The impact of EITC on education, labor market trajectories, and inequalities*

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Abstract

As a complement to the federal earned income tax credit (EITC), some states offer their own EITC, typically calculated as a percentage of the federal EITC. In this paper, we analyze the effect of state EITC on education using policy discontinuities at US state borders. Our estimates reveal that an increase in the state EITC leads to a statistically significant increase in the high school dropout rate. We then use a life-cycle matching model with directed search and endogenous educational choices, search intensities, hirings, hours worked, and separations to investigate the effects of EITC on the labor market in the long run and along the transitional dynamics. We show that a tax credit targeted at low-wage (and low-skilled) workers reduces the relative return to schooling, thereby generating a powerful disincentive to pursue long-term studies. In the long run, this results in an increase in the proportion of low-skilled workers in the economy, which may have important implications for employment, productivity, and income inequality. Finally, we use the model to determine the optimal design of the EITC.

JEL Classification: D15; E24; H24; I24; J6; J24

Keywords: EITC; Education; Human capital; Search and matching; Life cycle

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1 Introduction

The federal earned income tax credit (EITC) is a federal refundable tax credit targeted at low-income workers. Enacted by Congress in 1975, the federal EITC has gradually become one of the most important antipoverty programs in the United States. In 2020, the direct cost of the federal EITC to the US government was approximately $70 billion (0.35% of GDP).

The federal EITC was designed to "reward work" and incentivize participation in the labor market. The program is supposed to be "self-financed" through increases in employment and tax revenue. Because of the objectives of this tax credit, most studies have focused on its work-incentive effects. Empirical research suggests that the EITC mainly affects the female labor supply, increasing the labor force participation of single mothers (Eissa and Liebman, 1996; Meyer and Rosenbaum, 2001) but reducing the workforce participation of married women; it also slightly increases the participation of married men (Eissa and Hoynes, 2004). Some other studies suggest that the EITC affects the intensive margin, depending on the phase of the EITC where the worker is located (Hoffman and Seidman, 1990; Dickert et al., 1995).

While informative, these studies mainly address the short-term effects of EITC through labor force participation and hours worked, and thus tell only part of the story. As highlighted by Blundell et al. (2016), in-work benefits may have longer-term effects by influencing educational choices and labor market trajectories over the life cycle. Heckman et al. (2002) and Nichols and Rothstein (2015) questioned the potential perverse effects of EITC on educational attainment decisions and pointed out the lack of research on this topic.

As shown by Wasmer (2006) and Chéron et al. (2011), returns to human capital investments depend predominantly on search frictions in the labor market. When search is directed, which is supported by recent empirical studies (Banfi and Villena-Roldan, 2019), educational decisions have a significant impact on labor market trajectories by affecting both job-finding probabilities and labor incomes over the life cycle (Menzio et al., 2016; Chéron and Terriau, 2018; Albertini and Terriau, 2019). In this framework, in-work benefits targeted at low-paid (and low-skilled) workers increase the value of low-skilled employment and reduce the relative return to high-skilled jobs. Consequently, the EITC may disincentivize pursuit of further studies.[1]

In our study, we estimate the effect of EITC on education by taking inspiration from the minimum wage literature (Dube et al., 2010; Hagedorn et al., 2015). We exploit the fact that, since the mid-1980s, some states have implemented their own EITC (state EITC), set as a percentage of the federal EITC. We take advantage of the American Community Survey (ACS),[2] which provides yearly information on education, employment, hours worked, and earnings for various geographic areas. Our study compares data for all contiguous Public Use Microdata Area (PUMA) pairs located on opposite sides of a US state border. Our empirical analysis of policy discontinuities at state borders suggests that EITC has a significantly negative impact on education.

This result indicates that the EITC may have non-trivial consequences for labor market outcomes and income inequalities. First, all other things being equal, the EITC increases the earnings of low-skilled workers. Second, by making low-skilled

[1] According to the U.S. Department of Education, the percentage of high school dropouts among persons 16 to 24 years old has ranged between 6% and 11% during the 2000s and 2010s decades.

[2] See Appendix C.1 for more details.

jobs more attractive, the EITC reduces the returns to education, thereby discouraging young people from pursuing further studies beyond high school. Third, the EITC may affect unemployed workers, by increasing the marginal gain from search efforts, but also employed workers, who may respond by adjusting the number of hours worked. This may impact both the employment rate and average net income. Finally, the educational system response (change in the proportion of low-skilled workers) and labor market response (changes in search effort, hours worked, job creation, and job destruction) generate ambiguous effects on long-run net income inequalities.

We develop an original theoretical framework to quantify the general equilibrium effects and disentangle the different channels through which the EITC affects labor market trajectories. Our model builds on the dynamic labor supply literature (Heckman and MaCurdy, 1980), particularly models highlighting the key role of education on life-cycle earnings (Keane and Wolpin, 1997, 2007, 2010; Blundell et al., 2016). We go one step further by endogeneizing labor demand, thereby capturing not only households' responses to EITC (hours worked, education, search intensity, etc.) but also the responses of firms. By doing so, we consider the heterogeneity in labor market trajectories of skilled and unskilled workers, which are linked to firms' job creation and job destruction. Our study thus fully investigates labor market adjustments.

In our paper, we develop a life-cycle matching model with directed search, in which educational choices, search intensities, hirings, hours worked, and separations are endogenous. Whereas Menzio et al. (2016) propose an exogenous process of human capital accumulation, we consider that individuals choose their human capital investment before entering the labor market, in line with the works of Acemoglu (1996), Decreuse and Granier (2013), Abbott et al. (2019), and Albertini and Terriau (2019). We solve and estimate the model and show that it accurately replicates the life-cycle profile of several labor market variables, including income distribution and the distribution of workers across the different phases of the EITC.

We then investigate the effects of increasing the generosity of the EITC. This scenario increases the search intensity of skilled and unskilled unemployed workers. It also modifies the composition of the labor force by reducing the returns to education and increasing the proportion of low-skilled workers, which translates into a substantial decline in total employment and lifetime earnings.[3] Furthermore, we show that the EITC encourages workers located in the phase-out range and outside the EITC schedule (i.e., the vast majority of workers) to work fewer hours so as to benefit from the program. Consequently, aggregate hours worked decrease, mitigating extra income from the EITC. When considering the responses of the educational system and labor market, we show that the EITC does not achieve a significant reduction in income inequalities in the long run. Our study highlights the paradox of the EITC: it encourages the participation of low-paid workers but also provides incentives to become a low-paid worker. People react to an increase in EITC by leaving school early and reducing their work hours. Consequently, in the long run, the total employment rate declines and the net income of low-skilled workers does not increase as much as expected, considerably limiting the redistributive effects of the EITC.

We then use the model to determine the optimal design of the EITC. We show that it is possible to increase income, employment, and participation, and to improve welfare by approximately 3%. The optimal EITC is characterized by lower maximum bene-

[3] As shown by Bhuller et al. (2017), people who leave high school early have lower lifetime earnings and flatter age-earnings profile, all other things being equal.

fits and larger phase-in and phase-out ranges. Optimal EITC benefits workers with a broader range of earned income, particularly higher income, which encourages education. Inspired by the Working Families' Tax Credit in the United Kingdom, we introduce a minimum hours constraint below which employed workers cannot receive EITC. We show that introducing such a constraint limits the perverse effect of EITC on hours worked, while also increasing employment and welfare.

The rest of the paper is organized as follows. Section 2 describes the database and empirical strategy used to estimate the effect of EITC on education. Section 3 presents the model's assumptions and the theoretical framework. Section 4 describes the procedure used to estimate the structural model's parameters and compares the moments generated by the model with their empirical counterparts. Section 5 explores the long-term effects of EITC. Section 6 describes the optimal design of EITC. Section 7 presents the results of several robustness tests. Finally, Section 8 concludes.

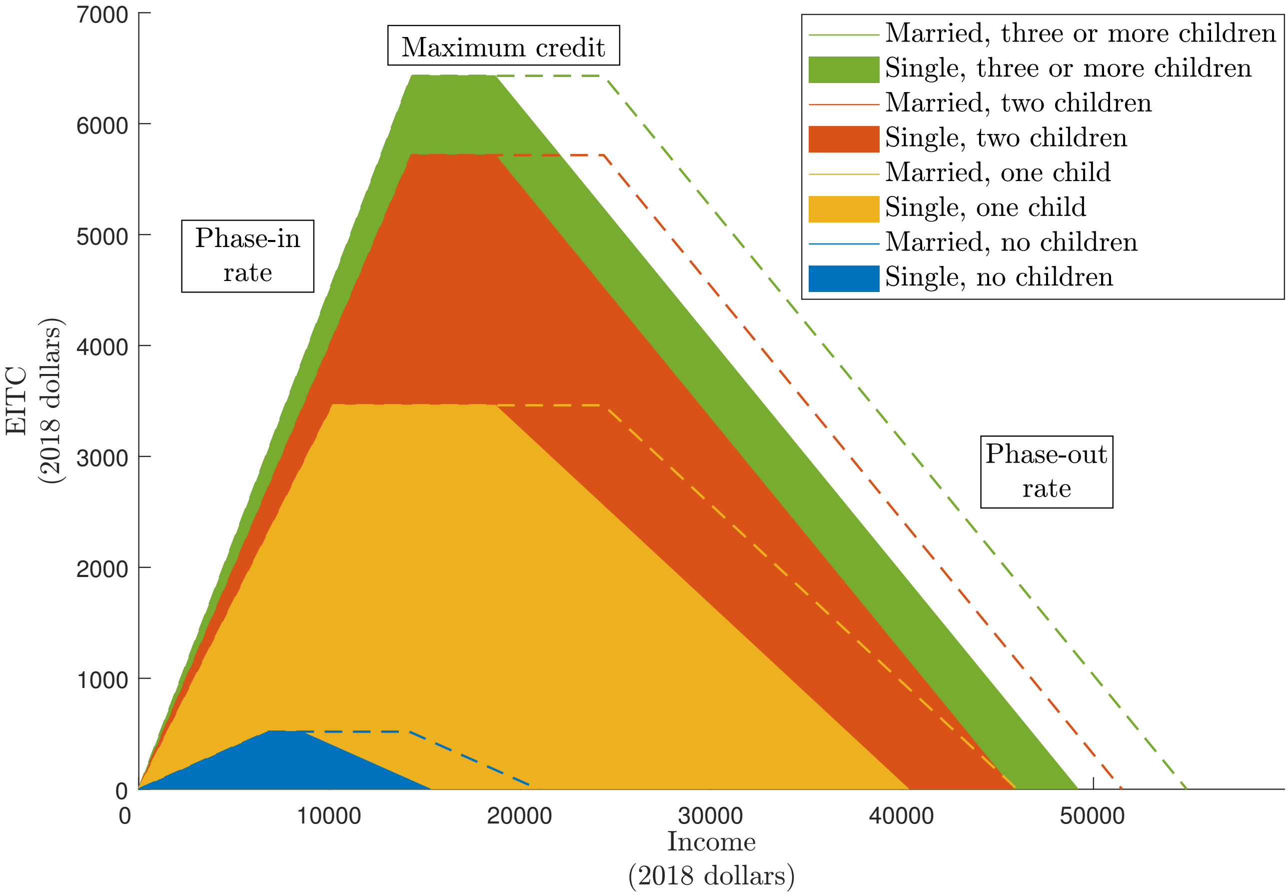
2 Empirical framework

2.1 Federal EITC and state EITC

The federal EITC is a benefit for low-income workers. Its amount varies based on the recipient's earnings and number of children, and its schedule is characterized by three phases: the "phase-in range", where the EITC equals a fixed percentage (the "phase-in rate") of earned income; the "plateau range", where the EITC remains at its maximum level (the "maximum credit"); and the "phase-out range", where the EITC decreases to zero at a fixed rate (the "phase-out rate"). For the 2018 tax year, the maximum tax credit for a tax filer was \$519 without children, \$3,461 with one child, \$5,716 with two children, and \$6,431 with three or more children. The credit may represent up to 45% of earned income.[4] The phase-in (phase-out) rates by family status are 7.65% (7.65%), 34.00% (15.98%), 40.00% (21.06%), and 45.00% (21.06%), respectively (Figure 1). The federal EITC parameters vary over time, mainly in response to inflation; they are described in Appendix A.

[4]For a tax filer with three or more children who earned \$14,290, *i.e.*, the minimum earned income to benefit from the maximum tax credit.

Figure 1: Federal EITC schedule, 2018



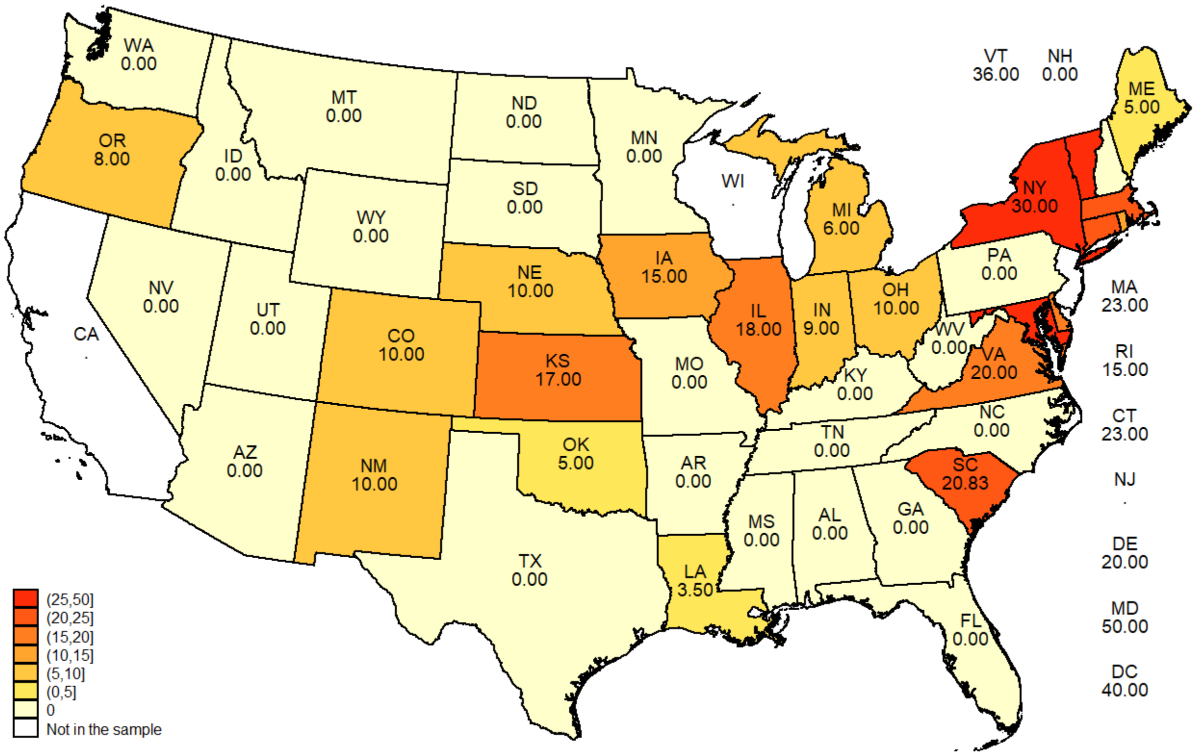
Source: Internal Revenue Service

As a complement to the federal EITC, some states offer their own EITC, typically calculated as a percentage of the federal credit[5] (see Appendix B). In 2005, 14 states and the District of Columbia had EITC provisions in their respective income tax laws. By 2018, 11 more states had begun offering their own EITC (see Figure 2). There are substantial differences in treatment intensity across states: i) There are 44 state-level changes in EITC over the period 2005-2018; ii) the state EITC (expressed as a percentage of the federal credit) varies across states and time from 3.5% to 50%. Moreover, no state had the same EITC shape as another during this period.

The fact that several states have implemented the same policy but with different percentage values offers a unique opportunity to identify the effects of in-work benefits on education.

[5]The only exception is California, which in 2015 implemented a state EITC not expressed as a percentage of the federal EITC.

Figure 2: State EITC (as a percentage of Federal EITC), 2018



Lecture: In Colorado, the state EITC is equal to 10% of the federal EITC.

Figure 2 shows that the EITC varies greatly from state to state. How much can an individual gain by moving from the least generous state (no EITC) to the most generous state (50% of the federal EITC)? Are the subsidies provided in the context of the EITC program large enough to affect educational choices? Figure 3 presents the gain from a state EITC according to the state's generosity (0%, 10%, 25%, or 50% of the federal EITC). For a single person with three or more children eligible for the maximum credit, moving from the least to the most generous state brings an annual gain of $3,216, all other things being equal. As indicated in Table 1, it can represent up to 22.50% of earned income. In comparison, for an individual paid the minimum wage and working 35 hours a week, a $1 increase in the minimum wage would bring an annual gain of $1,820.

Of course, individuals can move between EITC phases, for instance by adjusting their labor supply or becoming unemployed. Nevertheless, these figures suggest that the gains from state EITC can be substantial. As shown by French et al. (2022), young people are forward-looking and can react to reforms that will affect them only in the long term (e.g., pension reform), even if the amounts involved (*a fortiori* if they are discounted) are relatively small. This suggests that the labor supply and education of young individuals can be very sensitive to public policies. In Section 2.3, we propose an empirical strategy to estimate the effect of state EITC on educational choices.

Figure 3: State EITC (in dollars), 2018
(for a single person with three or more children)

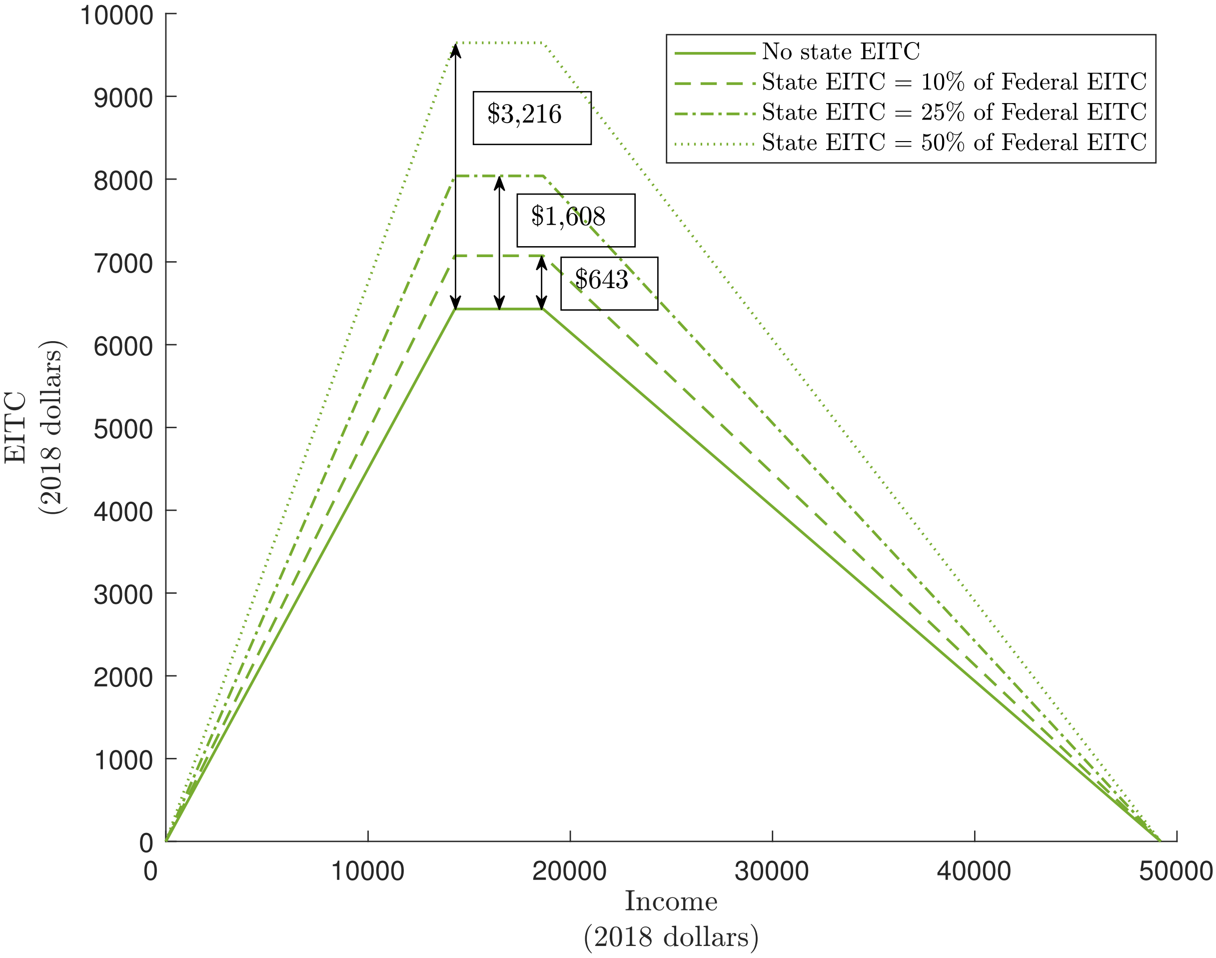


Table 1: State EITC, 2018
(for different types of households)

	State EITC = 10% of Federal EITC				State EITC = 25% of Federal EITC				State EITC = 50% of Federal EITC			
	Number of children				Number of children				Number of children			
	0	1	2	3	0	1	2	3	0	1	2	3
Annual benefit (in dollars)	52	346	572	643	130	865	1429	1608	260	1731	2858	3216
Annual benefit (in % of income)	0.77	3.40	4.00	4.50	1.91	8.50	10.00	11.25	3.83	17.00	20.00	22.50

Note: We consider here the extreme case of a single person receiving the maximum credit given the minimum income to be eligible. This represents the upper limit of earnings from the EITC (in % of income).

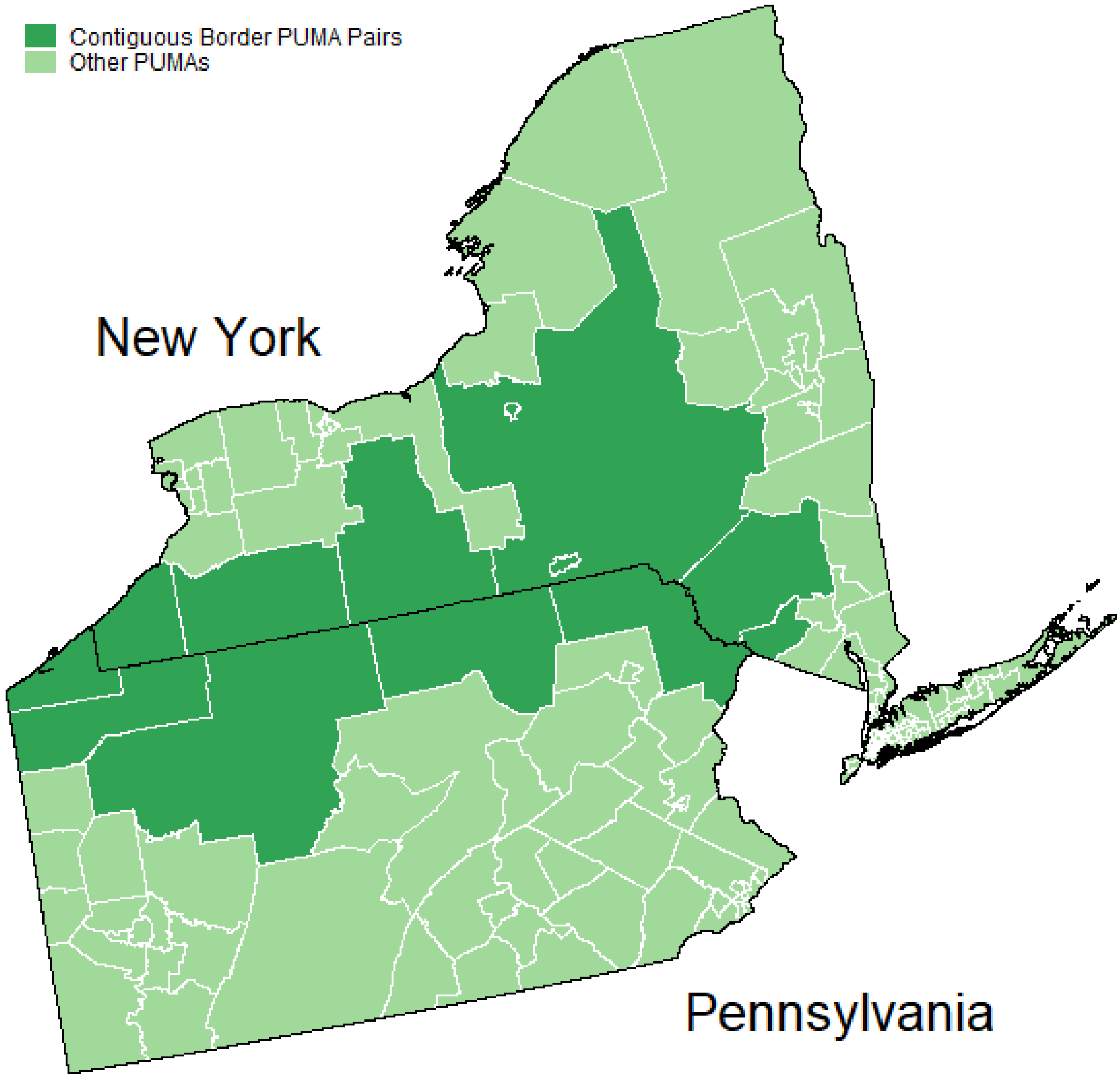
2.2 Data

We take advantage of the ACS[6] for the period 2005-2018. The ACS is the largest household survey in the United States (1-in-100 national random sample of the population). Each wave of the ACS contains more than 3 million observations. The ACS provides annual information on education, employment, hours worked, and earnings. More interestingly, ACS data are gathered from various geographic areas (e.g., nation, regions, states, etc.). The smallest identifiable geographic unit in the ACS 1-year is the Public Use Microdata Area or "PUMA". Each state is divided by the Census Bureau into PUMAs of at least 100,000 people. PUMAs are constructed based on county and neighborhood boundaries and do not cross state lines. Typically, counties with large populations are subdivided into multiple PUMAs, while PUMAs in more rural areas comprise groups of adjacent counties.

