The Earned Income Tax Credit and Occupational Skill Mismatch *

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Abstract

By exploring several expansions of the Earned Income tax Credit (EITC), this paper provides an intent-to-treat estimate of job match quality response to wage subsidies. As a conceptual framework, I develop a simple job search model with wage subsidies, which predicts that increases in the subsidy benefit increase the marginal opportunity cost of search, therefore increasing the search cost. The increase in the cost of search reduces the net-of-cost benefit of holding out or waiting for better job opportunities, creating incentives for job seekers to lower their reservation wages, hence reducing the potential of forming a better job match. The underlying hypothesis of this study based on the predictions of this search model is that the EITC may have an unintended consequence of creating worse job matches in an initial job taken after reentering the labor market. I define the quality of a job match as the difference between the set of skills required by an occupation and the set of abilities a worker possesses for learning those skills. Using a simulated instrument approach and data from the 1979 National Longitudinal Survey of Youth and the Occupational Information Network, results reveal that the EITC increases skill mismatch in an initial job, with the results driven by workers being overqualified for their jobs. Coefficient estimates show that much of the effect is concentrated among single women with some level of college education. Evidence also reveals that mismatch lowers the starting wage of workers. These findings suggest that the effort of policymakers to reduce welfare dependency by using wage subsidies to promote employment may lead to unintended consequences such as poor match quality and lower starting wages.

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1 Introduction

Concerns about the disincentives to work inherent in the U.S. welfare system have made the Earned Income Tax Credit (EITC), which transfers income to low- and moderate-income families while encouraging work, a cornerstone of work-contingent anti-poverty programs. Since its inception in 1975, the EITC has been expanded to benefit several U.S. households. In 2022, about 23 million eligible families and workers received approximately $57 billion in benefits from the EITC (Internal Revenue Service 2024). Unlike other traditional welfare programs, the EITC operates through the tax system as a refund, requiring individuals to have earned a positive income within a tax year to receive the benefit. Economic theory predicts that the EITC will increase employment among the targeted population. Consistent with these predictions, studies have shown that the EITC promotes work, especially among those more likely to be eligible for the credit (Eissa and Liebman 1996; Meyer and Rosenbaum 2001; Meyer 2002). Conventional wisdom suggests that the financial incentives from the EITC benefit may lead to unintended outcomes, such as eligible workers taking up low-quality jobs. The EITC may have this effect if, among eligible job seekers, the benefit affects the decision to search and find a suitable job match. Match quality is an important labor market phenomenon because it impacts various outcomes, such as the wages of workers. For example, Guvenen et al. (2020b) finds that mismatch slows wage growth in a worker's current occupation and leaves a scarring effect that adversely affects wages in future occupations, and Bowlus (1995) finds that the labor market internalizes mismatching through lower starting wages.

Despite the growing popularity of the EITC and its potential to impact job match quality, less is known about whether the EITC has any effect on job match quality. Specifically, it is not clear in the literature whether the increasing generosity of the subsidy benefit has affected the quality of initial job matches formed by eligible job seekers who are reentering employment.

The objective of this paper is to investigate whether the increasing generosity of the EITC, resulting from various expansions, has any effect on the quality of job matches formed in an initial job. To do that, I first develop a simple job search model with wage subsidies which predicts that increases in the EITC increase the marginal opportunity cost of search, therefore increasing the cost of search. The increase in the cost of search reduces the net-of-cost benefit of holding out for better opportunities, creating incentives for job seekers to lower their reservation wages, consequently reducing the potential of forming a better job match. Based on the prediction of this model, I test the hypothesis that the EITC may have an unintended consequence of creating worse job matches in an initial job taken after reentering the labor market.

