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

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We study turnover and compensation in the early care and education (ECE) sector using linked administrative records from three Texas state agencies that allow us to follow nearly three million individuals from high school through their labor market careers. We match each ECE worker to observationally equivalent workers who never entered the sector and estimate turnover and earnings differentials under multiple definitions. ECE workers exhibit 5–7 percentage points higher turnover and approximately 45% lower earnings than matched counterparts. We decompose these differentials into worker selection and sector effects. For turnover, selection dominates: workers who enter ECE exhibit higher turnover across *all* sectors, but ECE employment itself is associated with *lower* turnover, consistent with compensating amenities that partially stabilize an inherently unstable

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workforce. For earnings, both selection and sector effects contribute roughly equally to the penalty. The differentials vary substantially by race and education, with college-educated white workers facing the largest gaps. Approximately half of ECE leavers exit formal employment entirely, suggesting that turnover does not primarily reflect efficient reallocation.

1. Introduction

High turnover in the early care and education (ECE) sector has long been a concern for researchers and policymakers, yet measuring it precisely has proven difficult. These workers play a central role in early childhood development: they provide the daily interactions, routines, and responsive caregiving that research in developmental psychology has linked to children's cognitive and socioemotional growth.[1] Yet basic facts about workforce compensation and career dynamics remain poorly documented. Existing studies rely primarily on survey data with small samples and short panels, or on cross-sectional snapshots that cannot track workers over time. Moreover, different studies use different definitions of turnover and draw on different data sources, making it difficult to compare estimates across studies or to know whether reported differences reflect true variation or measurement artifacts. As a result, researchers have been unable to answer questions that are fundamental to designing effective workforce policies: How does turnover in ECE compare to other sectors employing similar workers? What earnings penalty, if any, do ECE workers face? And do these patterns vary systematically by worker characteristics?

We address these questions by constructing a novel longitudinal dataset that links administrative records from three Texas state agencies. We merge data from the Texas Education Agency (TEA), which contains K–12 enrollment and test score records, with information from the Texas Higher Education Coordinating Board (THECB) on postsecondary enrollment and degrees, and with quarterly employment and earnings records from the Texas Workforce Commission (TWC). This linkage allows us to follow the complete 1980 to 1989 birth cohort in Texas from high school through their labor market careers.[2] [3]

Using this data, we first identify all individuals who ever worked in the ECE sector. Then, we match them to observationally equivalent workers with the same probability of entering ECE based on demographics and high school test scores but who never did. This design enables us to estimate turnover and earnings differentials while controlling for selection on observable pre-market characteristics. Our approach builds on Blau (1993), who used CPS data to study the labor supply of the ECE sector. 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

[1]See, for example, Howes (1999) on the importance of stable caregiver-child relationships for attachment and learning.

[2]We restrict the sample to women, who constitute 94% of the ECE workforce, and exclude racial groups too small for reliable subgroup analysis.

[3]We adopt a cohort-based design that follows complete birth cohorts instead of sampling active workers at a point in time because it allows us to observe pre-market characteristics, construct a matched comparison group, and track workers across sectors over time.

probability of working in the ECE sector but never did during our analysis period. We do so because, as we document below, ECE workers constitute a highly selected group.

Our analysis uncovers several striking stylized facts about workers in the ECE sector. We estimate that turnover rates in the ECE sector are approximately 38.5%, compared to 32.4% for matched workers in other sectors. In regression specifications with match fixed effects, this translates to a gap of 5.3 percentage points, or about 16% higher turnover.[4] We also estimate an earnings penalty of approximately 45% for ECE workers relative to their matched counterparts. These differentials vary substantially by race and education. The turnover gap is smallest—in fact, negative—for African American workers with only a high school diploma, and largest for college-educated white workers. The earnings penalty increases steeply with educational attainment, ranging from 16.5% for African American workers with a high school diploma to over 55% for white workers with a four-year degree.

Perhaps the most important finding from our analysis concerns the decomposition of these differentials into worker selection versus sector effects. By including both a dummy for ever having worked in ECE and a separate indicator for current ECE employment, we can separate time-invariant differences between workers who enter the sector from the contemporaneous effects of ECE employment itself.[5] The decomposition reveals that the mechanisms underlying the turnover and earnings differentials are quite different.

For turnover, selection appears to dominate: workers who enter ECE at any point in their careers exhibit 9.8 percentage points higher turnover across all sectors, not just while working in ECE. Conditional on worker type, however, ECE employment is associated with lower turnover—approximately 3.6 percentage points lower under our primary definition. In other words, the sector attracts workers with high baseline instability but appears to partially stabilize them while employed. This pattern is consistent with qualitative evidence suggesting that ECE workers who remain in the sector, despite low pay, report deriving satisfaction from intrinsic rewards such as watching children develop and building relationships with families, while those who leave emphasize frustration with inadequate compensation (see McDonald, Thorpe, and Irvine 2018; Bull et al. 2024; Herman, Dearth-Wesley, and Whitaker 2023). For earnings, both channels work against ECE workers: those who enter the sector have systematically lower earnings potential (30 log points lower than

[4] These estimates use our primary "Academic Year" turnover definition, which counts a worker as having turned over if they were employed in the ECE sector in the third quarter of a calendar year but had left the sector by the end of the second quarter of the following year. Results are qualitatively similar under alternative definitions; see Section 4.

[5] This approach is similar in spirit to a correlated random effects models that can distinguish permanent individual heterogeneity from state dependence (e.g., see Hyslop 1999). However, we do not impose distributional assumptions on the unobserved heterogeneity; instead, we rely on the within-person variation in sector of employment.

matched workers across all jobs), and working in ECE further reduces their earnings by an additional 23 log points. One implication of this asymmetry is that improving compensation may address the sector effect on earnings, but it would not change the selection channel unless wages rise enough to attract workers from a different pool.

These findings speak to ongoing debates in both labor economics and child development policy. From a labor market perspective, our results document a substantial compensating differential in a sector that employs predominantly women and minorities.[6] The magnitude of the earnings penalty and its gradient with education may help explain why the sector struggles to attract and retain workers with stronger outside options. From a child development perspective, high turnover disrupts the continuity of care that research in developmental psychology identifies as important for young children's learning and attachment formation.[7] When teachers leave mid-year, children lose the stable relationships that support scaffolded instruction and secure attachment, which have been linked to later developmental outcomes (e.g., see Elicker and Fortner-Wood 1995; Moss et al. 1996).

Our analysis builds on an extensive literature examining teacher turnover in K–12 settings. Annual turnover rates in K–12 typically range from 10 to 20 percent and have been shown to harm student achievement, particularly in high-poverty schools (see Ronfeldt, Loeb, and Wyckoff 2013; Herman, Dearth-Wesley, and Whitaker 2019). Research in this area has also documented compensating differentials for teaching in disadvantaged schools; estimates suggest that wage premiums of 5 to 14 percent may be required to attract and retain teachers in high-minority or high-poverty settings (e.g., see Hanushek, Kain, and Rivkin 2004; Clotfelter et al. 2008). The ECE sector differs from K–12 in important respects: wages are dramatically lower, educational requirements are less stringent, and wage schedules are flatter.[8] These differences create steeper outside-option gradients for workers with more education, which may explain the heterogeneity we document.

However, the lack of data has made it challenging to investigate these issues. 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 Survey (CPS), or the Quarterly Workforce Indicators (QWI). In NSECE, the childcare pro-

[6]In our preliminary sample, 94% of ECE workers are female. Males are excluded from the analytical sample. African American and Hispanic workers are overrepresented relative to the general workforce.

[7]See, for example, Howes (1999) and Raikes (1993) on the relationship between caregiver stability and attachment, and Markowitz (2019) for evidence linking teacher turnover to child outcomes in Head Start.

[8]In 2019, median hourly wages for childcare workers was around \$11.65 versus \$34.43 for elementary teachers (McLean et al. 2021)

gram'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. A challenge in comparing turnover estimates across studies is that these different data sources and definitions can yield substantially different estimates, making it difficult to assess whether differences in reported turnover rates reflect true variation or measurement artifacts.

Importantly, none of these datasets track workers before they enter the ECE sector or follow them after they leave. This makes it impossible to construct a comparison group of similar workers who never entered ECE, or to observe ECE workers' outcomes when employed elsewhere. Without this information, researchers cannot separate how much of the observed differentials reflect the sector's characteristics versus the characteristics of workers who select into it. This decomposition is important for designing policies to improve retention: if high turnover reflects worker selection, then policies that improve working conditions may have limited effects; if it reflects sector characteristics, then such policies may be more effective.

More recently, a growing body of research has begun documenting the ECE workforce using longitudinal administrative data. Bassok et al. (2021) used data from the Louisiana Department of Education to study teacher retention. Their dataset, spanning Fall 2016 to Fall 2019, is a census of 5,900 lead teachers in toddler or preschool-aged classrooms in all publicly funded center-based ECE programs, including school-based sites, Head Start locations, and childcare programs. They find that over one-third of teachers leave their program annually and that the vast majority who leave exit the ECE sector entirely rather than moving to another site. Brown and Herbst (2022) examine ECE employment over the business cycle using Quarterly Workforce Indicators, documenting that childcare is substantially more exposed to macroeconomic fluctuations than other low-wage industries and recovers more slowly from downturns. The Center for the Study of Child Care Employment has produced a series of workforce indices documenting wages, turnover, and economic insecurity across states (see Whitebook et al. 2018). We contribute to this literature by offering an analysis that tracks individual workers across their careers — before ECE entry, during ECE employment, and after exit — and compares them to observationally equivalent workers who never enter the sector. Our data also allow us to construct multiple turnover measures, including definitions analogous to those used in the CPS and QWI, and examine whether our findings are robust across definitions.

