measure only counts turnovers in which the worker did not stay a full academic year. This definition is developmentally appropriate because children tend to move to other classrooms and have new teachers once the new academic year starts. Thus, in our definition, a turnover is when the worker begins in August and leaves in February, for example. For comparison purposes, we construct turnover rates in other sectors similarly.[19]

Figure 2 displays the turnover rates (overall and by education level) for the ECE workers in the ECE sector and the non-ECE workers when working in an industry other than the ECE. Overall, the turnover rates are 39% in the ECE Sector. However, note that the turnover rate for non-ECE workers is just slightly lower at 33%. When we break the sample by educational attainment groups, we find that the differences are minimal for High School or Some College workers but significantly larger for individuals with a four-year degree or above.

Our estimates of the turnover rates in the ECE sector are comparable to those reported elsewhere in the literature. For example, Bassok et al. (2021b) uses administrative data from Louisiana and estimates the turnover rate in the ECE sector to be 37%. Their turnover rates are higher for the childcare sector (46%) and lower for Head Start (34%) and school-based programs (26%). Brown and Herbst (2022) find that the quarterly turnover rate is approximately 12%, but it varies with the business cycle. When we analyze the rate quarter by quarter, our estimates are approximately 13%, thus roughly consistent with their findings. In their literature review on turnover in the ECE sector, Totenhagen et al. (2016) reports annual rates ranging between 26%

[19] We have also estimated turnover rates according to Bassok et al. (2013) who use the CPS data, and we find that the results are similar.

FIGURE 2. Turnover Rates for the ECE Sector and Non-ECE Workers



Let $y_{i,t}$ denote individual i's turnover status at period t. That is, the variable $y_{i,t}$ is a dummy variable that is equal to one if the individual i was employed in sector s in period t and the same individual is either not employed or moved to a different industry s' in $t+1$. In this section, we estimate variations of the following model:

$$y_{i,t} = X_{i,t}\beta + \gamma D^{ECE}_{i,t} + \alpha_{Sector} + \alpha_{Year} + \alpha_i + \varepsilon_{i,t} \quad (2)$$

where $X_{i,t}$ denote control variables that vary with time (potential experience and potential experience squared). The variable $D^{ECE}_{i,t}$ is equal to one if the sector in which the individual i was employed at t was the ECE Sector, and the α's denote the various fixed effects in our procedure. When we use the entire sample, our estimate of γ is 0.122 with a standard deviation of 0.003. This estimate implies that the turnover rate in the ECE sector is 12.2 percentage points (nearly 37%) greater in other sectors of the economy.

TABLE 5. Turnover Regressions Conditional on Education and/or Race/Ethnicity

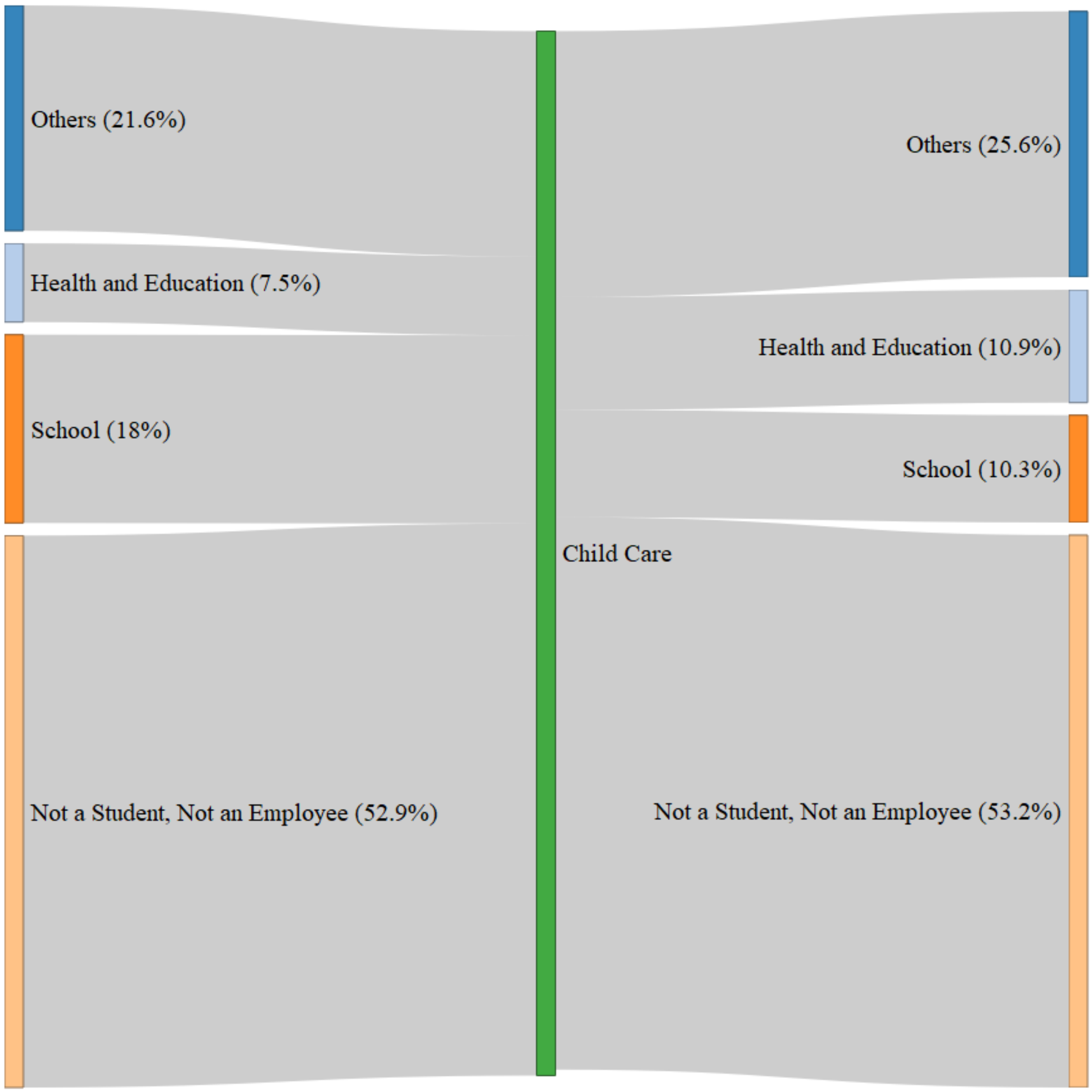
Panel A: African American Workers Only, By Education			
	High School	Some College	College or Above
ECE Sector	0.071***	0.056***	0.100***
	(0.014)	(0.010)	(0.023)
Panel B: Hispanic Workers Only, By Education			
	High School	Some College	College or Above
ECE Sector	0.104***	0.130***	0.101***
	(0.006)	(0.008)	(0.021)
Panel C: White Workers Only, By Education			
	High School	Some College	College or Above
ECE Sector	0.120***	0.153***	0.184***
	(0.009)	(0.007)	(0.012)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Note: This table shows estimates of γ in equation (2) when we break down our sample by educational attainment and race and ethnicity groups. ECE Sector is a dummy equal to 1 if the individual worked in the ECE sector during the year the turnover originated. We include fixed effects for sector, year, and for each individual. Controls include education years, potential experience (age – education years), and their squared counterparts. Sector fixed effects are two-digit NAICS code dummies. Year fixed effects are year dummies. We report robust standard errors in parentheses.

Table 5 compiles the regression coefficients when we break our sample by race or ethnicity (African American, Hispanic, and White) and education groups (High School, Some College, and College and Above). Thus, we have nine sets of estimates documenting heterogeneity across race or ethnicity and education groups. If we hold constant educational attainment, the turnover rates are greater for Caucasians and smaller for African-American workers (with Hispanic workers in between these two groups). In addition, conditional on race (or ethnicity), turnover rates tend to be higher for college workers.

Next, we present evidence about the sources and destinations when individuals transition into and out of the ECE sector, which we show in Figure 3. The left side of Figure 3 displays where the worker was one quarter before they entered the ECE sector. Nearly 53% of the workers were neither studying nor participating in the labor force in the quarter before moving to the ECE sector. Approximately 18% was enrolled in school.

FIGURE 3. Transitions in and out of the ECE Sector

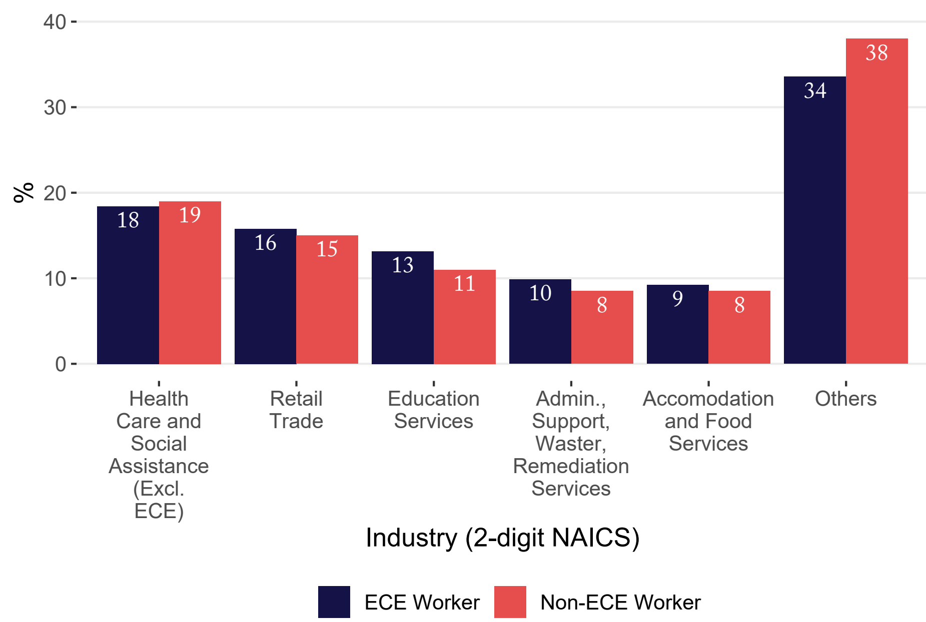


The ECE Sector is part of the Health and Social Assistance Category, which includes physician and dentist clinics, medical and diagnostic laboratories, hospitals, and health services. It also includes child and youth services, retirement homes, temporary shelters, and other community housing services. In contrast, the Educational Services Sector contains elementary and secondary schools, colleges and universities, and other educational entities. Combined, they represent the largest source (7.6 %) and destination (10.9 %) of ECE workers among the set of workers employed before and after their spell in the ECE sector, respectively.

We allocate to "Others" the remaining sectors ECE workers come from or go to. It is worth noting that many ECE workers come from and go to the Retail (6.3% and 5.4%), Accommodations and Food Services (4.1% and 3.4%), or Administration, Support, or Waste Management and Remediation Services sector (3.1% and 6.3%, respectively).[20]

Figure 4 shows that ECE workers work in similar sectors of Non-ECE workers when excluding the ECE sector itself. To construct this figure, we classify each employment spell according to the employer's NAICS code at the two-digit level (and we exclude employment spells in the ECE sector for the ECE workers). For example, 18% and 19% of the employment spells of the ECE and Non-ECE workers are in the Health Care and Social Assistance Sector (excluding ECE, which is part of this sector), respectively. The second sector with the most frequent employment spell for both groups is the Retail Trade (16% and 15%, respectively). This figure shows that the ranking and frequencies of the five industries are more or less the same. Both groups tend to work in similar sectors.

FIGURE 4. Most Commonly Worked Economic Sectors

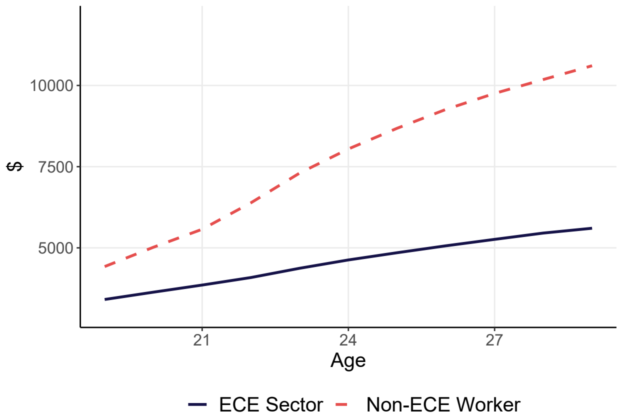


3.2. Quarterly Earnings

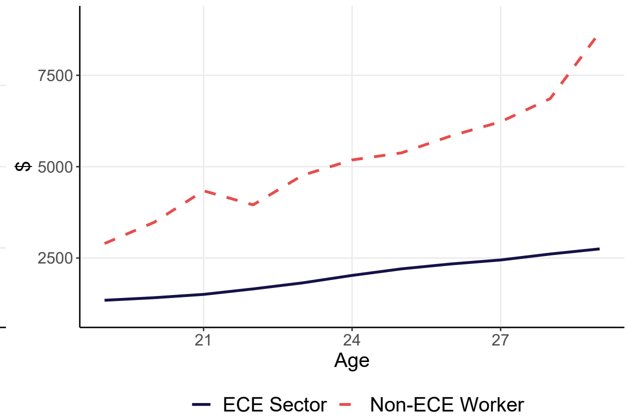
Figure 5A shows the dynamics of quarterly earnings. Conditional only on working, ECE workers earn approximately 30% less in all quarters than Non-ECE workers. Unfortunately, our UI data does not allow us to decompose this result into differences in hourly wages and hours worked.

[20] Figure A2 reports these statistics.

FIGURE 5. Earnings and Industry



A. Average Earnings Over Time



B. Standard Deviation of Earnings Over Time

Figure 5B displays the standard deviation of quarterly earnings over time. The distribution of earnings in the ECE sector has lower dispersion than the distribution of earnings in the Non-ECE Sector. This pattern is consistent with the densities of quarterly earnings (see Figure A1 in Appendix D). The distribution of earnings in the ECE earnings is less dispersed and more concentrated to the left.

Next, we report estimates of γ in equation (2) when the dependent variable $y_{i,t}$ is the natural log of earnings. We find that the quarterly earnings in the ECE sector are 19.8% lower than in other sectors (the standard deviation is 0.007). However, this "penalty" varies across education and race and ethnicity groups. Table 6 compiles the regression coefficients when we break our sample by race or ethnicity and education groups. First, we find evidence that the quarterly earnings in the ECE Sector are much lower for African-American or Caucasian workers with a high school diploma. In contrast, the penalty is much smaller for workers with a four-year degree or more. For Hispanic workers with a college degree, this penalty is negligible.

TABLE 6. Log Earnings Regressions Conditional on Education and/or Race/Ethnicity

Panel A: African American Workers Only, By Education

	High School	Some College	College or Above
ECE Sector	-0.308***	-0.181***	-0.131
	(0.062)	(0.052)	(0.163)

Panel B: Hispanic Workers Only, By Education

	High School	Some College	College or Above
ECE Sector	-0.145***	-0.191***	-0.015
	(0.015)	(0.017)	(0.046)

Panel C: White Workers Only, By Education

	High School	Some College	College or Above
ECE Sector	-0.269***	-0.230***	-0.154***
	(0.017)	(0.013)	(0.023)

*** p<0.01, ** p<0.05, * p<0.1. Note: This table shows estimates of γ in equation (2) when we divide the sample into educational attainment and race and ethnicity groups. The ECE Sector is a dummy equal to 1 if the individual worked in the ECE sector during the quarter. Sector fixed effects are two-digit NAICS code dummies. Year fixed effects are year dummies. We include individual fixed effects in all models. We report robust standard errors in parentheses.

3.3. Dynamics of Enrollment in Higher Education and Labor Force Participation

In Appendix E, we present the lifecycle profiles of enrollment in higher education and participation in the labor force. Our data shows that the dynamics of enrollment in higher education and labor force participation diverge at age 19. Non-ECE workers enroll in college at higher rates, and ECE workers are more likely to join the labor force earlier. In addition, ECE workers are more likely to neither work nor enroll in higher education between ages 19 and 29.

4. Structural Model

Next, we formulate and estimate a canonical dynamic discrete-choice model in which, at each period, an individual chooses to attend school, work, or engage in home production. We adopt this canonical model due to data limitations. Our dataset is longitudinally rich, but our labor market outcomes are limited as we do not observe hours worked, occupation, or the employer's identity. Still, the canonical model is rich enough to address transitions in and out of the ECE sector and to quantify the importance of selection out of the labor force due to unobserved heterogeneity. As a result, this model is sufficient to estimate a few parameters of interest, such as the elasticity of labor supply or turnover in the ECE sector. In addition, we use our model to simulate the impact of incremental ECE compensation schemes on retention.