Match quality has been operationalized using different measures (Jovanovic 1979; Akerlof et al. 1988; Rumberger 1987; Bowlus 1995; Groes, Kircher, and Manovskii 2015). To test my hypothesis, I follow the emerging literature on multidimensional match quality to define the quality of a job match as the difference between the set of skills required by an occupation and the set of abilities a worker possesses for learning those skills (Guvenen et al. 2020b; Lise and Postel-Vinay 2020; Addison, Chen, and Ozturk 2020). In my analysis, I focus on mismatch along four types of skills: cognitive math, verbal, science/technology/mechanics (STM), and non-cognitive attitudinal social skills. Also, I construct an aggregate measure of mismatch, which is a weighted average of the mismatch along the four skill dimensions.

The main dataset for the empirical analysis is the National Longitudinal Survey of Youth 1979 cohort (NLSY79), which I supplement with the Department of Labor's O*NET (Occupational Information Network) database, which contains information on characteristics of over 1000 occupations, including descriptors of the mix of knowledge, skills, and abilities (KSA) required to perform each occupation-specific task content. The NLSY79 dataset is well suited for this study for three main reasons. First, it provides a detailed record of demographic characteristics and histories of employment outcomes, such as hourly wages, occupation, and industry codes. Second, the NLSY79 also contains measures of occupation-relevant skills and abilities scores for each respondent who took the Armed Services Vocational Aptitude Battery (ASVAB). Finally, the NLSY79 contains attitudinal scales and sociability measures, which can be used to proxy for the non-cognitive attitudinal social skill endowment of individuals. I use the ASVAB test from the NLSY79 to obtain the ability endowment of workers and the KSAs from the O*NET to obtain occupational skill requirements. Relying on these two sets of information, I am able to measure the quality of the match for each occupation-worker pair in my analysis sample.

I conduct my empirical analysis using a simulated approach (See, Currie and Gruber 1996; Michelmore and Pilkauskas 2021; Michelmore, Strauss, and Wiemers 2024) to construct measures of the EITC benefit, which captures variation in the EITC benefit arising from several federal and state expansions and state implementations of the program. By leveraging this rich set of variations in the EITC benefit from 1980 to 2006, I provide an intent-to-treat estimate of how changes in the EITC generosity impact occupational skill mismatch among single non-college-educated women. I focus my analysis on single women with less than a college degree, as this group is more likely to be eligible for the EITC benefits. Additionally, I examine whether the EITC benefit affects starting wages and if skill mismatch impacts the starting wages of single non-college-educated women.

The results of my analysis indicate that increases in the EITC benefit generosity increase occupational skill mismatch in reentry jobs among single non-college-educated women. I find evidence that much of the mismatch results from workers being overqualified for their initial jobs. Evidence also shows that much of the mismatch effect is concentrated among single women with some level of college education. Additional analysis reveals that mismatch is driven by workers being poorly matched along the math, verbal, and STM skill dimensions. However, I find no evidence that the EITC affects mismatch along the attitudinal social skill dimension. Although my results show that the EITC negatively impacts workers' starting wages and estimates are economically meaningful, most are not statistically significant except among mothers. I find that being mismatched- whether being overqualified or underqualified for one's job- lowers the starting wage of workers, consistent with the findings from Bowlus (1995) that the labor market internalizes mismatch through a lower starting wage.

This paper contributes to the impact of the EITC on labor market outcomes. Several studies have examined the effects of the EITC on various outcomes in the labor market, including labor force participation among the targeted population. This study adds to the literature by investigating whether increases in the program's generosity may have the unintended consequence of creating worse job matches in an initial job taken after reentering the labor market. Understanding whether the EITC negatively affects job match quality will help policymakers recognize the unintended consequences associated with work-contingent welfare programs such as the EITC.

Results from this paper build on the large literature on public assistance programs and the job search outcomes of eligible workers. Most existing papers have shown the match quality effect of the Unemployment Insurance benefit (Centeno 2004; Mario Centeno and A. A. Novo 2006; Mário Centeno and Á. A. Novo 2006; Van Ours and Vodopivec 2008), with little attention given to the EITC. The EITC may affect the quality of job matches formed by eligible workers if the benefit from the program impacts the decision to search and find a suitable job match. In this paper, I present evidence on whether the EITC benefit affects the quality of job matches formed by workers when they reenter the labor market.