This study seeks to identify the effect of EITC on education using policy discontinuities at state borders. We compare all contiguous PUMA pairs sharing a state border (see Figure 4 for an example). As highlighted by Holmes (1998), Huang (2008), Dube et al. (2010), and Hagedorn et al. (2015), local economic areas are good control groups for at least two reasons: i) the policy (here, state EITC) is determined at state level and is largely exogenous from the point of view of an individual PUMA; ii) contiguous-border PUMAs are relatively similar, particularly with regard to employment, earnings, and education trends. In other words, using PUMAs as units of analysis minimizes endogeneity and makes the common trend assumption more credible.

[6]See Appendix C.1 for more details.

Figure 4: Contiguous-border PUMA pairs: Example for the states of New York and Pennsylvania



2.2.1 Sample

Our sample comprises all contiguous PUMA pairs sharing a state boundary on the US mainland. Consequently, Alaska and Hawaii are excluded. We also exclude California because its state EITC is not calculated as a percentage of the federal EITC. Finally, we exclude New Jersey and Wisconsin as the only two states where the credit rate depends on the number of children.[7] Our final sample thus includes 45 states and the District of Columbia. Among the 897 PUMAs, 314 are located along a state border. As some PUMAs are paired with more than one other PUMA, the final sample includes 401 distinct PUMA pairs.

[7]Including these two states and considering the credit rates for specific filing status leads to similar conclusions.

2.2.2 Descriptive statistics

Table 2 provides descriptive statistics for all PUMAs (column (1)) and all contiguous-border PUMA pairs (column (2))—the sample used in our estimates (see Section 2.3). In the sample of contiguous-border PUMA pairs, the state EITC represents on average 7.54% of the federal EITC. Among the 18–24-year-olds who had left high school, 8.66% have not completed high school, 48.59% have completed high school and are not enrolled in college, and 42.74% are enrolled in college.

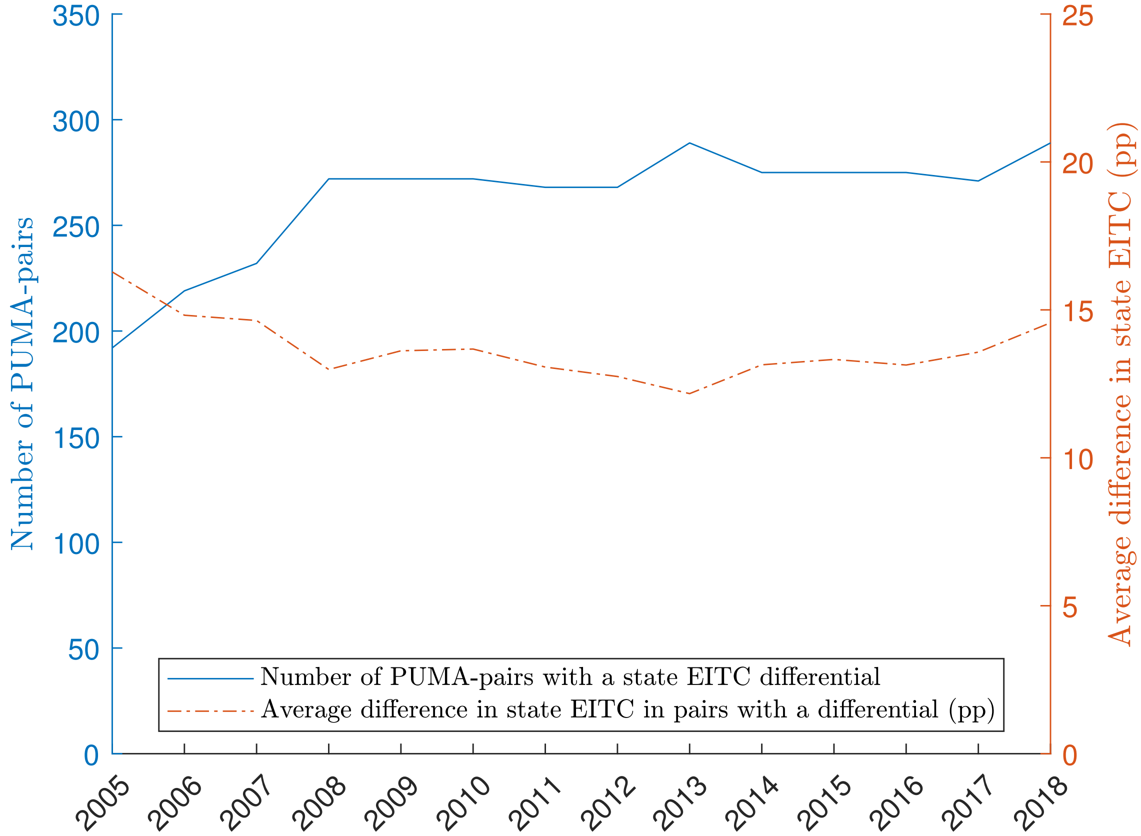
Table 2: Descriptive statistics

	(1)		(2)	
	All-PUMA sample		Contiguous border PUMA-Pair sample	
VARIABLES	Mean	s.d.	Mean	s.d.
States				
State EITC	9.6015	13.7397	7.5412	12.6949
Compulsory school age	16.7503	0.8572	16.8576	0.8584
Minimum wage	6.6297	2.4495	5.9824	2.8283
18–24-year-olds who have left high school				
Male	0.5036	0.0549	0.5105	0.0455
White	0.7470	0.1818	0.7952	0.1547
Black	0.1300	0.1461	0.1127	0.1366
Employed	0.6056	0.1023	0.6023	0.0889
Less than high school	7.6105	5.3272	8.6618	4.6857
High school	45.0566	9.2191	48.5941	7.2249
More than high school	47.3329	11.7087	42.7440	9.2444
Number of PUMAs	897		314	
Number of PUMA pairs	-		401	
Number of states	46		46	

Sample means are reported for all PUMAs (1) and for all contiguous-border PUMA pairs (2).
The state EITC is expressed as a percentage of the federal EITC.
Source: ACS 1-year, 2005-2018

Is the number of PUMA pairs with a state EITC differential and the average pair-based difference in state EITC large enough to identify an effect of state EITC on education? Figure 5 shows that, between 2005 and 2018, we observe a state EITC differential in at least 192 pairs (in 2005), with a maximum of 289 pairs (in 2018). Figure 5 also shows that there is a substantial difference in state EITC among PUMA pairs with a state EITC differential. Between 2005 and 2018, the average pair-based difference ranges between 12 and 16 percentage points. Put differently, contiguous PUMAs exhibit significant differences in state EITC over this period, which allows us to identify the impact of state EITC on education within contiguous PUMA pairs.

Figure 5: Number of PUMA pairs with a state EITC differential, and average difference in state EITC in pairs with a differential



Source: ACS 1-year, 2005-2018

2.3 Empirical strategy

Let i denote the PUMA, p denote the PUMA pair, and t denote time. We estimate the following model:

$$Y_{ipt} = \alpha_0 + \beta_e E_{it} + \beta_x X_{it} + \mu_i + \varpi_{pt} + \epsilon_{ipt} \tag{1}$$

where Y is the outcome variable, E is the state EITC (as a percentage of the federal EITC), X is a set of control variables, μ_i represents the PUMA fixed effect, ϖ_{pt} is the pair-time fixed effect, and ϵ_{ipt} is the error term. Note that X captures changes in the demographic characteristics of the population aged 18-24 years (sex and race), changes in the parental environment (parents' education, income, and number of EITC-eligible children[8], changes in labor market conditions (employment rate by education level), and changes in state policy variables (Supplemental Security Income, aid to families with dependent children, general assistance, and food stamps). For state policy variables, we consider both the percentage of recipients and the average benefit.[9] This ensures that our results are not driven by changes in the generosity of public programs other than the EITC. To account for serial and spatial correlations in the residuals, we follow the procedure described by Dube et al. (2010) to compute standard errors.

Our goal is to estimate the effect of EITC on education. As the EITC targets low-wage workers, we first investigate the impact of EITC on the high school dropout rate, defined as the percentage of 18–24-year-olds who are not currently enrolled in and have not completed high school (Bauman and Cranney, 2020).

[8]We define an EITC-eligible child as a household member (child, stepchild, sibling, grandchild, or foster child) who is either under the age of 19 or under 24 and enrolled as a full-time student. The qualifying child rules are available on the IRS website. See Appendix C for more details.

[9]Note that the *ACS* indicates only whether someone receives food stamps, not the amount received. As a robustness test, we collected data from the *US Department of Agriculture*, determined the average benefit for each state/year, and included this as an additional control variable in Equation (1). Our estimates remain unchanged.

Table 3: Effect of EITC on the high school dropout rate

VARIABLES	(1)	(2)	(3)	(4)
State EITC	0.0709**	0.0709**	0.0710**	0.0710**
	(0.0360)	(0.0358)	(0.0358)	(0.0358)
Controls				
PUMA pair × period dummies	YES	YES	YES	YES
Demographics	YES	YES	YES	YES
Parental environment	YES	YES	YES	YES
Labor market	YES	YES	YES	YES
State policy	YES	YES	YES	YES
Additional controls				
Compulsory school age	NO	YES	NO	YES
Minimum wage	NO	NO	YES	YES
Number of periods	14	14	14	14
Number of PUMA pairs	401	401	401	401
R-squared	0.8034	0.8034	0.8048	0.8048

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: ACS 1-year, 2005-2018

Demographics: *sex, race;* ***Parental environment:*** *parents' education, income, number of EITC-eligible children;* ***Labor market****: employment rate by education level;* ***State policy:*** *Supplemental Security Income, aid to families with dependent children, general assistance, food stamps*

Our estimates reveal that a 1-percentage-point increase in the state EITC (as a percentage of the federal EITC) leads to a rise in the high school dropout rate of 0.07 percentage point (see Table 3, column (1)). This result holds when we introduce compulsory school age or minimum wage as additional control variables (see columns (2-4)).[10]

We next examine the impact of EITC on high school completion and college enrollment. Our estimates indicate that a 1-percentage-point increase in state EITC leads to a drop in the high school completion rate of 0.07 percentage point but has no effect on college enrollment (not reported here). These results suggest that the EITC primarily affects people who are close to the high school completion decision margin. This is not surprising since the EITC targets low-wage and, thus, low-educated workers.

Finally, we estimate the effect of EITC on other labor market outcomes, and particularly hourly wages, for different age groups and education levels.[11] However, no significant effects were observed.

[10] Hernæs et al. (2017) and Bratsberg et al. (2019) use an approach close to ours. They exploit a geographically implementation of conditionality for social assistance in Norway to analyze the impact of welfare on education. They show that a decrease of 3.1 percentage points in the incidence rate of welfare is associated with an increase of 2.2 percentage points in the high school graduation rate.

[11] Results available upon request. See Section 3.1.2 for a discussion of the effect of EITC on hourly wages.

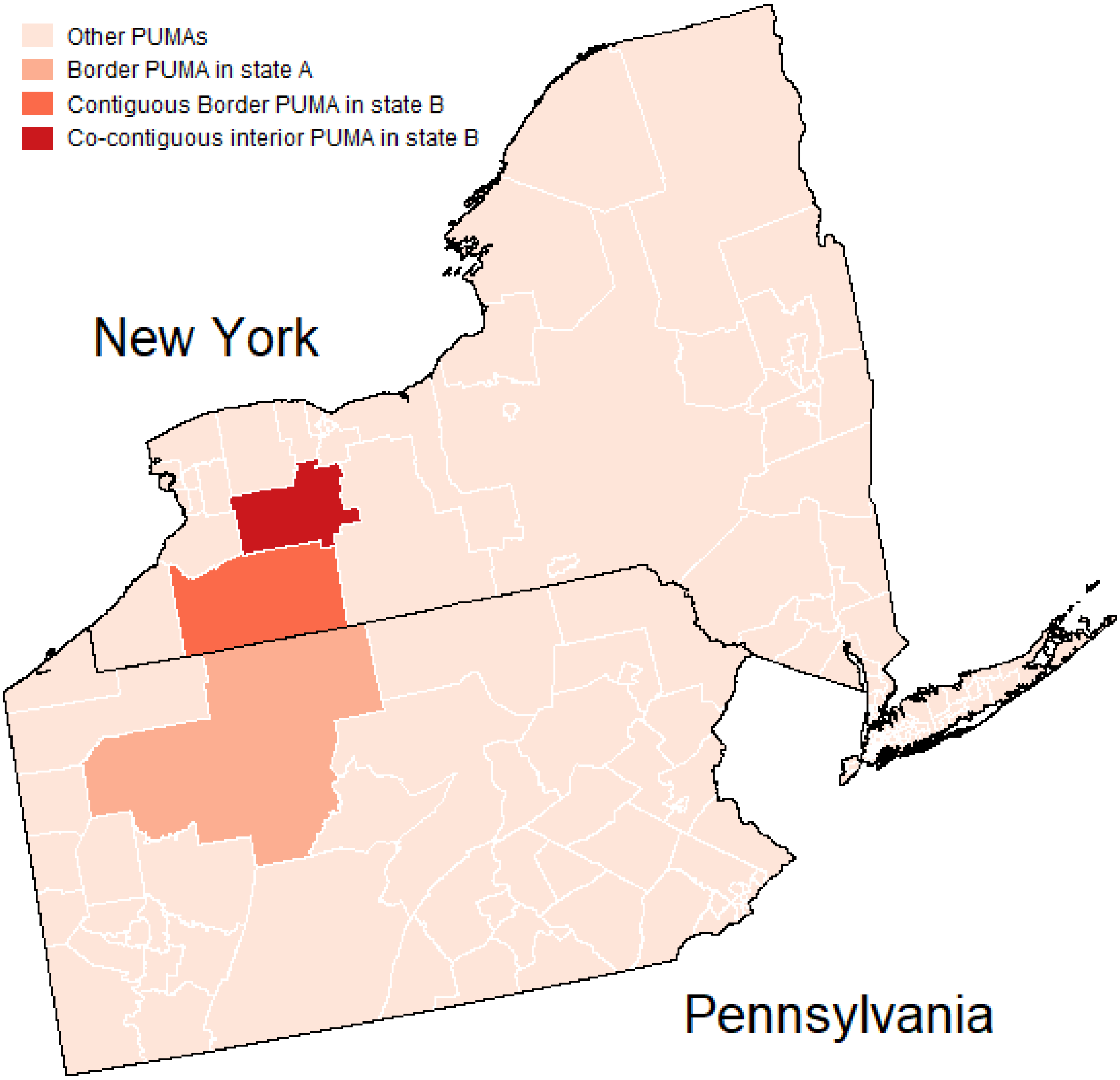
2.4 Spillover effects

Our results may be affected by spillover effects if individuals move across a state border to a contiguous PUMA in response to state welfare and taxation policies (Tiebout, 1956; Cebula and Alexander, 2006). When the EITC differs between neighboring states, one would expect low-skilled individuals to move to the state where the EITC is more generous. Interstate mobility is more likely when individuals live in counties close to state borders, resulting in relatively low moving costs. To test for spillover effects, we follow the strategy of Huang (2008): Instead of comparing two PUMAs sharing a state border, we now compare a PUMA located at the state border with a *co-contiguous interior PUMA*, specifically, a PUMA that is:

1. not immediately adjacent
2. separated by only one PUMA
3. not located at the state border
4. located on the opposite side of the state border

The first two conditions require the control PUMA to be *co-contiguous* with the treated PUMA, such that only a contiguous-border PUMA is between them. The last two conditions indicate that the control PUMA is *interior*, *i.e.*, located in the hinterland.

Figure 6: Robustness test - Alternative control group to test for spillover effects



Source: ACS 1-year

For clarity, an example is provided in Figure 6. Consider a PUMA (pale orange) located in Pennsylvania and sharing a border with New York. The contiguous-border PUMA (dark orange) represents the control PUMA in the benchmark estimation, while the co-contiguous interior PUMA (red) represents the control PUMA in the robustness test. If there are spillover effects, they should decrease with rising distance from the border. Estimates using co-contiguous interior PUMAs, which are further from state borders, should be less affected by spillover effects. By using this alternative control group, our conclusions remain unchanged (see Appendix D): an increase in the state EITC significantly increases the high school dropout rate, suggesting that our results are not driven by spillover effects.

3 Model

We develop a life-cycle matching model with directed search. Employment adjustments occur along the intensive and extensive margins. Educational choices, search intensities, hirings, hours worked, and separations are all endogenous. Before entering to the model's exposition, we discuss some key assumptions.

3.1 Modeling choices

This section documents the empirical facts that motivate certain modeling assumptions. We pay special attention to hours worked, hourly wages, and net social transfers to reproduce as closely as possible the labor market response to the EITC.

3.1.1 Hours worked

As explained by Moffitt (1985), the expected impact of the EITC on hours worked varies across the different phases of the credit. In the phase-in range, the substitution effect incentivizes working more hours, whereas the income effect incentivizes working fewer hours, making the net effect ambiguous. In the plateau range, there is only a negative income effect leading to an unambiguous reduction in hours worked. In the phase-out range, the substitution and income effects work in the same direction and both unambiguously incentivize working fewer hours. While empirical studies provide mixed results when considering specific population groups (men/women, single/married, without/with children, etc.), prior research investigating the whole population of EITC recipients confirms that hours worked increase in the phase-in range and decrease in the plateau and phase-out ranges (Hoffman and Seidman, 1990; Dickert et al., 1995). As the vast majority of EITC recipients are located in the phase-out range (Hoffman and Seidman, 2003), the EITC is expected to reduce average hours of work, conditional on working. In our model, we consider that hours worked may vary with EITC as a result of the worker's optimal decision.

3.1.2 Hourly wages

Predictions for the long-term impact of EITC on life-cycle trajectories depend crucially on how it affects wages. In the search and matching literature, the conventional approach consists in using a generalized Nash criterion to determine wages. Nash bargaining implies that employers may capture some of the tax credit by reducing pre-tax hourly wages. However, empirical research suggests that the impact of EITC on pre-tax hourly wages is close to zero (Hoffman and Seidman, 2003). Our estimates confirm this finding (see Section 2.3). Why are pre-tax hourly wages so rigid? One argument is that a large proportion of EITC recipients are paid the minimum wage; thus, employers cannot put downward pressure on pre-tax hourly wages (Eissa and Nichols, 2005). Another plausible explanation for wage stickiness is that employers do not know whether their employees receive EITC (Nichols and Rothstein, 2015). Until 2011, EITC recipients could receive a fraction of their credit with each paycheck, rather than a lump sum at tax-filing time, via the advance EITC program. To opt into this program, employees had to submit a withholding election form to their employer. However, as noted by Moffitt (2016), only 3% of EITC recipients opted into the program, leading to its cancellation. Such behavior suggests that workers do not want their employers to know that they are receiving EITC. Since employers lack information about an employee's eligibility for EITC and the amount they receive, it is not surprising to observe no significant effect on pre-tax hourly wages. From a theoretical point of view, the modest impact of in-work benefits on wages has led economists to consider that the best way to describe the labor supply response is to consider a labor supply model with exogenous pre-tax hourly wages and an endogenous intensive margin (Keane and Moffitt, 1998; Saez, 2002; Blundell, 2006; Blundell et al., 2016). In our model, we assume that pre-tax hourly wages are fixed and depend on education, human capital, and idiosyncratic productivity.

3.1.3 Net social transfer

The EITC may affect life-cycle earnings in two ways: directly as an in-work benefit but also indirectly as adjustments in education and the labor market cause changes in pre-tax income that induce variations in eligibility for other programs. Ignoring the indirect effect of EITC on other programs leads to misestimation of its effects on the educational choice, labor supply response, life-cycle earnings, and inequalities. To consider incentives from the transfer system, we follow the approach proposed by Blundell et al. (2016). More precisely, we compute the net social transfer (welfare less taxes) depending on age, family status, education, and labor force status.[12] This value of the net social transfer can then be mapped into the model's state space, allowing us to tractably capture the entire structure of the transfer system: a complex, non-concave, and discontinuous function of income, age, education, labor force status, and family status.

3.2 Heterogeneities

Age. As in Chéron et al. (2013), workers differ according to their age $a = \{a_0, a_1, ..., a_A\}$. The life cycle spans from age $a_0 = 16$ to age $a_A = 67$. We considered quarterly frequency. Age increases deterministically, such that age in the next period is $a' = a + 1$. In each period, the oldest generation retires and a new generation of the same size enters the labor force. This implies that the size of the labor force is constant. The fraction of the labor force retiring and entering is thus equal to $1/(a_A - a_0) \simeq 2\%$ on an annual basis.

Educational attainment. As in Albertini and Terriau (2019), each individual chooses her educational attainment $e \in \Omega_e$ before entering the labor market, with $\Omega_e = \{e_1, e_2, e_3\}$. e_1 corresponds to no educational attainment (or less than high school), e_2 corresponds to high school, and e_3 corresponds to higher than high school. For simplicity, we define educational attainment as 'low', 'middle', and 'high' skill. We assume that once an individual enters the labor market, educational attainment is maintained until retirement. The optimal educational decision is detailed later in this study.

[12] See Appendix C.4 for more details.

Human capital. We consider human capital accumulation to be a learning-by-doing process. This refers to the experience accumulated while employed. Human capital h has a finite discrete support $\Omega_h(e) = \{1, ..., H(e)\}$, which depends on the education level. We allow human capital to increase differently according to the initial skill e. After completing her education, each individual enters the labor market unemployed, with the lowest human capital level ($h = 1$). Human capital may appreciate during employment and depreciate during unemployment spells. Furthermore, we assume that human capital is general in the sense of Becker (1962). Consequently, a laid-off worker with human capital $h > 1$ may find a new job and start with the same level of human capital, provided that it does not depreciate during the period of unemployment. Following Ljungqvist and Sargent (1998), Ljungqvist and Sargent (2008), and Lalé (2018), we consider two Markov processes to characterize gradual transitions in human capital. $\mu_n(h, h')$ is the probability that an employed worker with human capital h moves to human capital h'. Similarly, $\mu_u(h, h')$ is the probability that an unemployed worker with human capital h moves to human capital h':

$$\mu_n(h,h') = \begin{cases} 1-\psi_n & \text{if} \quad h < H \quad \text{and} \quad h' = h, \\ \psi_n & \text{if} \quad h < H \quad \text{and} \quad h' = h+1. \end{cases}$$

$$\mu_u(h,h') = \begin{cases} 1-\psi_u & \text{if} \quad h > 1 \quad \text{and} \quad h' = h, \\ \psi_u & \text{if} \quad h > 1 \quad \text{and} \quad h' = h-1. \end{cases}$$

Note that an employed individual with $h = H$ cannot accumulate further human capital as $\mu_n(h, h') = 1$. Symmetrically, for an unemployed worker with $h = 1$, human capital cannot depreciate further, as $\mu_u(h, h') = 1$.

Family status. We consider each household[13] to have one of four family statuses (f): no children, one child, two children, or three or more children, $f = \{f_0, f_1, f_2, f_3\}$. As in Blundell et al. (2016), we assume that family status evolves stochastically.[14] The new family status f' is drawn for each period according to the conditional distribution $F_{a,e}(f'|f)$ with density $\boldsymbol{f}_{a,e}(f)$. The distribution is skill- and age-dependent to capture the observed evolution of family status across groups with different educational attainment and over the life cycle. This allows us to capture two important features of the dynamics of family composition: i) educated workers tend to have later and fewer children, as they spend more time in the educational system; and ii) the probability of having children is not constant over the life cycle—it increases up to the age of 40 and decreases thereafter (see Appendix J).[15]

Idiosyncratic productivity x denotes the idiosyncratic productivity component of an employed worker. It evolves according to a Markov process. For an existing employment relationship, the new individual productivity x' is drawn from the conditional

[13]For tractability, we model working-age individuals as single household heads with varying numbers of children, ignoring marital status and the EITC implications of marriage or divorce. Throughout the paper, "worker", "individual", and "household" are used interchangeably to refer to the same entity.