4.1. Choice Sets and Laws of Motion for the Endogenous State Variables

The choice set consists of five mutually exclusive options. We set $m = 1$ if the individual works in a sector other than ECE or Education and Health (EH). Let $m = 2$ or $m = 3$ if the individual works in the EH or ECE sector, respectively. In addition, we set $m = 4$ if the individual attends school. Finally, $m = 5$ denotes home production. Let $d_{i,a,m} = 1$ if the individual i chooses alternative m at age a. Otherwise, $d_{i,a,m} = 0$. Because these alternatives are mutually exclusive and exhaustive, the following constraint is binding:

$$\sum_{m=1}^{5} d_{i,a,m} = 1 \tag{3}$$

Let $\boldsymbol{x}_{i,a} = \{x_{i,a,1}, x_{i,a,2}, x_{i,a,3}\}$ and $g_{i,a}$ denote accumulated experience and years of schooling, respectively. They evolve in a deterministic way according to the following laws of motion:

$$\begin{aligned} x_{i,a+1,m} &= x_{i,a,m} + d_{i,a,m}, \quad m = 1, 2, 3; \\ g_{i,a+1} &= g_{i,a} + d_{i,a,4}. \end{aligned} \tag{4}$$

4.2. Wage Offer Functions and Unobserved Heterogeneity

We allow for unobserved (to the econometrician) heterogeneity by including a normally distributed type θ_i that is fixed across time. This unobserved heterogeneity variable influences the utility of each alternative and is included in the wage offer function. Thus, θ_i captures selection on unobservable components in our framework.

The wage offer function is the product of the occupation-specific market rental price p_m and the individual's human capital $e_{i,a,m}$, that is, $w_{i,a,m} = p_m e_{i,a,m}$. The individual's human capital function is given by:

$$e_{i,a,m} = \exp\left(h_{i,a,m} + \beta_{m,0}\theta_i + \beta_{m,5}C_i + \xi_{i,a,m}\right) \tag{5}$$

where $h_{i,a,m}$ is the human capital accumulated via learning-by-doing:

$$h_{i,a,m} = \sum_{j=1}^{3} \beta_{m,j,1}x_{i,a,j} + \beta_{m,2}x_{i,a,m}^2 + \beta_{m,3}g_{i,a} + \beta_{m,4}x_{i,a,m}g_{i,a}$$

Thus, the individual's human capital, $e_{i,a,m}$, includes the learning-by-doing component, $h_{i,a,m}$, the individual-specific unobserved heterogeneity, θ_i, cognitive ability, C_i, and a normal shock, $\xi_{i,a,m}$. This shock has mean zero, variance $\sigma^2_{\xi,m}$, and is independent across periods and alternatives. Importantly, the agent does not know the vector $\xi_{i,a}$ at the time she chooses sectors. Therefore, $\xi_{i,a,m}$ is not an element of the agent's information set (or state space).

The Health-Education and Early Childcare Education sectors ($m = 2, 3$ respectively), share all parameters of the skill function, except for the individual-specific heterogeneity $\beta_{m,0}$ and the variance of the shock $\xi_{i,a,m}$.[21]

4.3. Preferences

4.3.1. Work ($m = 1, 2, 3$)

The per-period utility function associated with working in the sector m, for $m = 1, 2, 3$, is given by

$$u_{i,a,m} = w_{i,a,m} + r_{i,a,m} + \varepsilon_{i,a,m}, \tag{6}$$

The reward for working in a particular sector is given by the wage function $w_{i,a,m}$ and a non-pecuniary reward $r_{i,a,m}$ specific to that sector. The remaining term $\varepsilon_{i,a,m}$ is the preference shock of choosing alternative m. The non-pecuniary reward of a sector, $r_{i,a,m}$:

$$r_{i,a,m} = \gamma_{m,0} + \gamma_{m,1}\mathbb{1}\{g_{i,a} \geq 16\} + \gamma_{m,2}\mathbb{1}\{d_{i,a-1,m} = 0\} + \gamma_{m,3}\theta_i, \tag{7}$$

where we allow for a sector-specific constant, a return for having completed a 4-year

[21] However, we allow the rental price p_m and the parameters of the utility functions to differ.

degree, and a switching cost, respectively.

4.3.2. Schooling and Home

The per-period utility of attending school is given by

$$u_{i,a,4} = \alpha_0 + \alpha_1\theta_i + \alpha_2 \mathbb{1}\{12 < g_{i,a} \leq 16\} + \alpha_3 a + \alpha_4 C_i + \varepsilon_{i,a,4}. \tag{8}$$

The parameters α_2 capture the schooling costs of attending college, α_3 captures the age effects in school enrollment, and α_4 captures the return to cognitive ability in school enrollment. The type-specific reward from attending school is given by $\alpha_1\theta_i$ and $\varepsilon_{i,a,4}$ is the school preference shock.[22]

Lastly, the utility from staying home consists of a type-specific component θ_i, age and age squared effects, demographic effects, and a home preference shock $\varepsilon_{i,a,5}$:

$$u_{i,a,5} = \alpha_5 + \alpha_6\theta_i + \boldsymbol{Z}_i\boldsymbol{\alpha_7} + \varepsilon_{i,a,5}. \tag{9}$$

4.4. Initial Conditions, Timing, and the State Space

The initial conditions consist of the education level at age 19, ($g_{i,19}$), the accumulated work experience at age 19, ($\boldsymbol{x}_{i,19} = 0$), cognitive ability, ($C_i$), and demographic characteristics ($\boldsymbol{Z}_i$). The decision process follows the timing structure described below:

1. Preference shocks ε_i are realized;
2. The individual chooses the activity m with highest utility;
3. The wage shocks $\xi_{i,a}$ are realized;
5. Experience $\boldsymbol{x}_{i,a}$ and education $g_{i,a}$ are updated according to the laws of motion (4);
6. Move to $a+1$ and return to 1 until reaching terminal age A.

The individual i's state space at age a is given by $\boldsymbol{S}_{i,a} = \{\theta_i, \boldsymbol{Z}_i, g_{i,a}, \boldsymbol{d}_{i,a-1}, \boldsymbol{x}_{i,a}, \varepsilon_{i,a}\}$. Note that it does not include the vector $\xi_{i,a}$.

[22] We remind the reader that we discarded individuals with less than a high school diploma because such a diploma is required for an individual to be a teacher in the ECE sector.

4.5. Identification

Heckman (1981); Heckman and Singer (1984); Keane and Wolpin (1997) discuss the identification of structural parameters in this canonical model. Because of the parametric assumptions we imposed in our structure, the problem in the last period is similar to a multinomial logit conditional on types. We identify the parameters of the wage offer function by estimating parametric control function type regressions from the last period data. Then, the utility function parameters are identified up to location and scale normalizations.

4.6. Estimation

4.6.1. Solving the Model

At any age a, the individual's objective is to maximize the expected present value over all possible sequences of future choices given the current state space $\boldsymbol{S}_{i,a}$. The preference shocks ε are assumed to be Type 1 Extreme Value. The wage shocks ξ are normally distributed conditional on types. Let $\bar{\delta}$ denote the discount factor. The value function at age a is given by:

$$V(\boldsymbol{S}_{i,a}, a) = \max_{d_{i,a,m}} \mathbb{E}\Big[\sum_{t=a}^{A} \bar{\delta}^{t-a} \sum_{m=1}^{5} u_{i,t,m} d_{i,t,m} | \boldsymbol{S}_{i,a}\Big]. \tag{10}$$

Next, we use Bellman equations to write the problem recursively. The value function is the maximum over the alternative-specific value functions:

$$V(\boldsymbol{S}_{i,a}, a) = \max_{m \in M}\{V_m(\boldsymbol{S}_{i,a}, a)\}, \tag{11}$$

where $V_m(\boldsymbol{S}_{i,a}, a)$, the alternative specific value functions, are defined as:

$$\begin{aligned} V_m(\boldsymbol{S}_{i,a}, a) &= \tilde{u}_m(\boldsymbol{S}_{i,a}, a) + \delta\mathbb{E}[V(\boldsymbol{S}_{i,a+1}, a+1)|\boldsymbol{S}_{i,a}, d_{i,a,m} = 1], \quad a < A, \\ V_m(\boldsymbol{S}_{i,A}, A) &= \tilde{u}_m(\boldsymbol{S}_A, A), \end{aligned} \tag{12}$$

where $\tilde{u}_m(\boldsymbol{S}_{i,a}, a) = \int_{\xi} u_m(\boldsymbol{S}_{i,a}, a) dF_{\xi}$. Thus, we follow Carneiro, Hansen, and Heckman (2003) and Cunha, Heckman, and Navarro (2005) and assume that the wage shock for sector m, $\xi_{i,a,m}$, is realized after the individual chooses the sector. These studies provide the empirical evidence that the individuals do not know (or act on) these residual terms when choosing sectors. In addition, this assumption delivers an expected value function that has a closed-form solution when the preference shocks are Type 1 Extreme Value, as shown in Rust (1987). Let $\tilde{V}_m(\boldsymbol{S}_{i,a}, a)$ denote the alternative-specific value function minus the current period preference shock $\varepsilon_{i,a,m}$,

$$V_m(\boldsymbol{S}_{i,a}, a) = \tilde{V}_m(\boldsymbol{S}_{i,a}, a) + \varepsilon_{i,a,m}.$$

Then, as shown in Rust (1987), the expected value function can be written as

$$\begin{aligned}\mathbb{E}[V(\boldsymbol{S}_{i,a}, a)|\boldsymbol{S}(a-1)] &= E\Big[\max_{d_{i,a,m}} \sum_{m=1}^{5} d_{i,a,m} \left\{\tilde{V}_m(S_{i,a}, a) + \varepsilon_{i,a,m}\right\}\Big] \\ &= \log\left(\sum_{m=1}^{5} \exp(\tilde{V}_m(\boldsymbol{S}_{i,a}, a))\right) + \bar{\gamma}, \end{aligned} \tag{13}$$

where $\bar{\gamma}$ is Euler's constant. Therefore, the probability that individual i will choose sector m at age a is:

$$\Pr(d_{i,a,m} = 1|\boldsymbol{S}_{i,a}) = \frac{\exp(\tilde{V}_m(\boldsymbol{S}_{i,a}, a))}{\sum_{j=1}^{5} \exp(\tilde{V}_j(\boldsymbol{S}_{i,a}, a))}.$$

Starting from the last period A, for a particular value of the parameters, we calculate the alternative specific value functions $V_m(\boldsymbol{S}_{i,A}, A)$ for all possible combinations of the state space $\boldsymbol{S}_{i,A}$. We proceed by backward induction to period $A-1$, where we compute the expected value $\mathbb{E}[V(\boldsymbol{S}_{i,A}, A)|\boldsymbol{S}_{i,A-1}, d_{i,A-1,m}]$ over $\boldsymbol{S}_{i,A}$ which allows us to obtain $V_m(\boldsymbol{S}_{i,A-1}, A-1)$. From here, we repeat this procedure until we reach $a = 1$. With the values of $V_m(\boldsymbol{S}_{i,a}, a)$ for all possible periods a and associated state space $\boldsymbol{S}_{i,a}$, it is then possible to simulate choices for any individual with a particular starting value of the state space.

To simplify the estimation, we discretize the unobserved heterogeneity θ_i into K fixed types θ_i^k with probabilities π_k. We choose $K = 4$ pairs of Guass-Hermite nodes and weights as the values and probabilities, respectively.

4.6.2. Method of Simulated Moments

We estimate the model parameters by Method of Simulated Moments (MSM).[23] We, therefore, retrieve the set of initial conditions for a subset of individuals and several empirical moments related to the model. This approach allows the simulation of the set of individuals starting from their initial conditions.

The MSM's objective is to minimize the weighted difference between empirical and simulated moments with respect to the unknown set of structural parameters ϕ. Let M_D denote the vector of moments calculated from the observed data, and $M_{S,R_N}(\phi)$ denote the vector of moments derived from R_N simulated samples of size N, where we make clear the dependence of the simulated moments to the structural parameters.[24] The minimization problem is:

$$\hat{\phi} = \arg\min_{\phi}(M_D - M_{S,R_N}(\phi))' W (M_D - M_{S,R_N}(\phi)),$$

where W is a positive definite weighting matrix.[25]

The simulation proceeds in the following manner. Given a set of parameters ϕ':

1. Solve the model by backward induction and obtain $V_m(\boldsymbol{S}_{i,a}, a)$ for all possible state points;
2. Draw sequential shocks $\{\varepsilon_{i,a,m}, \xi_{i,a,m}\}$ and compute:
   - 2a. Choice sequences $d_{i,a,m}$ for $m = 1, 2, 3, 4, 5$;
   - 2b. Earnings sequences $w_{i,a,m}$ for $m = 1, 2, 3$;
4. Repeat 1-2 for $i = 1, \ldots, N$.

We set the number of replication R_N to 20. The weighting matrix W is a diagonal matrix where each element of the diagonal is the variance of the empirical moments, computed by resampling the data 200 times.[26]

[23] We do so because the ERC servers, where the data resides, are not high-performance computing machines, and we cannot retrieve an entire data set containing all the information needed to estimate the parameters through maximum likelihood.

[24] For a given simulated sample r, let ζ_r denote the sequence of shocks $\{\varepsilon_{s,a,m}, \xi_{s,a,m}\}$ for $s = 1, \ldots, N$, and $M_{S,r}(\phi, \zeta_r)$ the vector of moments. We define $M_{S,R_N}(\phi) = \frac{1}{R_N}\sum_{r=1}^{R_N} M_{S,r}(\phi, \zeta_r)$. Note that ζ_r remains fixed throughout the estimation procedure to avoid noise in the objective function.

[25] The consistency and asymptotic properties of these kind of estimators are discussed in Gourieroux, Monfort, and Renault (1993).

[26] This particular weighting matrix is used in similar settings. See Eisenhauer, Heckman, and Mosso (2015); Todd and Zhang (2020).

We have a set of 50 parameters and 370 moments. The moments are:[27]

1. Choice frequency for each period (55 moments)
   - The fraction of individuals in each of the 3 sector categories
   - The fraction of individuals in school
   - The fraction of individuals at home
2. Earnings for each period (66 moments)
   - The average log earnings for each sector
   - The standard deviation of log earnings for each sector
3. Transition matrix of the five choices from current to next period (25 moments)
4. Correlations between endogenous variables (36 moments)
5. Turnover for each period and working sector (30 moments)
6. Linear Probability Model regressions for each decision (158 moments)

4.7. Parameter Estimates

Table 7 shows the structural parameter estimates and their standard errors. In Panel A, we show the estimates for the wage offer functions and the non-pecuniary component of the working options. We highlight that besides the constant and the parameter for the heterogeneity, all other parameters within the earnings offer function across Health-Education (HE) and ECE are constrained to be the same. We focus our discussion on the joint Health-Education and ECE parameters. We see that the natural log of labor income is a concave function of experience. On the other hand, one more year of schooling increases earnings by about 15% in all sectors. The non-pecuniary utility from the ECE sector is around $14,000 for non-college graduates. However, we estimate a large and negative impact of a college degree on the ECE sector relative to Others, with a penalty of around -$120,000. We also highlight the large negative penalty as age increases for the ECE sector. We estimate these parameters because the probability of working in the ECE sector are much lower for college and older individuals.

[27] See Appendix C for a detailed description of all moments

TABLE 7. Model Estimates

Panel A: Estimates for Working Choices

	Others		**Health-Educ (HE)**		**ECE**	
	Param.	S.E.	Param.	S.E.	Param.	S.E.
Rent	8.7136	0.0021	9.1309	0.0016	8.7311	0.0023
Heter.	-0.6039	0.0018	-0.0022	0.0006	-0.984	0.005
Exp. Others	0.2478	0.0003	0.0252	0.0001		
Exp. HE	0.0101	0.0002	0.0561	0.0003		
Exp. ECE	0.0013	0.0002	0.0225	0.0002		
Own Exp.^{2}	-0.0107	0.0	-0.0205	0.0002		
Own Exp.$\times$ Educ.	-0.0474	0.0005	-0.01	0.0003		
Education	0.1459	0.0005	0.1681	0.0001		
Achievement 2	0.2077	0.0033	0.1352	0.004		
Achievement 3	0.063	0.0164	1.0091	0.004		
Wage Shock Sd. Dev.	0.5107	0.0035	0.3594	0.0035	0.2135	0.0035
Non-Pecunary Component						
Constant	-	-	1.1196	0.0095	1.4714	0.0094
Educ > 3	-	-	-1.1507	0.025	-12.8052	0.1326
Age	-	-	-0.0286	0.0008	-0.0302	0.001
Switch Cost	-	-	-3.0786	0.0104	-3.7045	0.0144

Panel B: Estimates for Schooling and Home

	Schooling			**Home**	
	Param.	S.E.		Param.	S.E.
Constant.	2.5293	0.027	Constant	1.9543	0.008
Heter.	0.145	0.0083	Heter.	1.1493	0.0103
Post-grad util.	-1.6862	0.0218	Reduced Lunch	-0.1641	0.0029
Age	-0.4164	0.0028	Hispanic	0.0002	0.0001
Achievement 2	0.933	0.0261	White	0.0033	0.0005
Achievement 3	0.6285	0.0322			

Note: This table shows parameters estimates and standard errors from the model. Coefficient units outside the wage offer functions is $10,000. Sample consists of 328,682 individuals between 19 and 29 years old. Achievement is discretized into 5 dummies representing 5 quantiles. Achiev. 1: < 12, Achiev. 2: (12.0, 13.0], Achiev 3: > 13.0. Omitted category in Ethnicity dummies is African American.