The paper proceeds as follows. Section 2 provides a background on the EITC literature, and Section 3 reviews the literature related to this study. Section 4 provides the conceptual framework. In Section 5, I describe the data I use to perform the empirical analysis and how I create the variables used in the empirical model. Section 6 describes the identification and empirical strategy. I present empirical results in Section 7. Finally, I conclude in Section 8.

2 Background

The Earned Income Tax Credit(EITC) started in 1975 as a modest program to offset the Social Security payroll tax faced by low-income families. Eligible tax filers with no tax liabilities receive the total amount of the credit benefit as part of their tax refund. The program has been expanded several times to become one of the largest means-tested programs in the United States. Eligibility for the program and the benefit amount depends on Annual Gross Income (equal earnings if there are no self-employed earnings) and the number of qualifying dependents claimed by a taxpayer. For tax purposes, a qualifying dependent is a relative under age 18 (24 if a full-time student) and has resided with the claimant for at least six months within the tax year. The EITC has a nonlinear schedule, which means that the benefit phases in as earnings increase, reaches a plateau, and then begins to phase out until it reaches zero.

For a given income, subsidy payments are given by:

$$S(y) = \begin{cases} \tau_1 y & if \;\; 0 \leq y \leq y_{\tau_1} \\ B & if \;\; y_{\tau_1} < y \leq y_0 \\ B - \tau_2(y - y_0) & if \;\; y_0 < y < \hat{y} \\ 0 & if \;\; y \geq \hat{y} \end{cases} \tag{1}$$

where τ_1 is the subsidy rate in the phase-in region, B is the maximum benefit amount which phase-out at a rate of τ_2 when income exceeds the phase-out threshold, y_0. There is no subsidy payment for income greater than or equal to $\hat{y}$. The difference in the benefit rules based on earnings produces the trapezoidal shape of the EITC schedule. Figure 1 shows the structure of the EITC schedule for families with different numbers of qualifying children in selected years.

[Figure 1 about here]

Various expansions in the EITC have created changes in the benefit parameters over time. In the 1980s, the federal EITC was expanded under the Tax Reform Act 1986. The expansion increased the maximum credit available to households by raising the phase-in rate and regions and indexing the credit to inflation. Two federal expansions in the EITC occurred in the 1990s under the Omnibus Reconciliation Acts of 1990 (OBRA1990) and 1993 (OBRA1993). Before the OBRA1990 expansion, the same schedule was applied to all qualifying households. A slightly generous credit was made available to families with two or more qualifying children starting in 1991. The largest EITC expansion occurred under the OBRA1993, disproportionately affecting households of different sizes. The benefit was extended to workers without qualifying children for the first time, even though it was smaller compared to individuals with qualifying children. Households with two or more children experienced a substantial increase in the benefits such that by 1996, the average federal benefit that was available to such households was double that in 1993. The changes in the benefit rules rolled out over three years, starting in 1994. Figure 1 also illustrates the changes in the EITC schedule from these expansions. Some changes in the EITC also took place in the 2000s. In 2001, the benefit rules were adjusted for married couples by increasing the income level at which the benefit was phased out. There were no further federal expansions in the EITC in real terms until 2009 when a larger benefit was made available to households with three or more children under the American Recovery and Reinvestment Act (ARRA). The analysis period for this study ends in 2006 to avoid having biases in my estimates from the 2008 recession because some studies have shown that there is a cyclical variation in match quality.

Figure 2 shows a graphical illustration of the federal variation in the EITC benefit from 1980 to 2006 and the major expansions that occurred during that period. It is clear from the graph that the benefit has become more generous over time, especially towards households with more qualifying children starting from the 1990s.

[Figure 2 about here]

Some states have implemented their own EITC program. As of 2006, 20 states plus the District of Columbia had their own EITC program[1]. States differ in the years the program was implemented and the generosity of the benefits available to eligible families. State benefits are usually a fraction of the federal EITC benefit, except for some states, such as Minnesota, having their own EITC schedule. The overall generosity of the benefit ranges from 4% to 50% of the federal EITC, with some states having the benefit as either refundable or non-refundable. Table B1 in the appendix shows states that have an EITC program and the rules provided for the benefit between 1980 and 2006.