Our study also connects to the broader literature on compensating differentials and occupational sorting in care work. The Roy (1951) model of self-selection predicts that occupations with compressed wage structures will attract workers with lower outside options—a prediction consistent with our finding that workers who select into ECE have systematically lower earnings potential across all sectors. ECE represents an extreme case of wage compression: wages have remained stagnant even as demand has grown, consistent with Blau's (1993) finding of highly elastic labor supply to the childcare sector. Our matching approach advances on Blau's random comparison group by ensuring that we compare workers who are arguably at the margin of sector entry. The challenge is separating this selection from the compensating differentials that workers may accept in exchange for non-pecuniary job attributes. This identification problem is well documented in K–12 education, where rigid salary schedules complicate hedonic estimation of compensating differentials (see Goldhaber, Destler, and Player 2010), and in nursing, where decompositions of hospital wage premiums suggest that a third to a half reflects worker selection rather than compensating differentials for disamenities (Schumacher and Hirsch 1997; Di Tommaso, Strøm, and Sæther 2009). More broadly, evidence that intrinsically motivated care workers perform better but respond less to external incentives (Oxholm et al. 2025) suggests that these sectors attract workers partly through non-pecuniary rewards, but that disentangling selection from sector effects requires data that can track workers across settings.

We also examine where ECE workers go when they leave the sector. Among those who appear in formal employment records after exit, the most common destinations are educational services, health care and social assistance, retail, and food services, sectors that also employ matched non-ECE workers at similar rates, which provides some validation for our matching procedure. A substantial share of leavers do not appear in formal employment records in the subsequent quarter, though this likely overstates true non-employment given the well-known coverage limitations of state unemployment insurance data.[9]

The remainder of the paper is organized as follows. Section 2 describes the data and details the construction of the ECE worker sample and the matched comparison group. Section 3 outlines the methodological framework. Section 4 presents the main empirical findings. Finally, Section 5 summarizes the key insights and discusses directions for future research.

[9] State UI records do not capture employment in other states, self-employment, federal government employment, or informal work arrangements such as nannying. K–12 education and nursing exhibit comparable rates of transition to unobserved status, suggesting this reflects data coverage rather than sector-specific non-employment. See Section 4 for a more detailed discussion.

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.[10]

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 624410. Therefore, we study turnover at the industry level. 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). Estimates of composition between teaching and non-teaching staff are scarce, but Norton, Jordan and Whitehead, Joellyn (2199) conducts a survey in the state of Illinois during 2019 and find that about 77% of childcare center employees were teaching staff, 13% consisted of administrative staff, and the remaining 10% were facilities management and food services. 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 this specific NAICS code excludes Head Start programs in public schools, school-based pre-K, and self-employed individuals such as informal home-based services, babysitters, etc.

[10] 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).

2.2. Target Population

Our study follows individuals born between 1980 and 1989 who enrolled in Texas public schools. Our matching procedure relies on pre-market characteristics measured at age 18, including high school exit test scores, demographics, and school district. The TEA's standardized exit exams provide test score data beginning with the 1980 birth cohort, making this the earliest cohort for which complete pre-market records are available.[11] The 1989 endpoint provides a ten-year window, which we require because only about 4% of individuals in our data ever work in the ECE sector.

An alternative approach would identify all ECE workers active in a given period and trace back their educational and work histories. However, such a sample would include workers from older cohorts for whom exit test scores are unavailable, forcing a choice between dropping them and yielding a cohort-like sample regardless, or matching without test scores. The latter would leave a substantial gap in academic preparation unaddressed: in our data, unmatched non-ECE workers score 0.8 education-equivalent years higher than ECE workers on the exit exam, a difference that is eliminated by matching on test scores.[12]

By observing complete birth cohorts from age 18 before anyone has entered the labor market, we can construct a matched comparison group based on the propensity to enter ECE and follow the same individuals across sectors over time. This is essential for our decomposition of turnover and earnings differentials into worker selection and sector effects (Section 3).

2.3. Measures

We briefly define the key variables used in our analysis. Detailed descriptions of all variable construction are provided in Appendix A.

Each individual-quarter is classified into one of three mutually exclusive activities: employed, enrolled in school, or not employed and not a student. Employment status and sector are determined from TWC records. Since the data does not provide hours worked, only total earnings in the quarter, we retain only quarters in which earnings exceed a minimum threshold following Keane and Wolpin (1997) to exclude marginal employment spells that would mechanically inflate turnover.[13] Industry is identified by the employer's

[11] The TAAS (Texas Assessment of Academic Skills) was administered from 1997 to 2002, followed by the TAKS (Texas Assessment of Knowledge and Skills) from 2003 to 2006. Students take exit exams as juniors or seniors, so the 1980 birth cohort is the first to have complete exit exam records.

[12] This gap corresponds to approximately 0.6 standard deviations of the achievement distribution. See Table 3.

[13] We require quarterly earnings equivalent to at least 20 hours per week at minimum wage for 8 weeks. Appendix Table A1 reports the thresholds by quarter and year. Quarterly earnings are deflated to 2020 Q4

NAICS code.

We classify postsecondary degrees using the Classification of Instructional Programs (CIP). *Broad* degrees include Education (CIP 13), Health (CIP 34, 51), and Psychology (CIP 42). *Specialized* degrees are those specifically in early childhood education or child development (see Table A4 in Appendix C for the full list).

Achievement is based on the first attempt score on the Texas high school exit exam (TAAS or TAKS) in reading and mathematics, anchored to completed years of education by age 30. See Appendix B for the anchoring methodology.

Turnover Definitions

A recurring challenge in comparing turnover estimates across studies is that each relies on a different data source and must define turnover accordingly. Our quarterly administrative records allow us to construct and directly compare several commonly used measures within the same sample. We report three definitions of turnover. Note that because the ERC does not release employer identifiers, all three measures capture sector-level turnover (i.e., exit from the industry), not firm- or classroom-level turnover.

Academic Year turnover. We identify the worker's sector of employment in the third quarter of the calendar year (the beginning of an academic year) and check whether the worker remains in the same sector through the second quarter of the following calendar year (the end of the academic year). If not, it is a turnover. This definition excludes separations between the second and third quarters, when transitions between classrooms occur naturally (e.g., from infant to toddler rooms).

CPS-style turnover. Following Bassok et al. (2013), we construct a measure that mimics how sector turnover is calculated using the Current Population Survey. The CPS interviews individuals in the first quarter of the year and asks them to report their longest job spell in the previous year. We approximate this by identifying, for each calendar year, the sector in which the individual was employed for the most quarters. Ties are broken by highest earnings. A turnover occurs if the individual's modal sector changes from one year to the next.

Quarter-over-Quarter turnover. We compare the individual's sector of employment in consecutive quarters. A turnover occurs if the individual is employed in a sector in quarter t but is no longer in that sector in quarter $t + 1$. This is the highest-frequency measure and captures short-run transitions that the annual definitions smooth over.

prices using the CPI (Federal Reserve Bank of St. Louis 2023).

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.[14] 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. [15] After restricting the TEA, THECB, and TWC data sources to this specific set of individuals, we drop all invalid, duplicate, and inconsistent observations.[16]

After implementing the data-cleaning procedures, our analytical dataset has 2,768,093 individuals born between 1980-1989, in which about 4.1% (108,704) ever worked in the childcare sector.[17] Table 2 shows the demographic characteristics of the individuals in

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

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

[16]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.

[17]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

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.

our final sample. The first and second columns show demographics for all individuals who have never worked in the ECE sector (henceforth, Non-ECE Workers) and those who worked at least for at least one semester in the sector (henceforth, ECE Workers). 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.[18] 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

older children when they are not in school and may also offer pre-kindergarten or kindergarten educational programs."

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

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.

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.[19] 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 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, dummies for birth year, and their achievement based on their exit

[19]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.

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.

test scores.[20] [21] We estimate the probability that an individual will ever work in the ECE sector, $\Pr(D_i = 1|Z_i)$, by:

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

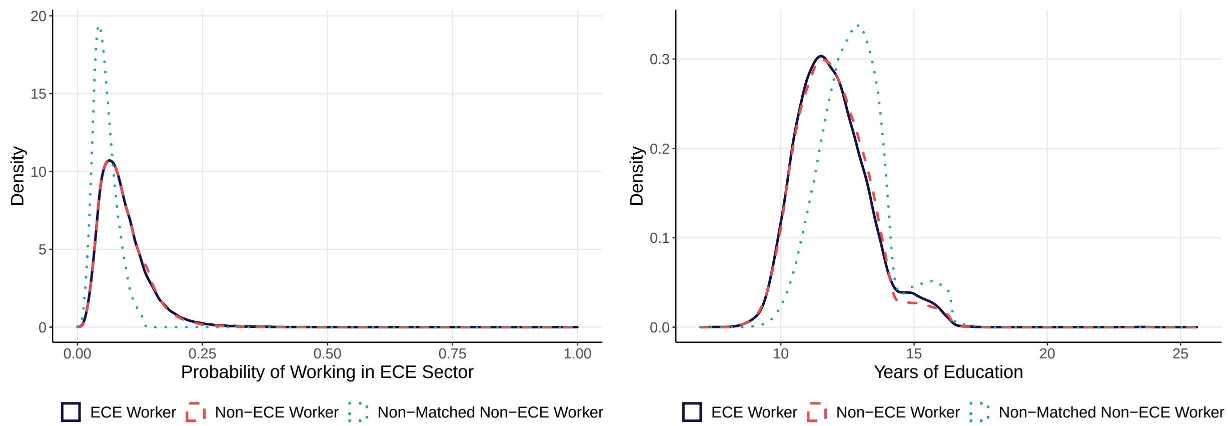
where $\Lambda(\cdot)$ is the cumulative distribution function of a Logistic distribution, and β is the parameter vector from a logit model. We then use a k-nearest neighbor search with no replacement to find, for each individual that ever worked in the ECE sector, $k = 5$ individuals that never worked in the ECE sector but with similar propensity scores.[22] We denote a treated individual and its $k = 5$ matched counterparts a "matched" group.