[14]Thus, the decision to have children is unrelated to the labor market situation. Introducing this concept would certainly enrich the model but is likely to drastically complicate the analysis. We discuss this issue in the last section.

[15]In our paper, family status refers to the *number of qualifying children within the household an individual belongs to*, not *the number of qualifying children the individual has*. This allows for considering the impact of the individual's education choices on her household income, as well as the impact of siblings, not just their own children. See Appendix J for more details.

distribution $X(x'|x)$. For a new match, the new individual productivity x' is drawn from the unconditional distribution $X_0(x')$.

3.3 Productivity and income

Given the amount of heterogeneity in the model, it is useful to define the productivity and wage corresponding to a firm-worker pair. Productivity is given by:

$$y(h,x,\ell,e) \quad = \quad A(e)\, h\, x\, \ell, \tag{2}$$

where $A(e)$ is an education-dependent scaling parameter and $\ell \in [0,1]$ corresponds to the number of working hours supplied by the individual.

Following Burdett et al. (2011), Bagger et al. (2014), and Blundell et al. (2016), we consider pre-tax hourly wages to be defined by the following rule:

$$w(h,x,e) \quad = \quad \max(w^h_{\min},\ A(e)\, x\, h^{\bar{\alpha}(e)}), \tag{3}$$

where $w^h_{\min}$ is the hourly minimum wage and $\alpha(e)$ is the elasticity of wages with respect to human capital.

As in Blundell et al. (2016), we compute the net social transfer (welfare less taxes) depending on age, family status, education, and labor force status. We map these revenues into the model's state space by defining $b(a,f,e,j)$ as the net monetary gain derived from all tax and welfare programs. $j = \{u,n\}$ denotes job status, *i.e.*, unemployed (u) or employed (n).

3.4 Modeling of the EITC

Our model seeks to capture the major characteristics of the EITC. For simplicity, we denote earned income by $\widetilde{w} = w\ell$. Workers can receive the tax credit depending on their earned income $\widetilde{w}$.[16] Let $\overline{\tau}$ denote the basic social security contribution rate, and let $c_{\max}$ denote the maximum tax credit. w_m and $\underline{w}$ are, respectively, the minimum and maximum earned income to benefit from the maximum tax credit (the lower and upper bounds of the plateau range). $\overline{w}$ corresponds to the maximum earned income to benefit from the EITC (the upper bound of the phase-out range). $\tau(\widetilde{w},f)$ denotes the social security contribution net of the tax credit. Formally, it may be written:

$$\tau(\widetilde{w},f) \quad = \quad \underbrace{\overline{\tau}\widetilde{w}}_{\substack{\text{basic}\\\text{tax}}} \; \underbrace{-\max\left(\min\left(\frac{\widetilde{w}}{w_m(f)},1,\frac{\overline{w}(f)-\widetilde{w}}{\overline{w}(f)-\underline{w}(f)}\right),0\right)c_{max}(f)}_{\text{EITC}}. \tag{4}$$

The parameters depend on family status, as in the original rule presented in Figure 1. Note that:

- If $\widetilde{w} \in [0, w_m[$, the EITC increases with earned income.
- If $\widetilde{w} \in [w_m, \underline{w}[$, the EITC does not vary with earned income, and is equal to $c_{\max}$.
- If $\widetilde{w} \in [\underline{w}, \overline{w}[$, the EITC decreases with earned income.
- If $\widetilde{w} \in [\overline{w}, +\infty[$, the EITC is zero.

[16] According to the regulation, earned income includes labor income and certain disability payments. For EITC recipients on average, wage and salary income represents 95% of earned income.

3.5 Matching

Following Menzio et al. (2016), we consider directed search over educational attainment e, age a, family status f, and human capital h. The number of hires per unit of time in each submarket is given by the following matching function:

$$m(h,a,f,e) \quad = \quad m(s(h,a,f,e)u(h,a,f,e),v(h,a,f,e)), \tag{5}$$

where $u \geq 0$ is the mass of unemployed workers, v denotes the mass of vacancies, and s stands for endogenous search effort. The matching function (5) is increasing and concave in its two arguments and exhibits decreasing return to scale. The job-finding probability per efficiency unit of worker search p and the vacancy-filling probability q are defined as follows:

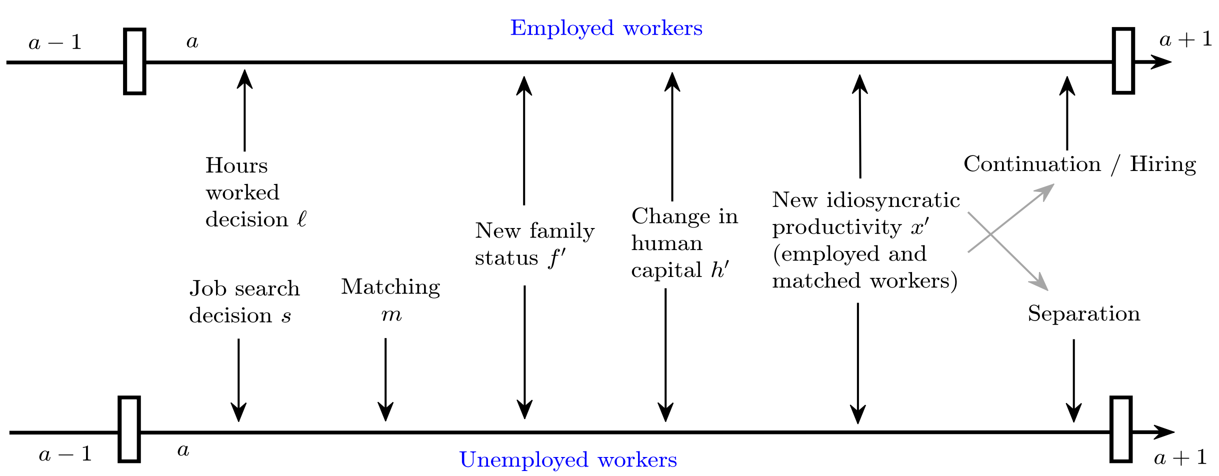
$$p(h,a,f,e) \quad = \quad m(h,a,f,e)/(u(h,a,f,e)s(h,a,f,e)), \tag{6}$$

$$q(h,a,f,e) \quad = \quad m(h,a,f,e)/v(h,a,f,e). \tag{7}$$

3.6 Timing of events

At the beginning of age a, employed individuals decide how many hours of work they will supply, while unemployed workers choose their optimal search effort. Matching between vacancies and unemployed workers occurs right after this decision. Then, all workers (employed or unemployed) draw a new family status and human capital level. Unemployed workers finding a new job and existing matches draw a new level of idiosyncratic productivity from two distinct distributions. Unemployed workers may be successfully hired or return to the unemployment pool. Symmetrically, an employed worker may continue the working relationship or leave the firm. Such separations may occur endogenously or exogenously. First, we assume that the worker may quit her job or be laid off by the firm. This event results from firm and worker optimal decisions, and is endogenously determined. Second, we assume that workers leave employment relationships at the exogenous rate δ_e. Figure 7 illustrates the timing of events. In the following sections, we describe the match acceptance, quit, and layoff decisions.

Figure 7: TIMING OF EVENTS



3.7 Bellman equations

Optimal continuation and acceptance decisions. W, U, J, and V denote the respective value functions for an employed worker, an unemployed worker, a filled job, and a vacant job. The optimal decisions are given by:

$$\begin{aligned}
\Omega(h,a,f,x,e) &= \mathbb{1}^F(h,a,f,x,e)\max[W(h,a,f,x,e),U(h,a,f,e)] \\
&+ (1-\mathbb{1}^F(h,a,f,x,e))U(h,a,f,e), && (8)\\
\Lambda(h,a,f,x,e) &= \mathbb{1}^W(h,a,f,x,e)\max[J(h,a,f,x,e),V(h,a,f,e)] \\
&+ (1-\mathbb{1}^W(h,a,f,x,e))V(h,a,f,e), && (9)\\
\text{with,} & \\
\mathbb{1}^F(h,a,f,x,e) &= \begin{cases} 1 & \text{if } J(h,a,f,x,e) > V(h,a,f,e) \\ 0 & \text{otherwise} \end{cases}, && (10)\\
\mathbb{1}^W(h,a,f,x,e) &= \begin{cases} 1 & \text{if } W(h,a,f,x,e) > U(h,a,f,e) \\ 0 & \text{otherwise} \end{cases}. && (11)
\end{aligned}$$

For an employed worker, Ω represents the optimal decision to continue the match. If the value of unemployment exceeds that of employment, the employee will quit. Otherwise, the relationship continues. For an unemployed worker, Ω represents the decision to accept or turn down the job offer. Ω depends on whether the firm is willing to continue the relationship, $\mathbb{1}^F(h,a,f,x,e) = 1$, or not. If not, $\mathbb{1}^F(h,a,f,x,e) = 0$, the firm unilaterally decides to end the relationship. We thus have inefficient separations (layoffs). Similarly, for a firm with a filled job, Λ provides the decision to maintain the employment relationship or lay off the worker. For a firm with an unfilled position, Λ determines whether a vacant job is transformed into a filled job. Λ depends on whether the employed worker is willing to continue the relationship or if the unemployed worker accepts the job offer, that is $\mathbb{1}^W(h,a,f,x,e) = 1$. Otherwise, the worker unilaterally decides to end the relationship (quit and job refusal).

Employed workers. We assume that employed workers choose how many hours they are willing to work, given the statutory constraint imposed by the EITC. The value function for an employed worker is expressed as follows:

$$W(h,a,f,x,e) = \begin{array}{l} \max\limits_{\ell\in\Omega_\ell}\left\{w(h,x,e)\ell - \tau(w(h,x,e)\ell) + b(a,f,e,n) - \eta(a,e)\frac{\ell^{1+\phi}}{1+\phi}\right\} \\ +\beta\sum\limits_{h'}\mu_n(h,h')\displaystyle\int\int\left[\begin{array}{c}(1-\delta_e)\,\Omega(h',a',f',x',e)\\ +\delta_e\;U(h',a',f',e)\end{array}\right]dX(x'|x)dF_{a,e}(f'|f). \end{array} \quad (12)$$

An employed worker[17] earns $w\ell$, pays taxes net of the EITC $\tau(w\ell)$, and receives net social transfer b. The fourth term on the right-hand side corresponds to the disutility from working. Following Imai and Keane (2004), $\eta(a,e)$ is a scaling function governing the change in disutility during the life cycle and across education levels. Indeed, less-educated workers are more likely than more-educated workers to occupy jobs that are more physically demanding and detrimental to their health. Consequently, the disutility from working may increase with age and differ across educational attainment

[17]We assume that having a child does not have a direct impact on utility but only an indirect effect through taxes and transfers, which can, in turn, influence education choices and labor supply. As highlighted by Bridgeland et al. (2006), having a child during one's studies can place additional pressure on parents, potentially leading them to drop out of high school to immediately join the workforce (which may increase the sensitivity to the EITC).

levels. ϕ represents the inverse of Frisch elasticity. The first-order condition with respect to ℓ provides the optimal decision on working hours:

$$w - w\frac{\partial \tau(w\ell)}{\partial \ell} - \eta(a,e)\ell^{\phi} = 0. \tag{13}$$

Given the non-differentiability of the tax function, we solve the optimal working hours problem ℓ numerically. The last term on the right-hand side shows the expected value of employment given the separation rate shock and changes in human capital, age, idiosyncratic productivity, and family status.

Unemployed workers. An unemployed worker receives an income $b(a,f,e,u)$. She decides her optimal search effort s given the search cost function $k(s)$, with $k'(s) > 0$ and $k''(s) \geq 0$, and the expected gain from searching. The value function is expressed as follows:

$$U(h,a,f,e) \quad = \quad \max_{s} \left\{ \begin{array}{c} b(a,f,e,u) - k(s) + \beta \sum_{h'} \mu_u(h,h') \times \\ \int \int \left[\begin{array}{c} (1 - p(h,a,f,e)\, s) U(h',a',f',e) \\ +p(h,a,f,e)\, s\Omega(h',a',f',x',e)) \end{array} \right] dX_0(x') dF_{a,e}(f'|f) \end{array} \right\} \tag{14}$$

An unemployed worker is matched with a vacant job at the rate $p \times s$ and decides whether to accept or reject the offer. Note that as long as she remains unemployed, her human capital is likely to depreciate with probability ψ_u. The first-order condition with respect to s provides the optimal search effort decision:

$$k'(s) = p(h,a,f,e)\beta \sum_{h'} \mu_u(h,h') \int \int \Omega(h',a',f',x',e) - U(h',a',f',e) dX_0(x') dF_{a,e}(f'|f). \tag{15}$$

According to the above condition, the marginal cost of searching for a job equates to the expected marginal value from an employment relationship.

Filled job. The value function for a firm with a filled job is given by:

$$J(h,a,f,x,e) \quad = \quad \max \left\{ 0, \begin{array}{c} y(h,a,f,x,e) - w(h,x,e)\ell(h,a,f,x,e) + \beta \sum_{h'} \mu_n(h,h') \times \\ (1-\delta_e) \int \int \Lambda(h',a',f',x',e) dX(x'|x) dF_{a,e}(f'|f) \end{array} \right\}. \tag{16}$$

A firm with a filled job receives a profit flow equal to productivity minus labor costs. The human capital of an employed worker may increase in each period, provided the match continues. With probability $1 - \delta_e$, the job is not exogenously destroyed. Given changes in family status and idiosyncratic productivity, the firm decides the optimal employment decision through Λ.

Vacant job. Each firm is free to open a vacant job directed toward a worker of educational attainment e, age a, family status f, and human capital h. To do so, the firm incurs a vacancy cost that depends on education level c_e. Formally, the Bellman equation associated with a vacant job can be written as:

$$V(h,a,f,e) \quad = \quad -c_e + \beta \left[\begin{array}{c} q(h,a,f,e) \int \Lambda(h,a',f,x',e) dX_0(x') \\ +(1 - q(h,a,f,e)) \max_{h,a,f,e} V(h,a,f,e) \end{array} \right], \tag{17}$$

3.8 Job creation and job destruction

Firms enter the labor market and open vacant positions until the expected market opportunities are exhausted, that is, when $V(h,a,f,e) = 0$. Plugging this condition into the value of a vacancy, Equation (17) leads to the following job creation condition:

$$\frac{c_e}{q(h,a,f,e)} = \beta \int \Lambda(h,a',f,x',e)dX_0(x') \tag{18}$$

Let $\mathbb{1}_d\{h,a,f,x,e\}$ be an indicator function defining optimal separation decisions. Equations (10) and (11) provide the private optimal strategies for the firm and worker, respectively. Since there is no bargaining over the surplus to set wages or hours in our model, this decision is not necessarily mutually beneficial for both parties. The effective optimal separation and match acceptance decision combines the two:

$$\text{Separation} \quad \mathbb{1}_d\{h,a,f,x,e\} = 1 - \mathbb{1}_c\{h,a,f,x,e\} \tag{19}$$
$$\text{Acceptance/Continuation} \quad \mathbb{1}_c\{h,a,f,x,e\} = \mathbb{1}^F\{h,a,f,x,e\} \times \mathbb{1}^W\{h,a,f,x,e\} \tag{20}$$

3.9 Educational choice

We borrow the modeling of educational choice from Chéron and Terriau (2018) and Albertini and Terriau (2019). Before entering the labor market, individuals choose their educational attainment $e \in \Omega_e$, with $\Omega_e = \{e_1, e_2, e_3\}$. The optimal schooling decision is based on several factors.

1 Each individual is endowed with an ability ζ defining her study aptitude. We assume that ζ[18] follows a normal distribution $Z(.)$.

2 The net cost of education includes tuition fees equal to Υ_e[19], which depends directly on educational attainment, and the cost of effort $\Phi(\zeta, e)$, related to the individual's ability to study. We assume that the function $\Phi(.)$ is continuous, decreasing, convex, and twice differentiable. The total cost of studies $\kappa(e,\zeta)$[20], expressed in monetary terms, is then:

$$\kappa(e,\zeta) = \Upsilon_e + \Phi(\zeta, e)$$

3 The duration of educational attainment e is d_e, with $d_1 < d_2 < d_3$. Length of studies has a direct incidence on the schooling decision, as it determines the opportunity cost and the discount factor for the future payoff.

4 After completing their educational attainment, individuals enter the labor market as unemployed. When individuals make their schooling decision, they cannot forecast with certainty their age and family status upon entering the labor market. However, they know the distribution of age and the distribution of family status by age and skill for individuals entering the labor market. Consequently,

[18]The probability density function of ζ is determined in Section 4 and displayed in Appendix E.
[19]Υ_e is determined using the *Digest of Education Statistics*. See Appendix F.
[20]The cost function $\kappa(e,\zeta)$ is determined in Section 4 and displayed in Appendix E.

individuals decide their educational attainment based on the expected payoff according to these distributions. The payoff corresponds to the sum of transfers until entry and the expected value at entry. Formally, it is expressed as follows:

$$\widetilde{U}(e) = \sum_{a=a_0}^{a_A} \beta^{a-a_0} \Big[\underbrace{\int U(1,a,f,e) \boldsymbol{f}_{a,e}(f) df \, p_e(a)}_{\text{Expected value on entry}} + \underbrace{\int b(a,f,e,u)(1-P_e(a)) \boldsymbol{f}_{a,e}(f) df}_{\text{Transfers during studies}} \Big]$$

with $\boldsymbol{f}_{a,e}(f) = dF_{a,e}(f'|f)^T \boldsymbol{f}_{a,e}(f)$.

$\boldsymbol{f}_{a,e}(f)$ is the unconditional density of family status. $p_e(a)$ is the probability density that a worker with education e enters the labor market at age a, and $P_e(a)$[21] is the associated distribution. The level of human capital is lowest ($h = 1$) as the individual has no experience. Individuals receive the net social transfer $b(a,f,e,u)$ during studies, dependent on their age a, education level e, family status f, and employment status u for unemployed. We use the density $p_e(a)$ to compute the average value function and the cumulative density $P_e(a)$ to calculate the expected sum of transfers received during studies.

The optimal educational decision is the solution of the following program:

$$e^\star_\zeta = \arg\max_{e \in \Omega_e} \Pi(\zeta, e), \tag{21}$$

with,

$$\Pi(\zeta,e) = \underbrace{\widetilde{U}(e)}_{\text{Payoff when entering the labor market}} \underbrace{- \mathbb{1}_{\{e \geq e_2\}} \sum_{a=a_0}^{a_0+d_2} \beta^{a-a_0} \kappa(e,\zeta)}_{\text{Cost of education (middle skilled)}} \underbrace{- \mathbb{1}_{\{e=e_3\}} \sum_{a=a_0+d_2}^{a_0+d_3} \beta^{a-a_0} \kappa(e,\zeta)}_{\text{Cost of education (high skilled)}}. \tag{22}$$

Individuals choose to pursue schooling until the marginal gain of an additional degree becomes lower than the associated marginal cost. Individuals choosing the lowest level of educational attainment do not pay any educational costs. Individuals choosing to graduate from high school only consider the second term on the right-hand side of Equation (22). Finally, those pursuing college studies bear all education costs.

The proportion of individuals in each skill category is given by:

$$\Gamma(e) = \int \mathbb{1}_{\{e^\star_\zeta = e\}} dZ(\zeta), \tag{23}$$

where $\mathbb{1}_{\{e^\star_\zeta = e\}}$ is an indicator variable taking the value 1 if $e^\star_\zeta = e$.

[21] $P_e(a)$ is determined using the *CPS* and displayed in Appendix G.

3.10 Laws of motion

The model is characterized by a continuum of individuals of mass one. Each individual is either employed or unemployed. The evolution of each type of worker is described by a law of motion. We use $n(h, a, f, x, e)$ to denote the stock of employed workers and $u(h, a, f, e)$ to denote the stock of unemployed workers. Let $a_{-1} = a - 1$ being the previous age, the laws of motion are given by:

$$\begin{aligned} n(h,a,f,x,e) &= \mathbb{1}_c\{h,a,f,x,e\} \Bigg[\underbrace{(1-\delta_e) \sum_{h'} \mu_n(h',h) \int\int n(h',a_{-1},f',x',e) dX(x|x') dF_{a_{-1},e}(f|f')}_{\text{Continuation employment}} \\ &+ \underbrace{\frac{dX_0(x)}{dx} \sum_{h'} \mu_u(h',h) \int u(h',a_{-1},f',e) p(h',a_{-1},f',e) s(h',a_{-1},f',e) dF_{a_{-1},e}(f|f')}_{\text{New matches}} \Bigg] \end{aligned} \tag{24}$$

$$\begin{aligned} u(h,a,f,e) &= \underbrace{\mathbb{1}_{\{h=h_1\}} \mathbb{1}_{\{f=f_1\}} \mathbb{P}_e(a)}_{\text{New entries after education}} \\ &+ \underbrace{\sum_{h'} \mu_n(h',h) \int\int n(h',a_{-1},f',x',e) \left[\begin{array}{c} (1-\delta_e)\mathbb{1}_d\{h,a,f,x,e\} \\ +\delta_e \end{array} \right] dX(x|x') dF_{a_{-1},e}(f|f')}_{\text{Separation from employment}} \\ &+ \underbrace{\sum_{h'} \mu_u(h',h) \int u(h',a_{-1},f',e) \left(1 - p(h',a_{-1},f',e) s(h',a_{-1},f',e) \int \mathbb{1}_c\{h,a,f,x',e\} dX_0(x') \right) dF_{a_{-1},e}(f|f')}_{\text{Non-matched workers}} \end{aligned} \tag{25}$$

The initial conditions are given by:

$$u(h, a_0, f, e) = 0 \quad \forall h \in \Omega_h,\ f \in \Omega_f,\ e \in \Omega_e \tag{26}$$
$$n(h, a_0, f, x, e) = 0 \quad \forall h \in \Omega_h,\ f \in \Omega_f,\ x \in \Omega_x,\ e \in \Omega_e, \tag{27}$$

which involves a labor force by age and education level $L(a, e)$ equal to:

$$L(a,e) = \sum_h \int \left[\int n(h,a,f,x,e)dx + u(h,a,f,e) \right] df = \sum_{a=a_0}^{a_A} P_e(a). \tag{28}$$

Owing to stochastic entries, the size of the labor force for each age a and each skill group e corresponds to the cumulative number of workers who entered between initial age a_0 and age a. When all workers have entered the labor market, the right-hand side of the above expression is equal to one. We obtain the number of workers for each age group and the total number of workers as follows:

$$L(a) = \sum_e \Gamma(e) L(a,e),$$
$$L = \frac{1}{a_A - a_0} \sum_a L(a).$$

Given that each worker leaves the labor force at age a_A, each age category has the same weight in the total labor force. Consequently, in each period a, the oldest generation is replaced by the new generation at rate $1/(a_A - a_0)$.