Figure 3 illustrates the variation in the state EITC for households with different numbers of qualifying children from 1980 to 2006. As seen in Figure 3A through 3D, the generosity of the benefit increases with the number of qualifying children, which is due to the state EITC being a fraction of the federal EITC.

[Figure 3 about here]

1. Colorado's EITC credit was enacted in 1999 and depended on whether the state had a surplus from its revenue. The credit was paid out between 1999 and 2001. The credit was made permanent in 2015 through legislation.

As the EITC benefit increases in generosity, eligible job seekers may be more motivated to accept any available job while continuing to search for a suitable match. This behavior may arise because a longer waiting period to search for a better match means more unclaimed money in EITC benefits. In my analysis, I explore the variations in federal and state EITC rates to estimate how changes in EITC generosity impact the quality of initial job matches among eligible job seekers, and the starting wages associated with these jobs.

3 Related Literature

The effects of the EITC on individual behaviors have been extensively studied.[2] However, there is scarce evidence on the effects of the EITC on the quality of job matches formed by eligible workers. In this section, I first provide an overview of the current stand of the EITC literature and then briefly discuss the literature on job match quality that relates to this study.

3.1 Previous Research on the EITC

The existing literature has largely focused on the effect of expansions of the EITC on labor supply. For example, Eissa and Liebman (1996) exploit changes in the EITC under the Tax Reform Act of 1986 (TRA86), which provided a natural experiment to study the effects of the EITC expansion and other aspects of the reform on the labor supply of single mothers. Eissa and Liebman find that the EITC expansion, which occurred under the TRA86, increased the relative labor force participation of single mothers by 2.8 percentage points. However, their results show no evidence of a change in the hours of work among single mothers compared to those without children. Consistent with the results from Eissa and Liebman, other studies with some using different datasets and empirical methods, have shown that the EITC has a positive effect on the labor force participation of eligible workers (See, Meyer and Rosenbaum 2001; Meyer 2002; Hotz, Mullin, and Scholz 2006; Wilson 2020; Michelmore and Pilkauskas 2021). Wilson (2020) provide evidence on whether expansions in the EITC affect the entry and exit decisions of eligible workers by using a fixed effects model. Results from this study show that expansions in the EITC increase the labor force attachment of less-educated single women by increasing their annual weeks worked and reducing the frequency of annual exit. Additionally, Michelmore and Pilkauskas (2021) show heterogeneity in mothers' labor supply response to the EITC and find that single mothers with children under age 3 are more responsive to the EITC than those with older children.

2. See Nichols and Rothstein (2015) for a comprehensive review of the existing EITC literature.

Evidence from the literature also supports that the EITC affects the duration of unemployment. For example, LaLumia (2013) apply the predictions of a cash-on-hand model to examine the effect of the EITC on unemployment duration among the EITC-eligible population. Using the EITC tax refund-related variation in liquidity across different calendar months, LaLumia finds that EITC-eligible mothers who enter into employment around the time of tax refund distribution have longer unemployment spells than their counterparts who enter into unemployment in different months.

Aside from the labor supply effects, the EITC may also affect other outcomes. For example, Leigh (2010) and Rothstein (2010) provide evidence showing that increases in the EITC are associated with a fall in the wages of workers more likely to receive the credit. Heckman, Lochner, and Cossa (2002) using different models of human capital accumulation, find mixed evidence on the effect of the EITC on skill formation. Concerning whether the EITC has any impact on family income, Neumark and Wascher (2001) and Hoynes and Patel (2015) provide evidence that supports that the EITC assists families to rise above poverty-level earnings. The increase in family income from the EITC may be a linkage to the findings in the literature that the EITC has a positive effect on household consumption (Barrow and McGranahan 2000; Smeeding, Phillips, and O'Connor 2000). Also, there is an expectation that the EITC may also affect family formation because of the marriage bonus and penalty inherent in the tax system. The benefit may create fertility incentives because the number of qualifying children in a household affects the benefit amount a household is eligible to receive. However, there exists inconclusive evidence in the literature on whether the EITC has any effect on family structure through marriage and fertility, even though most studies find little to no impact of the EITC on marriage and fertility (Ellwood 2000; Dickert-Conlin and Houser 2002; Michelmore 2014; Baughman and Dickert-Conlin 2009; Bastian 2017).