[20] Note that Z_i does not include educational attainment, as it is an endogenous variable about future outcomes.

[21] All variables included in Z_i are discrete with the exception of achievement. In practice, the matching estimator will perform an exact match on the discrete variables, and choose individuals with similar achievement scores.

[22] In a no-replacement algorithm, there is a possibility of ties occurring in terms of the predicted propensity score. In these cases, we randomly select individuals that are tied to each other.

FIGURE 1. Balancing of observable attributes after matching



A. Balancing of propensity score after matching

B. Empirical density of anchored test scores

Note: These figures show the densities of the probability of working in the ECE sector and high school exit test scores after conducting a propensity score matching. ECE Worker and Non-ECE Worker are the “treated” and “control” groups, while Non-Matched Non-ECE Worker represents the densities of those that were excluded from our sample due to the matching.

Table 3 and Figures 1A and 1B show the results of our matching exercise.[23] 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.

Figures 1A and 1B show the probability density of working in the ECE sector and anchored test 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. [24]

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 observa-

[23]We present the results from the logit regression in Table A5 in Appendix C.

[24]In Appendix D, 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.

TABLE 4. Descriptive Statistics of Final 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
Not Employed, Not a Student	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
Broad Degree	0.327	0.469	0	1
Specialized Degree	0.036	0.186	0	1
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	0.17	0.32	0	1

Note: 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. Broad and Specialized Degrees are degrees related to early childhood, such as teaching, psychology, and nursing. These variables are described in detail in the Data Section.

tions 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. About 33% of individuals were enrolled in a Broad degree at some point, while 3.6% were enrolled in a Specialized degree.

3. Empirical Framework

We leverage the design of our matched sample and estimate regressions to characterize the relationship between ECE employment and two outcomes: turnover and log earnings. Let $y_{i,t}$ denote individual i's outcome at time t. For turnover, $y_{i,t}$ is an indicator equal to one if individual i was employed in a given sector at the beginning of the period but had left by the end of the period.[25] For earnings, $y_{i,t}$ is the log of quarterly earnings.

Our baseline specification is:

$$y_{i,t} = X_{i,t}\beta + \gamma D_{i,t}^{ECE} + \alpha_{Year} + \alpha_{Match} + \varepsilon_{i,t}, \tag{2}$$

where $D_{i,t}^{ECE}$ is equal to one if individual i was employed in the ECE sector at the beginning of the period, $X_{i,t}$ denotes control variables, and the α's denote fixed effects.[26] We include match fixed effects, α_{Match}, a dummy variable equal to one if the individuals in the sample belong to the same matched group.[27] The coefficient γ captures the difference in outcomes between ECE and non-ECE employment for observationally similar workers.

The baseline specification pools all ECE employment spells and attributes the entire differential to sector of current employment. However, workers who select into the ECE sector may differ from matched workers in unobserved ways—for example, in their baseline attachment to the labor force or their earnings potential. To separate these sources, we augment the baseline with a dummy for ECE Worker status:

$$y_{i,t} = X_{i,t}\beta + \gamma_1 D_{i,t}^{ECE} + \gamma_2 W_{i}^{ECE} + \alpha_{Year} + \alpha_{Match} + \varepsilon_{i,t}, \tag{3}$$

where W_i^{ECE} is equal to one if individual i ever worked in the ECE sector during the sample period, regardless of current employment. The coefficient γ_2 captures persistent differences between individuals who enter ECE and those who never do—even when both are observed working outside the sector. The coefficient γ_1 captures the within-person difference in outcomes when the same worker is employed in ECE versus another sector. Together, γ_1 and γ_2 decompose the baseline estimate into a contemporaneous sector effect and a time-invariant selection component.

We also examine how the turnover differential evolves with sector-specific experience.

[25] We apply three definitions of turnover that differ in the time horizon used to measure sector exit. Section 2 describes each definition in detail.

[26] We include potential experience (age − education years) and its squared counterpart as controls.

[27] A matched group consists of an ECE Worker and the $k = 5$ individuals who never worked in the ECE sector but are observationally equivalent at 18 years old according to the predicted propensity score in Equation (1).

We augment equation (2) by including cumulative ECE experience and its interaction with current ECE employment:

$$y_{i,t} = X_{i,t}\beta + \gamma_1 D_{i,t}^{ECE} + \gamma_2 E_{i,t}^{ECE} + \gamma_3 D_{i,t}^{ECE} \times E_{i,t}^{ECE} + \alpha_{Year} + \alpha_{Match} + \varepsilon_{i,t}, \tag{4}$$

where $E_{i,t}^{ECE}$ is the number of quarters individual i has been employed in the ECE sector up to time t. The coefficient γ_2 captures the relationship between ECE experience and turnover regardless of current sector, while γ_3 captures the additional effect of experience while currently employed in ECE. A negative γ_3 would indicate that the turnover differential narrows with sector tenure.

Finally, we examine exit destinations for workers who leave the ECE sector. For each destination d (e.g., non-employment, education services, health care), we estimate a linear probability model:[28]

$$P(d_i = 1) = \delta_0 + \delta_1 \text{Broad}_i + \delta_2 \text{Specialized}_i + X_i\phi + \eta_i, \tag{5}$$

where the sample is restricted to individuals who experienced a turnover from the ECE sector. The dependent variable d_i is an indicator for whether the worker transitioned to destination d in the quarter following exit. Broad_i and Specialized_i are indicators for holding a broad ECE-related degree (education, health, or psychology) or a specialized early childhood degree, respectively.[29] The omitted category is workers without ECE-related credentials. Controls include age at exit and exit year. The coefficients δ_1 and δ_2 capture how educational credentials relate to the probability of transitioning to each destination, relative to workers without such credentials.

4. Results

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".[30] These two groups are similar in observable attributes and probability of working in the ECE sector when they were 18. 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.

[28] We also estimated a multinomial probit model that aggregates exit destinations, and estimated marginal effects were very similar. For exposition purposes, we present the individual linear probability models.

[29] Broad degrees consist of Education (CIP 13), Health (CIP 34, 51), and Psychology (CIP 42). Specialized degrees are those specifically in early childhood education or child development. See Table A4 in Appendix C for the full classification.

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

We organize our analysis in two parts. First, we examine turnover patterns: the overall differential, its decomposition into worker selection versus sector effects, and how sector-specific training relates to retention. Second, we apply the same framework to quarterly earnings.

4.1. Turnover

We observe labor force participation quarterly, which provides flexibility in how to define turnover. A challenge in comparing turnover estimates across studies is that researchers use different definitions, time horizons, and reference populations. We contribute to comparability by reporting turnover under three definitions, two of which are commonly used in the literature.

Our primary measure counts a turnover if the individual was employed in the ECE sector in the third quarter of a year but left the sector before the end of the second quarter of the following year, a worker who did not complete a full academic year. We refer to this as *Academic Year* turnover. We also construct a *CPS-style* measure that mimics how sector turnover is calculated using the Current Population Survey, and a *Quarter-over-Quarter* measure that captures transitions between consecutive quarters. All three measures are defined in Section 2.

Table 5 reports turnover rates, overall and by education level, for ECE workers in the ECE sector and for non-ECE workers employed outside the sector under several definitions of turnover described in the data section. Using academic year and CPS based measures, turnover in the ECE sector is 38.5% and 41.8%, respectively, which is consistent with prior estimates using comparable data. For example, Bassok et al. (2021), using Louisiana administrative data, estimates program level and sector level turnover rates of 37% and 46% between the 2017-18 and 2018-19 academic years. In contrast, CPS based studies typically report lower sector turnover rates, such as 23.6% in 2010 (Bassok et al. 2013), with the literature documenting annual rates ranging from 26% to 40% (Totenhagen et al. 2016). These differences likely reflect variation in measurement rather than true discrepancies, since CPS turnover relies on self reported industry and occupation in the longest held job over the prior year, whereas administrative data capture job transitions more directly. Finally, our quarter over quarter turnover rate is 21.5%, which is higher than the 12% reported by Brown and Herbst (2022), who compute turnover using aggregate hiring and separation flows. Across all three definitions, ECE workers exhibit higher turnover than matched Non-ECE workers. The differential ranges from 4.7 to 7.7 percentage points depending on the measure used.

We estimate regression equation 2 using the matched sample for each turnover defini-

Table 5. Turnover Rates (%) for the ECE Sector and Non-ECE Workers

	ECE Sector	Non-ECE Worker	Diff.
Academic Year Turnover	38.52	32.41	6.11***
CPS-style Turnover	41.77	34.10	7.67***
Quarter-Over-Quarter Turnover	21.50	16.83	4.67***

Note: $*: p < 0.10$, $**: p < 0.05$, $***: p < 0.01$. This table shows turnover rates for the ECE Sector and for Non-ECE Workers in any sector. Academic Year Turnover counts workers employed in Q3 who exit before Q2 of the following year. CPS Turnover follows the Current Population Survey methodology. Quarter-over-Quarter measures transitions between consecutive quarters.

tion. Table 6 reports these results. Estimates of γ range from 0.041 to 0.070, all statistically significant at 1%. The preferred specification with match fixed effects (Column 3) implies that turnover in the ECE sector is approximately 5.3 percentage points higher than in other sectors when using the Academic Year definition, and 7.0 percentage points higher using the CPS definition. The turnover penalty is smallest when using the Quarter-Over-Quarter definition.