3.11 Government budget

The government collects taxes from labor, makes transfers, and funds education. We distinguish two costs related to education: (1) C_p: the public cost of education, which corresponds to teacher salaries, public infrastructure, and some running costs; and (2) C_s: the educational grants given to students. The fiscal surplus $FS(t)$ is then:

$$FS = \sum_e \Gamma(e) \Big[\underbrace{\sum_h \sum_a \int \int n(h,a,f,x,e)[\tau(w(h,x,e)\ell(h,a,f,x,e)) - b(a,f,e,n)] \, df \, dx}_{\text{Labor income taxes net of EITC and social transfers}} \tag{29}$$

$$- \underbrace{\sum_h \sum_a \int [u(h,a,f,e) + (1-L(a,e))] b(a,f,e,u) df}_{\substack{\text{Social transfers} \\ \text{when unemployed}}} - \underbrace{\sum_{a=a_0}^{a_0+d_e} (C_p(e) + C_s(e))(1-L(a,e))}_{\text{Public cost of education}} \Big]$$

The government budget is balanced with lump-sum transfers T:

$$T = FS \tag{30}$$

3.12 Definition of the equilibrium

DEFINITION 1. *Given exogenous processes for human capital h, age a, family status f, idiosyncratic productivity x, labor market entry $P_e(a)$, and net social transfer $b(a,f,e,j)$; and given a terminal condition for the value function $W, U, J, V = 0$, and initial conditions for employment (n) and unemployment (u), the equilibrium is a list of (i) quantities $m(h,a,f,e)$, $p(h,a,f,e)$, $q(h,a,f,e)$, and $v(h,a,f,e)$; (ii) prices $y(h,a,x,f,e)$ and $w(h,a,x,e)$; (iii) value functions $W(h,a,f,x,e)$, $U(h,a,f,e)$, and $J(h,a,f,x,e)$; (iv) optimal decisions $\ell(h,a,f,x,e)$, $s(h,a,f,e)$, $\mathbb{1}_d\{h,a,f,x,e\}$, $\mathbb{1}_c\{h,a,f,x,e\}$; (v) optimal educational decisions $e^\star_\zeta$; (vi) stationary distributions of workers across skills Γ_e; (vii) stationary distributions of employment $n(h,a,f,x,e)$, unemployment $u(h,a,f,e)$, and labor force $L(a,e)$; and (viii) fiscal surplus FS and lump-sum transfer T_t, satisfying the following conditions:*

(i) *$m(h,a,f,e)$, $p(h,a,f,e)$, $q(h,a,f,e)$, and $v(h,a,f,e)$ are the solutions of the matching function* (5)*, the job-finding rate* (6)*, the vacancy-filling rate* (7)*, and the job-creation condition* (18)*, respectively;*

(ii) *Prices $y(h,a,x,f,e)$ and $w(h,a,x,e)$ satisfy equations* (2) *and* (3)*;*

(iii) *Value functions $W(h,a,f,x,e)$, $U(h,a,f,e)$, and $J(h,a,f,x,e)$ are solutions of the system that combines* (12)*,* (14)*, and* (16)*;*

(iv) *The optimal hours worked $\ell(h,a,f,x,e)$, search $s(h,a,f,e)$, separation $\mathbb{1}_d\{h,a,f,x,e\}$, and acceptance decisions $\mathbb{1}_c\{h,a,f,x,e\}$ solve* (13)*,* (15)*,* (19)*, and* (20)*;*

(v) *$e^\star_\zeta$ solves the educational choice program* (21)*;*

(vi) *Γ_e satisfies the stationary distribution* (23)*;*

(vii) *The distributions $L(a,e)$, $n(h,a,f,x,e)$, and $u(h,a,f,e)$ solve the law of motion described by* (24)*,* (25)*, and* (28)*;*

(viii) *FS and T satisfy the government budget defined by* (29) *and* (30)*.*

4 Numerical analysis

4.1 Functional forms

- Human capital is given by the following function:

$$h_i = \left(\frac{h_H - h_1}{H-1} \times i \right)^{\gamma_e}, \quad i = 1, ..., H.$$

The parameter $\gamma_e \in]0,1[$ shapes the curvature of human capital.

- We consider a Cobb-Douglas matching function:

$$m(u,v) = \chi u^{\nu} v^{1-\nu},$$

where χ represents the matching efficiency parameter and ν the elasticity of hirings with respect to unemployment.

- The search cost function takes the following form:

$$k(s) = \frac{k_0}{1+\xi} \left((1-s)^{-(1+\xi)} - 1 \right) - k_0\, s,$$

where k_0 and ξ are parameters governing the level and curvature of the search intensity function. This function ensures that the search intensity level lies between 0 and 1. We therefore define search intensity as the time devoted to searching.

- The education cost function is defined as:

$$\Phi(\zeta, e) = \kappa_0(e) \left(1 - \frac{1}{1 + \kappa_2(e) \exp(-\kappa_1(e)\zeta)} \right),$$

which corresponds to the general form of the logistic function (see Richards (1959)) and is S-shaped. κ_0 defines the upper left level, κ_1 governs the smoothness of the S-shape, and κ_2 controls for the S-shape's location on the x-axis.

- Abilities ζ are distributed according to the normal distribution with mean 0 and standard deviation 1.

- Labor disutility takes the following functional form:

$$\eta(a,e) = \begin{cases} \bar{\eta}_e & \text{if } a < a^\star \\ \bar{\eta}_e + \rho_e (a - a^\star)^2 & \text{otherwise} \end{cases}$$

$\bar{\eta}_e$ scales disutility across jobs with different educational attainment.[22] $a^\star$ is the age above which disutility increases with age at rate ρ_e.

4.2 Calibration and estimation

We calibrate some parameters using external information and use a minimization procedure to estimate the remaining parameters. We provide an online appendix describing in detail the solution method and estimation procedure.

[22]Our functional form is close to that used by Iskhakov and Keane (2020). In the spirit of Imai and Keane (2004), we capture age-varying labor disutility. Contrary to their approach, however, we here assume that $\eta(a,e)$ has a parametric form and is not a taste shock.

4.2.1 Parameter set externally

Labor market and heterogeneities. We consider monthly frequencies and a life-cycle horizon of 54 years with $a_0 = 16$ and $a_A = 67$. The discount factor is set to 0.9966, giving an annual real interest rate of approximately 4%. We consider five human capital levels. We set the bounds defining the range of human capital level $h_1 = 1$ and $h_H = 5$. Following Petrongolo and Pissarides (2001), we consider the elasticity of the matching function with respect to unemployment equal to 0.5. The idiosyncratic productivity x evolves according to an order-one autoregressive process with persistence ρ_x and standard deviation σ_x, estimated thereafter. The process is discretized using the Rouwenhorst method with $n_x = 3$ grid points. New matches draw idiosyncratic productivity from the unconditional distribution $X_0(x')$, which is considered uniform. The exogenous separation δ_e is set to the mean level observed from the *CPS* data.

The family status f evolves according to a four-state Markov process. The transition matrix is age- and education-dependent:

$$g_{a,e} = \begin{bmatrix} g_{a,e,1,1} & g_{a,e,1,2} & \cdots & g_{a,e,1,4} \\ g_{a,e,2,1} & g_{a,e,2,2} & \cdots & g_{a,e,2,4} \\ \vdots & \ldots & \ddots & \vdots \\ g_{a,e,4,1} & \cdots & \cdots & g_{a,e,4,4} \end{bmatrix}$$

The transition probabilities are estimated using the *CPS* and are thus exogenous. The paths of the transition probabilities are displayed in Appendix J.

Education. We consider that educational abilities are distributed normally with mean $\mu_\zeta = 0$ and standard deviation $\sigma_\zeta = 1$.[23] As in Donovan and Herrington (2019), public and private education costs (per year and per student) are taken from the *Digest of Education Statistics 2018*.[24] The average public cost of one year of study in high school represents 33.96% of the median wage, and 12.79% of the median wage for a college student. The private cost of one year of study in college amounts to 26.89% of the median annual income. Thus, $C_p(e_2) = 0.3396 \times w_{median}$, $C_p(e_3) = 0.1279 \times w_{median}$, and $C_s(e_3) = 0.2689 \times w_{median}$. To calculate educational attainment decisions, we use entries from the *CPS*. We estimate $\kappa_1(e)$ and $\kappa_2(e)$ to match the proportion of workers by skill category and the elasticity of education with respect to the EITC (see Section 4.2.2), but set $\kappa_0(e)$, the upper-left level of the cost function. For $e = e_1$, $\kappa_0(e_1) = 0$, there is no education cost. For $e > e_1$, we assume that education cost is equal to the maximum earned income of the skill category. We thereby obtain a rank-preserving cost function, *i.e.* $\Phi(\underline{\zeta}, e_2) < \Phi(\underline{\zeta}, e_3)$.

Labor market institutions. To calibrate the EITC tax schedule ($w_m(f)$, $\underline{w}(f)$, $\overline{w}(f)$, $c_{\max}(f)$), we use the values displayed in Appendix A in 2018 for each family status and each EITC phase. The net social transfer by age a, family status f, educational attainment e, and job status j, $b(a, f, e, j)$, is estimated using the *CPS* and reported in Appendix I. All these values are expressed in monetary terms. To set the values in the

[23]We impose these values for the normal distribution but estimate the educational cost function. Changing the support does not affect the model's quantitative implications since it simply scales the range of abilities.

[24]See Appendix F for more details.

model, we express them as fractions of the observed average earned income ($41,317). For the initial value of average earned income in the model, we compute initial estimates for the tax schedule parameters and the net social transfer over the life cycle. We then solve the model and calculate the average earned income. We adjust the tax schedule and net social transfer using the fraction calculated above, and repeat this procedure until convergence is achieved. All the calibrated parameters are reported in Table 4. We proceed similarly for the hourly minimum wage w^h, whose value we first initialize and subsequently update after solving the model to match the Kaitz index, which corresponds to $7.25/hours[25] divided by the average hourly wage rate of $24.85. The Kaitz index equals 29.18%.

Table 4: CALIBRATED PARAMETERS

Parameter	**Symbol**	**Value**			
Initial age	a_0	16			
Final age	a_A	67			
Discount factor	β	0.9966			
Human capital range	$[h_1, h_H]$	[1, 5]			
Matching function elasticity	ν	0.50			
Ability distribution mean	μ_ζ	0			
Ability distribution SD	σ_ζ	1			
Private cost of education	$[\Upsilon(e_2), \Upsilon(e_3)]$	[0.00, 0.48]			
Education cost function scale	$[\kappa_0(e_2), \kappa_0(e_3)]$	[2.78, 4.28]			
Hourly minimum wage	w^h	0.57			
Family status	f	**0C**	**1C**	**2C**	**3C+**
EITC Phase 1 limit	$w_m(f)$	0.29	0.44	0.61	0.61
EITC Phase 2 limit	$\underline{w}(f)$	0.36	0.80	0.80	0.80
EITC Phase 3 limit	$\overline{w}(f)$	0.65	1.73	1.96	2.10
EITC maximum tax credit	$c_{\max}(f)$	0.02	0.15	0.24	0.28

Note: Family status: no children (0C), 1 child (1C), 2 children (2C), 3 children and more (3C+).

,

4.2.2 Parameter set internally

The remaining parameters are estimated using a simulated method of moments, similar to the approach of Albertini and Terriau (2019). We have eight parameters that depend on educational attainment and seven parameters that are common across skill groups. We thus have 31 parameters to estimate. The set of structural parameters is given by:

$$\Theta = \{\gamma_e, \bar{\alpha}_e, \chi_e, c_e, \delta_e, A_e, \bar{\eta}_e, \rho_e, \phi, \psi_n, \psi_u, k_0, \xi, \rho_x, \sigma_x\}$$

Our goal is to reproduce the following life-cycle series: (i) employment rate by educational attainment; (ii) hours worked by educational attainment; (iii) earned income deciles D2, D4, D6, and D8, and (iv) the proportion of employed workers in each EITC phase (phase-in, plateau, phase-out). While the model is simulated over a life cycle

[25]Federal minimum hourly wage for nonfarm workers in the United States, https://fred.stlouisfed.org/series/FEDMINNFRWG

starting at age 16 and ending at age 67, we target series (i)–(iii) over the range 20–65 to avoid erratic movements due to few observations at either extreme of the age spectrum. We then have $I = 11$ life-cycle series observed at monthly frequencies over a 46-year window, which involves 6,072 moments. We use $\{\boldsymbol{Y}^d_{1,a}, \boldsymbol{Y}^d_{2,a}, ..., \boldsymbol{Y}^d_{L,a}\}^{65}_{a=20}$ to denote the set of life-cycle series $l = 1, ..., L$ calculated from the *CPS* data.

We use a root-finding procedure to obtain the parameters that make moments from the model as close as possible to their empirical counterparts. Formally, the optimization problem is:

$$\hat{\Theta} \;=\; \arg\min_{\Theta} \sum_{a=a_1}^{a_A} \sum_{l=1}^{L} \frac{||\boldsymbol{Y}^d_{l,a} - \boldsymbol{Y}^m_{l,a}(\Theta)||}{\boldsymbol{Y}^d_{l,a}} \tag{31}$$

where $\boldsymbol{Y}^m_{i,t}(\Theta)$ are the simulated life-cycle series from the model. We use an adaptive grid to solve the problem (31).[26] It consists in constructing a wide multidimensional grid that covers the space of the parameter values using low-discrepancy grid techniques, and refining the grid at each iteration around the values most likely to match the target.

The estimation procedure described above concerns a life-cycle series. In addition, we aim to replicate four moments: the proportion of low- and middle-skilled workers, and the elasticity of the proportion of low- and middle-skilled workers with respect to the EITC, as evaluated in Table 3. The observed proportions are $\Gamma(e_1) = 9.48\%$, $\Gamma(e_2) = 30.69\%$, and $\Gamma(e_3) = 59.83\%$. The elasticity involves that increasing $c_{\max}$ by 10%[27] increases the proportion of low-skilled workers by 0.71 percentage point and causes a similar decline in the proportion of middle-skilled workers. The proportion of high-skilled workers remains unchanged. This elasticity is converted into proportions $\Gamma(e_1)'$, and $\Gamma(e_2)'$, respectively representing the proportions of workers in the low- and middle-skill categories after an increase in the EITC. The parameters of the educational cost function, $\kappa_1(e)$ and $\kappa_2(e)$, with $e = \{e_2, e_3\}$, are pinned down to match the four targets. We solve and simulate the model for a value of $c_{\max}$ and for a value of $c'_{\max} = 1.1 \times c_{\max}$. We then solve for the values of $\kappa_1(e)$ and $\kappa_2(e)$ that match the four targets $\Gamma(e_1), \Gamma(e_2), \Gamma(e_1)'$, and $\Gamma(e_2)'$. As explained in the Supplementary Appendix, this step can be performed outside the main estimation procedure. In addition, because this step involves four moments and four parameters, the targets can be matched perfectly (see Table 6).

4.2.3 Estimation results

Does the model capture the main features of the data? Table 5 summarizes the estimated parameters, while Figures 8 to 10 show the life-cycle profiles of hourly wage, hours worked, employment rate, and earned income distribution[28].

[26]See the Supplementary Appendix for details of the solution technique and estimation procedure.

[27]The benchmark case corresponds to a situation where the state EITC is zero and where $c_{\max}$, which corresponds to the sum of the federal EITC and the state EITC, is exactly equal to the federal EITC. We then assume that the state EITC increases to reach 10% of the federal EITC, which in our model translates to a $c'_{\max} = 1.1 \times c_{\max}$. This corresponds to an increase in the state EITC of 10 percentage points, or an increase in $c_{\max}$ of 10%. In the remainder of the paper, we will use the symbol $\nearrow c_{\max}$ to refer to this 10% increase in $c_{\max}$.

[28]We provide additional results aiming at comparing the simulation from the model to the data in the supplementary appendix 7. We show that our model matches reasonably well those non-targeted moments.

This estimation involves a higher curvature of human capital for high-skilled workers, implying steeper wage growth over the life cycle.[29] Comparing high-skilled workers to low-skilled (middle-skilled) workers, total factor productivity (TFP) is nearly 42% (30%) higher, while the vacancy posting cost is 93% (13%) higher. However, the matching efficiency parameters of the three skill-level groups are nearly the same. Evidently, the job-finding rate increases with the education level. The scale parameters for labor disutility are almost equal for high- and middle-skilled workers but slightly (20%) lower for low-skilled workers. For all education levels, the human capital accumulation rate is more than seven times lower than the depreciation rate, meaning that, on average, a worker needs more than seven years of employment to compensate for one year of unemployment. Finally, the estimation involves a large standard deviation of the idiosyncratic productivity shocks in order to replicate the wage dispersion observed in the United States.

Figure 8 displays the average hourly wage, hours worked, employment rate, and monthly wage for low-, middle-, and high-skilled workers. In Panel (a), the observed hourly wage rate is nicely replicated, despite not being targeted by the estimation procedure, which confirms the goodness of fit. The model matches the important increase in hourly wages for high-skilled workers at the beginning of their life cycle (and for middle-skilled workers to a lower extent) and subsequent flattening. It also replicates the low increase in unskilled workers' hourly wages. The high-skilled workers' wage premium is relatively small at the beginning of the life cycle but reaches 1.5 and more than 2 times that of middle-skilled and low-skilled workers, respectively, by the end. This primarily reflects differences in the human capital accumulation process.

Figure 9 presents the nine deciles of earned income. The model accurately matches the thresholds of the deciles D2, D4, D6, and, to a lesser extent, D8. It replicates the low inequality among young workers resulting from low earned income dispersion and the subsequent increase, with a peak between ages 30 and 50. The estimation also replicates well the other untargeted deciles: D1, D3, D5, D7, and D9.[30] Lastly, Figure 10 displays the share of the population in each phase of the EITC. This estimation allows the model to reproduce the data accurately, notably the high share of workers in the phase-out range compared to the other two ranges. This is an important target because the response in terms of hours worked critically depends on the workers' EITC phase. Our model is able to capture the proportion of workers in each EITC phase, as well as the life-cycle dynamics.

[29] This is consistent with Bhuller et al. (2017) who used Norwegian population panel data, encompassing nearly lifelong earnings histories, to analyse the causal link between education and earnings over the life cycle. They show that additional schooling leads to higher lifetime earnings and steeper age-earnings profile, in line with predictions from human capital theory.

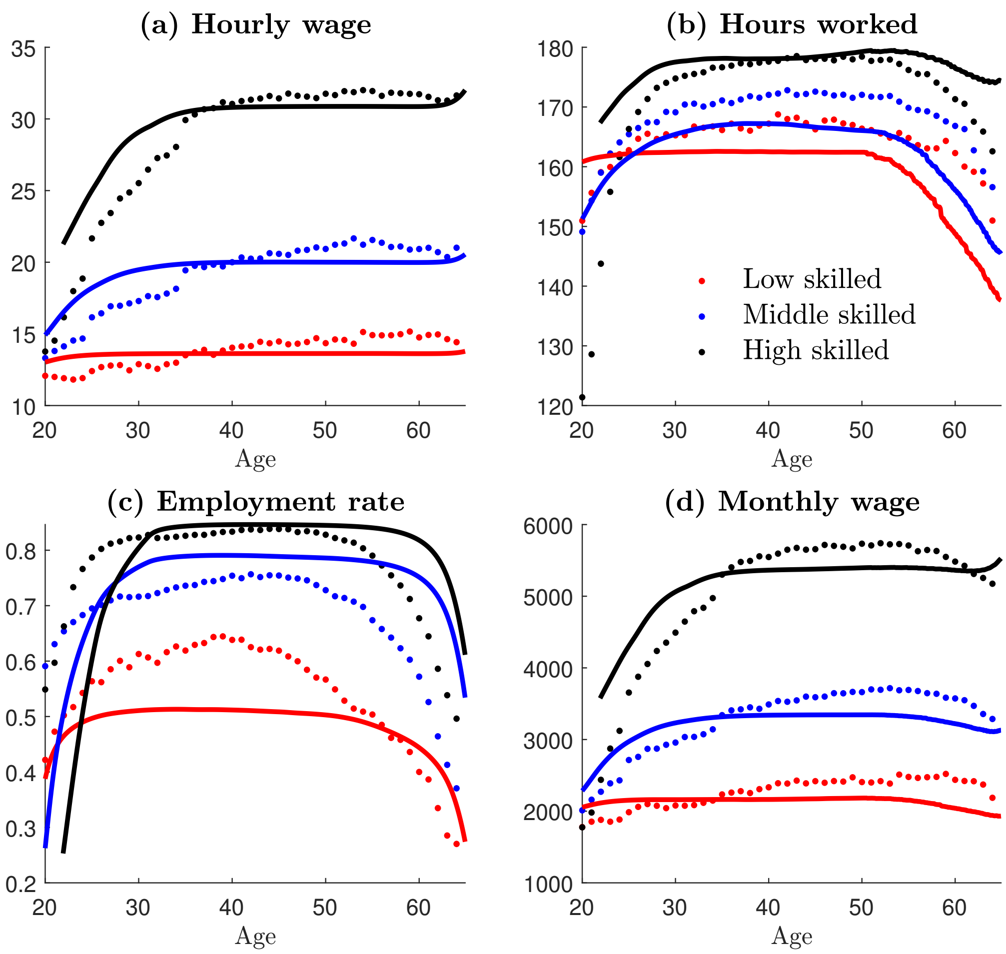
[30] Nonetheless, because we do not include very highly paid workers, the model fails to correctly match the last two deciles after age 30. This does not represent a major issue in the sense that workers at the top of the income distribution are not concerned with the EITC.

Table 5: **ESTIMATED PARAMETERS**

PARAMETER	SYMBOL	EDUCATION		
		Low	**Mid**	**High**
Curvature - human capital	γ	0.41	0.64	0.60
Curvature - hourly wage	$\bar{\alpha}$	0.36	0.60	0.82
Matching efficiency	χ	0.14	0.13	0.12
Vacancy posting cost	c	0.28	0.48	0.54
Exogenous separation rate	s	0.06	0.04	0.03
TFP	A	0.89	0.97	1.26
Labor disutility scale	$\bar{\eta}$	1.12	1.35	1.34
Labor disutility curvature (x10000)	ρ	0.12	0.19	0.11
Education cost function growth rate	$\phi_1(e)$	0	0.31	6.34
Education cost function elasticity	$\phi_2(e)$	0	1.18	0.27

		COMMON
Inverse of the Frisch elasticity	ϕ	1.18
Prob. switch human cap.	ψ_n	0.07
Prob. switch human cap.	ψ_u	0.52
Search cost scale	k_0	0.56
Search cost curvature	ξ	0.98
Persistence of idio. prod.	ρ_x	0.77
Standard deviation of idio. prod.	σ_x	0.25

Figure 8: LIFE-CYCLE PROFILE BY EDUCATIONAL ATTAINMENT



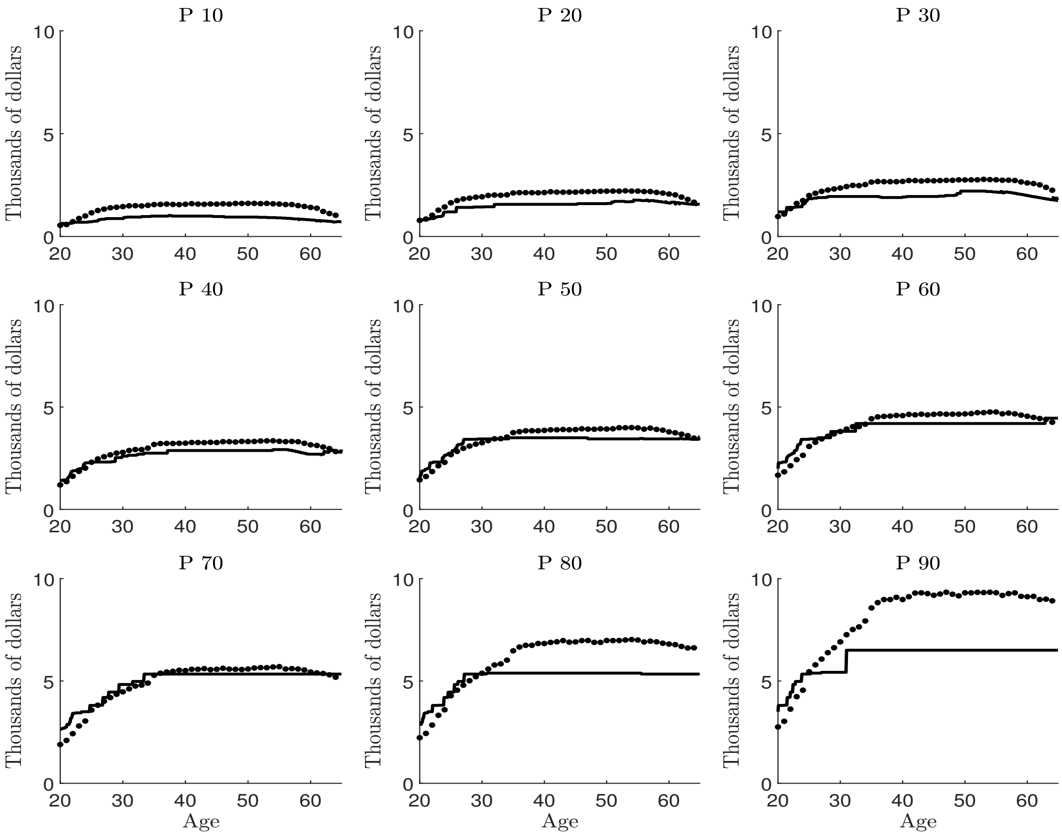
Source: CPS, 2005–2018. Note: Panel (b) shows the number of hours worked per month. See Appendix H for more details on the construction of life-cycle profiles. Dots: data, solid line: model.