4.8. Model Fit and Unobserved Heterogeneity

Figures A9, A10, and A11, and Table A5 displays simulations from the model using the estimated parameters and compare it with actual data. In general, the model estimates captures the general patterns of the data. Schooling frequency drops off as age increases, and employment in the Health-Education sector increases with age. Earnings of each sector is increasing and concave. Standard deviation of earnings are flat and around 1.0. The model has more difficulty in capturing turnover dynamics, but the general values are within the range. Finally, the transition matrix has a good fit. Others and HE sectors exhibit higher own attachment, while ECE displays only a 56% attachment from $t-1$ to t. Between sector transitions are similar between model and data, with ECE choices in $t-1$ transitioning to Others the most.

In Table A6, we display the distribution of unobserved types as estimated by the model. As explained in section 4, we fix 4 points using Gauss-Hermite weights and nodes as probabilities and values. For example, Type 1 has a 4.6% probability with value –2.33, and so on. However, we allow a coefficient to multiply the type of the individual in the utility of each choice. Table A6 shows the type value multiplied by the coefficient for each choice.

Due to the symmetry of the fixed values, Type 1 individuals will either have the most or least comparative advantage in a sector, while Type 4 will have the opposite advantage of Type 1. In general, Type 2 individuals have larger rewards in ECE and Others sectors, while Type 3 have advantages on School and Home.

This pattern is seen also in Table A7, where we show the relative frequencies of Types in each sector. Type 2 individuals are more likely to be employed in working sectors, while Type 3 individuals are more likely to be either in School or Home.

5. Treatment Effects and Ex-Ante Policy Evaluation

5.1. Static Treatment Effects

We simulate the model using the estimated parameters under a counterfactual situation where the ECE sector is unavailable in the choice set and compare it to our baseline simulation. Our motivation is understanding where ECE workers would go and how their earnings would change if the ECE sector were unavailable. Table 8 shows, for every period, what sector ECE workers choose in the counterfactual simulation whenever the ECE Sector was their choice in the baseline simulation. We see that in general, the HE sector is the most common second-best choice. When individuals are 19 years old, schooling is the third-best choice. However, working in another sector becomes the second best choice after age 20.

TABLE 8. 2nd Best Choice When ECE Sector is Not Available

Age	Others	HE	School	Home
19	0.18%	69.51%	25.5%	4.81%
20	26.66%	46.23%	20.97%	6.13%
21	33.91%	37.35%	21.72%	7.02%
22	35.46%	33.93%	23.86%	6.75%
23	35.29%	33.51%	23.96%	7.24%
24	35.65%	34.85%	22.48%	7.03%
25	36.56%	36.16%	19.57%	7.71%
26	36.92%	38.27%	17.23%	7.58%
27	36.81%	41.54%	13.57%	8.08%
28	37.12%	42.79%	10.7%	9.4%
29	38.53%	43.31%	7.5%	10.67%

We use these counterfactual choices to estimate the "treatment effect" of working in the ECE sector. We compute two different statistics. The first one, which we call the "treatment effect on the treated", is the difference between log earnings in the ECE sector from the baseline simulation and the log earnings of the second-best working sector:

$$TT = E[y_{i,a,ECE}|d_{i,a,ECE} = 1] - E[y_{i,a,SBWS}|d_{i,a,ECE} = 1]. \tag{14}$$

The variable $y_{i,a,SWBS}$ denotes the earnings in the second-best working sector. Note that this alternative is not necessarily the second-best among all alternatives because the individual could choose enrollment in school or home production, in which case we would not observe earnings. Therefore, we estimate the "treatment effect on the treated" by using the earnings in the best alternative among working other than the ECE (i.e., Others or HE).

The second statistic is what we call the 'treatment effect on the untreated', which is the difference between log earnings in the ECE sector and the other working sectors conditional on the individual choosing any other working sector on the baseline simulation. That is,

$$(15) \qquad TU = E[y_{i,a,ECE}|d_{i,a,Others} + d_{i,a,HE} = 1] - E[y_{i,a,FBWS}|d_{i,a,Others} + d_{i,a,HE} = 1].$$

The variable $y_{i,a,FBWS}$ denotes log earnings in the first-best working sector since it is the one they factually choose.

We present the results in Table 9. The first row shows the estimates for the treatment effect on the treated, while the second row displays our estimates of the treatment effect on the untreated. The first column presents the parameters according to equations (14) and (15), while the second and third rows presents our estimates when we disaggregate the first- or second-best working sector. According to the structural model, the estimates of the earnings penalty are -12% for the individuals who choose to work in the ECE Sector and slightly greater (-13%) for the workers who choose to work in the Non-ECE Sectors.

We can investigate how these treatment-effect parameters vary according to the first- or second-best working sector. For both treatment effect parameters, the penalty is much larger if the first- or second-best working alternative is "Others," and much smaller if HE.

TABLE 9. Treatment Effect Parameters

	ECE - Best	ECE - Others	ECE - HE
Treatment Effect on the Treated	-0.12	-0.13	-0.03
	(0.004)	(0.005)	(0.013)
Treatment Effect on the Untreated	-0.13	-0.19	-0.002
	(0.001)	(0.001)	(0.001)

5.2. Dynamic Treatment Effects

Our estimates indicate that working in the ECE sector has a short-term penalty in earnings. Next, we investigate if working in the ECE sector impacts the individual in the long run. To do so, we estimate a dynamic treatment effect (e.g., see Heckman and Navarro 2007; Heckman, Humphries, and Veramendi 2016). Our thought experiment is as follows. Consider an individual who chooses to work for the first time in the ECE sector at age $a = \bar{a}$. We observe this individual's accumulated experience in each industry and educational attainment at age 29. Then, we go back to age $a = \bar{a}$ and remove this individual's choice of working in the ECE sector. Therefore, this individual will now have to choose between working in the Others or HE sectors, enrolling in school, or engaging in home production. We then simulate this individual's life from $a = \bar{a}$ until age 29, and we obtain the estimates of the counterfactual accumulated experience in each industry and educational attainment at age 29.[28] The goal of this design is to understand what would have happened to individuals in the long run had they not chosen the ECE sector. Thus, we define the Dynamic Treatment Effect on the Treated as follows:

$$DTT = E[y_{i,29,CF}] - E[y_{i,29,B}], \tag{16}$$

where $y_{i,29,CF}$ denotes an outcome $y_{i,29,CF}$ denotes an outcome at 29 years old under the counterfactual simulation, while $y_{i,29,B}$ is the same outcome under the baseline simulation. In our simulations below, these variables are accumulated experience at age 29 (in each sector) and educational attainment at age 29.

TABLE 10. Dynamic Treatment Effects at 29 Years Old

	Dynamic Treatment Effect
Accumulated Experience by age 29 years	
Others	0.31
	(0.005)
HE	1.03
	(0.006)
ECE	-1.71
	(0.007)
Educational Attainment by age 29 years	0.30
	(0.004)

This table shows the impact of different outcomes at 29 years old between a counterfactual and baseline simulation. The counterfactual simulation removes the ECE sector as an option only the first time it is chosen, after which individuals have the choice to select it again. We compute the dynamic treatment effect, which is the difference in outcomes at 29 years old between the counterfactual simulation and the baseline simulation. First entry is the first time an individual ever entered the ECE sector. Duration is calculated as the number of consecutive years in a sector. Education is the number of accumulated years in school.

We present the results in Table 10. Experience in the ECE sector decreases by 1.71 years on average, while there is an increase of 1.03 years for the HE sector. The increase of accumulated experience in Others is of about 0.3 years. Finally, working in the ECE Sector for one period reduces educational attainment at age 29 by 0.3 years. These results indicate that the majority of individuals that are forced to not choose the ECE sector end up moving to the HE sector and they accumulate more education.

[28]Note that the individuals can make any choice after age $\bar{a}$, including the ECE sector.

5.3. Labor Supply and Turnover Elasticities

As we discussed in the introduction, Virginia and Texas have implemented pilot wage supplementation programs. As documented in Bassok et al. (2021a), the program in Virginia was uniform across the state. In Texas, these programs were initiated by the State using funds allocated by the Child Care and Development Block Grant (CCDBG) Act of 2014. The State requested each region to develop a wage supplementation plan for ECE workers as part of a broader effort to support childcare programs struggling due to the Covid-19 pandemic. As a result, these plans varied by regions, with values ranging from $120 to $3,900 bonuses per staff per year. These bonuses represent between 0.5% and 15.6% of the yearly earnings of childcare programs reported by the Bureau of Labor Statistics.

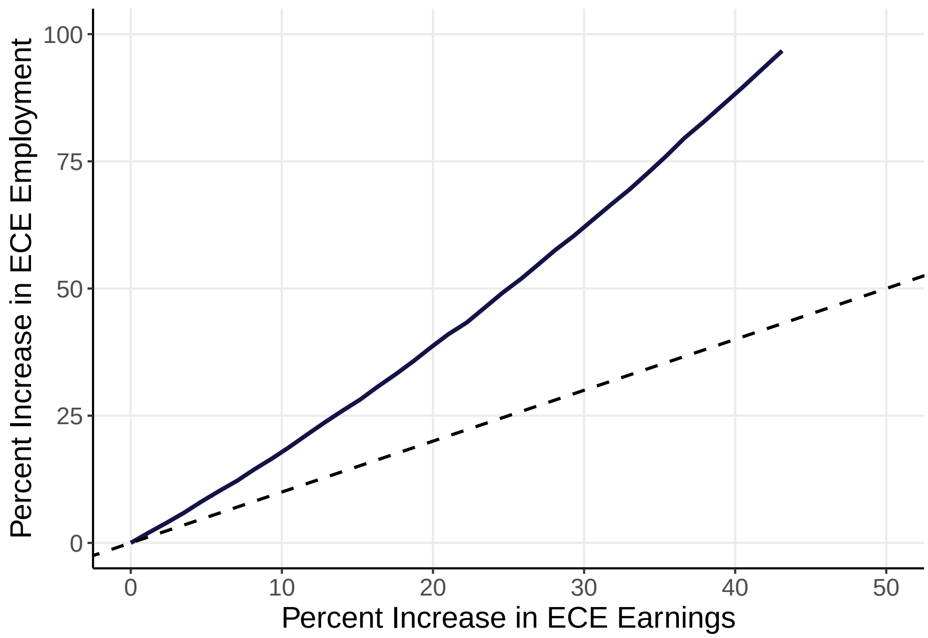


FIGURE 6. Impact of an Increase in Earnings on Employment in the ECE Sector

We use our model estimates to evaluate policies that provide these bonuses for workers in the ECE sector. We simulate rewards that represent 1% to 50% of the labor income. Specifically, we simulate the model using the estimated parameters but in every period we increase the ECE earnings offer function $w_{i,a,m}$ from Equation 6 by the desired percentage. These bonuses are static in the sense that we do not incorporate these increases to future offer functions. In other words, an individual choosing in period t whether to work in the ECE Sector incorporates the bonus in their decision making, but does consider that the bonus will also occur in periods $a+1,\dots,A$. This simulation provides estimates of the elasticity of labor supply in the ECE sector. As argued in Borowsky et al. (2022), this parameter is key to determine the costs of increasing the supply of high-quality childcare programs. Unfortunately, as these authors document, there are very few estimates of this crucial parameter in the literature. We use our data and model to fill this significant research gap.

Figure 6 shows that the labor supply elasticity is very high in the ECE sector. For example, a bonus that increases earnings by a 25% increase in labor income would lead to a 50% increase in employment in the ECE sector. Figure 6 also shows that the elasticity accelerates as the relative importance of the bonus increases. For example, the employment in the ECE sector doubles before the bonus represents a 50% rise in earnings.

There are only two estimates of the elasticity of labor supply for workers in the ECE sector. Blau (1993) uses the March CPS from 1977 to 1987 to obtain a sample of all female childcare workers and a random subsample of all other women in the same age range. His final sample contains 4,305 childcare workers, 7,180 other workers, and 3,710 nonworkers. In his model, workers choose both the sector and the hours worked if they choose to work. The estimate of the elasticity in the extensive margin is 1.2. In contrast, the estimate for the intensive margin is .74. Combining these two estimates generates an elasticity of labor supply equal to 1.94. In his influential book on childcare, Blau (2001) extends the analysis to 1987 and reports extensive, intensive, and overall estimates of the labor supply elasticity equal to 0.73, 0.42, and 1.15, respectively. Our estimate is slightly larger than the ones previously reported in the literature.

As discussed above, changes in wages also impact duration, which is key to delivering high-quality childcare services. Figure 7 displays how these bonuses impact turnover in the ECE sector. We find that the turnover elasticity is around 0.5, thus inelastic. For example, a 20% increase in earnings reduces turnover by 10%. In addition, this elasticity does not change with age.

Akai and Jibiki (2021) explore a policy change in Japan to estimate the impact of hourly wages on intention to leave the sector. Under the new policy, the government increased the subsidies to private (but not public) providers gradually. Importantly, the increase in the subsidy was tied to the average experience of childcare teachers in each provider. Thus, the subsidy rates increased more for programs with more experienced teachers (see Figure 1 in their paper). These authors use data from the 2013 and 2018 Survey of Licensed Childcare Providers in Tokyo and a difference-in-difference strategy to identify the parameters of interest. They find that the policy increased teachers' wages by 7%.

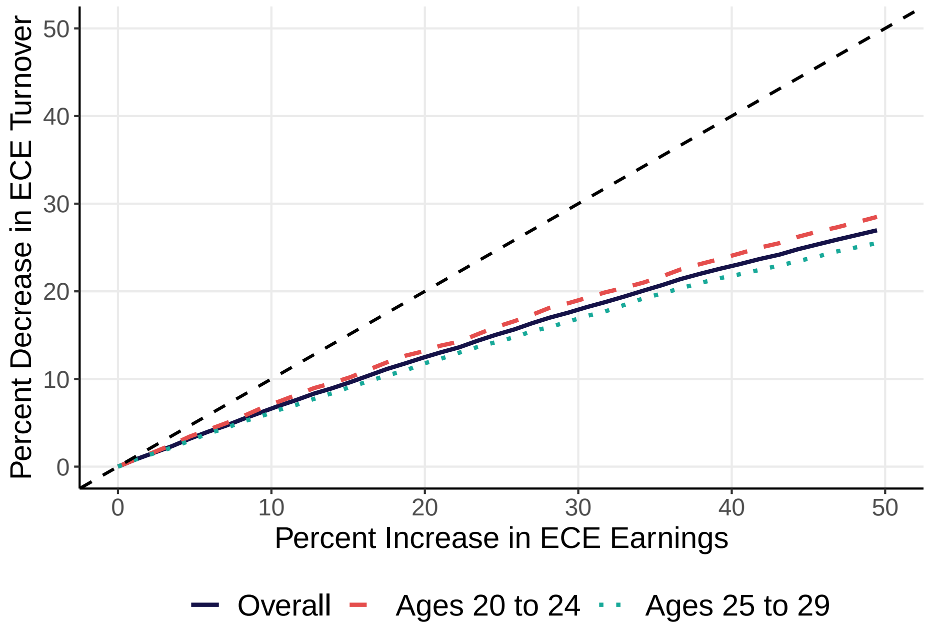


FIGURE 7. Impact of an Increase in Earnings on Turnover in the ECE Sector

Interestingly, their dataset does not have information on turnover. However, the survey elicits elicits the respondents' intention to leave their jobs. They find that the policy reduced intention to leave by 19%. This result means that a 7% increase in wages reduced the intention-to-leave by 19%. If we equate intention with actual turnover within a year, they find that the turnover elasticity is 2.7, thus significantly greater than our estimates. However, it is also possible that the intention to leave does not translate into turnover from one period to the next.

5.4. Wage Supplementation Policies

Next, we evaluate two policies aimed at increasing earnings in the ECE sector. Our policies reflect the wage supplementation programs implemented in Virginia and Texas. The first policy is to give a static $1,500 bonus to ECE workers in every period. [29] This bonus is similar to a signing bonus. We also simulate a $1,500 bonus conditional on having worked in the ECE Sector in the previous period. This bonus is similar to a retention award. Therefore, an individual choosing whether to work in the ECE Sector in period t takes into account that, in period $t + 1$, they will earn the bonus if they continue working in the sector.

The static bonus substantially impacts recruitment into the ECE Sector as it increases the fraction of ECE workers (i.e., individuals who work in the ECE Sector for at least a

[29] A $1,500 bonus represents an increase in earnings offer of about 17% in our simulated baseline.

quarter) by approximately 14%. In contrast, the dynamic bonus has negligible effects on recruitment. This difference between the two policies is because the dynamic bonus only kicks in if the individual chooses to work in the ECE sector for two periods. On the other hand, the static bonus applies to the current decision period. Table A8 shows that neither policy leads to changes to the composition of the ECE workforce by race or ethnicity, economic status, or achievement (anchored test scores).