Regardless of how turnover is measured, ECE workers exhibit significantly higher exit rates than observationally similar workers in other industries. The absolute rates differ across definitions (annual measures capture 35-40% turnover while quarterly measures capture 20%), but the differential is qualitatively robust: 4-7 percentage points, or 15-20% higher turnover relative to matched controls.

TABLE 6. Turnover Regressions

	(1)	(2)	(3)
Panel A: Academic Year Turnover			
ECE Sector	0.048***	0.039***	0.053***
	(0.0019)	(0.0019)	(0.0023)
Panel B: CPS-style Turnover			
ECE Sector	0.065***	0.060***	0.070***
	(0.0016)	(0.0016)	(0.0019)
Panel C: Quarter-Over-Quarter Turnover			
ECE Sector	0.039***	0.034***	0.041***
	(0.0008)	(0.0008)	(0.0012)
Controls	N	Y	Y
Match Fixed Effects	N	N	Y

Note: $*$: $p < 0.10$, $**$: $p < 0.05$, $***$: $p < 0.01$. This table shows estimates of γ in equation (2) for different specifications and definitions of turnover. 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 year and matched groups. Controls include potential experience (age − education years) and its squared counterpart. Matched group consists of an ECE Worker and its matched counterparts found in the matching procedure described in Section 2. We report clustered standard errors at the matched group level in parentheses.

The estimates in Table 6 capture the average turnover differential across all ECE employment spells. However, this average may mask important dynamics. If workers learn about match quality over time, or if the sector builds attachment through experience, we would expect the differential to evolve with tenure. We examine this by interacting the ECE Sector indicator with cumulative ECE experience.

Table 7. Turnover Regressions - ECE Experience

	Academic Year	CPS-style	Quarter-Over-Quarter
ECE Sector	0.307***	0.235***	0.160***
	(0.0038)	(0.0028)	(0.0020)
ECE Experience	-0.0159***	-0.010***	-0.0101***
	(0.0004)	(0.0004)	(0.0002)
ECE Sector $\times$ ECE Experience	-0.039***	-0.024***	-0.019***
	(0.0006)	(0.0005)	(0.0003)

Note: $*: p < 0.10$, $**: p < 0.05$, $***: p < 0.01$. This table shows estimates from estimating equation (4) for different definitions of turnover including ECE Experience as a control. ECE Experience is the number of quarters employed in the ECE Sector before experiencing a turnover. 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 year and matched groups. Controls include potential experience (age − education years) and its squared counterpart. Matched group consists of an ECE Worker and its matched counterparts found in the matching procedure described in Section 2. We report clustered standard errors at the matched group level in parentheses.

Table 7 introduces ECE Experience, the cumulative quarters an individual has worked in the ECE sector, and its interaction with current ECE employment. The coefficient on ECE Experience across all definitions indicates that workers with more ECE tenure exhibit lower turnover even when employed outside the sector, consistent with either selection (stable workers accumulate more tenure) or learning effects. The interaction term (between -0.039 and -0.019) reveals an additional stabilization effect while employed in ECE: each quarter of sector experience reduces in-sector turnover by an additional 3.9 percentage points beyond the baseline experience effect.

Together, the estimates imply that turnover declines substantially with ECE tenure. A worker with 8 quarters of ECE experience has predicted turnover roughly 44 percentage points lower than an otherwise similar worker with no ECE experience ($8 \times 0.055 = 0.44$ when in ECE). This steep gradient driven heavily by the interaction term suggests that the aggregate turnover differential is concentrated among workers in their first few quarters of ECE employment.

4.1.1. Decomposing the Gap: Worker Selection vs. Sector Effects

The steep decline in turnover with sector tenure suggests that early-career separations drive the aggregate differential. But does this reflect workers learning they are poor fits, or does it reflect who enters in the first place? That is, does this differential reflect the workers ECE attracts or the conditions they encounter? We decompose the turnover gap to distinguish selection from sector effects.

While our matching procedure improves comparability based on observable characteristics measured early in life, it cannot fully account for unobserved differences such as intrinsic earnings potential, potential attachment to the labor force, or baseline turnover propensity. To understand the role of such unobserved heterogeneity, we estimate specifications that include both a dummy for ECE Worker status, indicating whether an individual ever worked in the ECE sector during the sample period, and a separate dummy for current employment in the ECE sector. Under this specification, the coefficient on “ECE Sector” captures the within person difference in outcomes when the same worker is employed in ECE versus another sector. The coefficient on “ECE Worker” captures persistent differences between individuals who ever enter ECE and those who never do, even when both are observed working outside the sector. This decomposition allows us to separate contemporaneous sector effects from time invariant worker selection, while holding fixed the original matched group structure by including Match fixed effects.

Table 8 presents the results of this exercise for turnover under several definitions. Column (1) reproduces the baseline estimates. Column (2) replaces the sector indicator with the ECE Worker dummy. Column (3) includes both indicators simultaneously.

TABLE 8. Decomposing Turnover and Earnings: Worker Selection vs. Sector Effects

	(1) Baseline	(2) Worker Only	(3) Both
Panel A: Academic Year Turnover			
ECE Sector	0.053***		-0.036***
	(0.0024)		(0.0030)
ECE Worker		0.089***	0.098***
		(0.0013)	(0.0015)
Panel B: CPS-style Turnover			
ECE Sector	0.070***		-0.004
	(0.0019)		(0.0021)
ECE Worker		0.081***	0.082***
		(0.0011)	(0.0013)
Panel C: Quarter-Over-Quarter Turnover			
ECE Sector	0.041***		-0.009***
	(0.0012)		(0.0013)
ECE Worker		0.054***	0.056**
		(0.0007)	(0.0008)
Panel D: Log Earnings			
ECE Sector	-0.449***		-0.229***
	(0.003)		(0.003)
ECE Worker		-0.303***	-0.246***
		(0.002)	(0.002)

Note: $*:\ p < 0.10$, $**:\ p < 0.05$, $***:\ p < 0.01$. This table decomposes turnover and earnings differentials into worker selection (ECE Worker = ever worked in ECE) and contemporaneous sector effects (ECE Sector = currently in ECE). Panels A–C report turnover outcomes (binary indicators); Panel D reports log quarterly earnings. Column (1) shows the baseline specification; Column (2) includes only the ECE Worker dummy; Column (3) includes both. All specifications include fixed effects for year and matched groups. Controls include potential experience and its square. Standard errors clustered at the matched group level in parentheses.

Turnover. For Academic Year turnover, the decomposition in Column (3) reveals that workers who enter the ECE sector exhibit substantially higher turnover across all sectors, as reflected in the positive coefficient on the ECE Worker dummy. Conditional on worker type, however, employment in the ECE sector itself is associated with lower turnover. In other words, while ECE attracts workers who are more likely to separate from jobs overall, these workers are less likely to exit during the academic year when employed in ECE.

This sector stabilization effect does not appear when turnover is measured using CPS-style or quarter-over-quarter definitions. Under these alternative measures, the coefficient on the ECE Sector dummy is statistically insignificant or very small, while the ECE Worker coefficient continues to capture higher overall turnover among individuals who ever enter the sector. This suggests that the high turnover observed in the sector is due to worker selection rather than a specific penalty of the ECE sector itself. The stabilization observed for Academic Year turnover appears specific to separations that occur across academic year boundaries. This may reflect different margins of labor supply adjustment, though we cannot distinguish explanations with available data.

Importantly, across all three turnover definitions, the ECE sector is not associated with *higher* turnover once we account for worker type. The Academic Year measure shows the strongest stabilization effect (-3.6 percentage points), while CPS-style and quarter-over-quarter measures show sector effects near zero. The consistent finding is that the sector itself does not destabilize workers under any definition; rather, the elevated turnover observed in ECE reflects the characteristics of workers who select into the sector. The degree of stabilization varies by measurement horizon, with annual measures capturing stronger effects than quarterly measures, but the qualitative conclusion is robust: selection, not sector conditions, drives the turnover differential.

More broadly, the negative sector effect on turnover is consistent with ECE offering compensating amenities that partially offset low wages. Qualitative evidence supports this interpretation: McDonald, Thorpe, and Irvine (2018) find that ECE workers who remain in the sector emphasize intrinsic rewards (meaningful work with children, relationships with families), while those who leave cite inadequate compensation and management concerns. Our decomposition quantifies this dynamic: the sector attracts workers with high baseline instability but is associated with lower turnover, potentially reflecting non-pecuniary job attributes.[31]

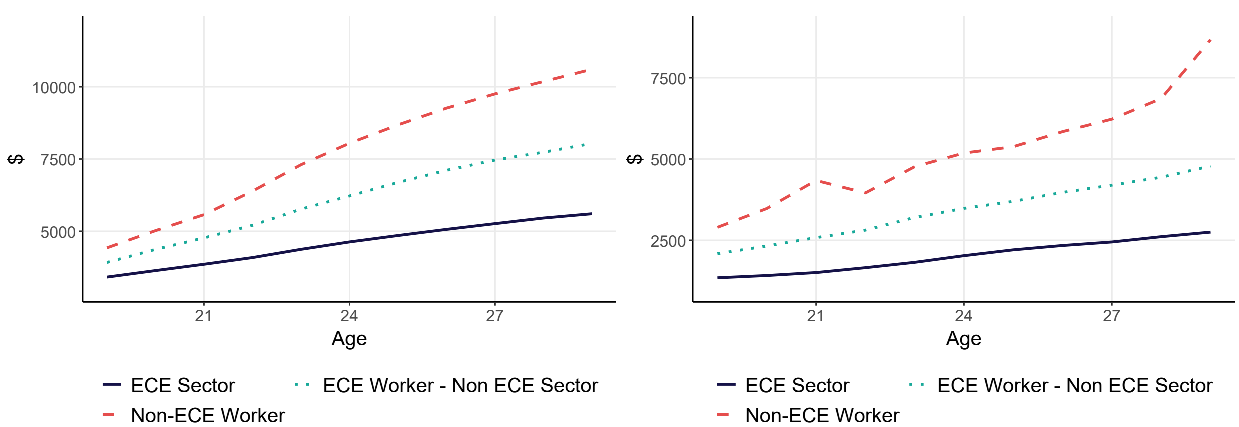
We note two important limitations. First, we cannot directly test the compensating