Table 6: EDUCATION TARGETS

	Benchmark value			$\nearrow c_{\max}$		
	Low	Middle	High	Low	Middle	High
Data	9.48	30.69	59.83	10.18	29.99	59.83
Model	9.48	30.69	59.83	10.18	29.99	59.83

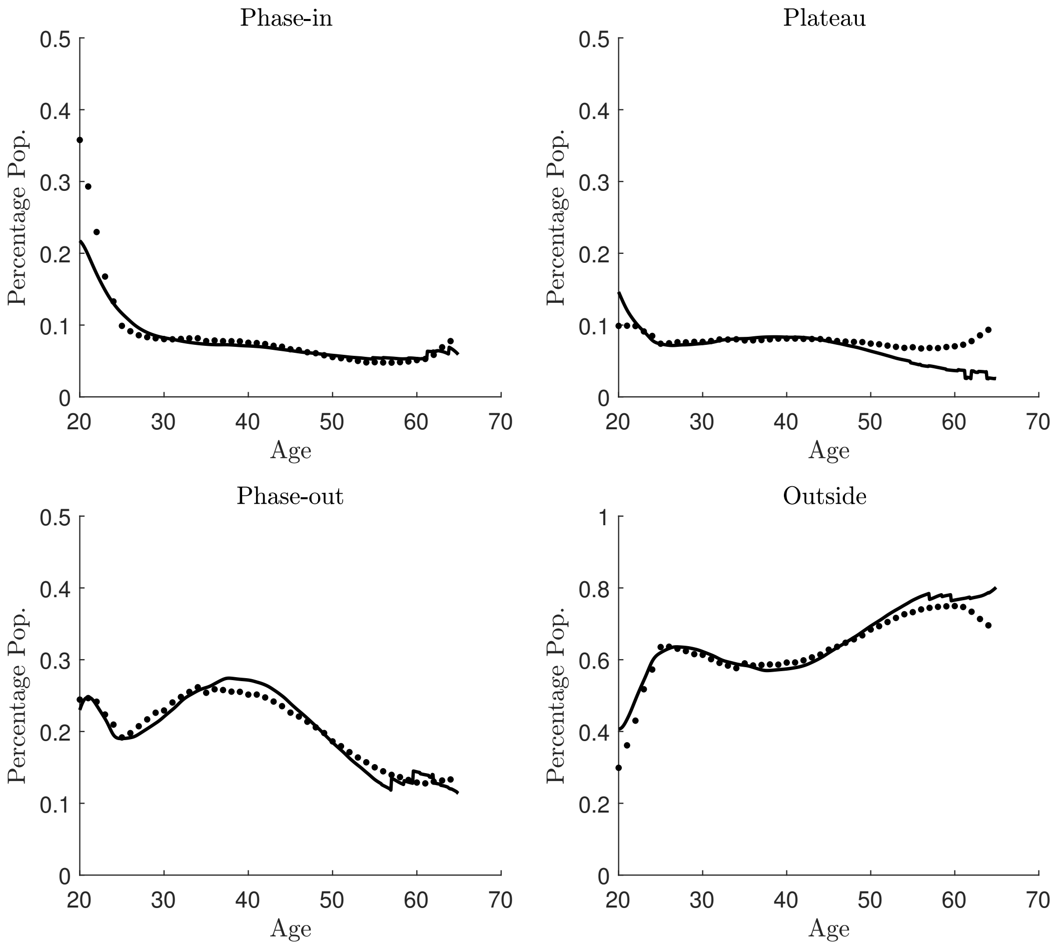
Interpretation: a 10% increase in $c_{\max}$ increases the percentage of low-educated workers from 9.48 to 10.18%, which represents a 7.4% increase in the proportion of low-educated workers.

Figure 9: EARNED INCOME DECILES OVER THE LIFE CYCLE



Source: CPS, 2005–2018. Note: Monthly earned income (hourly wage rate times hours worked) for all employed workers at each age. Values from the model are scaled using the average earned income across all employed workers for comparison purposes. Dots: data, solid line: model.

Figure 10: PROPORTION OF WORKERS IN EACH PHASE OF THE EITC SCHEDULE



Source: CPS, 2005–2018. Dots: data, solid line: model.

5 Quantifying the impact of a change in the EITC

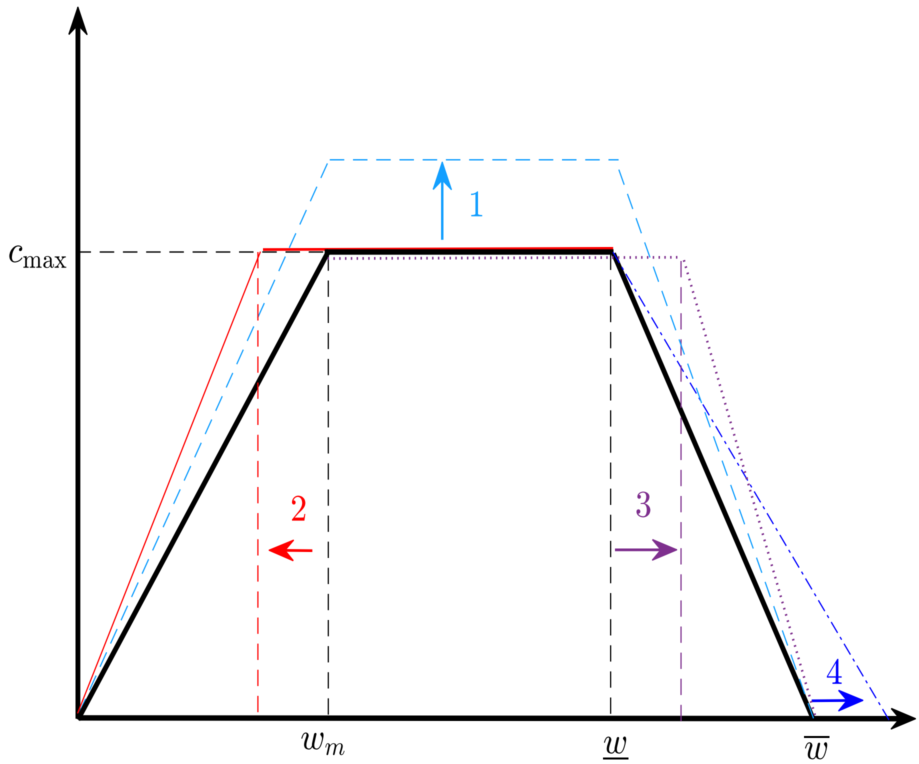
5.1 Changing one parameter

We now use our model to assess the impact of a change in the EITC on labor market outcomes.[31] As highlighted in Figure 11, the EITC design has a trapezoidal shape and can be modified in many directions. However, most of the EITC changes made during 2005–2018 concerned only one parameter. Most states have set up their own EITC, defined as a percentage of the federal EITC, with varying degrees of generosity. This means keeping constant the thresholds w_m, $\underline{w}$, and $\overline{w}$ (set at the federal level) and increasing the maximum credit $c_{\max}$. We propose here to examine the impact of an

[31] Keane and Wolpin (2000) also explore the impact of wage subsidies on low-wage workers in a dynamic labor supply model in which both education and human capital are endogenous. The originality of our approach lies in examining the impact of the EITC (a special form of low-wage subsidy) in a model in which job creation is endogenous.

increase in $c_{\max}$[32] (Case 1 in Figure 11) of 10%.[33]

Figure 11: CHANGE IN EITC



(1) 10% increase in $c_{\max}$, (2) 10% increase in w_m, (3) 10% increase in $\underline{w}$, (4) 10% increase in $\overline{w}$.

Hours and earnings We begin by analyzing the effects of a 10% increase in $c_{\max}$ on hours worked and earnings (see Table 7). Our simulations reveal that such an EITC increase leads to an increase (decrease) in hours worked for workers in the phase-in (phase-out) range, while having no effect on workers on the plateau or outside the EITC. To understand the effect on hours worked, it is essential to connect this to the EITC design (see Figure 1). In the phase-in range, it appears that the EITC provides an incentive to increase hours worked, *i.e.*, the substitution effect is larger than the income effect. In the phase-out range, the EITC acts as an implicit tax: each additional hour of work reduces the EITC amount by the phase-out rate. This implicit tax provides a strong incentive to decrease hours worked (Hotz, 2003; Trampe, 2007). An increase in $c_{\max}$ amplifies these effects as slopes of the phase-in and phase-out ranges become steeper. Finally, workers whose earned income is just below the eligibility threshold are encouraged to reduce the number of hours worked to benefit from the EITC, while those farther away (to the right) are unaffected by the reform. As previously mentioned in the literature (Scholz, 1993; Eissa and Hoynes, 2008; Athreya et al., 2010), the vast majority of EITC recipients are in the phase-out range. Consequently, an increase in the EITC leads to a substantial reduction in average hours worked.

What is the effect on earned income? Because the hourly wage is rigid, earned income follows the same dynamics as hours worked: it slightly increases in the phase-

[32] Results corresponding to a variation in the other parameters (Cases 2–4 in Figure 11) are available in the Supplementary Appendix.

[33] This corresponds roughly to the average state EITC or an increase of one standard deviation.

in range, stays stable in the plateau range, decreases substantially in the phase-out range, and slightly decreases for workers outside the EITC schedule. Regarding net income, the reform translates into a significant increase, ranging from 3% to 5%, for recipients in the phase-in range and approximately 2% for those on the plateau. In the phase-out range, the EITC compensates for the loss of earned income implied by the reduction in hours, and net income remains broadly unchanged. Individuals outside the EITC schedule are unaffected by the reform.

Table 7: EARNING EFFECTS

VARIABLES	BENCHMARK			$\nearrow c_{\max}$		
	Low	Mid	High	Low	Mid	High
PHASE-IN						
Hours worked	138.29	113.77	106.80	2.21	1.52	1.21
Gross earning	728.39	641.01	564.19	2.21	1.53	1.21
Net earning	1008.74	835.54	701.40	5.09	4.00	3.31 1
PLATEAU						
Hours worked	131.35	129.29	140.35	0.00	-0.00	0.01
Gross earning	929.13	1019.51	1145.29	-0.04	-0.02	0.05
Net earning	1149.51	1321.01	1522.64	1.87	2.27	2.51
PHASE-OUT						
Hours worked	167.79	150.61	150.61	-0.98	-1.41	-1.41
Gross earning	1976.12	2058.47	1850.81	-0.92	-1.04	-1.28
Net earning	2243.31	2184.72	2085.79	0.56	-0.19	0.22
OUTSIDE EITC						
Hours worked	176.91	186.66	186.66	-0.01	-0.00	-0.00
Gross earning	2020.07	3298.49	4549.38	-0.01	-0.04	-0.01
Net earning	2020.07	3298.49	4549.38	-0.01	-0.04	-0.01

We simulate 10,000 individuals' life-cycle trajectories and compute the average values for each EITC phase. Individuals with the same educational attainment are compared between the benchmark and the alternative scenario. We thus focus on the impact of the EITC change on hours worked and earnings, absent any change in the composition of the labor force. All values are expressed on a monthly basis. Hours worked: average number of hours worked expressed in levels in the benchmark. Earned income: hourly wage rate times hours worked. Net income: earned income + EITC (without social transfers). Earned income and net income are expressed in dollars in the benchmark. For $\nearrow c_{\max}$*, all variable values are expressed as percentage deviations from the benchmark. Interpretation: a 10% increase in* $c_{\max}$ *produces a 2.21% increase in hours worked for the low-skilled.*

Education, search, and employment We now investigate the effects of a 10% increase in $c_{\max}$ on education, search, and employment (see Table 8). This allows us to highlight the *composition effects*, *i.e.*, the change in the proportions of low-/middle-/high- skilled workers in the economy. The first three columns of Table 8 present the values of some key variables (in levels) in the benchmark economy. Initially, 9.48% of individuals are low-skilled, 30.70% are middle-skilled, and 59.83% are high-skilled. An increase in $c_{\max}$ leads to a composition effect: the proportion of low-skilled workers increases by 7.42%, that of middle-skilled workers decreases by 2.3%, and that of high-skilled workers remains unchanged. Table 8 also reveals that an increase in the EITC generates a positive effect on participation (one goal of the EITC): search intensity increases, particularly for low-skilled workers. However, as mentioned above, the policy leads to a reduction in average hours worked, which reduces job creation and, therefore, the contact rate. These effects have opposite directions. Overall, the effect on employment is positive for low-skilled workers and negative for middle- and high-skilled workers. However, the proportion of low-skilled workers (characterized by a much lower employment rate) increases in the economy. Table 9 shows that the resulting composition effect leads to a significant fall in aggregate employment. We conduct a decomposition exercise to quantify the extent to which changes in aggregate variables can be attributed to changes in education, contact rate, search intensity, or acceptance decision.[34] The analysis reveals that the composition effect plays a minor role in explaining the decline in hours worked but a significant role in the decrease in employment. Holding the job finding rate constant results in a slight decline in both hours worked and employment. However, when the increase in search intensity is muted, the decline in employment is significantly larger. The decision to accept and continue employment appears to have virtually no effect on the variables.

Table 8: LABOR MARKET EFFECTS

VARIABLES	BENCHMARK			$\nearrow c_{\text{max}}$		
	Low	Mid	High	Low	Mid	High
Education	9.48	30.69	59.83	7.38	-2.28	0.00
Hours worked	159.08	162.57	176.71	-0.04	-0.13	-0.16
Employment	48.44	73.79	76.08	0.11	-0.03	-0.01
Search intensity	29.91	41.86	49.04	0.61	0.12	0.03
Contact rate	17.43	29.27	23.38	-0.31	-0.19	-0.08
Separation rate	12.25	8.65	5.40	0.00	-0.00	0.00
Phase-in	16.54	12.36	3.87	-0.36	-0.25	-0.08
Plateau	18.99	10.97	3.32	0.56	0.45	0.40
Phase-out	34.20	27.10	15.48	-0.02	0.08	0.08
Outside	30.27	49.57	77.32	-0.14	-0.08	-0.03

Notes: Variable values are expressed as percentage deviations from the benchmark. The results are obtained by simulating the model's steady state under the benchmark calibration and the alternative scenario by iterating on Bellman equation and stationary distribution (see Supplementary Appendix). Interpretation: a 10% increase in c_{max} produces a 7.38% increase in the proportion of low-educated workers.

[34] This exercise involves simulating the impact of an increase in EITC by allowing all variables to adjust, then muting one channel at a time to identify the contribution of each channel.

Table 9: DECOMPOSING AGGREGATE EFFECTS

VARIABLES	BENCHMARK LEVEL	$\nearrow c_{\max}$ ALL EFFECTS	NO Δ IN EDUCATION	NO Δ IN MATCHING RATES	NO Δ IN SEARCH INTENSITY	NO Δ IN ACCEPTANCE DECISION
Hours worked	170.70	-0.16	-0.14	-0.15	-0.16	-0.16
Employment	72.76	-0.25	-0.01	-0.21	-0.29	-0.25
Search intensity	45.03	-0.09	0.09	-0.08	-0.20	-0.09
Contact rate	24.63	-0.47	-0.13	-0.31	-0.50	-0.47
Separation rate	7.05	0.36	0.00	0.36	0.36	0.36
Prop. Phase-in	7.68	0.16	-0.22	0.12	0.14	0.16
Prop. Plateau	7.16	1.26	0.47	1.21	1.26	1.26
Prop. Phase-out	20.82	0.30	0.06	0.32	0.28	0.30
Prop. Outside	64.35	-0.26	-0.05	-0.25	-0.25	-0.26

Notes: Variable values are expressed as percentage deviations from the benchmark. The results are obtained by simulating the model's steady state under the benchmark calibration and the alternative scenario by iterating on Bellman equation and stationary distribution (see Supplementary Appendix). The aggregate impact includes changes in the composition of workers (except in column 4) due to changes in education decisions.

5.2 Varying one parameter over a range of values

The effects of a change in the EITC can be nonlinear and may depend on the sign or magnitude of the change. To explore the nonlinear effects, we simulate our economy over a plausible range of $c_{\max}$,[35] *i.e.*, from $c'_{\max} = 0.5c_{\max}$ to $c'_{\max} = 2c_{\max}$. The lower bound corresponds to a 50% reduction in the EITC whereas the upper bound corresponds to a doubling of the EITC. Figure 12 presents the values of the aggregate variables.

Panel (a) shows that a higher maximum EITC translates into an increase in the proportion of low-skilled workers and an equivalent decrease in the proportion of middle-skilled workers; this effect becomes stronger as $c_{\max}$ increases. Average hours worked decreases significantly when the EITC increases (Panel (d)), regardless of the skill level. This effect is particularly pronounced among middle- and high-skilled workers, who are mainly located in the phase-out range and outside the EITC schedule[36]. They are encouraged to reduce their hours when the EITC becomes more generous. This drop in hours worked reduces job profitability, job creation and, therefore, the contact rate (Panel (f)). Conversely, the EITC incentivizes participation in the labor market (Panel (e)), particularly for low-skilled workers, a significant proportion of which are located in the phase-in range. For low-skilled workers, the effect on participation slightly dominates the negative effect on hours worked and the contact rate, whereas for middle- and high-skilled workers the latter effect dominates the former. Consequently, as the EITC increases, the employment rate remains relatively flat for low-skilled workers but decreases for middle- and high-skilled workers (Panel (c)). Finally, as the share of low-skilled workers (characterized by a relatively low employment rate) increases as the EITC rises, we see a sharp drop in total employment: a doubling of the EITC translates into a 4pp drop in the employment rate.

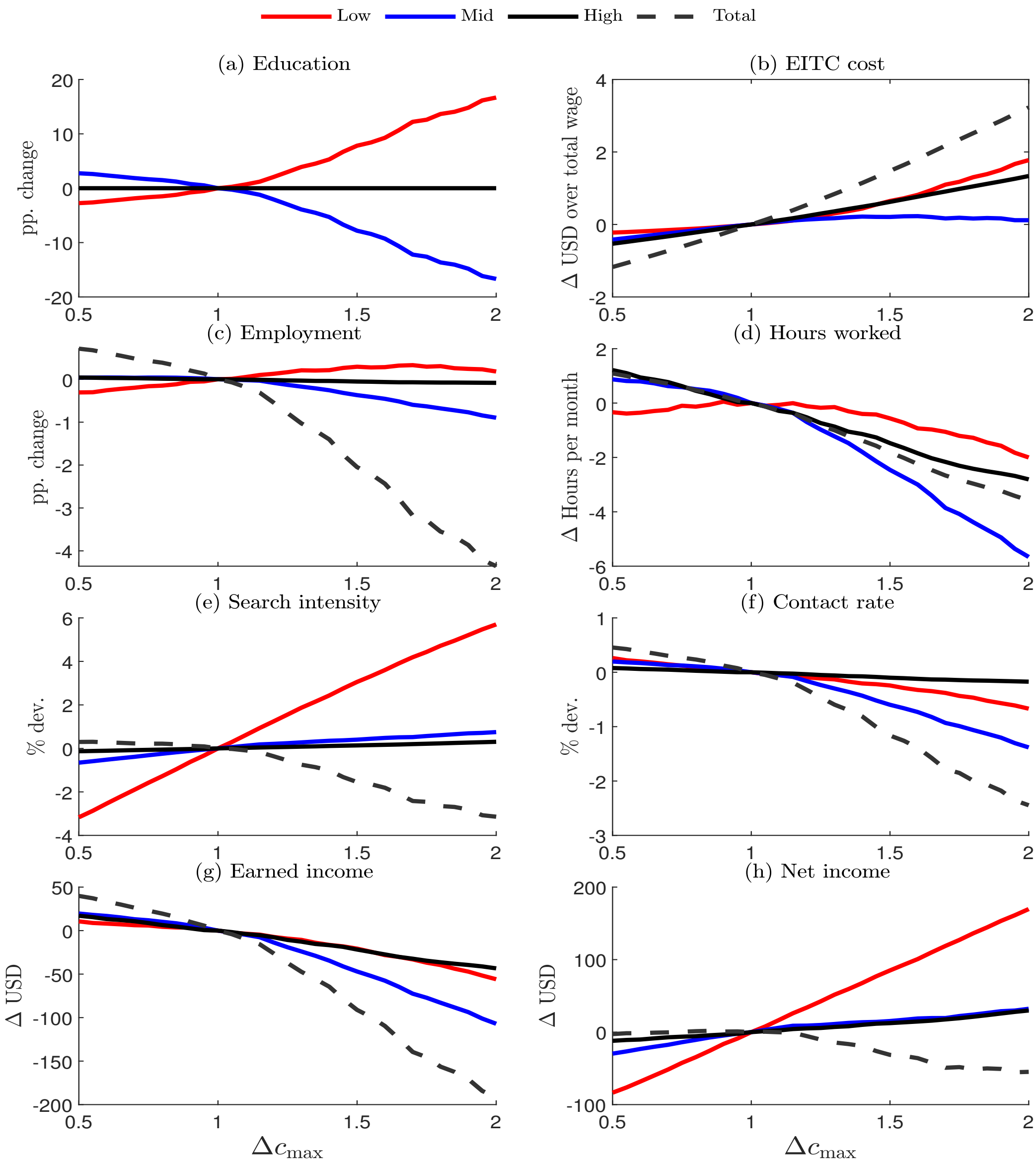
[35] Results corresponding to a variation in the other parameters (Cases 2–4 in Figure 11) are available in the Supplementary Appendix.

[36] Figure 10 shows the evolution of the employment share across EITC phases.

Earned income (Panel (g)) follows the same path as hours worked. Both display non-linearities. Note that for earned income, the total impact is larger than that for each skill group owing to the composition effect described above. Panel (h) shows that decreasing the EITC by 50% would reduce the net income of low-skilled workers by almost $100 per month, whereas increasing the EITC by 100% would raise their net income by nearly $200, denoting a linear relationship. The net income of middle- and high-skilled workers also increases, albeit modestly. Overall, these increases by skill group do not counterbalance the composition effect, causing total net income to fall as the EITC increases.

Finally, Panel (b) displays the variation in EITC cost, expressed as the ratio of government expenditure to the benchmark total payroll (*i.e.*, the pre-reform total payroll). Unsurprisingly, EITC cost increases as $c_{\max}$ rises. At the highest value in this range, the additional cost represents approximately 3% of the benchmark total payroll.

Figure 12: Change in $c_{\max}$



$c_{\max}$ varies between -50% and +100%.

Earned income: hourly wage rate times hours worked. Net income: earned income + EITC (without social transfers).

6 Optimal EITC

At this stage, two conclusions can be drawn: i) the EITC has many transmission channels (hours worked, education, search intensity, etc.); and ii) the EITC generates non-linear effects. Having highlighted the mechanisms at play in a framework accounting for several labor market decisions, we next consider what would be the optimal EITC design from a welfare perspective.

The EITC schedule is defined by four parameters: w_m, $\underline{w}$, $\overline{w}$, and $c_{\max}$. Our objective is to find the set of parameters that maximizes welfare.[37] To discipline our experiment, we impose the following three constraints on the maximization program:

(1) **The *ex-post* EITC cost incurred by the optimal policy must not exceed the *ex-ante* EITC cost in the benchmark economy.** Note that the *ex-post* EITC cost takes into account all changes in agents' decisions resulting from the alternative EITC design (hours worked, education, search intensity, etc.). We impose this constraint for two reasons. First, the optimal policy may imply an extra cost that may be politically implausible. Second, we consider a balanced budget rule financed by lump-sum taxes. Since markets are complete, these taxes are non-distortive. The optimal policy may generate an additional cost, which can be financed by a lump-sum tax or by a potentially distorting tax (payroll tax, income tax, etc.). This requires consideration of a large number of scenarios on the type of financing envisaged. We thus restrict our analysis of welfare-improving policies that can be implemented at no additional cost.

(2) **The existing percentage differences in EITC parameters between family statuses must be preserved.** As Figure 1 shows, the EITC schedule depends on family status (marital status and number of children). For instance, the maximum EITC for a household with two children is 65% higher than that of a household with one child. We assume that these differences hold for family-dependent parameters for two reasons.[38] First, optimizing on EITC parameters by considering disjoint values by family status involves a total of 17 parameters, which is considerably more cumbersome from a numerical point of view. Second, allowing the optimization program to find parameters that do not preserve the initial rank by family status in all dimensions will likely affect fertility decisions. For instance, if the maximum EITC is higher for a single person without any child than for a couple with two children, one might expect a change in the decision to have children.[39] While the EITC's impact on fertility decisions is certainly an important dimension, it is well beyond the scope of this paper. By considering a rank-preserving EITC with respect to family status, we believe that we mute as much as possible potential changes in fertility decisions.

[37] The various welfare measures are presented in Appendix K. The Supplementary Appendix describes the numerical method used to search for the optimal policy.

[38] Assuming that the differences hold does not mean that $c_{\max}(f)$ will be identical to the benchmark value. We seek the optimal value of $c_{\max}(f_1)$ and obtain $c_{\max}(f)$, $f = f_2, f_3, f_4$ given the initial percentage differences between family statuses.

[39] As shown by Keane and Wolpin (2010), tax policies and welfare programs may impact fertility and marriage decisions.

(3) **We assume that $c_{\max} \geq 0$, $w_m(f) \leq \underline{w}(f)$ and $\overline{w}(f) \geq \underline{w}(f) + c_{\max}(f)$.** The first condition means the EITC is always positive or nil. The second condition means that the EITC has a trapezoid shape or, if bounded, a triangle shape with no plateau phase. Finally, the last condition means that in the phase-out range, an increase in earned income cannot cause a decline in net income (after receiving EITC) .

No EITC Our first experiment entirely mutes the EITC. To achieve this, we impose $c_{\max} = 0$, which implies an EITC of zero for all workers. The results are presented in column (2) of Table 10. Removing the EITC produces a 1.21% increase in total welfare compared to the benchmark economy. We also observe an increase in the proportion of middle-skilled workers (+3.5pp) and an equivalent decrease in the proportion of low-skilled workers. Aggregate hours are higher (+1.5 hour per month), boosting job-creation and the employment rate (+1pp). From a welfare perspective, the EITC in itself seems to generate distortions in the labor market.