These two policies also attract a different composition of movers. As Table 11 shows, the static bonus attracts primarily workers who would be in the HE sector without this intervention. In contrast, the dynamic bonus draws uniformly from all industries.

Table 12 shows the impact of these wage supplementation programs on duration and turnover in the first spell of ECE employment and total experience in the ECE sector by age twenty-nine years. Duration is the number of consecutive periods a person is employed, while turnover indicates the proportion of individuals leaving the industry each period. The dynamic bonus has a slightly larger impact on turnover, duration, and accumulated experience. The duration in the first ECE employment spell and overall accumulated experience increase by around 6.5% for the static case and around 8% for the dynamic one. In addition, the static and dynamic bonuses reduce the turnover rate by 6.82% and 8.18%, respectively.

Table 11. Movers of Wage Supplementation Policies

Sector in Baseline	Static $1,500 Bonus	Dynamic $1,500 Bonus
Others	19.3%	30.1%
HE	54.9%	23.1%
School	20.7%	22.4%
Home	5.1%	24.4%

This table shows which sectors individuals would be in the absence of counterfactual wage supplementation programs. The percentages denote which sector they come from due to the policy.

The impact of the simulated policies can be compared to an experiment conducted in Virginia and analyzed in Bassok et al. (2021a). In 2019, Virginia implemented a program that offered up to a $1,500 compensation bonus if educators in early childhood settings remained in their position over 8 months. Thus, this policy is similar to the dynamic bonus we consider in our analysis. The authors of the study conducted a Randomized Controlled Trial to assess the impact of the bonus on turnover. They found that the turnover rate decreased by 49.6%. Interestingly, the $1,500 bonus in Virginia represents a 4.4% increase in earnings. These findings indicate a turnover elasticity of -11.2, which indicates a very large elasticity over 300% greater than the one reported by Akai and Jibiki (2021). If the Virginia

RCT has external validity, then it is possible to greatly impact turnover with policies that have very low costs.[30] [31]

TABLE 12. Impact of Wage Supplementation Policies on Outcomes

	Baseline Value	Static $1,500 Bonus (% Change)	Conditional $1,500 Bonus (% Change)
Duration at first spell	1.95	6.12%	7.97%
Turnover at first spell	0.47	-6.82%	-8.18%
Accumulated Experience in the ECE Sector	1.86	6.75%	8.22%

This table shows the impact of different earnings policies. The "Baseline" column shows the same statistics implied by the model with no policy. The second column shows the percent change in overall composition after a static $1,500 bonus, the third column shows the percent change in composition after a conditional $1,500 bonus. Duration is calculated as the number of consecutive years in a sector, and turnover is the fraction of individuals who leave the ECE sector at the end of the period. Accumulated experience is the number of periods that the individual worked (consecutively or not) in the ECE sector by age twenty-nine years.

Our dynamic bonus reduces turnover rates by only 8.2%, thus a much smaller rate. In contrast, the $1,500 represents a 17% increase in annual earnings in our sample. Therefore, under the dynamic bonus, the elasticity is approximately -0.48, or 23 times smaller than the elasticity implied by the estimates reported in Bassok et al. (2021a). Our estimates indicate that it will require much more ambitious wage supplementation programs to impact turnover rates significantly.

Several factors can explain the difference in impacts. While Bassok et al. (2021a) analyzes a sample of early childhood educators that includes Assistant Teachers and Lead Teachers in childcare programs but also from early childhood programs in school sites. Our sample consists of workers in the ECE sector, which includes more than educators and teachers.

Second, the sample of childcare (Assistant and Lead) Teachers in their paper is quite different from ours. Their average age is 41 years old, with an average ECE experience of 10 years, 47% of educators with at least a bachelor's degree, and an estimated annual earnings of $33,800. On the other hand, our sample consists of individuals between 19 and 29 years old, with 18% with a bachelor's degree, and average annual earnings of $16,500.

[30] Bassok et al. (2021a) report the effects of the program for Assistant Teachers and Lead Teachers in childcare programs separately. Thus, it is possible to estimate the elasticity for these two groups separately. If we do so, we find that the Assistant Teachers turnover elasticity is -12.3 and for Lead Teachers is -7.3.

[31] Bassok et al. (2021a) find no effect on turnover for teachers in early childhood programs in school sites. Indeed, the turnover rates in the control and treatment groups are 6.4% and 7.3%, respectively.

6. Conclusion

We study retention in the childcare sector. To do so, we construct a longitudinal dataset of individuals born between 1980 and 1989 who attended a public school in Texas. We identify all individuals who worked in the early care and education sector for at least one quarter. Additionally, we matched them to other workers with the same probability of working in the ECE sector but never did during the period of our analysis.

We use fixed effect models in our non-structural analysis. The fixed effect models estimate that the turnover in the ECE sector is 12 percentage points greater than in other sectors of the economy. Furthermore, these models estimate an earnings penalty of 20% in the ECE sector. We uncover much heterogeneity across education and race and ethnicity groups. In addition, although the ECE and Non-ECE workers are observationally similar at age 18, their lifecycle profiles of enrollment in higher education and participation in the labor market start to diverge at age 19. Non-ECE workers are more likely to enroll in higher education, while ECE workers are more likely to join the labor force early (between ages 19 and 23).

Our structural model fits the data well. Our model estimates that the labor supply elasticity in the ECE sector is approximately 2, and the elasticity of turnover is about -0.5. Our model also suggests that the earnings premium is slightly lower at 12%. We use our model to simulate the impact of wage supplementation interventions comparable to pilots in Virginia and Texas. We show that such bonuses have minor effects on retention in the ECE sector.

Our study is limited in several ways. When individuals are working, we do not observe the number of hours worked in the quarter. We also lack information about the establishment, such as size, number of employees, location (e.g., urban vs. rural), or licensed capacity. Thus, we cannot investigate why earnings are so much lower in the ECE sector. We can, however, rule out particular possibilities. We adopt two distinct methodological approaches that account for unobserved heterogeneity. Both methods estimate substantial earnings penalties in the ECE sector. Thus, unobserved components of human capital are unlikely to explain why earnings in the ECE sector are so much lower.

First, earnings in the ECE sector could be lower because workers work fewer hours. This explanation is possible because most ECE teachers in our dataset leave the labor force immediately after leaving the ECE sector (see Figure 3. Therefore, their annual hours may be lower than those of other sectors.

Second, wage rates in the ECE sector are lower than what they would be in another industry because of compensating differentials. For example, individuals who work in childcare are parents of young children, and the childcare firm may allow teachers to enroll their children in the program and charge them a discounted rate. McClure (2021) argues that such a benefit could reduce retention.

Third, customers are unable to differentiate low- from high-quality programs (e.g., see Gordon, Herbst, and Tekin 2021). When these informational frictions are severe, parents are unwilling to pay a premium for high-quality programs. In this case, the market equilibrium is one in which most programs are low-quality, charge low tuition, and pay low wage rates.

Fourth, regulations in the childcare market increase the cost of operating a home- or center-based program, reduce the supply of seats, and potentially diminish wages in this industry. Indeed, a large body of literature finds that more stringent regulations reduce the availability of seats in home- and center-based programs, particularly in markets where families are economically disadvantaged.[32] However, to our knowledge, studies have yet to be conducted on the impact of regulations on teacher pay.

Finally, childcare firms may engage in monopsonistic wage setting practices (e.g., see Card 2022, for a discussion of this literature). Such a situation could occur if ECE workers search for employment in locations with very few firms and, thus, little competition for labor. Our analysis shows that these workers have employment opportunities in many other sectors of the economy, so the local markets must have very few firms in such sectors. Another possibility is that there is collusion in this market. Again, such a possibility would have to be consistent with the fact that this industry is extremely diffuse as Statista Research Department (2022) reports that the ten largest providers serve less than six percent of the children in this market. Another challenge for this explanation is that for-profit firms in this sector have profit margins of 1% (Davies and Grunewald 2019).

We also uncovered that the earnings penalty varies with race or ethnicity and educational attainment. These findings are consistent with the results reported by Boyd-Swan and Herbst (2018). These authors conducted a resume audit experiment and provided evidence indicating the existence of racial and ethnic discrimination in hiring practices. In addition, their data shows that customer discrimination may explain some of the hiring behaviors of program directors.

Identifying the factors determining this penalty is a necessary next step in research because one needs to understand the cause to design interventions to increase retention. If the duration of employment spells continues to be low, the investments in professional development will not translate into better developmental outcomes for children.

[32] Hotz and Wiswall (2019) and Herbst (2023) provide in-depth discussions about the literature investigating how regulations impact the supply of childcare.

References

Acemoglu, Daron, and Jörn-Steffen Pischke. 1999. "The Structure of Wages and Investment in General Training." *Journal of Political Economy* 107 (3): 539–572.

Akai, Yukiko, and Akiei Jibiki. 2021. "An Analysis of the Labor Supply of Childcare Providers." Working Paper, Japanese Economic and Social Research Institute.

Araujo, M. Caridad, Pedro Carneiro, Yyannú Cruz-Aguayo, and Norbert Schady. 2016. "Teacher Quality and Learning Outcomes in Kindergarten." *The Quarterly Journal of Economics* 131 (3): 1415–1453.

Bassok, Daphna, Justin B Doromal, Molly Michie, and Vivian C Wong. 2021a. "The Effects of Financial Incentives on Teacher Turnover in Early Childhood Settings: Experimental Evidence from Virginia." Working Paper, University of Virginia.

Bassok, Daphna, Maria Fitzpatrick, Susanna Loeb, and Agustina S. Paglayan. 2013. "The Early Childhood Care and Education Workforce from 1990 through 2010: Changing Dynamics and Persistent Concerns." *Education Finance and Policy* 8 (4): 581–601.

Bassok, Daphna, Anna J. Markowitz, Laura Bellows, and Katharine Sadowski. 2021b. "New Evidence on Teacher Turnover in Early Childhood." *Educational Evaluation and Policy Analysis* 43 (1): 172–180.

Becker, Gary S. 1962. "Investment in Human Capital: A Theoretical Analysis." *Journal of Political Economy* 70 (5): 9–49.

Berlinski, Samuel, Maria Marta Ferreyra, Luca Flabbi, and Juan David Martin. 2020. "Child Care Markets, Parental Labor Supply, and Child Development." Working Paper 12904, IZA Institute of Labor Economics.

Blau, David M. 1993. "The Supply of Child Care Labor." *Journal of Labor Economics* 11 (2): 324–347.

Blau, David M. 2001. *Child Care Problem: An Economic Analysis.*: New York: Russell Sage Foundation.

Bodere, Pierre. 2022. "Dynamic Spatial Competition in Early Education: an Equilibrium Analysis of the Preschool Market in Pennsylvania." Working Paper, New York University.

Borowsky, Jonathan, Jessica H. Brown, Elizabeth E. Davis, Chloe Gibbs, Chris M. Herbst, Aaron Sojourner, Erdal Tekin, and Matthew J. Wiswall. 2022. "An Equilibrium Model of The Impact of Increased Public Investment in Early Childhood Education." Working Paper 30140, National Bureau of Economic Research.

Bowlby, John. 1969. *Attachment and Loss, Vol. 1.* New York: Basic Books.

Boyd-Swan, Casey, and Chris M Herbst. 2018. "The Demand for Teacher Characteristics in the Market for Child Care: Evidence from a Field Experiment." *Journal of Public Economics* 159: 183–202.

Brown, Jessica, and Chris M. Herbst. 2022. "Child care over the business cycle." *Journal of Labor Economics* 40 (S1): 429–468.

Bryk, Anthony S., and Barbara Schneider. 2002. *Trust in Schools: A Core Resource for Improvement.*: Russell Sage Foundation.

Burchinal, Margaret. 2018. "Measuring Early Care and Education Quality." *Child Development Perspectives* 12: 3–9.

Card, David. 2022. "Who Set Your Wage?" *American Economic Review* 112 (4): 1075–90.

Carneiro, Pedro, and Rita Ginja. 2014. "Long-Term Impacts of Compensatory Preschool on Health and Behavior: Evidence from Head Start.” *American Economic Journal: Economic Policy* 6 (4): 135–173.

Carneiro, Pedro, Karsten T. Hansen, and James J. Heckman. 2003. “Estimating Distributions Of Treatment Effects With An Application To The Returns To Schooling And Measurement Of The Effects Of Uncertainty On College Choice.” *International Economic Review* 44 (2): 361–422.

Chaparro, Juan, Aaron Sojourner, and Matthew J. Wiswall. 2020. “Early Childhood Care and Cognitive Development.”Technical report, NBER Working Paper 26813.

Clotfelter, Charles T., Helen F. Ladd, and Jacob L. Vigdor. 2006. “Teacher-Student Matching and the Assessment of Teacher Effectiveness.” *The Journal of Human Resources* 41 (4): 778–820.

Cryer, Debby, Sara Hurwicz, and Mark Wollery. 2000. “Continuity of Caregiver for Infants and Toddlers in Center-based Child Care: Report on a Survey of Center Practices.” *Early Childhood Research Quarterly* 15 (4): 497–514.

Cunha, Flavio, James J. Heckman, and Salvador Navarro. 2005. “Separating uncertainty from heterogeneity in life cycle earnings.” *Oxford Economic Papers* 57 (2): 191–261.

Davies, Phil, and Rob Grunewald. 2019. “Hardly Child’s Play.” https://www.minneapolisfed.org/article/2011/hardly-childs-play.

Deming, David. 2009. “Early Childhood Intervention and Life-Cycle Skill Development: Evidence from Head Start.” *American Economic Journal: Applied Economics* 1 (3): 111–134.

Derman-Sparks, Louise, Evelyn K. Moore, Edna Runnels Ranck, and Charlotte J. Anderson. 2016. “Two Teachers Look Back: The Ypsilanti Perry Preschool, Part I.” *YC Young Children* 71 (4): 82–87.

Dougan, William, Jorge Luis García, and Illia Polovnikov. 2023. “High-Quality Early-Childhood Education at Scale: Evidence from a Multisite Randomized Trial.”Technical report, NBER Working Paper 31694.

Duncan, Greg J., and Aaron. J. Sojourner. 2013. “Can Intensive Early Childhood Intervention Programs Eliminate Income-based Cognitive and Achievement Gaps?” *Journal of Human Resources* 48 (4): 945–968.

Eisenhauer, Philipp, James J. Heckman, and Stefano Mosso. 2015. “Estimation of Dynamic Discrete Choice Models by Maximum Likelihood and the Simulated Method of Moments.” *International Economic Review* 56 (2): 331–357.

Elicker, James, and Cheryl Fortner-Wood. 1995. “Adult-child Relationships in Early Childhood Programs.” *Young Children* 51 (1): 69–78.

Federal Reserve Bank of St. Louis. 2023. “Federal Reserve Economic Data (FRED).” https://fred.stlouisfed.org/series/CPIAUCSL.

Garces, Eliana, Duncan Thomas, and Janet Currie. 2002. “Longer-Term Effects of Head Start.” *American Economic Review* 92 (4): 999–1012.

García, Jorge Luis, James J. Heckman, and Victor Ronda. 2023. “The Lasting Effects of Early-Childhood Education on Promoting the Skills and Social Mobility of Disadvantaged African Americans and Their Children.” *Journal of Political Economy* 131 (6): 1477–1506.

Garza, Rubén. 2009. “Latino and White High School Students’ Perceptions of Caring Behaviors: Are We Culturally Responsive to our Students?” *Urban Education* 44 (3): 297–321.

Gordon, James A., Chris M. Herbst, and Erdal Tekin. 2021. “Who’s minding the kids? Experimental evidence on the demand for child care quality.” *Economics of Education Review* 80: 102076.

Gourieroux, C., A. Monfort, and E. Renault. 1993. “Indirect Inference.” *Journal of Applied Economet-*

rics 8: S85–S118.

Guerrero-Rosada, Paola, Christina Weiland, Meghan McCormick, JoAnn Hsueh, Jason Sachs, Catherine Snow, and Michelle Maier. 2021. "Null Relations Between CLASS Scores and Gains in Children's Language, Math, and Executive Function Skills: A Replication and Extension Study." *Early Childhood Research Quarterly* 54: 1–12.

Guin, Kacey. 2004. "Chronic Teacher Turnover in Urban Elementary Schools." *Education Policy Analysis Archives* 12.

Harris, Douglas N., and Tim R. Sass. 2011. "Teacher Training, Teacher Quality and Student Achievement." *Journal of Public Economics* 95 (7-8): 798–812.

Heckman, J., and B. Singer. 1984. "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data." *Econometrica* 52 (2): 271–320.

Heckman, James J. 1981. "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process." *MIT Press, Cambridge, MA* 179: 195.