[31] Another commonly cited nonpecuniary feature of ECE jobs is access to discounted or priority childcare, which may make these positions especially attractive to mothers who would otherwise remain at home, but less attractive once that benefit is no longer salient. CPS-style and quarter-over-quarter measures, by contrast, capture higher-frequency transitions more likely to reflect short-term shocks or hours adjustments, margins that may be less sensitive to caregiving-related considerations and therefore do not exhibit the same stabilization pattern.

amenities interpretation: the administrative data used in this study do not contain information on fertility, household structure, or caregiving responsibilities. At best, what we can say is that the annual employment cycle may interact with worker characteristics in ways our data cannot fully identify. Second, the interpretation of the ECE Sector coefficient relies on the assumption that ECE employment has no lagged or dynamic effects on future labor market outcomes. If working in ECE affects subsequent earnings or turnover after exit, or if individuals adjust labor market behavior in anticipation of entering the sector, then the within-person comparison may still partially reflect selection or reverse causality. As a result, these estimates should be viewed as informative about the timing and nature of turnover in ECE, rather than as definitive causal parameters.

Earnings. We apply the same decomposition framework to earnings. Panel D in Table 8 shows the baseline earnings penalty of -44.9 log points (Column 1). Column (2) shows that workers who ever enter ECE earn 30.3 log points less than matched workers across all jobs, not just when working in ECE. Figure 2B shows that the distribution of earnings in the ECE sector has lower dispersion than in other sectors. This wage compression is consistent with the flat career progression commonly documented in early childhood settings.

FIGURE 2. Earnings and Industry



A. Average Earnings Over Time

B. Standard Deviation of Earnings Over Time

Note: This figure shows the average and standard deviation of quarterly earnings for ECE Workers in the ECE sector, ECE Workers outside the ECE sector, and Non-ECE Workers in any sector between ages 19 and 29. Earnings are deflated to 2020 Q4 prices. All differences between groups are statistically significant at the 1% level.

ECE Worker status alone is associated with a sizeable negative coefficient (e.g., -0.303 in Column 2), suggesting these individuals earn less across all jobs, not just when working in ECE. When we include both variables (Column 3), we observe that the two coefficients roughly add up to the original estimate, indicating that the negative wage effect is split approximately evenly between current sector employment and unobserved worker characteristics.

The decomposition in Column (3) reveals that the earnings penalty is split approximately evenly between selection and sector effects. The ECE Worker status alone is associated with a sizeable negative coefficient (e.g., -0.303 in Column 2), suggesting these individuals earn less across all jobs, not just when working in ECE. When we include both variables (Column 3), we observe that the two coefficients roughly add up to the original estimate, indicating that the negative wage effect is split approximately evenly between current sector employment and unobserved worker characteristics. This decomposition aligns with the descriptive evidence in Figure 2A: i) ECE Workers earn less than Non-ECE Workers even when working outside ECE (the selection component), ii) they earn even less when working in ECE (the sector component), and iii) the sector's low earnings dispersion reflects the flat career progression commonly documented in early childhood.

Unlike turnover, the sector effect on earnings is unambiguously negative: ECE employment is associated with lower earnings even after accounting for worker selection. This asymmetry has policy implications. For turnover, selection dominates: the sector attracts unstable workers but partially stabilizes them. For earnings, both channels work against ECE workers. Policies focused solely on improving worker selection, for example, recruiting workers with higher earnings potential, would address only half of the observed differential. The remaining half reflects the sector's wage structure.

4.1.2. Entry Sources and Exit Destinations

We have characterized who enters ECE (workers with high baseline instability and lower earnings potential), what happens while they are employed (partial stabilization but substantial earnings penalties), and how these patterns decompose into selection and sector effects. We now examine what happens when workers leave: where do they go, and what do they earn? If leavers transition to higher-paying sectors—K-12 education, healthcare, or other industries—then high turnover may simply reflect ECE's role as a stepping stone in career progression. If instead leavers exit formal employment, turnover represents a loss of trained workers from the labor force entirely. We examine post-exit destinations to distinguish these possibilities. These post-exit outcomes also speak to whether early turnover reflects efficient sorting, where workers discover poor fit and reallocate to better-matched employment.

The most striking finding is that the majority of ECE leavers do not transition to other employment. Table 9 shows that across all three turnover definitions, approximately half of workers who exit ECE are neither employed nor enrolled in school one quarter later. Among those who do find formal employment, the most common destinations are Education Services, Health Care, and Retail—sectors that also employ matched non-ECE workers at similar rates (Table A10). This similarity in sector distributions reinforces the validity of our matching procedure: ECE and non-ECE workers appear to draw from the same set of outside options.

TABLE 9. Activity After a Turnover

	Academic Year	CPS-Style	Quarter-Over-Quarter
Not Employed, Not a Student	50.98	54.07	53.20
Education Services	9.13	5.32	6.32
Health Care	8.42	4.73	5.91
Retail Trade	6.80	4.45	5.41
Admin. Support, Waste, Remediation	6.08	3.65	4.96
School	-	16.63	10.32
Others	18.60	11.11	13.87

Note: $*: p < 0.10$, $**: p < 0.05$, $***: p < 0.01$. This table shows the most common activities for ECE Workers after experience a turnover, by different measure of turnover. By construction, Academic Year turnover does not allow a transition into school. Sectors follow NAICS classification.

The prevalence of non-employment among leavers is difficult to reconcile with efficient sorting. If high turnover reflected workers discovering poor fit and reallocating to better-matched jobs, we would expect most leavers to appear in other industries, not to disappear from formal employment records.

We acknowledge that the high rate of transition to unobserved status (51%) primarily reflects the well-documented coverage limitations of state unemployment insurance records. These records exclude employment in other states, self-employment, federal government employment, and informal work arrangements common in child care, such as nannying and unlicensed home-based care.[32] Together, these features of the data suggests that our estimates overstate true labor force exit.

That said, the data limitations do not fully resolve the efficient sorting question. Even if we conservatively assume that half of the "not employed, not a student" category reflects informal work or interstate moves rather than genuine non-employment, approximately 25% of ECE leavers would still be exiting the formal labor force entirely. This rate exceeds what we would expect if turnover primarily reflected workers discovering better-matched

[32]This is a standard limitation of state UI records and affects all sectors similarly. K-12 education and nursing exhibit comparable rates of transition to unobserved status (40-60% depending on the measure), as can be seen in Table A11.

opportunities elsewhere. Moreover, among leavers who do appear in formal employment records, roughly half of the destinations are sectors with low skill transferability (Retail, Accommodation, Administrative Support). The combination of high exit to unobserved status and limited upward mobility among observed movers suggests that ECE turnover does not primarily reflect efficient reallocation toward better labor market matches.

To examine how exit destinations vary with worker characteristics, we estimate separate linear probability models for each destination. The dependent variable is an indicator equal to one if the worker transitions to that destination in the quarter following ECE exit; the key regressors are indicators for holding a broad degree (education, health, or psychology) or a specialized degree (early childhood education, child development). The omitted category is workers with no ECE-related credentials. We include controls for age at exit and exit year.

Table 10 reports the results. Each column represents a different exit destination; each row reports the coefficient on a degree indicator. Coefficients represent percentage point differences in the probability of transitioning to that destination, relative to workers without ECE-related credentials. For example, the -0.057 in the first column of Panel A indicates that workers with broad degrees are 5.7 percentage points less likely to exit to non-employment than workers without such credentials.

Exit destinations differ markedly by educational background. Table 10 shows that workers with ECE-related credentials are far less likely to exit to non-employment—between 6 and 14 percentage points less likely for those with broad degrees, and 3 to 17 percentage points for those with specialized degrees, depending on the turnover measure. These workers instead transition to related fields where their training has value. Specialized degree holders—those with credentials specifically in early childhood education or child development—are significantly more likely to enter Education Services, consistent with K-12 teaching as a natural career progression. Broad degree holders—those with general training in education, health, or psychology—are more likely to enter Health Care, consistent with nursing or social work as alternative pathways.

Notably, specialized degree holders are less likely to transition into lower-skill service sectors such as Retail, Accommodation, and Administrative Support. This pattern suggests that sector-specific credentials not only reduce turnover while in ECE (as shown earlier) but also provide structured exit pathways when workers do leave. Workers without such credentials face a starker labor market: ECE or non-employment.