Optimal 1 The second experiment seeks to find the set of EITC parameters that maximizes welfare. The optimal policy implies a shift to the right of the EITC schedule (red line in Figure 13). More precisely, the optimal policy involves a weaker slope in the phase-in range, a lower maximum EITC, and an extension of the scheme to higher incomes. For instance, for a household with no children, the plateau is reached when earned income is around \$4,000 per month, compared to less than \$1,000 in the benchmark. Column (3) of Table 10 shows the impact of this policy on welfare and labor market performance. Implementing Optimal 1 produces a 2.90% increase in total welfare compared to the benchmark economy. Because the EITC is more generous to high-income earners, it provides a strong incentive for individuals to pursue studies. This translates into an increase in the proportion of middle-skilled workers (+7pp) and an equivalent decrease in the proportion of low-skilled workers. The policy also leads to a sharp rise in hours worked (+2.5 hours per month) and the employment rate (+2pp).

Optimal EITC 2 (with constraint on hours worked) Section 5.1 shows that an increase in $c_{\max}$ i) encourages low-skilled individuals to participate in the labor market; ii) incites most workers to reduce hours worked to benefit from the increased generosity of the program; and iii) increases the proportion of low-skilled workers in the long run by reducing the relative return to education. As noted by Keane and Moffitt (1998), the perverse effects of the EITC stem not from the program itself but its design. In the previous experiment, the optimal policy (without constraints on hours worked) seeks to counter perverse effects on the intensive margin and education by extending the EITC to middle- and high-income earners. As shown above, Optimal 1 (which implies a shift to the right of the EITC schedule) incentivizes low-skilled individuals to participate in the labor market while also making middle- and high-income jobs more attractive. Individuals are encouraged to pursue education, and hours worked and employment are higher, notably because of the composition effect. Another way to achieve this goal, as suggested by Keane et al. (1995), is to make eligibility for the tax credit conditional on a minimum number of hours worked, as illustrated by the Working Families' Tax Credit (WFTC) in the United Kingdom. To qualify for the WFTC, an individual must work at least 30 hours a week if aged 25–59 years and at least 16 hours a week if aged 60 years or older. The eligibility criteria are also based on family status,[40] with lower minimum hours worked per week for households with children. The general purpose of hours-contingent policies is to reduce the disincentive effects of tax credits. We investigate this issue by introducing a constraint on hours worked in the spirit of the WFTC. We use $\ell^\star$ to denote the minimum number of hours worked to benefit from the EITC. Let $\tau(w(h,x,e)\ell,a)$ be the social security contribution tax net of the tax credit, which can be expressed as follows:

$$\tau(w(h,x,e)\ell,a) = \begin{cases} \overline{\tau}w(h,x,e)\ell - EITC & \text{if } \ell \geq \ell^\star \quad \text{or } a > 60, \\ \overline{\tau}w(h,x,e)\ell & \text{otherwise.} \end{cases} \tag{32}$$

If the individual is over 60 years old, she is entitled to the EITC regardless of the number of hours worked. If aged 60 years or less, she is allowed to collect the EITC only if her hours worked exceed the minimum level $\ell^\star$. Our objective is to determine the set of EITC parameters (which now includes $\ell^\star$) that maximizes welfare.[41]

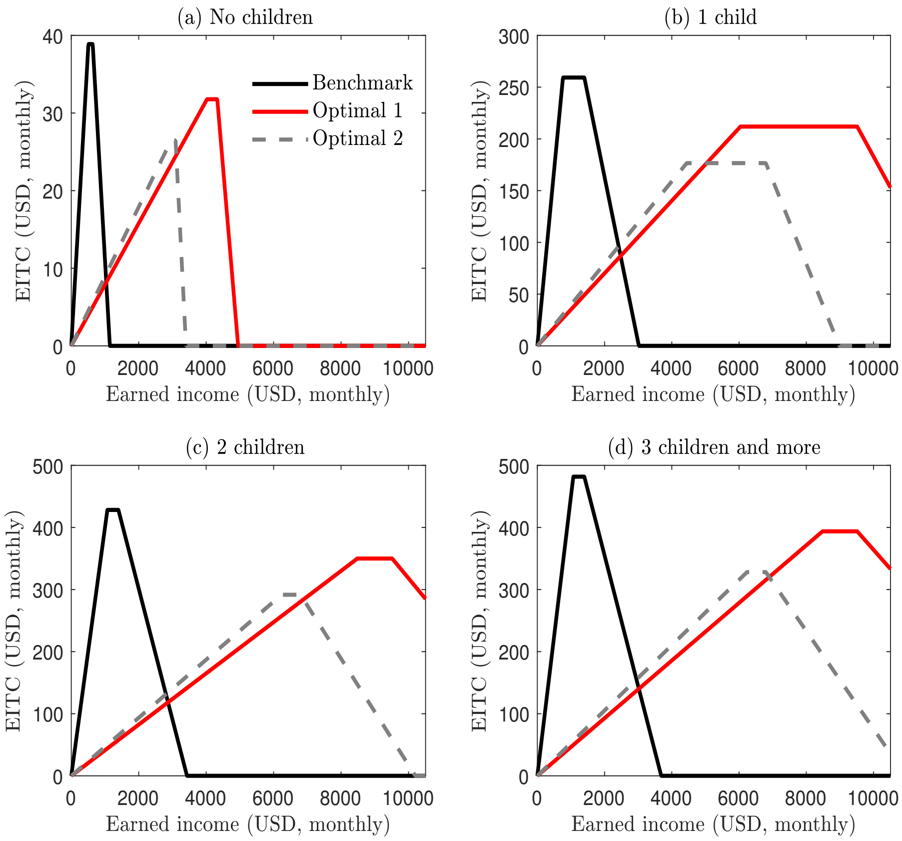
The results are reported in Figure 13 (gray dashed line) and in column (4) of Table 10. Compared with Optimal 1, the inclusion of a minimum hours constraint generates: i) a slightly lower maximum benefit, ii) lower earned income at the start of the plateau range, and iii) a shorter plateau. Interestingly, Optimal EITC 2 policy implies a relatively high minimum number of hours worked: employed workers should work for 80% of the maximum number of hours to become eligible for the EITC,[42] a value close to that proposed by Keane et al. (1995), who suggested imposing a minimum of 20 hours worked per week. Only 20% of workers in the phase-in range do not collect the EITC because they work for too few hours. The composition effect is different. On the one hand, the plateau range is located in a lower range of earned income than in Optimal 1, which should reduce the strong composition effect observed therein. On the other hand, the hours constraint impacts only low-income workers, creating an incentive to obtain a higher education level. The latter effect seems to dominate the former and slightly amplifies the composition effect. Introducing an hours constraint thus brings employment and welfare gains similar to those in Optimal 1.

[40] See. https://www.gov.uk/working-tax-credit for more details.

[41] In the Supplementary Appendix, we provide simulations of a change in the minimum number of hours worked, ranging from zero (benchmark case) to one (maximum hours level), all other EITC parameters being fixed at their benchmark values.

[42] The majority of employed workers do collect the EITC. These moments are available upon request.

Figure 13: OPTIMAL EITC SCHEDULE - TARGET WELFARE



Note. Optimal 1: optimal EITC parameters $\{w_m, \underline{w}, \overline{w}, c_{\max}\}$*. Optimal 2: Optimal 1 + minimum hours constraint.*

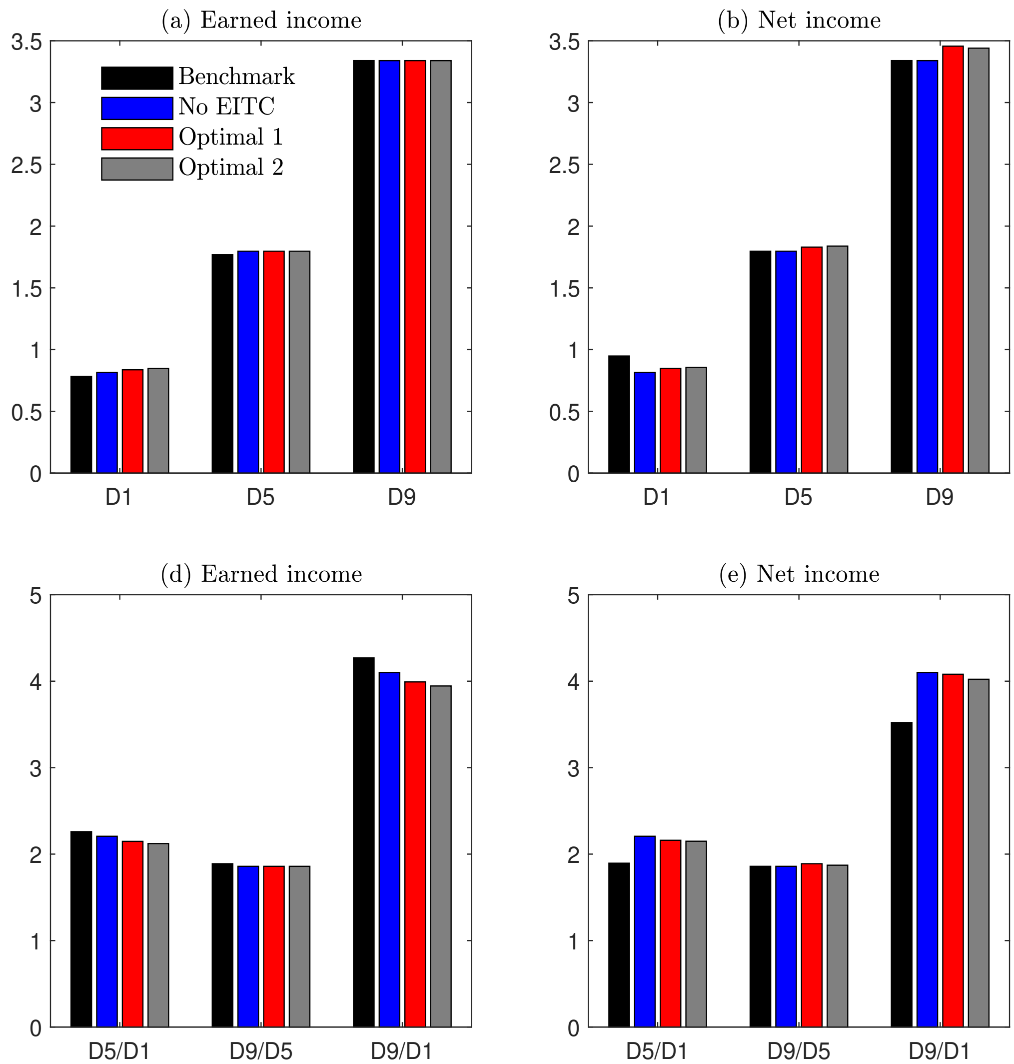
Table 10: OPTIMAL TAX SCHEDULE

	(1) BENCHMARK	(2) NO EITC	(3) OPTIMAL 1	(4) OPTIMAL 2
Welfare	100.00	101.21	102.90	102.98
EITC cost	2.16	0.00	2.16	2.15
Prop. Low edu.	9.48	6.02	2.64	2.22
Prop. Mid edu.	30.69	34.15	37.53	37.95
Prop. High edu.	59.83	59.83	59.83	59.83
Hours worked	170.70	172.21	173.37	174.24
Employment	72.76	73.61	74.74	74.90
Search intensity	45.03	45.04	45.97	46.03
Contact rate	24.63	25.21	25.75	25.86
Gross income	3217.36	3273.68	3313.02	3324.47
Net income	3294.57	3273.68	3384.23	3395.52
Hours constraint				80 %

Welfare is defined as the discounted sum of consumption streams for every worker aged a to a_A (see Appendix K for more details). The hours constraint is expressed as a proportion of full time (maximum hours worked). Optimal 1: no constraint on hours worked. Optimal 2: constraint on hours worked. Earned income (monthly, USD): hourly wage rate times hours worked. Net income (monthly, USD): earned income + EITC (without social transfers).

Figure 14 shows the impact of the different EITC schedules on long-run inequalities. A change in the EITC has very little impact on the distribution of net income. This is mainly explained by the fact that individuals reduce their labor supply when the EITC becomes more generous. Otherwise stated, the EITC simply compensates for the loss of income induced by the reduction in hours worked. Moreover, because an increase in the EITC translates into a lower employment rate, the effect on inequalities is even more limited when the unemployed are included.

Figure 14: EFFECTS ON INCOME DISTRIBUTION



Note. Optimal 1: optimal EITC parameters $\{w_m, \underline{w}, \overline{w}, c_{\max}\}$. *Optimal 2: Optimal 1 + minimum hours constraint. Earned income: hourly wage rate times hours worked. Net income: earned income + EITC (without social transfers).*

Transitional dynamics. Lastly, we simulate the transitional dynamics following the reforms.[43] Our simulations show that while labor market variables by skill category adjust quickly, it takes several decades to capture the full effects on aggregate variables. This is mainly because of the adjustment to educational choices: following a reform, cohorts that have not yet entered the labor market adapt their educational choices. As new cohorts enter the labor market, the proportions of workers in each skill category adjust, which modifies the aggregate variables through a composition effect. This process continues until all the cohorts that were already in the labor market when the reform was implemented (and could not, therefore, modify their educational choices)

[43]See Appendix L.

leave the labor market, *i.e.*, after approximately 50 years. These simulations suggest that it takes almost half a century to reach a new steady state and to capture the full effects of a policy affecting educational choices.

What transitional dynamics are implied by each EITC schedule? Our simulations suggest that removing the EITC is detrimental for low- and middle-skilled workers in terms of employment, net income, and welfare.[44] The positive effect on high-skilled workers together with the composition effect generates an increase in total welfare in the long run. Optimals 1 and 2 also reduce the net income of low-skilled workers because the EITC becomes less generous for low-income earners. This effect is smaller than in the *No EITC* scenario. In addition, the two optimal policies cause rapid increases in employment, hours worked, and welfare for each skill category. Interestingly, all the alternative scenarios involve a decline in welfare of approximately 1 % in the short run and an overshoot thereafter. This can be explained by the high responsiveness of hours worked and both earned and net income: they adjust instantaneously, whereas the impact on employment and education takes more time. For the former, the average time for a firm to fill a vacancy is given by $\frac{1}{q}$. For the latter, it takes 52 years to completely change the composition of the population as new cohorts enter the labor market in each period.

7 Robustness tests

In this section, we analyze the sensitivity of our results along three dimensions.[45] The first robustness check considers alternative targets for the elasticity of education with respect to the EITC. The second focuses on agents' expectations of the duration of changes in the EITC. The third robustness check explores alternative welfare measures. Finally, we discuss the limitations of our approach and potential extensions for future research.

7.1 Alternative targeted elasticity

As shown above, a large portion of the EITC's impact comes from its effect on education. When estimating the model, we target the elasticity of education with respect to the EITC obtained in Section (2.3). The elasticity is represented as the change in educational attainment following a 10% increase in the maximum benefit. It is used this as a target for structural estimation. However, our simulations suggest that the effects of the EITC on labor market variables are nonlinear (see Section 5.2). Does the results hold if the benchmark calibration target the elasticity based on an increase in $c_{\max}$ of 5% to generates an increase in low-skilled workers by half of that initially considered (0.7pp/2=0.35pp). We rerun the simulations in Section 5.1 under a calibration[46] based on an increase in $c_{\max}$ by 5% and 50%. We found that the results remain approximately the same, both qualitatively and quantitatively.

[44] As the welfare of low-skilled workers is very low, small changes in the EITC produce large percentage deviations.

[45] To save space, calculations and simulations for this section are reported in the Supplementary Appendix.

[46] In the benchmark, $c'_{\max} = c_{\max} \times 1.1$ causes an increase in low-skilled workers by 0.7pp. Under the 5% increase in $c_{\max}$ calibration, the low-skilled workers increase by 0.35pp., and under the 50% it increases by 3.5pp.

7.2 Uncertainty in EITC duration

How do economic agents perceive the permanence of changes in the EITC? Up to now, we have (implicitly) assumed in our model that EITC changes are permanent and that agents form their decisions on this basis. Our model is estimated to reproduce the elasticity of education with respect to the EITC (obtained in Section 2.3) under the assumption that reform is permanent. This elasticity drives the composition effect, which is a key channel for quantifying the overall impact on labor market outcomes. However, agents may consider that an increase in the EITC's generosity will likely end in a few years' time, for reasons including budget balancing, government turnover, new political mandates, and state-dependent budget policies related to the business cycle. In this case, as noted by Keane and Wolpin (2007), empirical results are not comparable with model predictions without additional assumptions. If the estimated elasticity corresponds to a situation in which agents believe that EITC changes are temporary, the model's outcome may be ambiguous, owing to two opposite effects. On the one hand, if agents consider that the EITC change is likely to end in the near future, the expected values of employment and unemployment will be affected only modestly. All other things being equal, this *horizon effect* should limit agents' reactions to EITC changes in terms of their search intensity, hours worked, job acceptance, and job separation. On the other hand, our model should replicate the observed elasticity of education to EITC changes. This means that small variations in the expected values of employment and unemployment generate strong variations in educational choices, *i.e.*, education decisions are more sensitive than in the benchmark. Recalibrating the model to account for the higher sensitivity of education to the EITC involves a stronger composition effect, which may cancel out the horizon effect. We propose to address this point in two ways: one empirical, the other theoretical.

Empirical perspective. Do agents expect EITC reform to be permanent or temporary? Unfortunately, our data do not allow us to determine agents' expectations regarding the duration of reform. However, we can examine past EITC changes and analyze their duration to judge how credible it is to consider that agents anticipate the permanence of reform.

There were 44 state EITC changes during 2005–2018, including 36 increases and 8 decreases. Only two decreases of more than 5pp were recorded.[47] Only one state (North Carolina, in 2014) decided to terminate the program. EITC decreases are relatively scarce. Over this period, most states increased the generosity of their respective EITC. The central question is whether these increases persisted for long enough to affect educational choices. If individuals anticipate that a reform will be transitory and no longer apply by the time they enter the labor market, an increase in the EITC is unlikely to affect their educational decisions. Therefore, the anticipated duration of a policy is crucial.

To address this issue, we compute the survival function of a state EITC increase, *i.e.*, the probability that an EITC increase will survive up to a specified point in time. We first define survival as meaning that there is no change (rise or fall) in the state EITC following the increase. As shown by Figure 21 in Appendix M, there is a 0.50 probability that an EITC increase will survive for at least 5 years and a 0.40 probability that it will survive for at least 10 years. We then define survival as meaning that there is

[47] Recall that a state EITC is expressed as a percentage of the federal EITC.

no decline in the state EITC following the increase (*i.e.*, the policy survives if it remains unchanged or if the program becomes even more generous). As shown in Figure 22 in Appendix M, there is a 0.75 probability that an EITC increase will survive for at least 5 years and a 0.70 probability that it will survive for at least 10 years.

These figures suggest that increases in EITC are relatively long-lasting. Individuals who experience an increase in the EITC may thus reasonably expect the program to continue as is or to become even more generous. This supports the intuition that increases in the EITC last for a sufficiently long period to impact educational choices. However, is it credible to assume that an increase in the EITC could be permanent, as implicitly assumed in our model?

To address this question, we next run a sensitivity analysis and explore the robustness of our results under different anticipation scenarios.

Theoretical perspective. We now assess the extent to which our results depend on assumptions about agents' expectations. To do so, we consider that $c_{\max}$ may vary over time. Let $c_{\max}(s)$ be the state-dependent maximum EITC and s be the aggregate state.[48] $\boldsymbol{s} = \{\boldsymbol{s}_1, \boldsymbol{s}_2\}$ follows a two-state Markov process with transition matrix $S(\boldsymbol{s}'|\boldsymbol{s})$:

$$S(\boldsymbol{s}'|\boldsymbol{s}) = \begin{bmatrix} p_1 & 1-p_1 \\ 1-p_2 & p_2 \end{bmatrix}$$

p_1 is the probability of the economy switching from the benchmark EITC to a changed EITC. p_2 governs the reform's persistence. In the previous simulations, $p_1 = p_2 = 1$. To quantify the impact of the *horizon effect*, we consider that $p_2 < 1$. This process modifies the model to account for the uncertainty in parameter variation. The entire model is presented in the Supplementary Appendix. Simulations show that a larger elasticity amplifies the reaction of individuals to enter the labor market as low-skilled, thereby offseting the horizon effect. If the observed elasticity is derived under the assumption that agents expect a limited duration of EITC changes, then the impact of EITC extensions is stronger than that under the assumption of a permanent change.

7.3 Alternative welfare measure

In life-cycle models, agents live for a finite time period. Consequently, welfare is generally defined as the discounted sum of consumption streams for every agent from age a to a_A. This measure assigns a greater weight to the youngest cohorts, since they benefit from a longer time horizon. As a robustness test, we consider an alternative definition of welfare, corresponding to the sum of every individual's current consumption weighted by the number of individuals in each state.[49] This measure is not based on discounting, and therefore gives equal weight to all cohorts. Under this definition, we obtain the same qualitative results but smaller quantitative effects. Eliminating the EITC slightly improves welfare, whereas Optimal 1 and 2 increase welfare to a greater extent. The optimal EITC, with or without an hours constraint, extends to higher earned incomes and involves similar composition effects.

[48] For the sake of exposition, we only present the case where $c_{\max}$ varies, but this exercise can be applied to any or all other parameters.

[49] See Appendix K for further details.

8 Discussion and conclusion

The United States, United Kingdom, and some other countries have implemented in-work benefits targeting low-income (and low-skilled) workers. Our paper provides some evidence that such programs can disincentivize individual investment in education. Our empirical strategy, based on contiguous PUMA pairs and policy discontinuities at state borders, indicates that an increase in the state EITC (as a percentage of the federal EITC) leads to a significant rise in the high school dropout rate.

We then develop a life-cycle matching model with directed search in which educational choices, search intensity, hirings, hours worked, and separations are endogenous, seeking to investigate the long-term effects of EITC. We show that the EITC achieves its initial goal by increasing labor market participation. However, we also highlight two perverse effects. First, a tax credit targeting low-wage (and low-skilled) workers reduces their relative return to schooling. Individuals thus react to an increase in the EITC by reducing their investment in education, leading in the long run to a significant increase in the proportion of low-skilled workers in the economy. Second, we show that most EITC recipients are initially in the phase-out range or outside the EITC schedule. Consequently, when the EITC increases, workers typically react by reducing their hours worked to benefit from the tax credit. This drop in labor supply translates into not only a fall in earned income (for which the EITC increase slightly compensates) but also a substantial drop in job creation and employment (despite a positive effect on participation).

We then investigated how to optimally design the EITC. We show that the beneficial effect on participation can be achieved while also mitigating the negative effects on hours worked and education by shifting the EITC schedule to the right and extending it to higher incomes. It is even possible to further increase employment and welfare by introducing a constraint on hours worked to be eligible for the credit. However, we also show that the EITC does not play a significant role in reducing income inequalities in the long run, after accounting for all the above effects.

Beyond analyzing the impact of EITC on educational choices and labor market dynamics, our study makes several important contributions to the literature. First, we show that the full effect of a policy can be appreciated only from a life-cycle perspective, considering not only the labor market response but also individual reactions before entering the labor market (in terms of educational choices). In this sense, we show that studies ignoring the impact of policies on education also ignore part of the critique leveled by Lucas et al. (1976). Second, our simulations show that the instantaneous employment response of the labor market (which is frequently used to assess the EITC's impact) is small compared to the long-run impact of a fall in the education rate. Therefore, studies evaluating the short-term effects of EITC only tell part of the story. Third, in a life-cycle setting, we challenge the traditional view that progressive taxation or in-work benefits targeting low-paid workers necessarily reduces income inequality. Fourth, we show that it is not the EITC itself that produces perverse effects but its design. A more appropriate design would make it possible to take advantage of the positive effect on participation while also limiting the perverse effects on working hours and education.

Although our study makes several contributions, it also raises questions that leave rooms for several extensions. First, although the effects reported in this paper are huge, the EITC could be even more damaging. As shown by Björklund et al. (2006), there is a large correlation between the education levels of parents and their children. Various contributions suggest that while parental income plays a minor role in college attendance, family background explains a large part of this intergenerational correlation (Cameron and Heckman, 1998, 2001; Carneiro and Heckman, 2002). Children's taste for education may be inherited from their parents. Better-educated parents may also offer greater assistance with homework and provide better information about the quality of schools or employment prospects. We have considered that the distribution of study aptitude (ζ) is constant over time. However, it is possible that this distribution shifts to the left in the long run because of a decline in parental education. In this case, the long-term effect of EITC on education could be even worse. In this sense, the scenarios we presented can be considered as lower bounds of the EITC's potential long-term effects.

Second, we consider in this paper that the stochastic process for family status is exogenous and independent of aggregate variables and the EITC. In the quantitative analysis of optimal EITC policy, we imposed restrictions to circumvent the effect on fertility decisions. However, as shown by Francesconi (2002), Sheran (2007), Keane and Wolpin (2010) and Eckstein et al. (2019), schooling, marriage, and fertility decisions are closely linked and can be affected by tax policies and welfare programs.