Heckman, James J., John Eric Humphries, and Gregory Veramendi. 2016. "Dynamic Treatment Effects." *Journal of Econometrics* 191 (2): 276–292.

Heckman, James J., and Salvador Navarro. 2007. "Dynamic Discrete Choice and Dynamic Treatment Effects." *Journal of Econometrics* 136 (2): 296–341.

Herbst, Chris M. 2017. "Universal child care, maternal employment, and childrenâs long-run outcomes: Evidence from the US Lanham Act of 1940.." *Journal of Labor Economics* 35 (2): 519–564.

Herbst, Chris M. 2023. "Child Care in the United States: Markets, Policy, and Evidence." *Journal of Policy Analysis and Management* 42 (1): 255–304.

Hotz, V. Joseph, and Matthew Wiswall. 2019. "Child Care and Child Care Policy: Existing Policies, Their Effects, and Reforms." *The ANNALS of the American Academy of Political and Social Science* 686 (1): 310–338.

Howes, Carollee. 1999. *Attachment Relationships in the Context of Multiple Caregivers*. 671–687. New York, NY: Guilford Press.

Institute of Medicine. 2015. *Transforming the Workforce for Children, Birth Through Age 8: A Unifying Foundation.*: National Academies Press.

Katz, Eliakim, and Adrian Ziderman. 1990. "Investment in General Training: The Role of Information and Labour Mobility." *Economic Journal* 100 (403): 1147–1158.

Keane, Michael P., and Kenneth I. Wolpin. 1997. "The Career Decisions of Young Men." *Journal of Political Economy* 105 (3): 473–522.

Lajoie, Susanne P. 2005. "Extending the Scaffolding Metaphor." *Instructional Science* 33 (5-6): 541–557.

Macrine, Sheila L., and Eileen D. Sabbatino. 2008. "Dynamic Assessment and Remediation Approach: Using the DARA Approach to Assist Struggling Readers." *Reading & Writing Quarterly* 24 (1): 52–76.

Markowitz, Anna. 2019. "Within-Year Teacher Turnover in Head Start and Children's School Readiness." Working Paper 70, EdPolicyWorks.

McClure, Robin. 2021. "Child Care Benefits to Help Teacher Retention." https://www.verywellfamily.com/child-care-as-teacher-incentive-616834.

Moss, Ellen, Sophie Parent, Catherine Gosselin, Denise Rousseau, and Diane St-Laurent. 1996. "Attachment and Teacher-reported Behavior Problems During the Preschool and Early School-

age Period." *Development and Psychopathology* 8: 511 – 525.
Mountjoy, Jack. 2021. "Community Colleges and Upward Mobility." Working Paper 29254, National Bureau of Economic Research.
Palincsar, Annemarie S., and Ann L. Brown. 1984. "Reciprocal Teaching of Comprehension-fostering and Comprehension-monitoring Activities." *Cognition and Instruction* 1 (2): 117–175.
Phillips, Deborah, Lea J. E. Austin, and Marcy Whitebook. 2016. "The Early Care and Education Workforce." *Future of Children* 26 (2): 139–158.
van de Pol, Janneke, Monique Volman, and Jos Beishuizen. 2010. "Scaffolding in Teacher–Student Interaction: A Decade of Research." *Educational Psychology Review* 22 (3): 271–296.
Raikes, Helen. 1993. "Relationship Duration in Infant Care: Time with a High-Ability Teacher and Infant-Teacher Attachment." *Early Childhood Research Quarterly* 8 (3): 309–325.
Rivkin, Steven, Eric Hanushek, and John Kain. 2005. "Teachers, Schools, and Academic Achievement." *Econometrica* 73 (2): 417–458.
Ronfeldt, Matthew, Susanna Loeb, and James Wyckoff. 2013. "How Teacher Turnover Harms Student Achievement." *American Educational Research Journal* 50: 4–36.
Rust, John. 1987. "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher." *Econometrica* 55 (5): 999–1033.
Staiger, Douglas, and Jonah Rockoff. 2010. "Searching for Effective Teachers with Imperfect Information." *Journal of Economic Perspectives* 24 (3): 97–118.
Statista Research Department. 2022. "Top 10 largest for-profit child care organizations in the U.S. in 2017, by capacity.." https://www.statista.com/statistics/719471/top-10-largest-for-profit-child-care-organizations-by-capacity-us/.
Stevens, Margaret. 1994. "A Theoretical Model of On-the-job Training with Imperfect Competition.." *Oxford Economic Papers* 46 (4): 537–562.
Swanson, H. Lee, and Catherine M. Lussier. 2001. "A Selective Synthesis of the Experimental Literature on Dynamic Assessment." *Review of Educational Research* 71 (2): 321–363.
Todd, Petra E., and Weilong Zhang. 2020. "A dynamic model of personality, schooling, and occupational choice." *Quantitative Economics* 11 (1): 231–275.
Totenhagen, Casey J., Stacy Ann Hawkins, Deborah M. Casper, Leslie A. Bosch, Kyle R. Hawkey, and Lynne M. Borden. 2016. "Retaining Early Childhood Education Workers: A Review of the Empirical Literature." *Journal of Research in Childhood Education* 30 (4): 585–599.
Tram, Henry, and Adam Winsler. 2011. "Teacher and Center Stability and School Readiness Among Low-income, Ethnically Diverse Children in Subsidized, Center-based Child Care." *Children and Youth Services Review* 33: 2241–2252.
Verschueren, Karine, and Helma M Y Koomen. 2012. "Teacher-child Relationships from an Attachment Perspective." *Attachment and Human Development* 14 (3): 205–211.
Vygotsky, Lev S. 1978. *Mind in Society: The Development of Higher Psychological Processes*. Cambridge, MA: Harvard University Press.
Weiland, Christina, Kchersti Ulvestad, Jason Sachs, and Hirokazu Yoshikawa. 2013. "Associations Between Classroom Quality and Children's Vocabulary and Executive Function Skills in an Urban Public Prekindergarten Program." *Early Childhood Research Quarterly* 28: 199–209.
Whitebook, Marcy, Caitlin McLean, Lea J.E. Austin, and Bethany Edwards. 2018. "Early Childhood Workforce Index – 2018." Center for the Study of Child Care Employment, University of

California, Berkeley.
Whitebook, Marcy, Deborah Phillips, and Carollee Howes. 2014. “Worthy Work, STILL Unlivable Wages: The Early Childhood Workforce 25 Years after the National Child Care Staffing Study.” Center for the Study of Child Care Employment, University of California, Berkeley.
Wood, David, Jerome S. Bruner, and Gail Ross. 1976. “The Role of Tutoring in Problem Solving.” *Journal of Child Psychology and Psychiatry* 17 (2): 89–100.

Appendix A. Data

We now describe in more detail how each data source was cleaned, which is also summarized in Table 1. In the TEA data, we first restrict the individuals to those born between 1980 and 1989. Due to privacy requirements, the birth year of an individual is not included, only his or her age on September 1st. We calculate birth year as $BirthYear = AcademicYear - Sept1stAge - 1$. We also drop invalid unique identifiers, individuals with varying birth year, sex, and ethnicity across years, and duplicates with respect to ID, district, and year. The end result is a longitudinal data with around 3.2 million individuals across 19 million observations.

The THECB data also includes September 1st age of individuals, so we could have proceeded in the same manner as in the TEA data to select those born between 1980 and 1989. This scenario would include anyone who did not attend any K-12 in Texas. To keep access to K-12 education, we decided to include only those individuals born between 1980 and 1989 that were found in the TEA data. We also drop invalid identifiers and exact duplicates. Additionally, many individuals were enrolled in two different institutions or majors, so we keep the one with highest credit-hours in that period. The end result is a longitudinal data with 9 million individuals across 66 million observations.

Finally, the TWC data does not contain any demographic information, so it is necessary to restrict the individuals to those found in the TEA that were born between 1980 and 1989. The TWC data is an employment report that companies have to report for unemployment insurance purposes. However, the only information available is the NAICS sector code of the individual's employer and the quarterly wage. Therefore, an individual in a quarter can have multiple 'sector jobs', and the total quarter wage does not account for hours worked.

Take as an example a worker starting January 1st. This person worked for 2 weeks and left the job. Then, in February, the worker started in another job in the same sector for 3 weeks, and in March the worker moved to a different job in another sector. In the TWC data, this individual will show as three different observations (with the same identification), two of them with the same NAICS code. Similarly, if this worker had actually been in two simultaneous jobs, it would still show up as two different observations.

We cannot identify whether the individual was in a 'true simultaneous' jobs situation or if it was simply a transition. However, we identify a main job of the individual in a quarter and we deal with observations with very low wages (signaling that it was most likely a short tenure job).

We first deal with very low wages by identifying 'valid' job spells. We consider a valid spell one in which the individual earned at least the equivalent of working 20 hours per week during at least 2/3 of the quarter (8 weeks) at minimum wage.[33] In Table A1, we show the wage cutoff and the percentage of spells that lie above the cutoff. Every observation that had a wage below the cutoff was dropped of the sample.

TABLE A1. Job spells cutoff according to earnings

Year	Min. Wage	Wage Cutoff	% of Valid Spells	Number of Valid Spells
Before 2007	$5.15	824	66.3	34,938,780
2008	$5.85	936	78.2	6,511,620
2009	$6.55	1048	81.1	6,172,918
After 2010	$7.25	1160	86.6	63,195,880

Note: The wage cutoff is calculated by multiplying the minimum wage of the year and 8×20, representing the equivalent of a job spell that lasts for two-thirds of a quarter at 20 hours per week. Any observation that had a wage below the cutoff was dropped.

After keeping only observations that reported a minimum quarterly wage, we then identify the main job spell of a quarter for any individual. We consider as the main job the sector-job that had the highest reported wage in that quarter. Table A2 shows the number of individual-quarter observations that reported having more than one job.

TABLE A2. Number of individual-quarter observations with more than one job

# Jobs	N
1	110,819,198
2	7,158,563
3	339,875
4	25,794
5 or more	10,523

Note: This table reports the frequency of number of jobs an individual has in any given quarter.

The final TWC data has 2,813,972 unique individuals across 89 quarters from 1997Q1 to 2019Q1[34]. We construct a balanced panel with these dimensions and merge in information

[33] This is similar to the method used in Keane and Wolpin (1997). In that case, the NLSY asked retrospectively for work status during the first, seventh, and thirteenth week of each quarter for a total of 9 weeks during a year. Therefore, an individual was considered as working during that year if he was working in at least two-thirds for at least 20 hours per week on average.

[34] We also document very high wages that are inconsistent with the other reported wages for that individual. We classify a high wage as an outlier if: (i) it was higher than $10,000; (ii) the previous and the following wage earned was at least 10 times smaller; and (iii) it was the largest wage observed for that person and it was at least 10 times higher than the second largest observed wage. Note that for criteria (ii) we consider a previous or following wage not only consecutive quarters but the closest observed wage. For these outliers, if there was a previous and following consecutive quarter with observed wages, we replace it with the mean of these two values. In all other cases, we delete that observation and consider the person not employed.

from the TEA, THECB, and TWC. For the TEA and THECB, the data was reported yearly so all quarters of a year are used. Of all quarters in which there was a TWC observation, about 35% also were quarters where the individual was either in the TEA or THECB. In these cases, we consider the main activity as being either 'In school' or 'In college'. Table A3 shows how many individual-quarter observations were both reported in the TEA or THECB and TWC.

TABLE A3. Activity in a quarter, conditional of being reported as working in TWC

Activity	N
In School	8194518
In College	20545364

Note: This table reports the number of observations when an individual was both in TEA or THECB and TWC. In these cases, we classify the main activity of the individual in that quarter as being either the TEA or THECB reports.

Appendix B. Anchoring Test Scores

In this section, we describe the procedure we follow to anchor raw test scores on a common metric. Let S_i and θ_i denote educational attainment and academic skills, respectively. We assume that:

$$S_i = \theta_i + \varepsilon_i, \tag{A1}$$

where ε_i is an error term uncorrelated with θ_i. Let $M_{i,t,j}$ denote the student i's score on the j^{th} standardized test of type t. In our dataset, $J = 2$ (math and ELA) and $T = 2$ (TAAS and TAAK). We assume that:

$$M_{i,t,j} = \lambda_{0,t,j} + \lambda_{1,t,j}\theta_i + \eta_{i,t,j}. \tag{A2}$$

We note that a student only takes one type of test, so either the TAAS or the TAKS. Given the type t, the student takes the math and ELA tests. If $\lambda_{1,t,j}$ is different from zero, then the mapping between academic skills and test scores is not comparable across tests. Furthermore, $\eta_{i,t,j}$ is measurement error, which means that test scores are noisy measures of academic ability. As we show below, this measurement error brings additional problems into the analysis. We assume independence between ε_i and $\eta_{i,t,j}$ as well as between $\eta_{i,t,j}$ and $\eta_{i,t,k}$ for $j \neq k$.

B.1. Anchoring to a Common Metric

Let $\boldsymbol{M}_{m,t,j}$ denote the set of students whose score on test type t and discipline j is equal to m:

$$\boldsymbol{M}_{m,t,j} = \{i; M_{i,t,j} = m\}. \tag{A3}$$

Let $N_{m,t,j}$ denote the number of students in the set $\boldsymbol{M}_{m,t,j}$. Then, the anchored test score $s_{i,t,j}$:

$$s_{i,t,j} = \frac{1}{N_{m,t,j}} \sum_{i \in \boldsymbol{M}_{m,t,j}} S_i. \tag{A4}$$

If we assume that $N_{m,t,j}$ is large, it follows that:

$$\begin{aligned}
s_{i,t,j} &= \mathbf{E}\left[S_i | M_{i,t,j} = m\right]; \\
s_{i,t,j} &= \mathbf{E}\left[\theta_i + \varepsilon_i | M_{i,t,j} = m\right]; \\
s_{i,t,j} &= \mathbf{E}\left[\theta_i | M_{i,t,j} = m\right]; \\
s_{i,t,j} &= \mu_\theta + \frac{\lambda_{1,t,j}\,\sigma_\theta^2}{\lambda_{1,t,j}^2\,\sigma_\theta^2 + \sigma_{t,j}^2}\left(m - \lambda_{0,t,j} - \lambda_{1,t,j}\,\mu_\theta\right); \\
s_{i,t,j} &= \frac{\sigma_{t,j}^2}{\lambda_{1,t,j}^2\,\sigma_\theta^2}\mu_\theta + \frac{\lambda_{1,t,j}^2\,\sigma_\theta^2}{\lambda_{1,t,j}^2\,\sigma_\theta^2 + \sigma_{t,j}^2}\theta_i + \frac{\lambda_{1,t,j}\,\sigma_\theta^2}{\lambda_{1,t,j}^2\,\sigma_\theta^2 + \sigma_{t,j}^2}\eta_{i,t,j},
\end{aligned}$$

where from the 3rd to the 4th line we use equation A2 and the fact that θ_i follows a Normal distribution.

With this equation, we can construct a measure of θ_i, $\tilde{s}_{i,t,j}$, as follows:

$$\tilde{s}_{i,t,j} \equiv \frac{s_{i,t,j} - \frac{\sigma_{t,j}^2}{\lambda_{1,t,j}^2\,\sigma_\theta^2 + \sigma_{t,j}^2}\mu_\theta}{\frac{\lambda_{1,t,j}^2\,\sigma_\theta^2}{\lambda_{1,t,j}^2\,\sigma_\theta^2 + \sigma_{t,j}^2}} = \theta_i + \frac{1}{\lambda_{1,t,j}}\eta_{i,t,j}. \tag{A5}$$

We can identify $\tilde{s}_{i,t,j}$ from the available data. Note that $\mu_\theta = E[S_i]$ by assumption. For $\lambda_{1,t,1}, \lambda_{1,t,2}, \sigma_{t,j}^2, \sigma_\theta^2$, note that:

$$
\begin{aligned}
Cov(S_i, M_{i,t,1}) &= \lambda_{1,t,1}\sigma_\theta^2; \\
Cov(S_i, M_{i,t,2}) &= \lambda_{1,t,2}\sigma_\theta^2; \\
Cov(M_{i,t,1}, M_{i,t,2}) &= \lambda_{1,t,1}\lambda_{1,t,2}\sigma_\theta^2; \\
Var(M_{i,t,j}) &= \lambda_{1,t,j}^2\sigma_\theta^2 + \sigma_{t,j}^2.
\end{aligned}
$$

If $\lambda_{1,t,j} \neq 0 \forall j$, we obtain

$$
\frac{Cov(M_{i,t,1}, M_{i,t,2})}{Cov(S_i, M_{i,t,2})} = \lambda_{1,t,1}
$$

$$
\frac{Cov(M_{i,t,1}, M_{i,t,2})}{Cov(S_i, M_{i,t,1})} = \lambda_{1,t,2}
$$

Then, from $Cov(S_i, M_{i,t,1}) = \lambda_{1,t,1}\sigma_\theta^2$ we obtain σ_θ^2. We can identify the last component, $\sigma_{t,j}^2$, from $Var(M_{i,t,j})$.