The closest related paper to this study is Dahl, DeLeire, and Schwabish (2009). Dahl and colleagues examine whether the 1993 EITC expansion had any effect on the type of jobs taken by eligible workers. Results show that the expansion was associated with an increase in long-run earnings growth, suggesting that the EITC did not create incentives for workers to take up "dead-end" jobs. Whereas Dahl, DeLeire, and Schwabish (2009) consider whether workers are taking up jobs that have room for advancement in terms of earning growth, this study focuses on whether the EITC affects the quality of the match formed by eligible workers, measuring match quality as the difference between workers and occupation characteristics. Moreover, in the case of Dahl and colleagues, earning growth may not be a sufficient measure to use in determining whether EITC-eligible workers are taking better jobs since growth in earnings is a component of wage effects and labor supply effects, and the EITC has a positive impact on the latter.[3] Also, evidence of earning growth does not suggest a higher starting wage for these workers.

In sum, the EITC affects workers' labor supply decisions and impacts other behaviors. In this paper, I investigate whether the EITC has any effects on the quality of initial job matches formed by workers when they reenter the labor force and the starting wage associated with these jobs. Additionally, I examine whether match quality has any impact on starting wages. The study explores the EITC expansions in the 1980s and 1990s and other state-level changes in the EITC instead of a single expansion to study the impact of the EITC on job match quality. Examining the effects of the EITC using this approach offers evidence of the effect of the program as a whole and not just a single expansion (Whitmore Schanzenbach and Strain 2021).

3.2 Previous Research on Job Match quality

A broader body of literature studies job match quality in the labor market. Match quality can be examined along several dimensions. From a theoretical perspective, the quality of a job match can be described in an abstract term. For example, Jovanovic (1979) characterizes match quality as a worker-job-specific component that makes a worker more productive in one job over another. This notion of match quality has been operationalized empirically using measures such as lack of education match and lack of job flexibility. Lack of education match measures the deviation of a worker's education from that required in a job. A lack of flexibility measures constraints such as fixed work hours. There is an emerging strand of the match quality literature that operationalizes match quality empirically using the difference between a multidimensional set of skills workers possess and that required in their occupation (Guvenen et al. 2020b; Lise and Postel-Vinay 2020; Addison, Chen, and Ozturk 2020).

Each of these types of match quality has implications for labor market outcomes. Using a theoretical model, Jovanovic (1979) shows that variation in the quality of a worker-employer match generates different tenure across jobs. Empirical investigators of match quality have also demonstrated that lack of education match affects job satisfaction, quit rate, and wages (Rumberger 1987; Hersch 1991). Also, evidence in the literature provides support that lack of skill match quality lowers wage growth (Guvenen et al. 2020b; Lise and Postel-Vinay 2020; Addison, Chen, and Ozturk 2020), depress human capital accumulation, and reduces the return to occupational tenure (Guvenen et al. 2020b). Furthermore, Goldin (2014) shows that within occupations that disproportionately reward hours and job continuity, there exists

3. See Eissa and Liebman (1996) and Meyer and Rosenbaum (2001) for a positive impact of the EITC on employment, and Chetty, Friedman, and Saez (2013) for a positive and significant increase in earnings among EITC recipients due to intensive margin labor supply response.

a large gender gap in earnings, a nonlinear (convex) relationship between earnings and hours, and workers who want flexibility experience large earning penalties.