Table 10. Exit Destinations by Degree Type

	Not Employed, Not a Student	Education Service	Health Care and Soc. Assist.	Retail, Accomod., Admin.
Panel A: Academic Year Turnover				
Broad Degree	-0.057***	0.017***	0.044***	0.001
	(0.0073)	(0.0043)	(0.0045)	(0.0056)
Spec. Degree	-0.031*	0.064***	-0.001	-0.022*
	(0.0132)	(0.0094)	(0.0069)	(0.0094)
Panel B: CPS-style Turnover				
Broad Degree	-0.141***	-0.0011	0.012***	-0.019***
	(0.0058)	(0.0043)	(0.0028)	(0.0036)
Spec. Degree	-0.174*	0.020***	-0.011***	-0.040***
	(0.0099)	(0.0054)	(0.0038)	(0.0055)
Panel C: Quarter-Over-Quarter Turnover				
Broad Degree	-0.093***	0.008***	0.020***	-0.011***
	(0.0045)	(0.0024)	(0.0025)	(0.0033)
Spec. Degree	-0.112***	0.032***	-0.012**	-0.034***
	(0.0082)	(0.0050)	(0.0036)	(0.0053)

Note: $* : p < 0.10, ** : p < 0.05, *** : p < 0.01$. Each column reports coefficients from a separate linear probability model where the dependent variable is an indicator for the specified exit destination. Broad Degree indicates credentials in education, health, or psychology; Specialized Degree indicates credentials specifically in early childhood education or child development. The omitted category is workers without ECE-related credentials. All specifications include controls for age at exit and exit year. Standard errors in parentheses.

4.2. Robustness and Extensions

4.2.1. Alternative Matching: k=10 Controls

Our baseline matching procedure assigns five matched controls to each ECE worker. To assess sensitivity, we replicate the main analyses using ten matched controls. Results are reported in Appendix E. The estimates are quantitatively similar to the baseline. In fact, the estimates differentials increase in absolute terms by about 0.5-1.0 p.p. The decomposition into worker selection and sector effects across all three measures are now all statistically significant at 1% and have consistent signs.

4.2.2. Heterogeneity by Demographics

We examine heterogeneity by race/ethnicity and education in Appendix C.[33] The turnover differential is largest for college-educated white workers (+20.3 pp) and smallest, in fact, negative, for African American workers with a high school diploma (-3.4 pp). The earnings penalty increases with education across all groups, ranging from 16.5% for African American workers with a high school diploma to 55.1% for white workers with a college degree.

These patterns are consistent with differential outside options. College-educated workers, particularly white workers, have viable alternatives in K-12 teaching, nursing, and other professional occupations. For these workers, the ECE sector's low wages and limited advancement opportunities make exit attractive. Less-educated workers, by contrast, have fewer alternatives and may value ECE's compensating amenities more highly.

4.3. Discussion

The decomposition into worker selection and sector effects is the central empirical finding of this paper, and its interpretation warrants some discussion. The qualitative literature on ECE workforce dynamics offers one lens through which to read the results. McDonald, Thorpe, and Irvine (2018), based on in-depth interviews with ECE workers in Australia, documents a sharp divide between stayers and leavers: workers who remain in the sector despite low pay report deriving satisfaction from watching children develop, building relationships with families, and feeling that their work has social value, while those who leave emphasize frustration with wages that do not reflect their skills and limited opportunities for advancement.[34] Our finding that the ECE sector is associated with lower turnover, conditional on worker type, is consistent with the view that non-pecuniary rewards sustain attachment among workers who might otherwise be expected to exit. However, we note that the institutional context in Australia differs substantially from Texas (e.g., higher unionization, a national quality framework, government-set wage floors), and that our data cannot directly test this interpretation. The negative sector coefficient on turnover could also reflect limited outside options, household constraints, or other factors our data do not capture.

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

[33] Full results are presented in Appendix Tables A6, A7, and A8.

[34] Similar qualitative and mixed-methods evidence can be found in Bull et al. (2024) for Australia and Herman, Dearth-Wesley, and Whitaker (2023) for Pennsylvania.

and Herbst (2018), who conducted a resume audit experiment and provided evidence indicating the existence of racial and ethnic discrimination in hiring practices in the ECE sector. In addition, their data shows that customer discrimination may explain some of the hiring behaviors of program directors. While our descriptive design cannot identify discrimination directly, the heterogeneity we document is consistent with their experimental evidence.

Our estimates should be interpreted with appropriate caution. While our matching procedure ensures comparability on observed characteristics at age 18, we cannot rule out selection on unobservables. The decomposition into selection and sector effects relies on the assumption that ECE employment has no lagged or dynamic effects on future labor market outcomes. If working in ECE affects subsequent earnings or turnover propensity after exit, or if individuals adjust their labor market behavior in anticipation of entering the sector, then the within-person comparisons may still partially reflect selection or anticipation effects rather than true sector effects.[35] As a result, these estimates are best viewed as informative about the patterns and correlates of turnover and earnings in ECE, rather than as definitive causal parameters.

Moreover, we face some data limitations. 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 cannot rule out differences in unobserved heterogeneity that make ECE workers less productive, low working hours, or the existence of compensating differentials (see, e.g., McClure 2021, who argues that childcare firms allow teachers to enroll their children in the program and charge them a discounted rate). Importantly, our turnover measure captures exit from the sector, not from a specific classroom or center. Workers who move between ECE programs within the sector would not register as turnover in our data, though such moves may still disrupt children's continuity of care. Finally, customers may be unable to differentiate low- from high-quality programs (e.g., see Gordon, Herbst, and Tekin 2021). If such informational frictions are severe, parents may be unwilling to pay a premium for high-quality programs, and the market equilibrium is one in which most programs are low-quality, charge low tuition, and pay low wage rates.

There are, however, studies that suggest that other potential explanations are not likely to fully account for the patterns we document. Regulations in the childcare market increase

[35] Estimating dynamic models that can fully disentangle unobserved heterogeneity from state dependence would require valid exclusion restrictions that we do not have in the current data (see, e.g., Taber 2000, for discussion).

the cost of operating a home- or center-based program, reduce the supply of seats, and potentially diminish wages in this industry.[36] However, the analysis by Garcia-Vazquez (2024) suggests that the magnitude of regulation effects on wages is relatively small: a move from typical regulation on the number of children per adult to the most stringent regulation increases wages between 1.78% and 2.75%, which is too small to explain the magnitude of the earnings gap we document. Childcare firms may also engage in monopsonistic wage setting practices (e.g., see Card 2022, for a discussion of this literature), though the industry is extremely diffuse—Statista Research Department (2022) reports that the ten largest providers serve less than six percent of the children in this market—and for-profit firms in this sector have profit margins of 1% (Davies and Grunewald 2019), which limits the scope for rent extraction.

5. Conclusion

We study retention and compensation in the early care and education 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 ECE sector for at least one quarter and match them to other workers with the same conditional probability of working in the ECE sector but who never did during the period of our analysis.

We estimate that turnover in the ECE sector is 5 to 7 percentage points greater than in other sectors of the economy, depending on how turnover is measured. Furthermore, these models estimate an earnings penalty of approximately 45% in the ECE sector. We uncover much heterogeneity across education and race and ethnicity groups. The turnover gap is smallest—in fact, negative—for African American workers with only a high school diploma, and largest for college-educated white workers. The earnings penalty increases steeply with educational attainment, ranging from 16.5% for African American workers with a high school diploma to over 55% for white workers with a four-year degree.

We also decompose these differentials into worker selection versus sector effects. For turnover, selection appears to dominate: workers who enter ECE at any point in their careers exhibit 9.8 percentage points higher turnover across all sectors, not just while working in ECE. Conditional on worker type, however, ECE employment is associated with lower turnover—approximately 3.6 percentage points lower under our primary definition. For earnings, both channels work against ECE workers. The decomposition indicates that roughly half of the observed earnings penalty reflects selection and half reflects

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

contemporaneous sector effects. When ECE workers leave the sector, a substantial share do not appear in formal employment records, and those who do tend to enter sectors with limited skill transferability rather than better-matched employment.[37]

These findings are relevant to ongoing policy debates about the ECE workforce. The decomposition suggests that the turnover and earnings challenges have different sources and may therefore require different responses. Policies that address only the sector effect on earnings—for example, wage subsidies—would not change the selection channel unless compensation rises enough to attract workers from a different pool. Conversely, policies that focus only on who enters the sector, such as credential requirements, may do little to improve conditions for current workers. The decomposition presented here cannot predict the effects of specific interventions, but it does suggest that both dimensions are quantitatively important.

Identifying the factors that determine the turnover and earnings differentials documented here is a necessary next step in research because one needs to understand the cause to design interventions to increase retention. Linked employer-employee data with firm identifiers, hours information, and occupation codes would allow researchers to distinguish classroom-level from sector-level turnover and to separate hours from hourly wages in the earnings penalty. If the duration of employment spells continues to be low, investments in professional development will not translate into better developmental outcomes for children.

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[37] As discussed in Section 4, this figure likely overstates true non-employment given the coverage limitations of state unemployment insurance records.

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Appendix A. Data

A.1. Variable Definitions

- *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.
- *Broad and Specialized courses*: THECB data contains information on the degree the individual was enrolled in. We create dummies equal to 1 if the individual was at some point enrolled in college at specific degrees. Degrees are classified using the Classification of Instructional Programs (CIP) developed by the U.S. Department of Education. They are divided into 2-digit broad categories and more specific 4 to 6 digit codes. We categorize degrees into "Broad" and "Specialized" according to their relevance to a career in Early Childhood Education. Broad degrees consists of Education (CIP 13), Health (CIP 34, 51), and Psychology (CIP 42). Examples of specific degrees are Teacher Education, Birthing and Parenting, Developmental and Child Psychology (see Table A4 in Appendix C for the full list).
- *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.[38] 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.[39]

- *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 the ECE sector if the employer's NAICS code is 624410.

- *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 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.

A.2. Data Cleaning

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 be-

[38] 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.

[39] 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.

tween 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.[40] In Table A1, we show

[40]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.

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[41]. We construct a balanced panel with these dimensions and merge in information 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,

[41]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.