Given that $s_{i,j,t}, S_i, M_{i,t,j}$ are all observed in the data, it is trivial to construct estimates of $\tilde{s}_{i,t,j}$.

B.2. Addressing Measurement Error

Equation A5 provides an estimator of θ_i contaminated with measurement error $\frac{1}{\lambda_{1,t,j}}\eta_{i,t,j}$. To deal with this, note that for each individual i and test type t, we have J tests. Therefore, since η is i.i.d with mean zero, we obtain a consistent and unbiased estimate of θ_i from:

$$
\hat{\theta}_i = \frac{1}{J}\sum_{j=1}^{J}\tilde{s}_{i,t,j}. \tag{A6}
$$

Appendix C. Moments Used in Estimation

We give a more detailed description of the moments used in estimation. Let $d_{i,a,m} = 1$ if individual i chooses sector m in time period a. Choice frequencies for each sector m are calculated within a period: $\frac{1}{N}\sum_{i=1}^{N} d_{i,a,m}$. Since there are 5 sectors and 11 time periods, we have 55 moments. To calculate the average and standard deviation of log-earnings, we follow a similar procedure but condition on the individual having worked in that time period. For example, average log earnings are calculated as $\frac{1}{N_{a,m}} \sum_{i=1}^{N_{a,m}} \ln w_i(a)$, where $N_{a,m}$ are the individuals who chose to work in sector m in time period a.

For turnover, we calculated for each one of the working sectors for all periods excluding the first one. The turnover for sector m in period a is calculated as:

$$tt_{a,m} = \frac{1}{N_{a-1,m}} \sum_{i=1}^{N_{a-1,m}} d_{i,a,m}.$$

We compute correlations across individuals and time periods for 9 endogenous variables, namely, dummies for choice in each sector, experience in each sector, and accumulated education. Finally, we also run 5 pooled linear probability model regressions, one for each binary choice:

$$d_{i,a,m} = X_{i,a}\beta + \varepsilon_{i,a},$$

and use $\hat{\beta}$ as the moments. For each working sector regression, we include polynomials of education and experience of all sectors, interactions between education and experience, polynomials of age, a dummy equal to 1 if education is greater than 14, lag and lead choices and earnings, ethnicity, reduced lunch, and achievement dummies. For schooling, we include education, a dummy equal to 1 if education is greater than 14, age polynomials, and lag and lead choices, besides achievement dummies. Finally, for home, we include polynomials for education and experience, interactions between education and experience, lag and lead choices, and ethnicity and reduced lunch dummies.

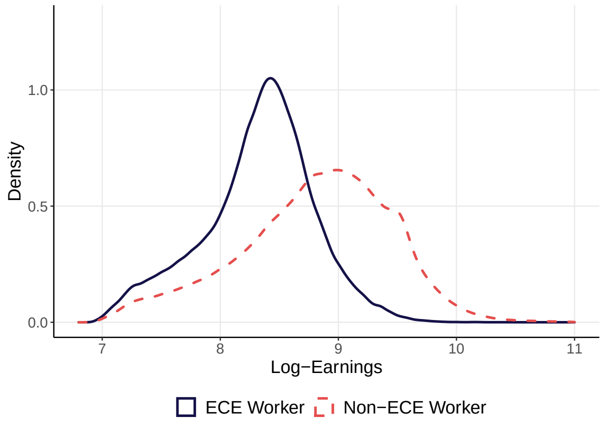
Appendix D. Additional Tables and Figures

TABLE A4. Logit Regression for Matching Algorithm

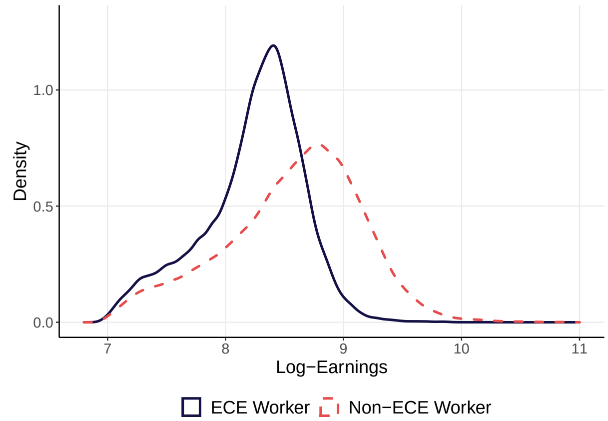
	Coefficient
Constant	2.728***
	(0.349)
Ethnicity (Omitted: African American)	
Hispanic	-0.413***
	(0.015)
White	-0.307***
	(0.015)
Reduced Price Lunch	0.158***
	(0.012)
Test Scores	-0.360***
	(0.004)
Observations	777,231

Note: This table shows estimates from a logit regression where the dependent variable is whether the individual ever worked in the ECE sector. Additional control variables include birth year dummies and dummies for the school district that individual attended their last year of high school. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

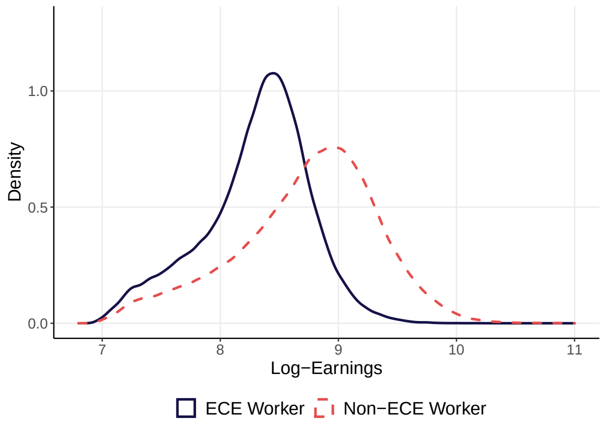
FIGURE A1. Kernel Density Estimation of Log-Earnings by Education Level



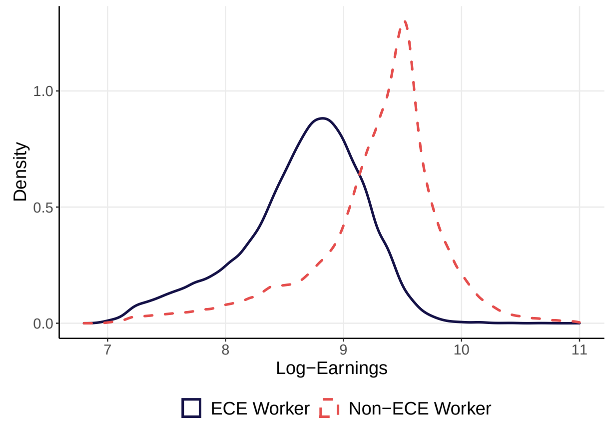
A. Overall



B. High School Only



C. Some College



D. 4-year or more

FIGURE A2. Transition In and Out of the ECE Sector - More Sectors

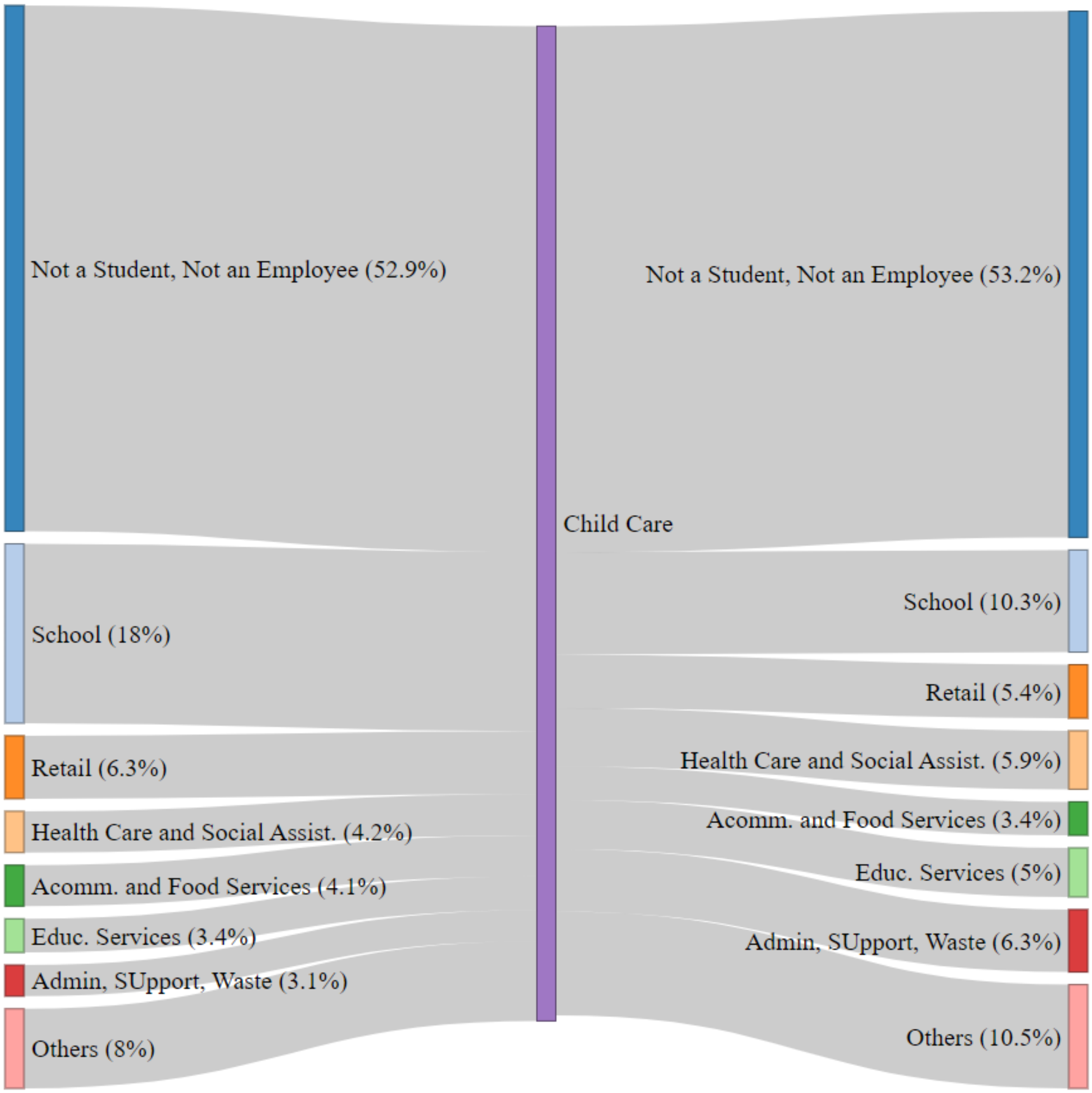
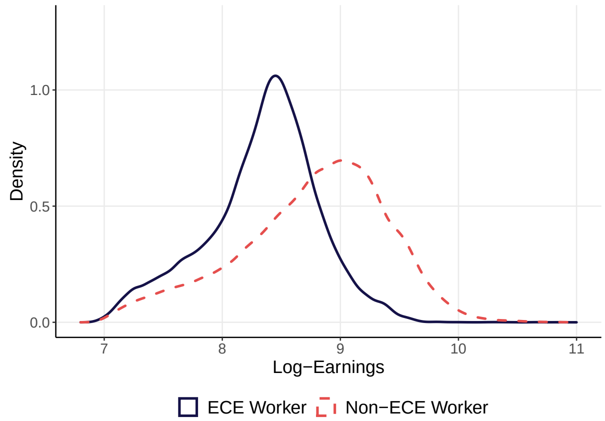
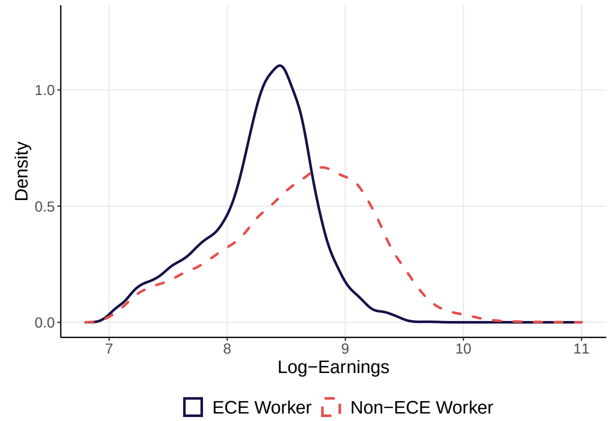


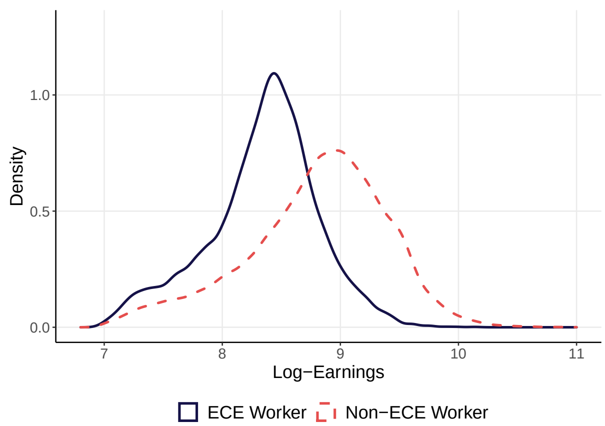
FIGURE A3. Kernel Density Estimation of Log-Earnings by Ethnicity and Eligibility Status for Free or Reduced-Price Lunch



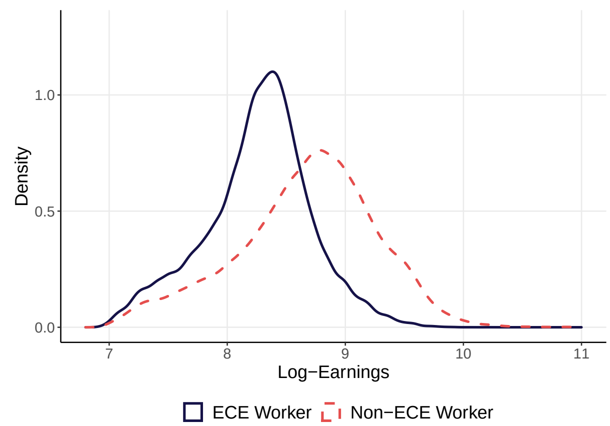
A. Afr. Am. & Not Eligible for Reduced-Price Lunch



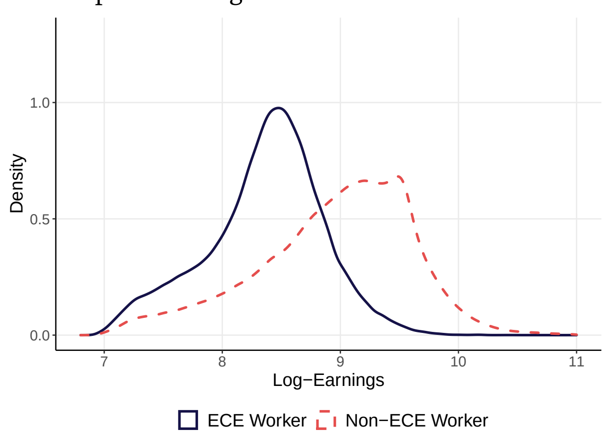
B. Afr. Am. & Eligible for Reduced-Price Lunch



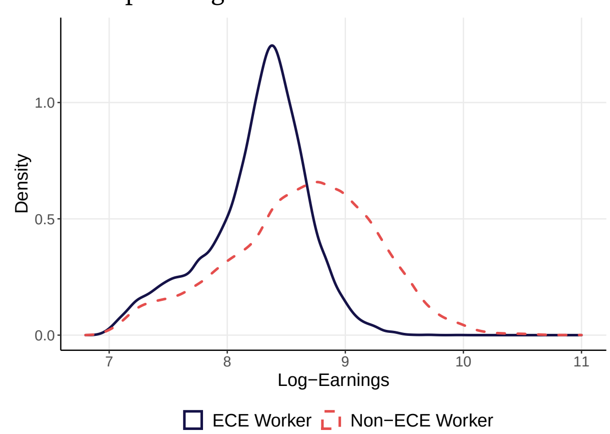
C. Hisp. & Not Eligible for Reduced-Price Lunch