Third, if in-work benefits do not improve the situation of low-skilled workers and do not reduce inequalities, what policies should be implemented to achieve these objectives? Our study shows that human capital is a key driver of labor market trajectories and life-cycle earnings. This suggests that a natural way to reduce income inequalities is to reduce skill inequalities. In this sense, policies that increase the return to human capital investments, such as education or vocational training subsidies, may be good candidates. This would require a model in which investment in training is endogenous as in Ben-Porath (1967) or Chéron and Terriau (2018). These issues are on our research agenda.

Replication package The data and code underlying this research is available on Zenodo at https://doi.org/10.5281/zenodo.15599174

Data Availability Statement The data used in this study come from two publicly available sources: the American Community Survey (ACS) and the Current Population Survey (CPS), both provided by the U.S. Census Bureau. The datasets are accessible free of charge through the Integrated Public Use Microdata Series (IPUMS) platform. Users can access and download the data after completing a free registration and agreeing to the terms of use at:

- https://usa.ipums.org/usa/ for ACS (Ruggles et al., 2025)
- https://cps.ipums.org/cps/ for CPS (Flood et al., 2024)

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Appendix

A Federal EITC parameters

Table 11: Federal EITC parameters

Year	Number of children	Phase-in rate	Phase-in range	Maximum credit	Phase-out rate	Phase-out range
2018	No children	7.65	0 - 6 780	519	7.65	8 490 - 15 270
	One child	34.00	0 - 10 180	3 461	15.98	18 660 - 40 320
	Two children	40.00	0 - 14 290	5 716	21.06	18 660 - 45 802
	Three children	45.00	0 - 14 290	6 431	21.06	18 660 - 49 194
2017	No children	7.65	0 - 6 670	510	7.65	8 340 - 15 010
	One child	34.00	0 - 10 000	3 400	15.98	18 340 - 39 617
	Two children	40.00	0 - 14 040	5 616	21.06	18 340 - 45 007
	Three children	45.00	0 - 14 040	6 318	21.06	18 340 - 48 340
2016	No children	7.65	0 - 6 610	506	7.65	8 270 - 14 880
	One child	34.00	0 - 9 920	3 373	15.98	18 190 - 39 296
	Two children	40.00	0 - 13 930	5 572	21.06	18 190 - 44 648
	Three children	45.00	0 - 13 930	6 269	21.06	18 190 - 47 955
2015	No children	7.65	0 - 6 580	503	7.65	8 240 - 14 820
	One child	34.00	0 - 9 880	3 359	15.98	18 110 - 39 131
	Two children	40.00	0 - 13 870	5 548	21.06	18 110 - 44 454
	Three children	45.00	0 - 13 870	6 242	21.06	18 110 - 47 747
2014	No children	7.65	0 - 6 480	496	7.65	8 110 - 14 590
	One child	34.00	0 - 9 720	3 305	15.98	17 830 - 38 511
	Two children	40.00	0 - 13 650	5 460	21.06	17 830 - 43 756
	Three children	45.00	0 - 13 650	6 143	21.06	17 830 - 46 997
2013	No children	7.65	0 - 6 370	487	7.65	7 970 - 14 340
	One child	34.00	0 - 9 560	3 250	15.98	17 530 - 37 870
	Two children	40.00	0 - 13 430	5 372	21.06	17 530 - 43 038
	Three children	45.00	0 - 13 430	6 044	21.06	17 530 - 46 227
2012	No children	7.65	0 - 6 210	475	7.65	7 770 - 13 980
	One child	34.00	0 - 9 320	3 169	15.98	17 090 - 36 920
	Two children	40.00	0 - 13 090	5 236	21.06	17 090 - 41 952
	Three children	45.00	0 - 13 090	5 891	21.06	17 090 - 45 060
2011	No children	7.65	0 - 6 070	464	7.65	7 590 - 13 660
	One child	34.00	0 - 9 100	3 094	15.98	16 690 - 36 052
	Two children	40.00	0 - 12 780	5 112	21.06	16 690 - 40 964
	Three children	45.00	0 - 12 780	5 751	21.06	16 690 - 43 998

2010	No children	7.65	0 - 5 980	457	7.65	7 480 - 13 460
	One child	34.00	0 - 8 970	3 050	15.98	16 450 - 35 535
	Two children	40.00	0 - 12 590	5 036	21.06	16 450 - 40 363
	Three children	45.00	0 - 12 590	5 666	21.06	16 450 - 43 352
2009	No children	7.65	0 - 5 970	457	7.65	7 470 - 13 440
	One child	34.00	0 - 8 950	3 043	15.98	16 420 - 35 463
	Two children	40.00	0 - 12 570	5 028	21.06	16 420 - 40 295
	Three children	45.00	0 - 12 570	5 657	21.06	16 420 - 43 279
2008	No children	7.65	0 - 5 720	438	7.65	7 160 - 12 880
	One child	34.00	0 - 8 580	2 917	15.98	15 740 - 33 995
	Two children	40.00	0 - 12 060	4 824	21.06	15 740 - 38 646
2007	No children	7.65	0 - 5 590	428	7.65	7 000 - 12 590
	One child	34.00	0 - 8 390	2 853	15.98	15 390 - 33 241
	Two children	40.00	0 - 11 790	4 716	21.06	15 390 - 37 783
2006	No children	7.65	0 - 5 380	412	7.65	6 740 - 12 120
	One child	34.00	0 - 8 080	2 747	15.98	14 810 - 32 001
	Two children	40.00	0 - 11 340	4 536	21.06	14 810 - 36 348
2005	No children	7.65	0 - 5 220	399	7.65	6 530 - 11 750
	One child	34.00	0 - 7 830	2 662	15.98	14 370 - 31 030
	Two children	40.00	0 - 11 000	4 400	21.06	14 370 - 35 263

From 2002, the values of the start and end points of the phase-out range were increased for married taxpayers filing jointly. Specifically, the values for these taxpayers were $1,000 higher than the listed values during 2002–2004, $2,000 higher during 2005–2007; $3,000 higher in 2008; $5,000 higher in 2009; $5,010 higher in 2010; $5,080 higher in 2011; $5,210 higher in 2012; $5,340 higher in 2013; $5,430 higher in 2014; $5,520 higher in 2015; $5,550 higher in 2016; $5,590 higher in 2017; and $5,690 higher for families with children and $5,680 for families without children in 2018.

B State EITC parameters

Table 12: STATE EITC PARAMETERS

State	Tax year	Rate as % of federal EITC
CO	2015 – 2018	10.00
CT	2011 – 2012	30.00
	2013	25.00
	2014 – 2016	27.50
	2017 – 2018	23.00
DC	2005 – 2007	35.00
	2008 – 2018	40.00
DE	2006 – 2018	20.00
IA	2005 – 2006	6.50
	2007 – 2012	7.00
	2013	14.00
	2014 – 2018	15.00
IL	2005 – 2011	5.00
	2012	7.50
	2013 – 2016	10.00
	2017	14.00
	2018	18.00
IN	2005 – 2008	6.00
	2009 – 2018	9.00
KS	2005 – 2006	15.00
	2007 – 2009	17.00
	2010 – 2012	18.00
	2013 – 2018	17.00
LA	2008 – 2018	3.50
ME	2005	4.92
	2006 – 2008	5.00
	2009 – 2010	4.00
	2011 – 2018	5.00
⋮	⋮	⋮
⋮	⋮	⋮
MA	2005 – 2015	15.00
	2016 – 2018	23.00
MD	2005 – 2018	50.00
MI	2008	10.00
	2009 – 2011	20.00
	2012 – 2018	6.00
NC	2008	3.50
	2009 – 2012	5.00
	2013	4.50
NE	2006	8.00
	2007 – 2018	10.00
NM	2007	8.00
	2008 – 2018	10.00
NY	2005 – 2018	30.00
OH	2013	5.00
	2014 – 2018	10.00
OK	2005 – 2018	5.00
OR	2005 – 2007	5.00
	2008 – 2013	6.00
	2014 – 2018	8.00
RI	2005 – 2014	25.00
	2015	10.00
	2016	12.50
	2017 – 2018	15.00
SC	2018	20.83
VA	2006 – 2018	20.00
VT	2005 – 2017	32.00
	2018	36.00

Source: National Bureau of Economic Research’s Taxsim table, corrected by the authors

C Data description

In our study, we utilized four datasets provided by IPUMS (Flood et al., 2024; Ruggles et al., 2025):

i) American Community Survey (ACS)

ii) Current Population Survey - Basic Monthly Survey (CPS-BMS)

iii) Current Population Survey - Earner Study (CPS-ES)

iv) Current Population Survey - Annual Social and Economic Supplement (CPS-ASEC)

This appendix fully describes the datasets used in our study.

C.1 American Community Survey (ACS)

C.1.1 Description

The ACS is a 1-in-100 national random sample of the population, specifically designed to analyze long-term trends in education, employment, income, and family patterns. ACS 1-year estimates are published each year and are available for a broad range of geographical areas. The smallest identifiable geographic unit is the Public Use Microdata Area (PUMA). PUMAs cover the entire United States. Each state is divided into a series of PUMAs containing at least 100,000 persons. PUMAs are built on county and neighborhood boundaries and do not cross state lines. In our study, we use the ACS 1-year for 2005–2018, extracted from IPUMS at `https://usa.ipums.org/usa/`, to estimate the effect of state EITCs on education using policy discontinuities at state borders.

C.1.2 Sample

Our sample is restricted to respondents who participated in the ACS between 2005 and 2018. Our empirical strategy requires limiting the sample to states that express their EITC as a percentage of the federal EITC (regardless of the number of children) and share a border with at least one other state that follows the same approach. For these reasons,

i) we drop Alaska and Hawaii, which do not share a border with another state;

ii) we exclude California, which has implemented a state EITC not expressed as a percentage of the federal EITC since 2015; and

iii) we exclude New Jersey and Wisconsin, which are the only two states where the credit rate depends on the number of children.

C.1.3 Variables

The variable *State EITC* is determined at the state level. For other variables, we use PUMA as the unit of analysis.

Year: This variable corresponds to the IPUMS variable YEAR.

State EITC: This variable corresponds to the state EITC (as a percentage of the federal EITC), reported in Appendix B.

PUMAs: PUMA definitions are altered after each decennial census, so PUMA codes are not consistently comparable across time. To support spatio-temporal analysis, we use IPUMS variable CPUMA0010, which identifies consistent PUMAs over the period 2005–2018. We then use the boundary files provided by IPUMS (see the next subsection for more details) to match each PUMA to its state.

Age: This variable corresponds to the IPUMS variable AGE.

High school dropout rate: Among 18–24-year-olds (IPUMS variable AGE = 18–24) who are not enrolled in high school or a lower education level (IPUMS variable GRADEATT $\neq$ 1-5), the percentage who have not completed high school (IPUMS variable EDUC < 6).

High school completion rate: Among 18–24-year-olds (IPUMS variable AGE = 18–24) who are not enrolled in high school or a lower education level (IPUMS variable GRADEATT $\neq$ 1-5), the percentage who hold a high school diploma or alternative credential (IPUMS variable EDUC = 6-11).

Male: This variable equals one if the respondent is male (IPUMS variable SEX = 1), and zero otherwise.

Race: This variable corresponds to the IPUMS variable RACE.

C.1.4 Supplementary material

Boundary files for PUMAs: We use the IPUMS GIS boundary files available at `https://usa.ipums.org/usa/volii/boundaries.shtml` to define the PUMA boundaries and compute the contiguity matrix of PUMAs.

Boundary files for states: We use the IPUMS GIS boundary files available at `https://www.nhgis.org/` to define state boundaries and compute the contiguity matrix of states.

C.2 Current Population Survey - Basic Monthly Survey (CPS - BMS)

C.2.1 Description

The CPS - BMS is the primary source of labor force statistics for the US population. It provides a comprehensive body of monthly data on employment and labor force characteristics. In our study, we use the CPS - BMS, extracted from IPUMS at `https://cps.ipums.org/cps/`, to compute the life-cycle transition matrices across employment and family statuses. We also use the CPS - BMS to determine employment rates by age and education.

C.2.2 Sample

Our sample is restricted to individuals who participated in the Basic Monthly Survey (BMS) between 2005m1 and 2018m12. We use the IPUMS variable CPSIDP to identify individuals across CPS samples. We use the all-age sample to determine the number of EITC-eligible children, then compute the monthly transition matrices from age 20 to 69.

C.2.3 Variables

Time: This variable is constructed by combining the IPUMS variables YEAR and MONTH.

Age: This variable corresponds to the IPUMS variable AGE and is top-coded at 80.

Low-skilled: This variable equals one if the respondent has not completed high school (IPUMS variable EDUC < 70), and zero otherwise.

Middle-skilled: This variable equals one if the respondent has completed high school (IPUMS variable EDUC = 70–73), and zero otherwise.

High-skilled: This variable equals one if the respondent has completed at least one year of college (IPUMS variable EDUC > 73), and zero otherwise.

Employed: This variable equals one if the respondent is employed (IPUMS variable EMPSTAT = 1–12), and zero otherwise.

Married: This variable equals one if the respondent is married (IPUMS variable MARST = 1–2), and zero otherwise.

Number of EITC-eligible children: This variable identifies the number of EITC-eligible children a respondent has. An EITC-eligible child is a household member (child, stepchild, sibling, grandchild, or foster child) (IPUMS variable RELATE = 301, 303, 701, 901, or 1242) who is either under 19 (IPUMS variable AGE < 19) or younger than 24 and a full-time student (IPUMS variable AGE < 24 & IPUMS variable EMPSTAT = 33).

C.2.4 Supplementary material

Life-cycle transition matrices across employment status: We use the variable *Employed* to define employment status (=Nonemployed, E=Employed). We follow Menzio et al. (2016) and Albertini and Terriau (2019) to determine the age profile of transitions across employment status:

i) we consider that an individual experiences a NE transition if she is nonemployed in a given month and employed the next month.

ii) we consider that an individual experiences an EN transition if she is employed in a given month and nonemployed the next month.

iii) we consider that an individual experiences an EE pattern if she is employed in a given month and still employed the next month.

iv) we consider that an individual experiences a NN pattern if she is nonemployed in a given month and still nonemployed the next month.

The life-cycle transition matrices across employment statuses are determined using monthly transitions for a given age. Transition matrices are determined separately for each skill level.

Life-cycle transition matrices across family statuses: We use the variable *Number of EITC-eligible* *children* to define the family status (Child0=No EITC-eligible children, Child1=One EITC-eligible children, Child2=Two EITC-eligible children, Child3=Three or more EITC-eligible children). We then adopt a similar approach to determine the age profile of transitions across family statuses. The life-cycle transition matrices across family statuses are determined using monthly transitions for a given age. Transition matrices are determined separately for each skill level.

C.3 Current Population Survey - Earner Study (CPS - ES)

C.3.1 Description

Every household participating in the CPS is interviewed each month for two 4-month periods, separated by 8 months. The fourth- and eighth-month interviews include additional labor questions that form the CPS-ES and provide rich, reliable information on current earnings and hours worked. In our study, we use the CPS - ES, extracted from IPUMS at `https://cps.ipums.org/cps/`, to compute the life-cycle profiles of wages and hours worked.

C.3.2 Sample

Our sample is restricted to individuals who participated in CPS - ES) between 2005 and 2018. We use the all-age sample to determine the number of EITC-eligible children, and then compute the life-cycle profiles from age 20 to 69.

C.3.3 Variables

Age: This variable corresponds to the IPUMS variable AGE and is top-coded at 80.

Low-skilled: This variable equals one if the respondent has not completed high school (IPUMS variable EDUC < 70), and zero otherwise.

Middle-skilled: This variable equals one if the respondent has completed high school (IPUMS variable EDUC = 70–73), and zero otherwise.

High-skilled: This variable equals one if the respondent has completed at least one year of college (IPUMS variable EDUC > 73), and zero otherwise.

Employed: This variable equals one if the respondent is employed (IPUMS variable EMPSTAT = 1–12), and zero otherwise.

Married: This variable equals one if the respondent is married (IPUMS variable MARST = 1–2), and zero otherwise.

Number of EITC-eligible children: This variable identifies the number of EITC-eligible children a respondent has. An EITC-eligible child is a household member (child, stepchild, sibling, grandchild, or foster child) (IPUMS variable RELATE = 301, 303, 701, 901, or 1242) who is either under 19 (IPUMS variable AGE < 19) or younger than 24 and a full-time student (IPUMS variable AGE < 24 & IPUMS variable EMPSTAT = 33).

Male: This variable equals one if the respondent is male (IPUMS variable SEX = 1), and zero otherwise.

Race: This variable corresponds to the IPUMS variable RACE.

Hours worked per month: This variable corresponds to the number of hours usually worked per week in the current job (IPUMS variable UHRSWORK1) multiplied by 52/12.

Monthly wage: This variable corresponds to the income usually earned per week in the current job (IPUMS variable EARNWEEK) multiplied by 52/12.

Hourly wage: This variable corresponds to the *Monthly wage* divided by the number of *Hours worked per month*.

C.3.4 Supplementary material

All dollar amounts are adjusted for inflation using the IPUMS variable CPI99. All values are expressed in 2018 dollars.

C.4 Current Population Survey - Annual Social and Economic Supplement (CPS - ASEC)

C.4.1 Description

The CPS - ASEC is a supplemental survey that provides rich data on income and tax liabilities. In our study, we use the CPS - ASEC, extracted from IPUMS at `https://cps.ipums.org/cps/`, to compute the net social transfer over the life cycle.

C.4.2 Sample

Our sample is restricted to individuals who participated in the ASEC between 2005 and 2018. We use the all-age sample to determine the number of EITC-eligible children, and then compute the net social transfer from age 20 to 69.

C.4.3 Variables

Age: This variable corresponds to the IPUMS variable AGE and is top-coded at 80.

Low-skilled: This variable equals one if the respondent has not completed high school (IPUMS variable EDUC < 70), and zero otherwise.

Middle-skilled: This variable equals one if the respondent has completed high school (IPUMS variable EDUC = 70–73), and zero otherwise.

High-skilled: This variable equals one if the respondent has completed at least one year of college (IPUMS variable EDUC > 73), and zero otherwise.

Employed: This variable equals one if the respondent is employed (IPUMS variable EMPSTAT = 1–12), and zero otherwise.

Married: This variable equals one if the respondent is married (IPUMS variable MARST = 1–2), and zero otherwise.

Number of EITC-eligible children: This variable identifies the number of EITC-eligible children a respondent has. An EITC-eligible child is a household member (child, stepchild, sibling, grandchild, or foster child) (IPUMS variable RELATE = 301, 303, 701, 901, or 1242) who is either under 19 (IPUMS variable AGE < 19) or younger than 24 and a full-time student (IPUMS variable AGE < 24 & IPUMS variable EMPSTAT = 33).

Welfare: This variable corresponds to the IPUMS variable INCWELFR and denotes the amount received by a respondent from various public assistance programs commonly referred to as "welfare."

Unemployment Benefits: This variable corresponds to the IPUMS variable INCUNEMP and denotes the amount received by a respondent in unemployment benefits.

Worker's Compensation: This variable corresponds to the IPUMS variable INCWKCOM and denotes the amount received by a respondent in worker's compensation.

Educational Assistance: This variable corresponds to the from IPUMS variable INCEDUC and denotes the amount received by a respondent in educational assistance.

Income Tax Liability: This variable identifies the net transfer from the income tax system, excluding the EITC. It is measured by the sum of federal and state income tax liabilities after deducting tax credits (IPUMS variables FEDTAXAC and STATAXAC). It includes the child tax credit but excludes the EITC (IPUMS variable EITCRED), whose structure is directly reproduced in our programs.

Net social transfer: This variable denotes the net social transfer, depending on age, education, labor force status, and family status. It corresponds to: *Welfare* + *Unemployment Benefits* + *Worker's Compensation* + *Educational Assistance* − *Income Tax Liability*.

C.4.4 Supplementary material

All dollar amounts are adjusted for inflation using the IPUMS variable CPI99. All values are expressed in 2018 dollars.

D Effect of EITC on the high school dropout rate - Alternative control group to test for spillover effects

Table 13: EFFECT OF EITC ON THE HIGH SCHOOL DROPOUT RATE - ALTERNATIVE CONTROL GROUP TO TEST FOR SPILLOVER EFFECTS

VARIABLES	(1)	(2)	(3)	(4)
State EITC	0.0578**	0.0580**	0.0580**	0.0582**
	(0.0268)	(0.0265)	(0.0269)	(0.0267)
Controls				
PUMA-pair × period dummies	YES	YES	YES	YES
Demographics	YES	YES	YES	YES
Parental environment	YES	YES	YES	YES
Labor market	YES	YES	YES	YES
State policy	YES	YES	YES	YES
Additional controls				
Compulsory school age	NO	YES	NO	YES
Minimum wage	NO	NO	YES	YES
Number of periods	14	14	14	14
Number of PUMA pairs	401	401	401	401
R-squared	0.8103	0.8103	0.8110	0.8110

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

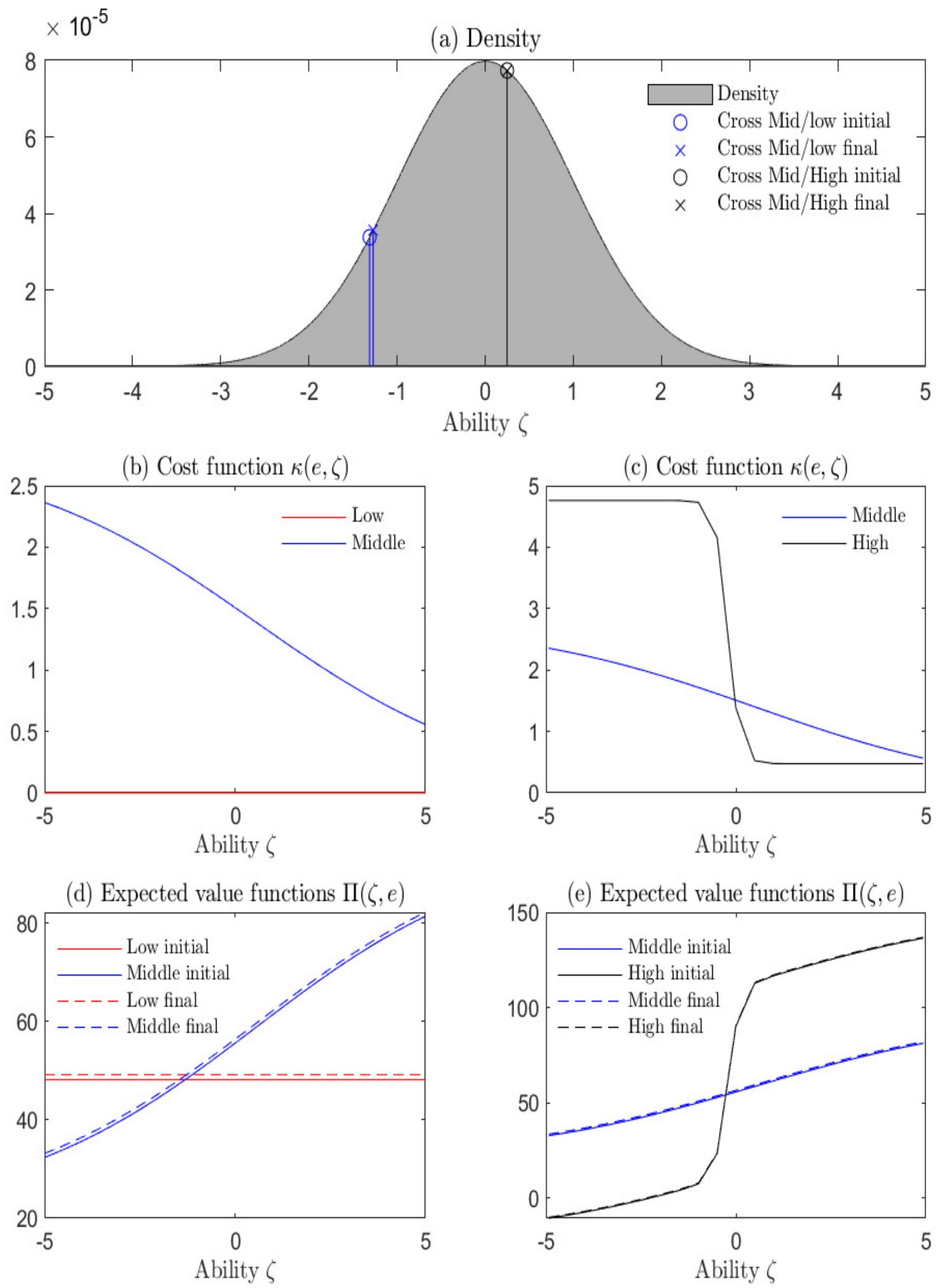
Source: ACS 1-year, 2005–2018

Demographics: *sex, race;* ***Parental environment:*** *parents' education, income, number of EITC-eligible children;* ***Labor market****: employment rate by education level;* ***State policy:*** *federal/state supplemental security income, aid to families with dependent children, general assistance, food stamps*

Our estimates reveal that a 1-percentage-point increase in state EITC (as a percentage of the federal EITC) leads to a 0.07-percentage-point rise in the high school dropout rate.