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:

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

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:

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

Appendix C. Additional Tables and Figures

Table A4. List of Degrees - Broad and Specific

Broad	2-digit Code	Specific	6-digit Code
Education	13	Elementary Education	13.1202
Health	34	Teacher Education	13.1206
Psychology	42	Early Childhood Teacher Education	13.1207-10
Health Prof. and Clinical	51	Teaching Aides	13.1501;02;99
		Birthing and Parenting	34.0102
		Dev. and Child Psych.	42.2703
		Educational Psych.	42.2806
		Clinical Child Psych.	42.2807
		Maternal/Neonatal Nursing	51.3806
		Pediatric Nursing	51.3809
		Nursing Assistant	51.3902

Note: This table shows which degrees were used to classify workers in Broad and Specific Degrees. 2-digit and 6-digit codes come from the Classification of Instructional Programs (CIP). If a worker attended college and at some point registered credits under one of these degrees, they were classified as a Broad or Specific.

Table A5. 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. Test scores are in the scale of completed years of education. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A6. Academic Year 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	-0.034**	-0.038***	0.106***
	(0.0121)	(0.0080)	(0.0206)

Panel B: Hispanic Workers Only, By Education

	High School	Some College	College or Above
ECE Sector	0.002	0.028***	0.139***
	(0.0082)	(0.0065)	(0.0161)

Panel C: White Workers Only, By Education

	High School	Some College	College or Above
ECE Sector	0.027***	0.059***	0.203***
	(0.0073)	(0.0052)	(0.0090)

Note: $*$: $p < 0.10$, $**$: $p < 0.05$, $***$: $p < 0.01$. 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 year and matched groups. Controls include potential experience (age − education years) and its squared counterpart. Matched group consists of an ECE Worker and its matched counterparts found in the matching procedure described in Section 2. We report clustered standard errors at the matched group level in parentheses.

Table A7. CPS 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	-0.018	0.001	0.089***
	(0.0098)	(0.0061)	(0.0169)

Panel B: Hispanic Workers Only, By Education

	High School	Some College	College or Above
ECE Sector	0.017***	0.050***	0.116***
	(0.0066)	(0.0050)	(0.0130)

Panel C: White Workers Only, By Education

	High School	Some College	College or Above
ECE Sector	0.034***	0.078***	0.167***
	(0.0059)	(0.0040)	(0.0076)

Note: $*: p < 0.10$, $**: p < 0.05$, $***: p < 0.01$. This table shows estimates of γ in equation (2) using the CPS turnover measure 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 year and matched groups. Controls include potential experience (age − education years) and its squared counterpart. Matched group consists of an ECE worker and its matched counterparts found in the matching procedure described in Section 2. We report clustered standard errors at the matched group level in parentheses.

TABLE A8. Quarter-over-Quarter 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	-0.013*	-0.010**	0.069***
	(0.0058)	(0.0039)	(0.0094)

Panel B: Hispanic Workers Only, By Education

	High School	Some College	College or Above
ECE Sector	0.008*	0.031***	0.075***
	(0.0038)	(0.0031)	(0.0070)

Panel C: White Workers Only, By Education

	High School	Some College	College or Above
ECE Sector	0.027***	0.045***	0.111***
	(0.0035)	(0.0025)	(0.0043)

Note: $*: p < 0.10$, $**: p < 0.05$, $***: p < 0.01$. This table shows estimates of γ in equation (2) using the CPS turnover measure 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 year and matched groups. Controls include potential experience (age − education years) and its squared counterpart. Matched group consists of an ECE worker and its matched counterparts found in the matching procedure described in Section 2. We report clustered standard errors at the matched group level in parentheses.

TABLE A9. 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	-0.165***	-0.245***	-0.306***
	(0.011)	(0.007)	(0.018)

Panel B: Hispanic Workers Only, By Education

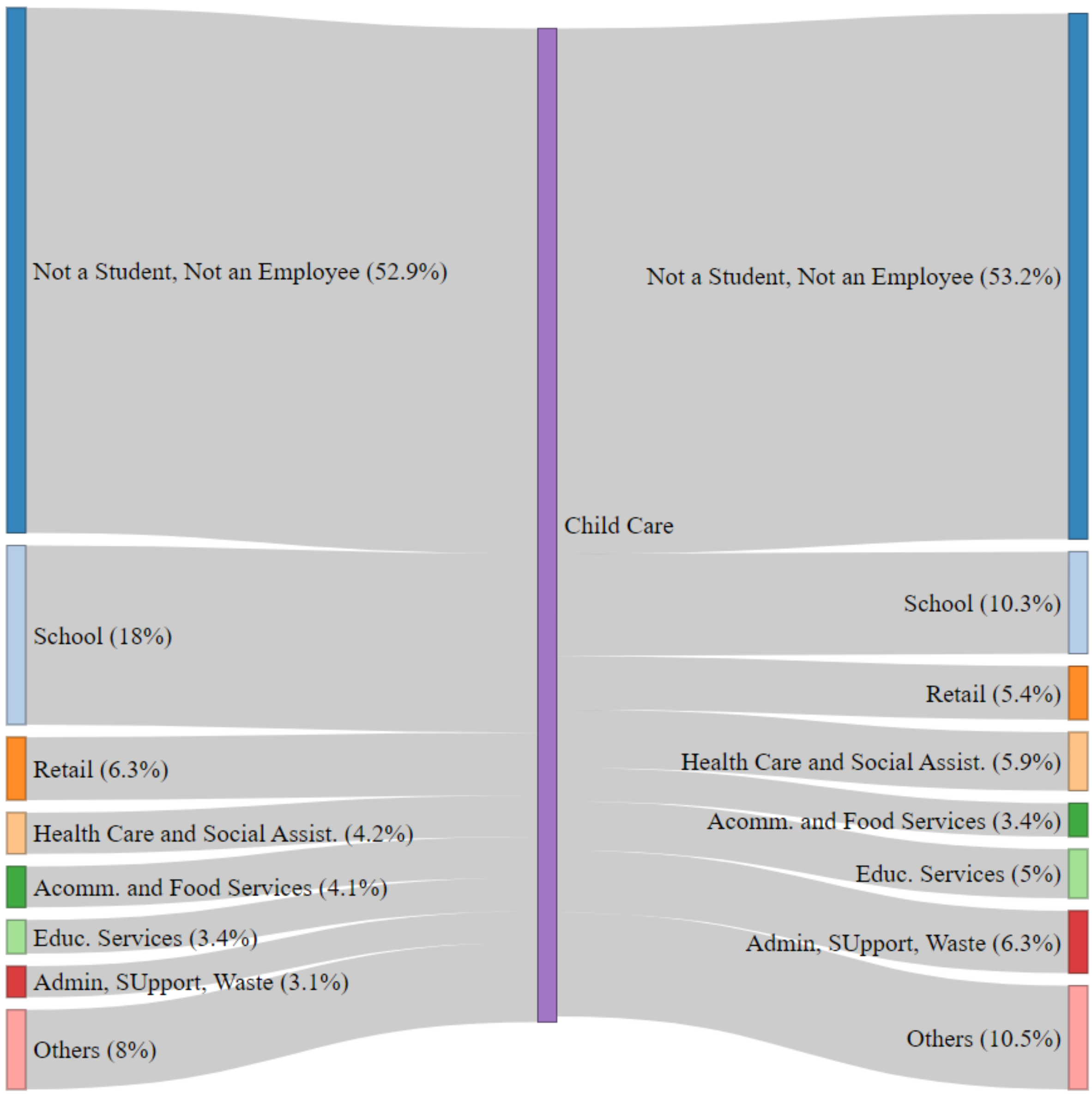
	High School	Some College	College or Above
ECE Sector	-0.221***	-0.304***	-0.342***
	(0.007)	(0.006)	(0.016)

Panel C: White Workers Only, By Education

	High School	Some College	College or Above
ECE Sector	-0.247***	-0.356***	-0.551***
	(0.007)	(0.005)	(0.010)

Note: $*: p < 0.10$, $**: p < 0.05$, $***: p < 0.01$. 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. We include fixed effects for year, quarter, and matched groups. Controls include potential experience (age - education years) and its squared counterpart. Matched group consists of an ECE Worker and its matched counterparts found in the matching procedure described in Section 2. We report clustered standard errors at the matched group level in parenthesis.

FIGURE A1. Transition In and Out of the ECE Sector



Appendix D. 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. Figure A2 presents data on college enrollment. Figures A2A and A2B display college enrollment rates and accumulated credit hours by a quarter from age 19 to

Table A10. Most Commonly Worked Economic Sectors (%)

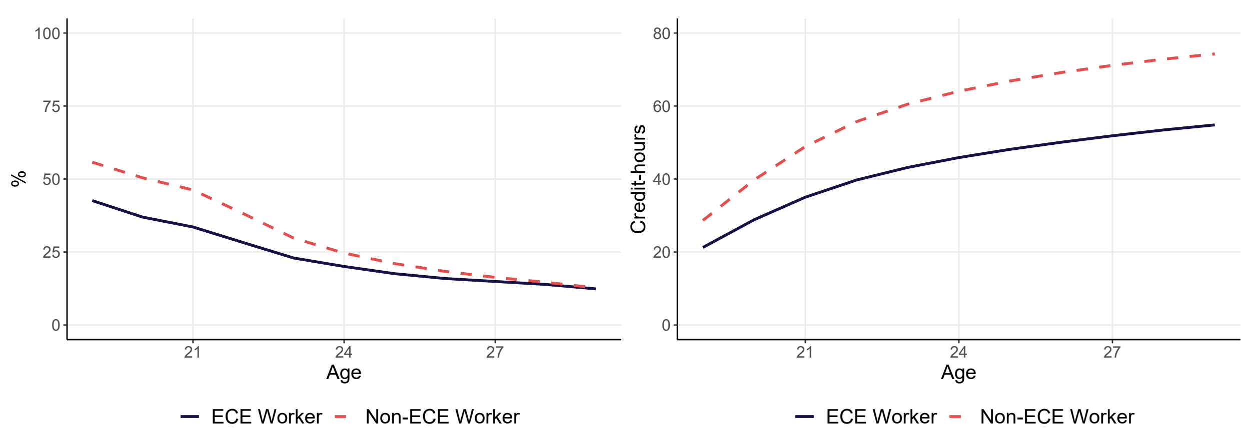
	ECE Worker	Non-ECE Worker	Diff.
Health Care and Soc. Assist.	19.30	19.27	0.03
Education Services	12.86	10.41	2.45***
Admin. Support, Waste, Remediation	9.94	8.85	1.09***
Retail Trade	9.54	9.36	0.18***
Accomod. and Food Services	9.43	9.01	0.42***
Others	38.92	43.08	-4.16***

Note: $*: p < 0.10$, $**: p < 0.05$, $***: p < 0.01$. This table shows the most common sectors for ECE and Non-ECE Workers, excluding ECE employment. By construction, Non-ECE Workers never work in ECE. Sectors follow NAICS classification.