D. Hisp. & Eligible for Reduced-Price Lunch

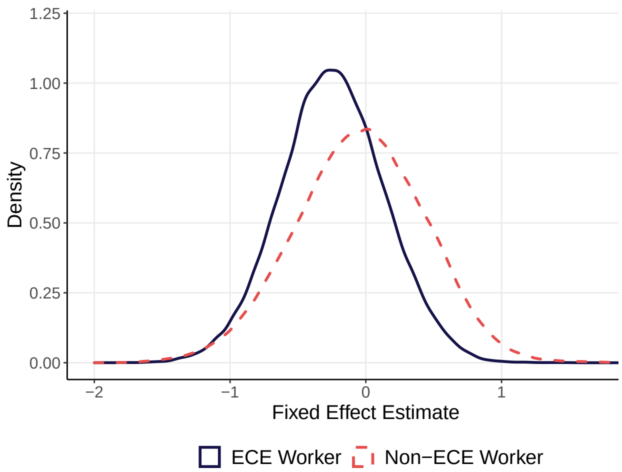


E. White & Not Eligible for Reduced-Price Lunch

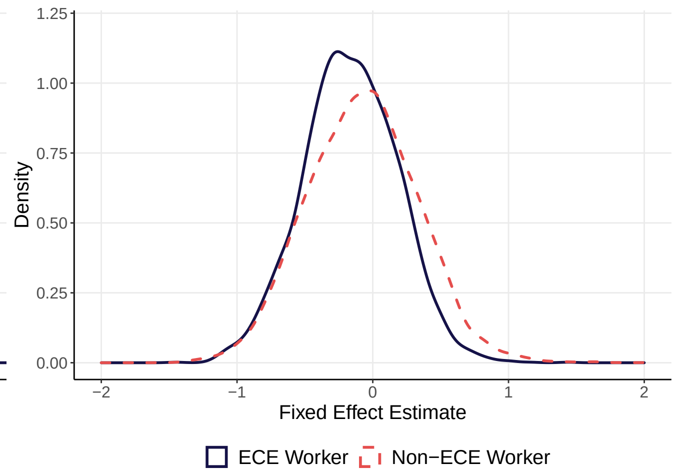


F. White & Eligible for Reduced-Price Lunch

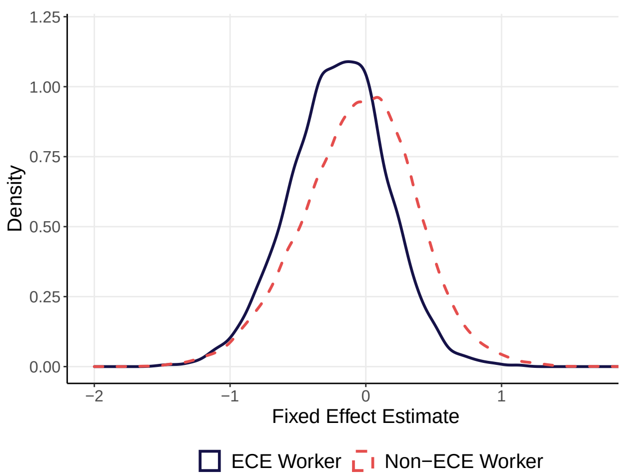
FIGURE A4. Fixed Effect Estimates by Ethnicity and Education



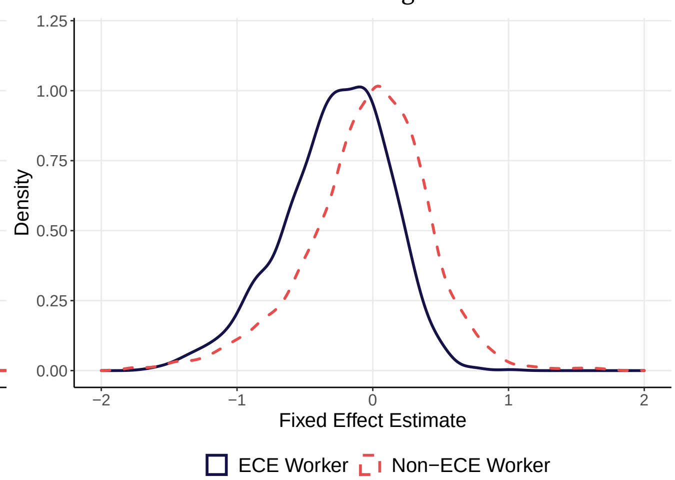
A. Overall



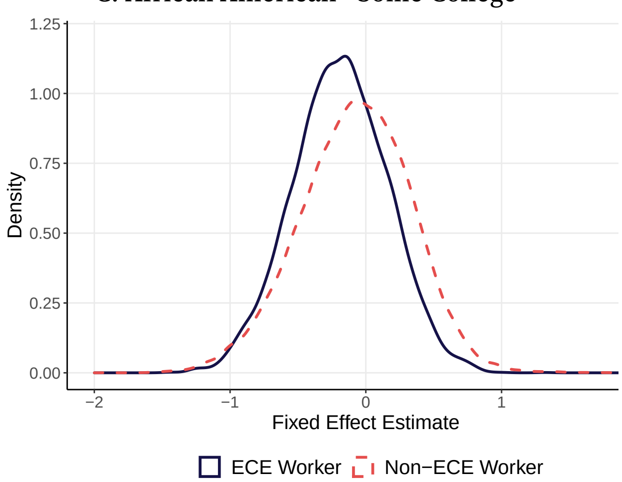
B. African American - High School



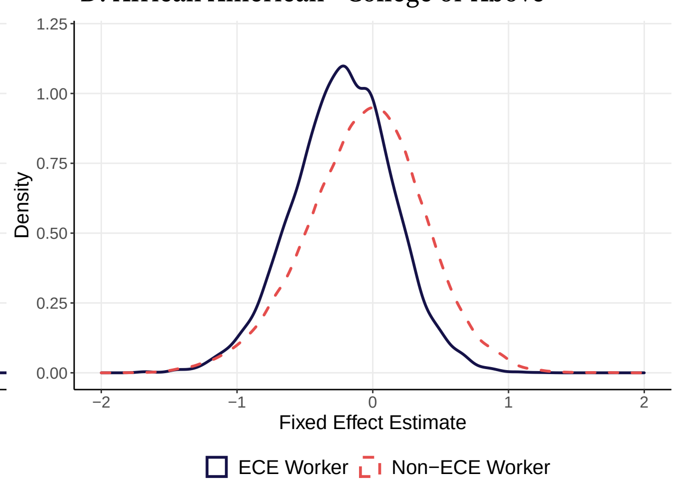
C. African American - Some College



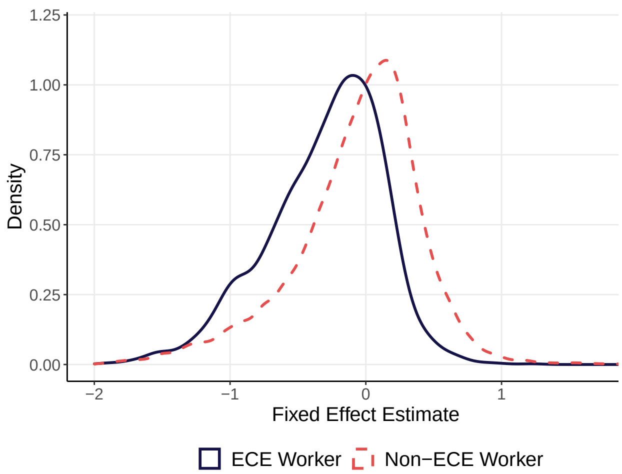
D. African American - College or Above



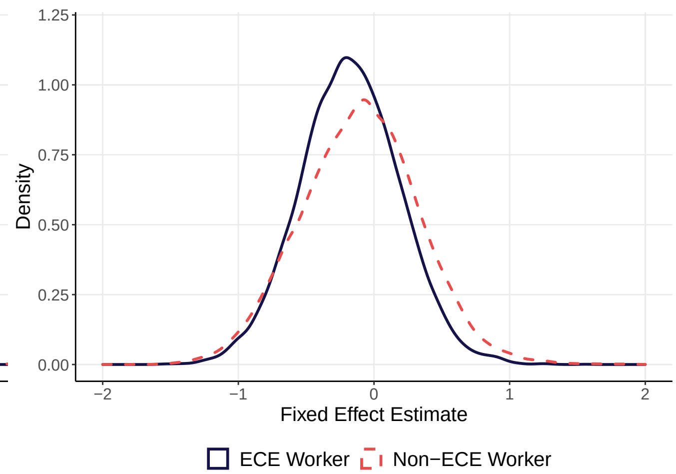
E. Hispanic - High School



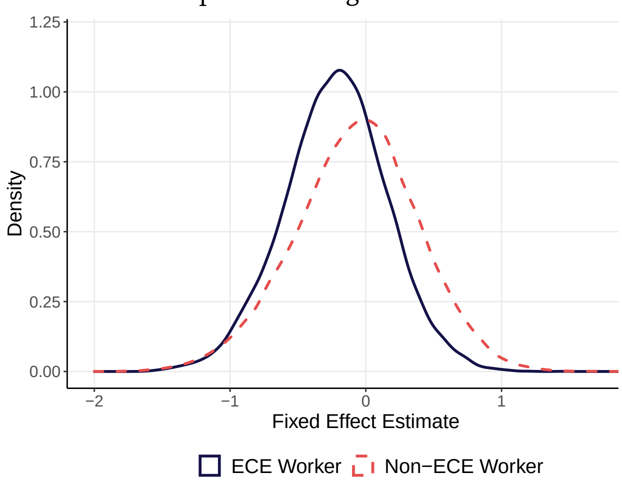
F. Hispanic - Some College



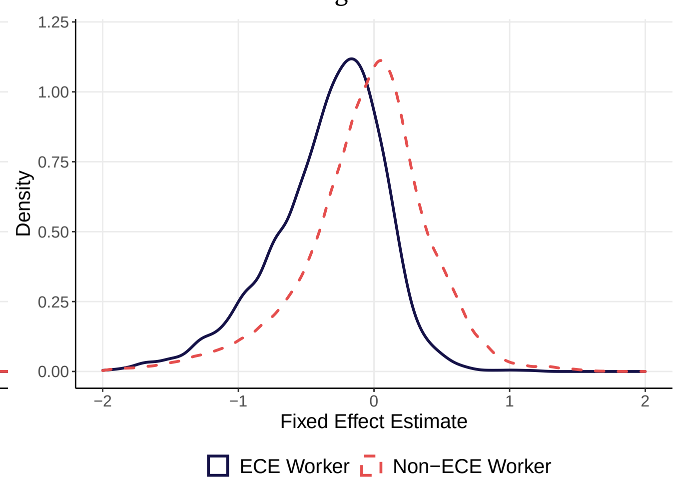
G. Hispanic - College or Above



H. White - High School



I. White - Some College



J. White - College or Above

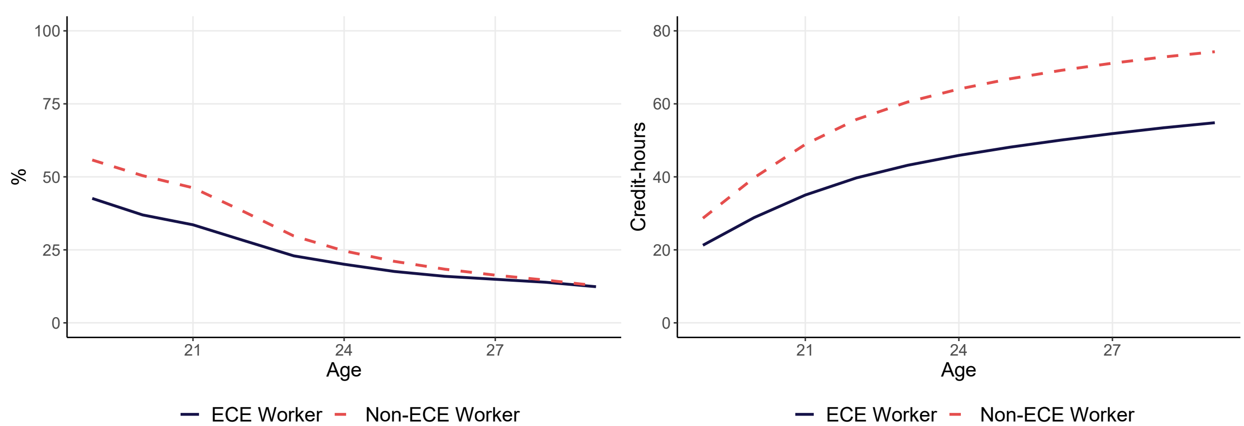
Appendix E. Dynamics of Enrollment in Higher Education and Labor Force Participation

Next, we compare their life paths starting at 19. In what follows, we describe patterns of college enrollment, participation in the labor force, and accumulation of labor market experience.

College Enrollment. Figures A5 and A6 present data on college enrollment. Figures A5A and A5B display college enrollment rates and accumulated credit hours by a quarter from age 19 to 29. These figures demonstrate that ECE workers are less likely to enroll in college after high school (Figure A5A). And, conditional on college registration, they accumulate fewer credit hours (Figure A5B).

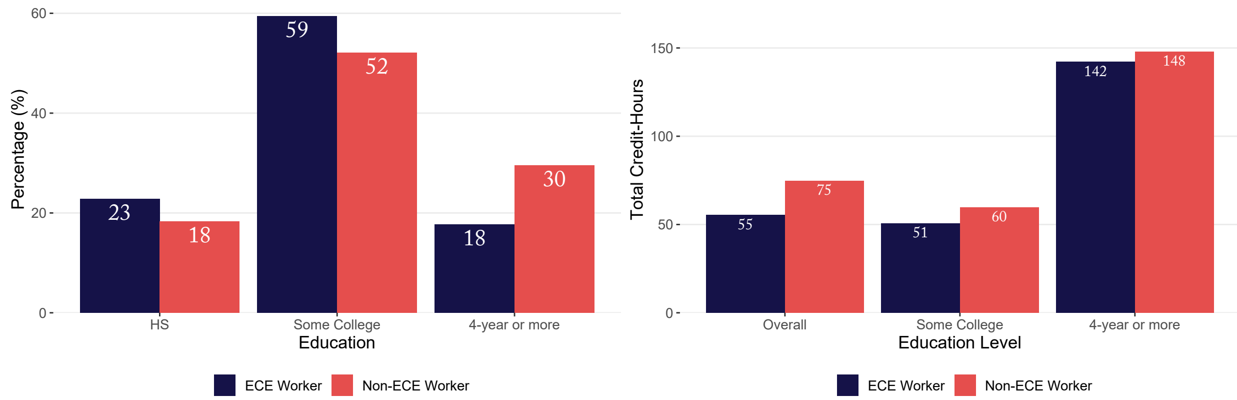
Figures A6A and A6B report completed educational attainment and accumulated credit hours by age 29. ECE workers are much less likely to have four-year degrees than Non-ECE counterparts. Non-ECE workers have accumulated more credit hours even when they achieve similar degree levels. For example, conditional on Some College, Non-ECEs have nine more credit hours on average, equivalent to three more courses.

FIGURE A5. College Enrollment and Cumulative Credit Hours Over Time



A. College Enrollment B. Accumulated Credit-Hours

FIGURE A6. Completed Education and Total Credit Hours by 29 Years Old



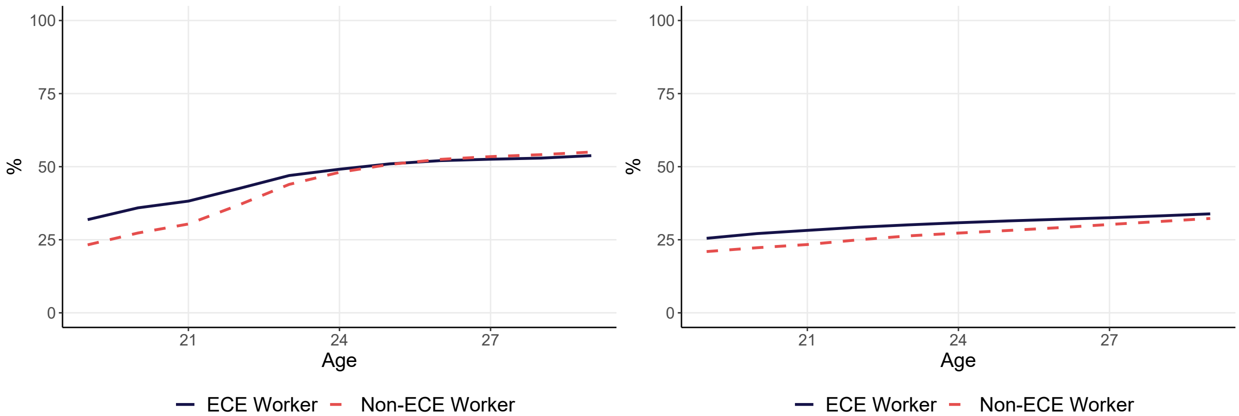
A. Completed Education Level

B. Accumulated Credit-Hours

Participation in the Labor Force. Figure A7A shows that ECE Workers are likelier to enter the labor force after graduating high school. Up until 24 years old, ECE workers are, on average, nine percentage points more likely to be in the labor force. However, Non-ECE workers catch up by 24 years old, when most individuals leave college.