E Density, costs and expected values related to education

Figure 15: DENSITY, COSTS AND EXPECTED VALUES RELATED TO EDUCATION

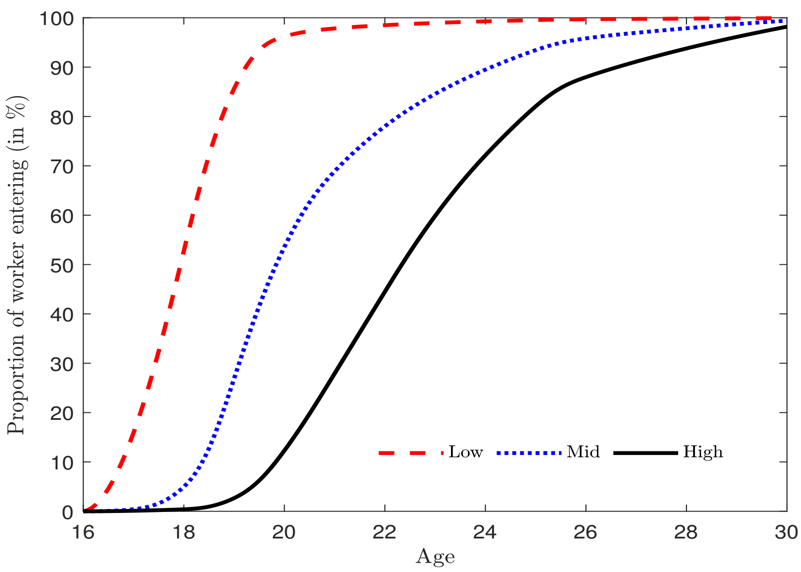


F Public and private costs of education

To calibrate college costs, we follow Donovan and Herrington (2019) by using the tables of the *Digest of Education Statistics*[50], taking 2018 as the reference year. C_s denotes the annual private college costs. We use Table 301.10 to calculate the number of students enrolled in every degree-granting institution (public, non-profit, and for-profit). Table 330.10 gives us the average tuition fees per undergraduate student in all institutions combined. We calculate the public cost of education C_p from the revenues of public and private institutions. We use Tables 333.10, 333.40 and 333.55 for the public aid received by public, non-profit, and for-profit institutions, respectively. We sum the federal and local funding for grants and contracts for every institution. The total cost divided by the number of students gives the average cost per undergraduate student enrolled in a degree-granting institution:

G Labor market entries

Figure 16: LABOR MARKET ENTRIES



H Life-cycle wage profiles

To construct the life-cycle wage profiles, we estimate the following model:

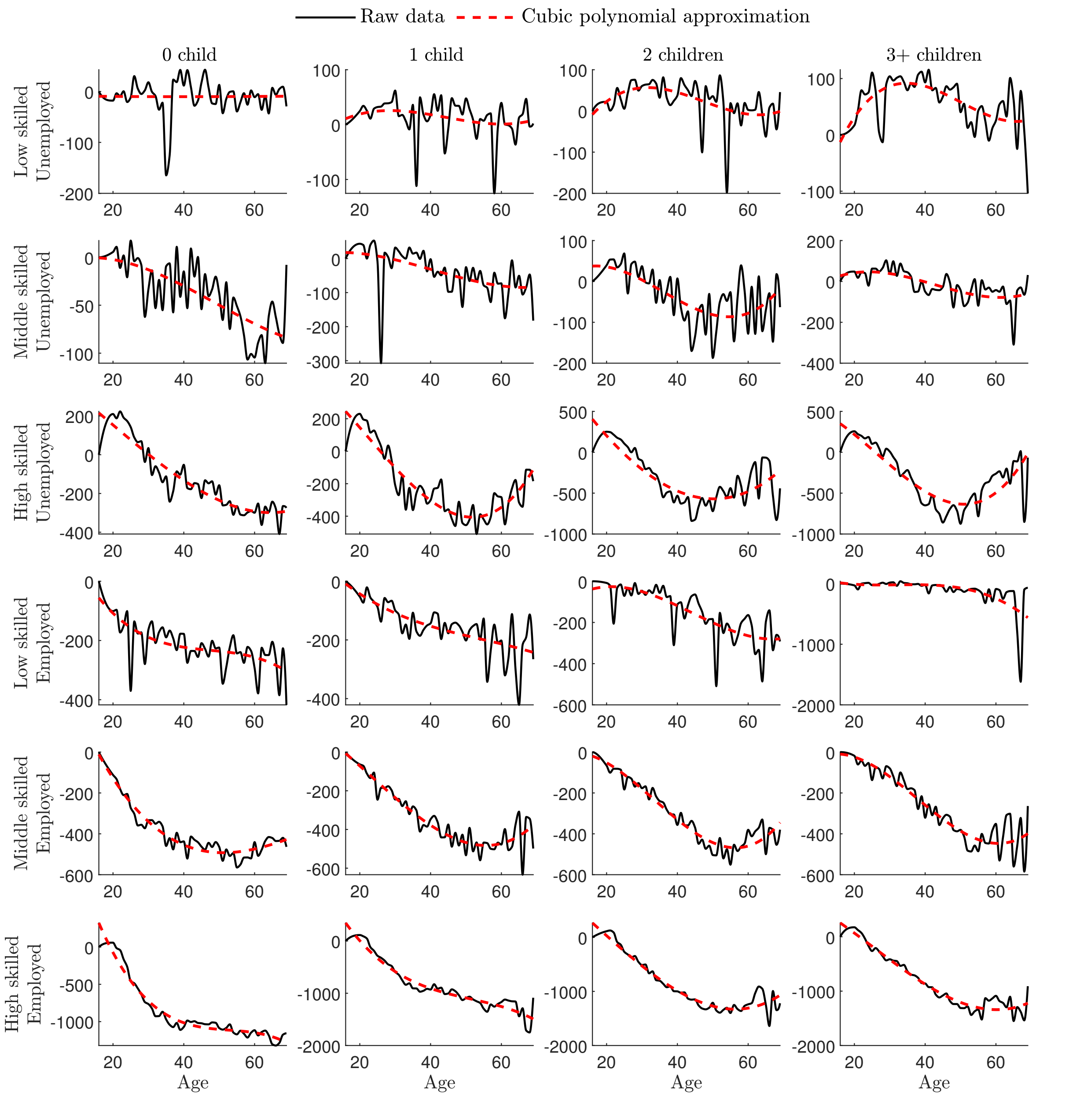
$$\omega_{it} = \alpha_1 + \sum_{j=0,1,2} \beta_a^j Age_{it} \mathbb{1}_{\{h_{it}=j\}} + \beta_c C_{it} + \beta_t D_t + \gamma_i + u_{it} \tag{33}$$

where ω is the wage, C is a set of sociodemographic characteristics, D is a set of year dummy variables, and γ_i is an individual-specific effect. $h_{it} = 0$ if a worker is low-skilled, $h_{it} = 1$ if a worker is middle-skilled, and $h_{it} = 2$ if a worker is high-skilled. We then use the age and education effects to construct the mean life-cycle profiles (see Figure 8), which represent the empirical counterparts of the profiles simulated by our model.

[50]See Snyder et al. (2019)

I Net social transfer

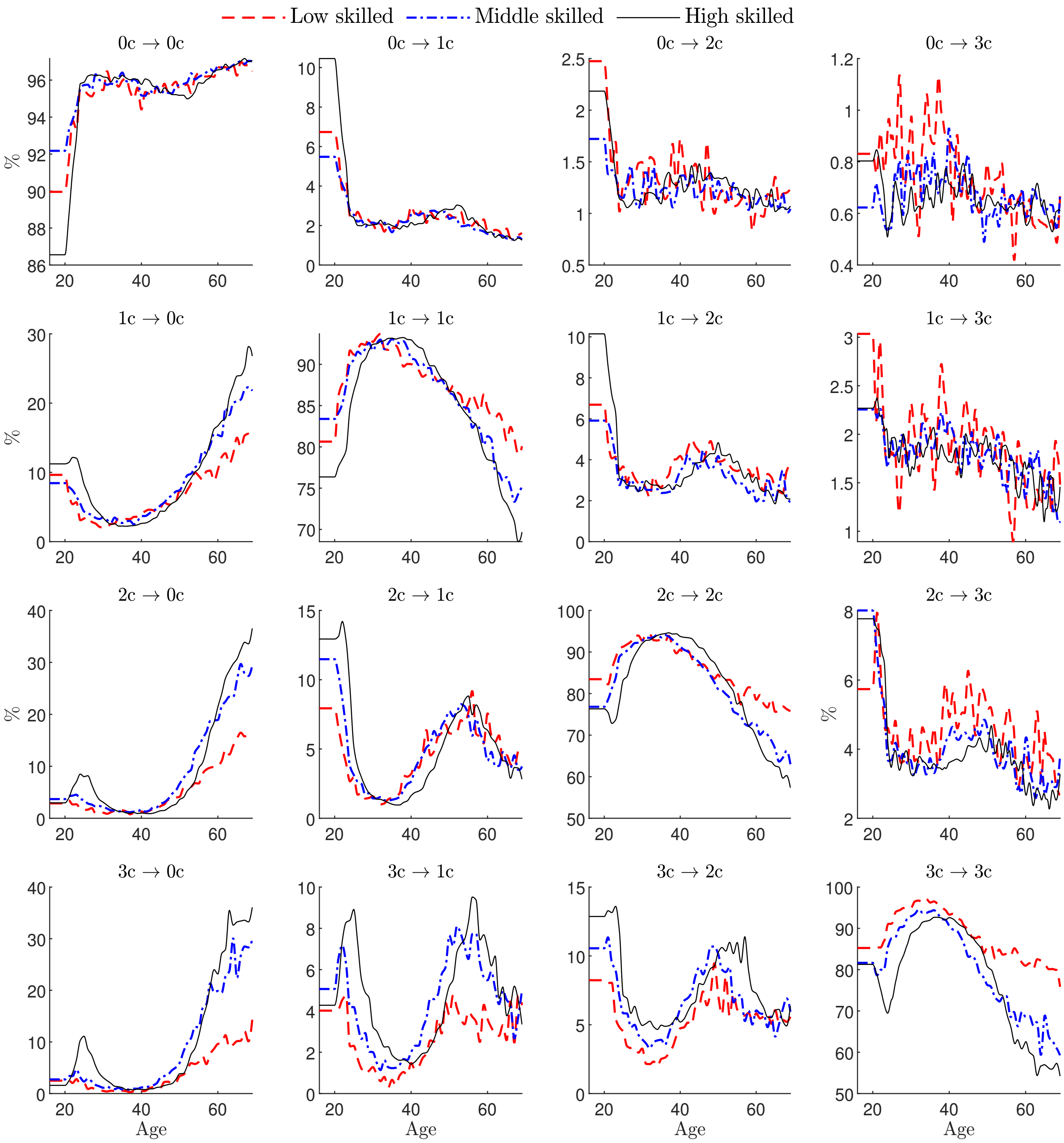
Figure 17: NET SOCIAL TRANSFER



Welfare less taxes, depending on age, education, labor force status, and family status (see Appendix C.4 for more details). 0C: No EITC-eligible child; 1C: One EITC-eligible child; 2C: Two EITC-eligible children; 3C+: Three or more EITC-eligible children.

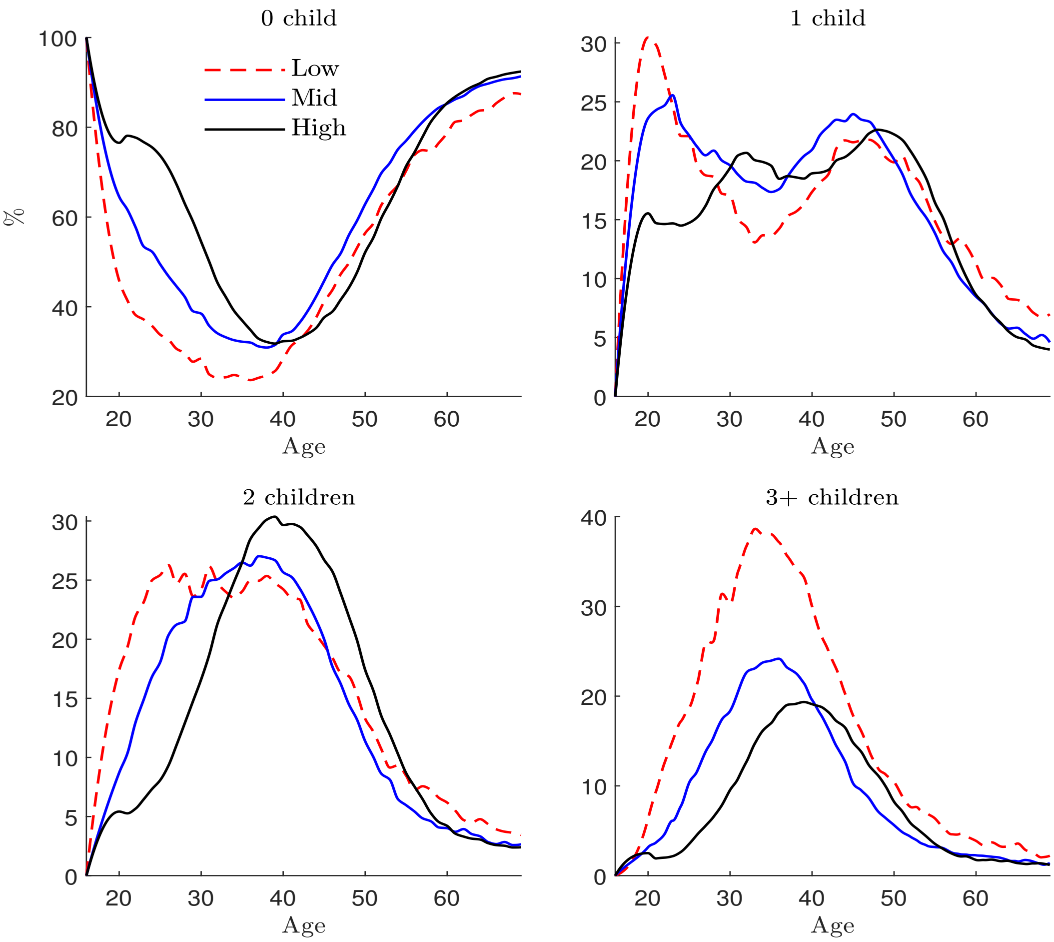
J Transition probabilities and family status proportions

Figure 18: TRANSITION PROBABILITIES



Probabilities of transitioning from one family status to another, based on the CPS - BMS (see Appendix C.2 for more details). 0C: No EITC-eligible child; 1C: One EITC-eligible child; 2C: Two EITC-eligible children; 3C+ : Three or more EITC-eligible children. Transition rates are displayed on an annual basis. Note: We consider here the number of qualifying children in the individual's household, not just the individual's own children. This includes her children, siblings, or even herself if she qualifies as her parents' child.

Figure 19: FAMILY STATUS PROPORTIONS



Family status proportions by age and education level, based on the CPS - BMS (see Appendix C.2 for more details).

K Welfare calculation

For clarity, we use **bold** letters to define the aggregate values (weighted and summed using firms and workers distributions of age a) across all states (h, f, x, e). Aggregate consumption is defined by:

$$\boldsymbol{C}(a) \quad = \quad \boldsymbol{w}(a) + \boldsymbol{b}(a) + \boldsymbol{EITC}(a) - \boldsymbol{T}(a) + \boldsymbol{\Pi}(a)$$

where $\boldsymbol{w}(a), \boldsymbol{b}(a), \boldsymbol{EITC}(a), \boldsymbol{T}(a), \boldsymbol{\Pi}(a)$ correspond to total wages, total transfers, total EITC, total lump-sum taxes, and total profits, respectively. Note that the balanced-budget rule can be written as:

$$\boldsymbol{T}(a) \quad = \quad \boldsymbol{b}(a) + \boldsymbol{EITC}(a) + \boldsymbol{C_s}(a) + \boldsymbol{C_p}(a)$$

where $\boldsymbol{C_s}(a)$ denotes the public cost of education and $\boldsymbol{C_p}(a)$ the cost of student grants. The previous equations simplify to:

$$\boldsymbol{C}(a) \quad = \quad \boldsymbol{w}(a) + \boldsymbol{\Pi}(a)$$

Total profit is given by:

$$\boldsymbol{\Pi}(a) \quad = \quad \boldsymbol{y}(a) - \boldsymbol{w}(a) - \boldsymbol{c}(a)$$

where $\boldsymbol{y}(a)$ is total output and $\boldsymbol{c}(a)$ is the total vacancy posting cost. Therefore:

$$\boldsymbol{C}(a) \quad = \quad \boldsymbol{y}(a) - \boldsymbol{c}(a)$$

Present welfare by age level can thus be written as:

$$\mathcal{W}(a) \quad = \quad \underbrace{\boldsymbol{C}(a)}_{\text{Consumption}} - \underbrace{\boldsymbol{D}(a)}_{\substack{\text{Labor} \\ \text{disutility}}} - \underbrace{\boldsymbol{K}(a)}_{\substack{\text{Search} \\ \text{costs}}} - \underbrace{\boldsymbol{E}(a)}_{\substack{\text{Education} \\ \text{costs}}},$$

where,

$$\begin{aligned}
\boldsymbol{C}(a) &= \sum_e \Gamma(e) \sum_h \int_x \int_f y(h,f,x,e) n(h,a,f,x,e) - c_e v(h,a,f,e) df\, dx \\
\boldsymbol{D}(a) &= \sum_e \Gamma(e) \sum_h \int_x \int_f n(h,a,f,x,e) \eta(a,e) \frac{\ell(h,a,f,x,e)^{1+\phi}}{1+\phi} df \\
\boldsymbol{K}(a) &= \sum_e \Gamma(e) \sum_h \int_f u(h,a,f,e) k(h,a,f,e) df \\
\boldsymbol{E}(a) &= \sum_e \Gamma(e) \mathbb{1}_{\{a \leq d_e\}} \int_\zeta \kappa(e,\zeta) dZ(\zeta)
\end{aligned}$$

Welfare is defined as the discounted sum of consumption streams for every worker aged a–a_A:

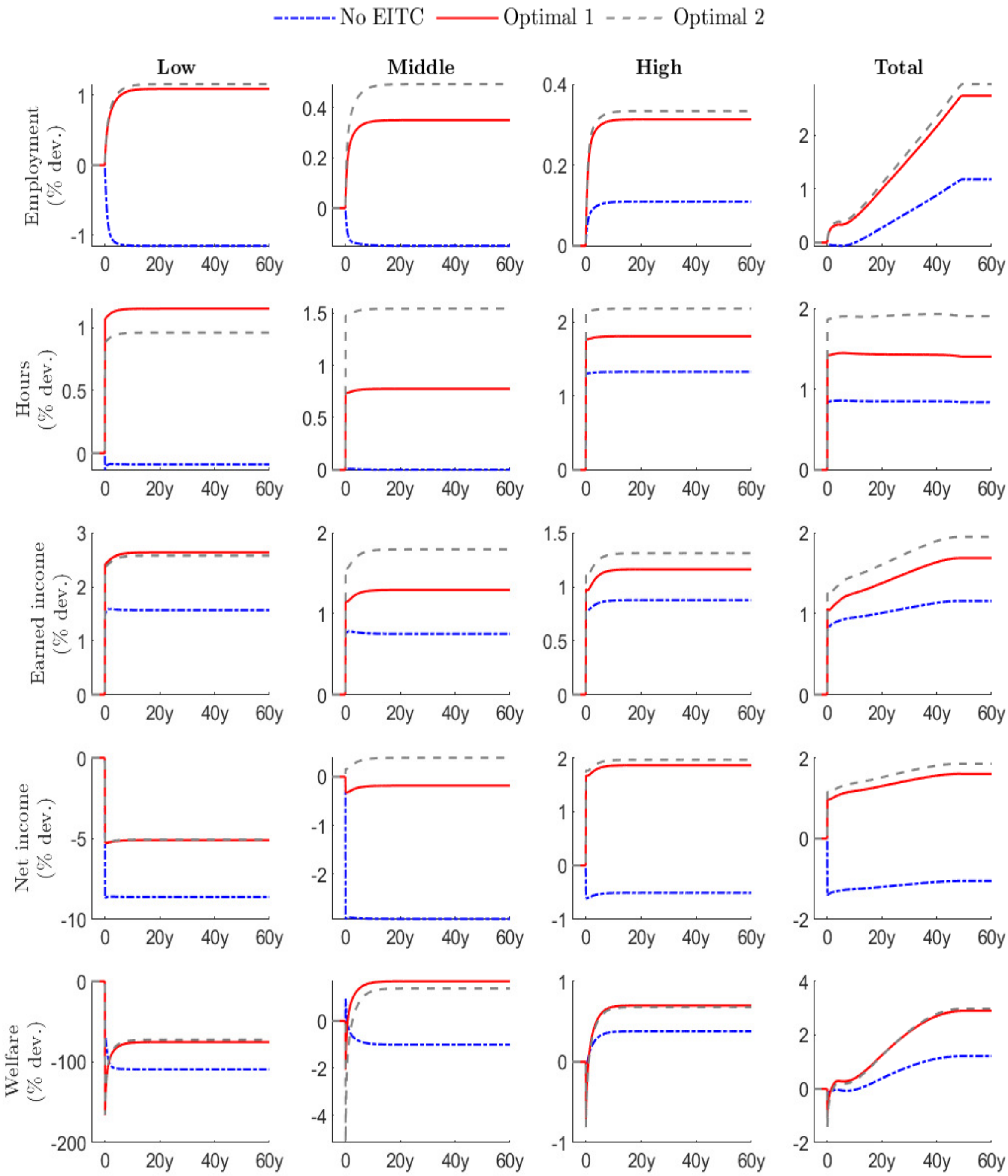
$$\overline{\mathcal{W}} \quad = \quad \sum_{a=1}^{n_a} \sum_{a'=a}^{n_a} \beta^{a'-a} \mathcal{W}(a') L(a')$$

The alternative welfare measure computes the average consumption level:

$$\overline{\mathcal{W}} \quad = \quad \sum_{a=1}^{n_a} L(a) \mathcal{W}(a)$$

L Transitional dynamics of optimal EITC

Figure 20: TRANSITIONAL DYNAMICS OF OPTIMAL EITC



We implement the alternative scenarios as unexpected reforms. Column (4) sums variables by skill using the proportion of individuals in each skill category, which changes as new cohorts enter the labor market.

M Survival function of an EITC increase

Figure 21: SURVIVAL FUNCTION OF AN EITC INCREASE (NO CHANGE IN STATE EITC)

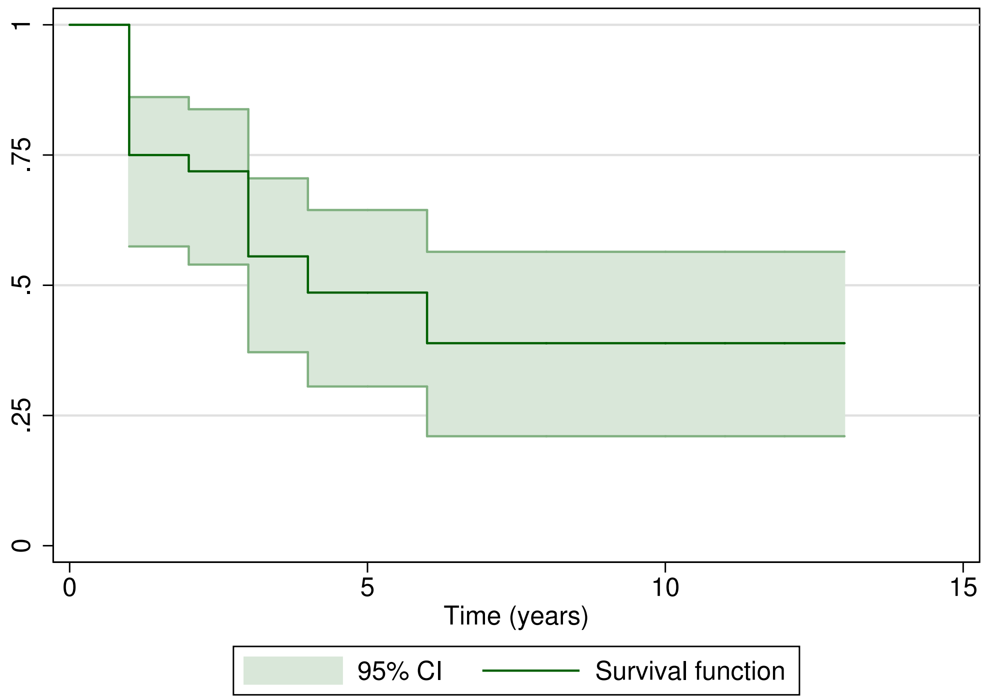


Figure 22: SURVIVAL FUNCTION OF AN EITC INCREASE (NO DECREASE IN STATE EITC)