29. These figures demonstrate that ECE workers are less likely to enroll in college after high school (Figure A2A). And, conditional on college registration, they accumulate fewer credit hours (Figure A2B).

Table A12 reports 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 A2. College Enrollment and Cumulative Credit Hours Over Time



A. College Enrollment

B. Accumulated Credit-Hours

Note: All differences between ECE and Non-ECE workers are statistically different than zero at the 1% level.

TABLE A11. Most Common Activity After Turnover (%) - Comparable Sectors

	Academic Year	CPS-Style	Quarter-Over-Quarter
Panel A: NAICS 611110 - Elementary and secondary schools			
Not Employed, Not a Student	64.58	46.26	50.13
Education Services	6.11	3.05	4.26
Health Care	6.03	3.21	4.36
Retail Trade	3.50	2.14	3.36
Admin. Support, Waste, Remediation	3.35	1.82	2.82
School	-	34.75	23.30
Others	16.43	8.77	11.77
Panel B: NAICS 623110 - Nursing care facilities			
Not Employed, Not a Student	43.92	47.33	46.65
Health Care	29.69	17.02	21.80
Admin. Support, Waste, Remediation	7.13	5.08	6.04
Retail Trade	4.36	2.89	3.67
Accom. and Food	3.73	2.73	2.94
School	-	17.86	10.42
Others	11.16	7.07	13.87

Note: $*$: $p < 0.10$, $**$: $p < 0.05$, $***$: $p < 0.01$. This table shows the most common sectors for ECE and Non-ECE Workers, excluding ECE employment. By construction, Non-ECE Workers never work in ECE. Sectors follow NAICS classification.

Participation in the Labor Force. Figure A3A shows that ECE Workers are more likely 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.

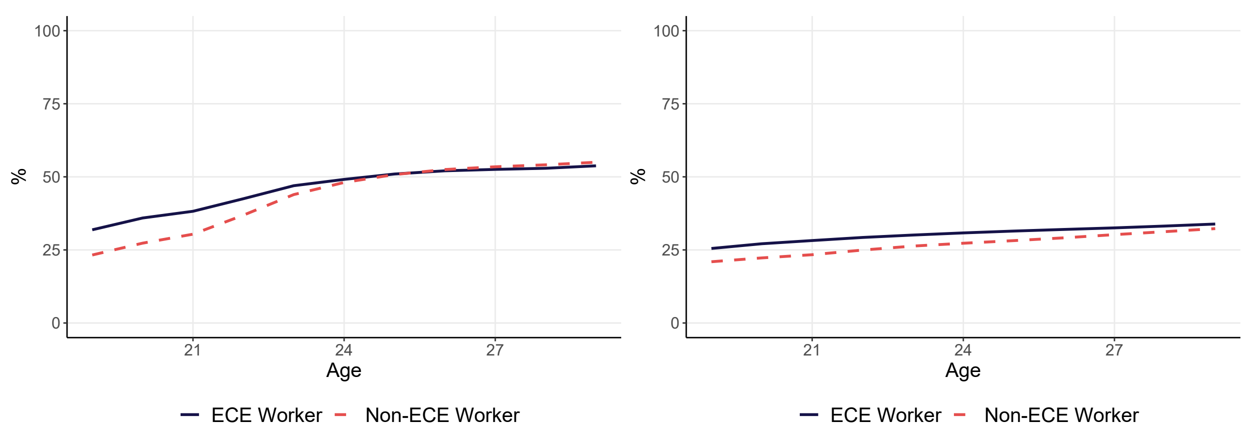
Interestingly, Table A12 shows that accumulated experience at 29 years old, represented by the total number of quarters worked, is not so different between the two groups. On average, ECE workers accumulate 1.5 more quarters than Non-ECE workers, and this difference drops to 0.5 conditional on those with 4-year degrees. 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 A3B 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.

TABLE A12. ECE and Non-ECE Workers at 29 years old

	ECE Worker	Non-ECE Worker	Diff.
Completed Education Level (%)			
High School Only	22.81	18.33	4.48***
Some College	59.46	52.14	7.32***
4-year or more	17.73	29.53	-11.80***
Accumulated Credit Hours			
Overall	55.31	74.78	-19.47***
Some College	50.63	59.64	-9.01***
4-year or more	142.13	147.91	-5.78***
Accumulated Experience (Quarters)			
Overall	21.16	19.67	1.49***
High School Only	25.55	24.50	1.05***
Some College	20.83	20.01	0.82***
4-year or more	16.62	16.08	0.54***

Note: $*: p < 0.10$, $**: p < 0.05$, $***: p < 0.01$. This table shows the highest completed educational level, accumulated credit hours, and accumulated experience in quarters for ECE and Non-ECE Workers at 29 years old.

FIGURE A3. Labor Force Attachment Over Time



A. Labor Force Participation

B. Not Enrolled, Not Employed

Note: All differences between ECE and Non-ECE workers are statistically different than zero at the 1% level, except labor force participation at 25 years old, where the values are statistically the same.

Appendix E. Robustness: Using 10 matched controls

In this section, we replicate the main results of the paper using 10 matched controls instead of 5 to assess the sensitivity of the matching procedure.

TABLE A13. Turnover Rates (%) for the ECE Sector and Non-ECE Workers

	ECE Sector	Non-ECE Worker	Diff.
Academic Year Turnover	38.52	31.59	6.93***
CPS-style Turnover	41.77	34.10	7.67***
Quarter-Over-Quarter Turnover	21.50	16.83	4.67***

Note: $* : p < 0.10$, $** : p < 0.05$, $*** : p < 0.01$. This table shows turnover rates for the ECE Sector and for Non-ECE Workers in any sector. Academic Year Turnover counts workers employed in Q3 who exit before Q2 of the following year. CPS Turnover follows the Current Population Survey methodology. Quarter-over-Quarter measures transitions between consecutive quarters.

TABLE A14. Turnover Regressions - 10 controls

	(1)	(2)	(3)
Panel A: Academic Year Turnover			
ECE Sector	0.062***	0.053***	0.060***
	(0.0019)	(0.0019)	(0.0023)
Panel B: CPS-style Turnover			
ECE Sector	0.077***	0.072***	0.077***
	(0.0016)	(0.0016)	(0.0019)
Panel C: Quarter-Over-Quarter Turnover			
ECE Sector	0.047***	0.042***	0.046***
	(0.0008)	(0.0008)	(0.0012)
Controls	N	Y	Y
Match Fixed Effects	N	N	Y

Note: $*: p < 0.10$, $**: p < 0.05$, $***: p < 0.01$. This table shows estimates of γ in equation (2) for different specifications and definitions of turnover. 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 year and matched groups. Controls include potential experience (age − education years) and its squared counterpart. Matched group consists of an ECE Worker and its matched counterparts found in the matching procedure described in Section 2. We report clustered standard errors at the matched group level in parentheses.

TABLE A15. Decomposing Turnover and Earnings: Worker Selection vs. Sector Effects

	(1) Baseline	(2) Worker Only	(3) Both
Panel A: Academic Year Turnover			
ECE Sector	0.060***		-0.041***
	(0.0023)		(0.0030)
ECE Worker		0.096***	0.107***
		(0.0013)	(0.0015)
Panel B: CPS-style Turnover			
ECE Sector	0.077***		-0.008***
	(0.0019)		(0.0021)
ECE Worker		0.088***	0.090***
		(0.0011)	(0.0013)
Panel C: Quarter-Over-Quarter Turnover			
ECE Sector	0.046***		-0.012***
	(0.0011)		(0.0013)
ECE Worker		0.058***	0.061***
		(0.0007)	(0.0008)
Panel D: Log Earnings			
ECE Sector	-0.493***		-0.236***
	(0.003)		(0.003)
ECE Worker		-0.330***	-0.272***
		(0.002)	(0.002)

Note: $*: p < 0.10$, $**: p < 0.05$, $***: p < 0.01$. This table decomposes turnover and earnings differentials into worker selection (ECE Worker = ever worked in ECE) and contemporaneous sector effects (ECE Sector = currently in ECE). Panels A–C report turnover outcomes (binary indicators); Panel D reports log quarterly earnings. Column (1) shows the baseline specification; Column (2) includes only the ECE Worker dummy; Column (3) includes both. All specifications include fixed effects for year and matched groups. Controls include potential experience and its square. Standard errors clustered at the matched group level in parentheses.