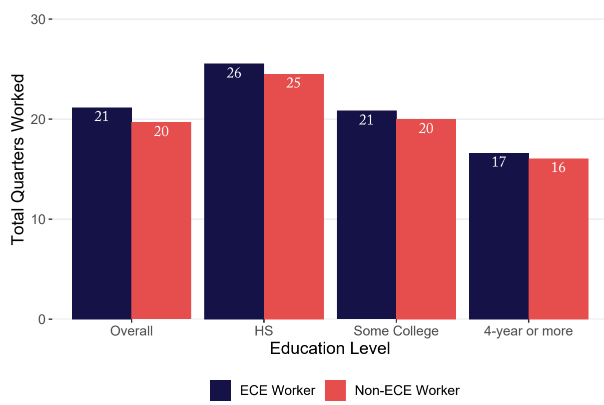
Interestingly, Figure A8 shows that accumulated experience at 29 years old, represented by the total number of quarters worked, is not so different between the two groups. This finding indicates that although Non-ECE workers stay outside the labor force in their early years, they have a stronger attachment to the labor force later. Figure A7B supports this finding by showing ECE workers are more likely to be neither in the labor force nor in school at all times by around five percentage points. Therefore, by the age of 29 years, ECE workers accumulate less human capital through education but slightly more through work.

FIGURE A7. Labor Force Attachment Over Time



A. Labor Force Participation B. Not Enrolled, Not Employed

FIGURE A8. Accumulated Experience in Quarters

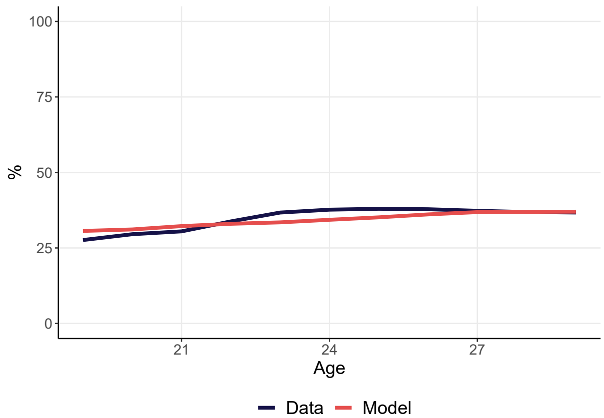


Our regression equation (2) included controls for time-varying factors but not time-invariant ones. For example, we did not have achievement scores. We expect the individual fixed effects to capture these terms in equation (2). Figure A4 compares the density of fixed effects for the ECE and Non-ECE workers by education and race and ethnicity groups. The ECE density has a lower mean and variance than the Non-ECE one. The figure also shows that the distance between the modes of the two density functions increases with educational attainment for all races and ethnicities.

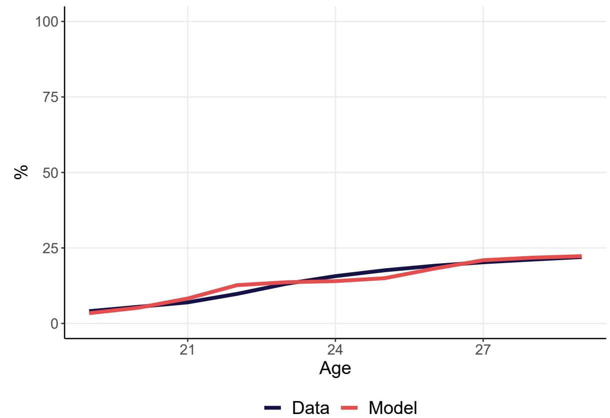
Appendix F. Structural Model: Fit and Unobserved Heterogeneity

F.1. Model Fit

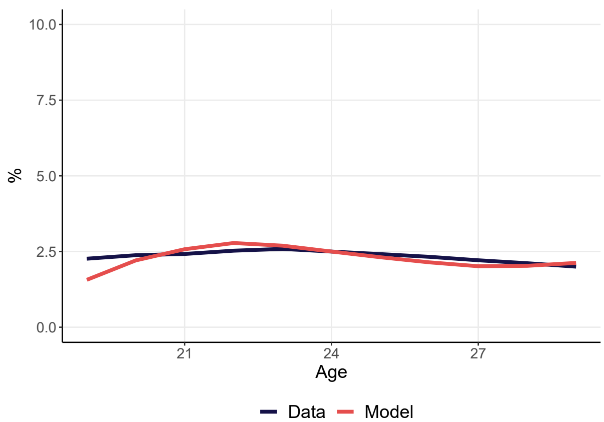
FIGURE A9. Model Fit - Choice Frequencies



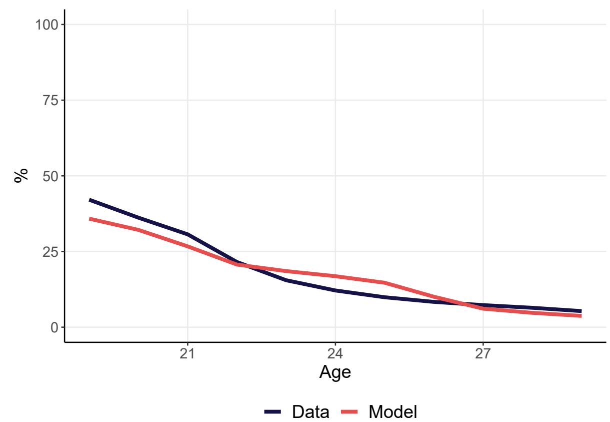
A. Others Sector



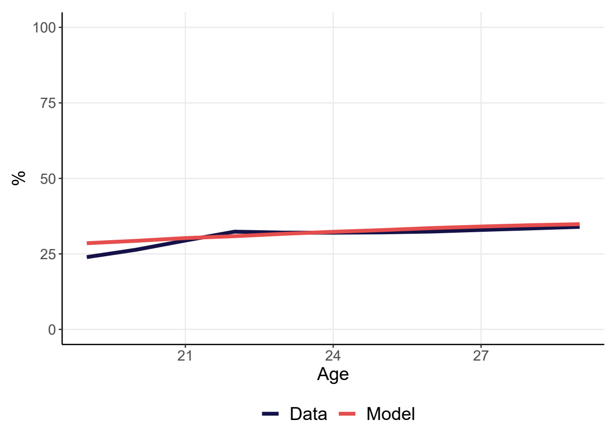
B. Health-Educ Sector



C. ECE Sector

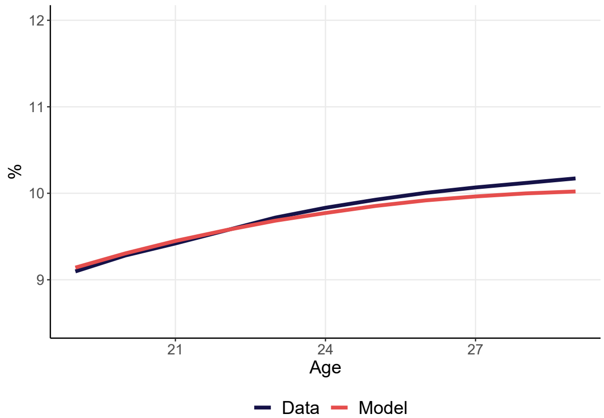


D. School

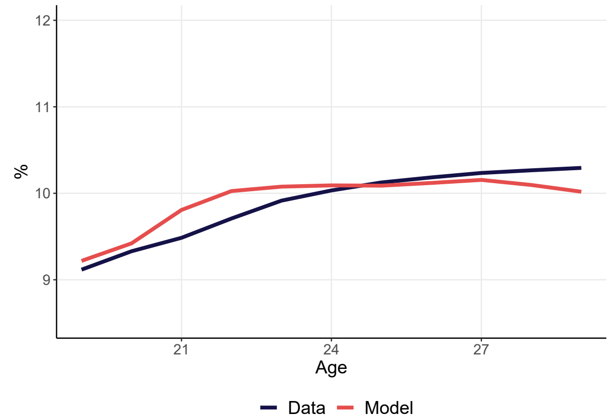


E. Home

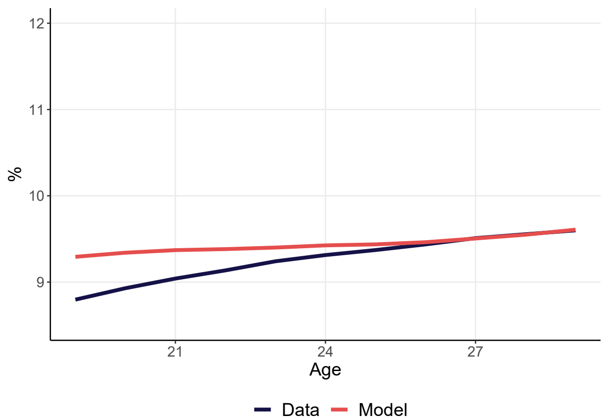
FIGURE A10. Model Fit - Earnings



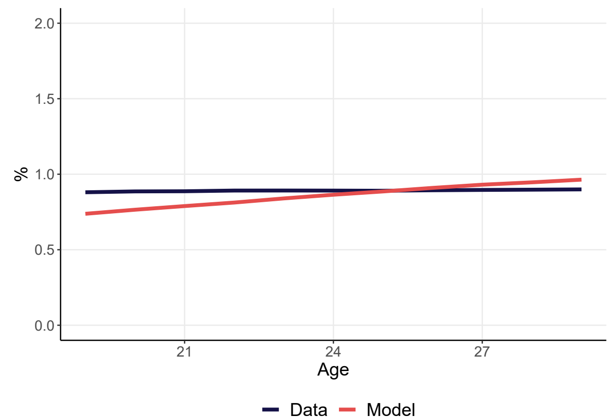
A. Mean Log Earning - Others Sector



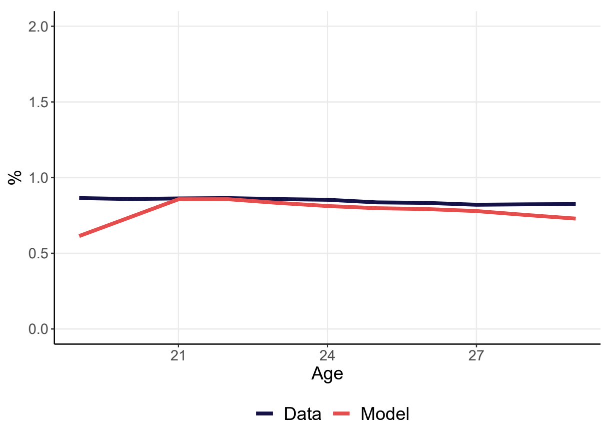
B. Mean Log Earning - Health-Educ Sector



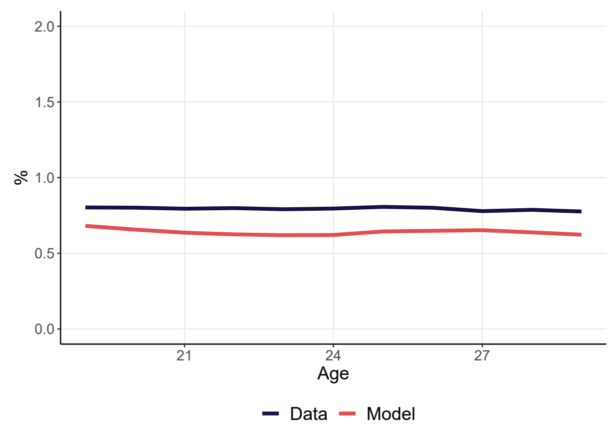
C. Mean Log Earning - ECE Sector



D. St. Dev. Log Earning - Others Sector

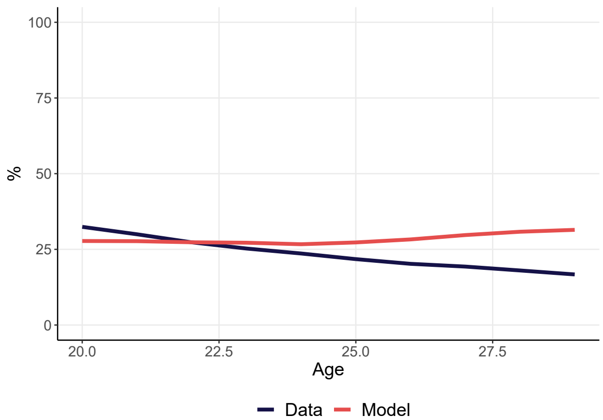


E. St. Dev. Log Earning - Health-Educ Sector

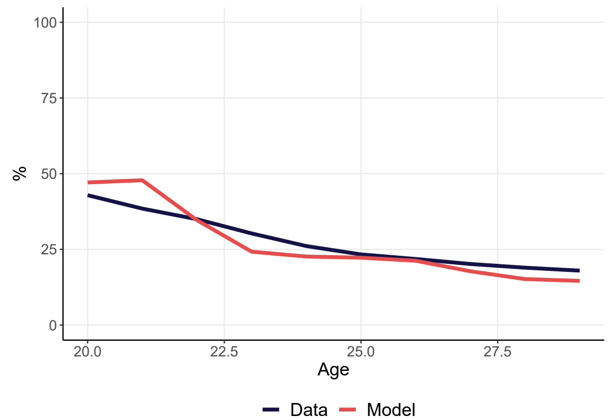


F. St. Dev. Log Earning - ECE Sector

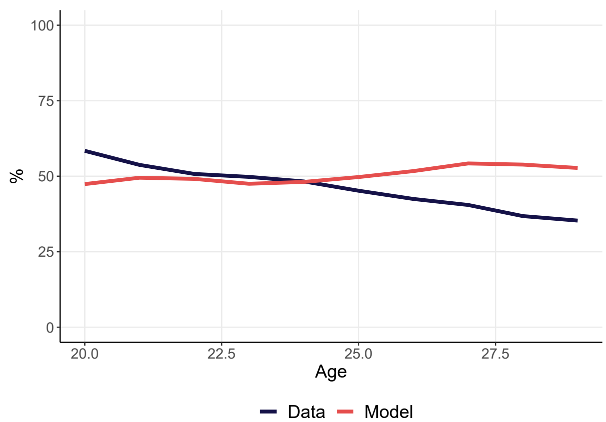
FIGURE A11. Model Fit - Turnover



A. Others Sector



B. Health-Educ Sector



C. ECE Sector

TABLE A5. Model Estimates

Data

	Others	EH	ECE	School	Home
Others	0.77	0.04	0.01	0.03	0.15
EH	0.08	0.76	0.01	0.03	0.12
ECE	0.15	0.08	0.54	0.03	0.20
School	0.09	0.04	0.01	0.62	0.24
Home	0.18	0.08	0.02	0.07	0.65
Simulated					
	Others	EH	ECE	School	Home
Others	0.71	0.06	0.02	0.02	0.18
EH	0.11	0.79	0.01	0.01	0.09
ECE	0.26	0.02	0.56	0.05	0.11
School	0.10	0.06	0.01	0.66	0.17
Home	0.21	0.04	0.01	0.07	0.67

F.2. Unobserved Heterogeneity

TABLE A6. Unobserved Heterogeneity Types - Coefficient Estimates

	Coefficient Estimate	Type 1	Type 2	Type 3	Type 4
	Value	-2.334	-0.742	0.742	2.334
Others	-0.604	1.474	0.468	-0.468	-1.474
HE	-0.002	0.053	0.017	-0.017	-0.053
ECE	-0.984	2.506	0.796	-0.796	-2.506
School	0.145	-0.408	-0.13	0.13	0.408
Home	1.1493	-2.937	-0.933	0.933	2.937
Frequency	-	4.61%	45.49%	45.29%	4.62%

Table A7. Unobserved Heterogeneity Types - Simulated Distribution Among Choices

	Type 1	Type 2	Type 3	Type 4
Others	0.06%	80.29%	19.42%	0.23%
EH	10.23%	76.08%	13.47%	0.22%
ECE	0.00%	76.32%	23.51%	0.17%
School	18.38%	15.71%	64.08%	1.82%
Home	0.00%	7.55%	79.19%	13.25%

Table A8. Impact of Wage Supplementation Policies on the ECE Workforce Composition

	Baseline Value	Static $1,500 Bonus (% Change)	Conditional $1,500 Bonus (% Change)
ECE Workers	0.11	13.8%	0.31%
Demographic and Economic Characteristics			
White & Not Economically Disadvantaged	0.41	0.14%	-0.92%
Black & Not Economically Disadvantaged	0.11	-0.88%	-0.68%
Hispanic & Not Economically Disadvantaged	0.12	0.19%	-0.26%
White & Economically Disadvantaged	0.06	-0.62%	3.18%
Black & Economically Disadvantaged	0.10	0.90%	1.83%
Hispanic & Economically Disadvantaged	0.21	-0.20%	0.58%
Achievement	11.81	0.06%	0.22%

This table shows the impact of different earnings policies. The "Baseline" column shows the same statistics implied by the model with no policy. The second column shows the percent change in overall composition after a static $1,500 bonus, the third column shows the percent change in composition after a conditional $1,500 bonus. ECE Workers denote the proportion of individuals that at some point work in the ECE sector. Ethnicity, Econ. (Economically Disadvantaged dummy), and Achievement are proportions. Achievement is derived from 3 dummies representing the different ranges in the distribution. We transform them into a continuous variable by using the midpoint of each interval.