This study is also related to the literature on social policies and post-unemployment outcomes, such as job match quality. Much of this literature has focused on the effects of Unemployment Insurance (UI) on post-unemployment outcomes related to the quality of job match. Theoretically, UI benefits are associated with moral hazards and liquidity effects, which have the potential to affect the duration of a search, as well as the type of work job seekers look for and accept. Marimon and Zilibotti (1999) uses a search-matching model to show that the UI encourages job seekers to wait and form better job matches. Acemoglu and Shimer (2000) uses a quantitative model to show that UI increases labor productivity by encouraging risk-averse workers to seek high-productivity jobs and firms to create such high-productivity jobs. Centeno (2004) examine the effect of unemployment insurance on job match quality, operationalizing match quality using post-unemployment job tenure (Jovanovic 1979). Exploiting the variation in the state-level UI generosity, Centeno finds that an increase in the generosity of unemployment insurance leads to better job match quality captured by longer job tenure. Also, Farooq, Kugler, and Muratori (2020) examines the effects of the UI on wages and the mechanism behind why UI may improve the post-unemployment wages of job seekers eligible for the benefit. Using the Longitudinal Employer-Household Dynamics (LEHD) and exploiting the variation in the UI benefit duration across states, authors find that increases in the UI generosity increase earnings, the post-unemployment quality of employer-employee matches with the effect being larger for women, less educated workers, young workers, and nonwhites.

Less attention has been given to studying whether the Earned Income Tax Credit (EITC) has any effect on the outcomes of job seekers who are potentially eligible for the program, even though the subsidy benefit from the EITC has the potential to affect which jobs they accept. This paper contributes to this strand of the literature by first examining whether the EITC impacts skill mismatch and the starting wage associated with a reentry job among single non-college-educated women and then investigating the implications of mismatch among this policy-relevant group.

4 Conceptual Framework

I use a simple partial equilibrium search model in a stationary environment to illustrate how wage subsidies affect the cost of job search, the reservation wage, and the implication of these effects for match quality. For simplicity, assume that the range of the wage distribution only includes jobs that would make a worker eligible for the subsidy benefit. The analysis consists of two parts. The first part lays the model with subsidy benefits and establishes the relationship between the subsidy and search cost. The second part derives the relationship between the subsidy level and the reservation wage and the implication of increasing generosity of the subsidy level for match quality.

4.1 Subsidies, Costs, and Benefits of Search

Assume a continuous time framework where people have infinite lives. At the beginning of the model, $t = 0$, people are unemployed. Because individuals do not know the exact wage for each job offer in advance, they must search while they are unemployed to find the best wage offer available to them. If people search, they incur an out-of-pocket cost of c per period. Wage information is only revealed when the offer is made. During the search process, an individual receives one wage offer per period from a probability distribution with a density function $f(w)$ and makes a rational decision to accept or reject the offer and continue searching. If an offer is accepted in a period, it leads to employment forever, starting in the next period, at a constant wage w with a subsidy of b. The distribution of the wage offer is assumed to be unchanging over time and known to the job seeker. Offers received in each period from the wage distribution are independent of each other. Individuals make decisions to maximize their lifetime wealth. I assume that the model has no liquidity constraint so that individuals can save and borrow at a constant interest rate of r.

Assuming hours of work are fixed, let $W(w, b)$ be the present discounted value of lifetime wealth associated with accepting a job that offers a wage w, which generates a positive subsidy b, and working forever afterward at that wage. Under the assumptions in the model, the present discounted value of the job is:

$$W(w, b) = \frac{w + b}{r} \tag{2}$$

Let V be the present discounted value of lifetime wealth associated with searching during the next period, such that the value of search is:

$$rV = -c + E\left\{Max\left[\frac{w + b}{r} - V, 0\right]\right\} \tag{3}$$

Where the last term in the Equation can be rewritten in continuous time as:

$$E\left\{Max\left[\frac{w + b}{r} - V, 0\right]\right\} = \frac{1}{r}\int_{rV}^{\infty}(w + b - rV)f(w)dw \tag{4}$$

Substituting Equation (4) into Equation (3) yields:

$$rV = -c + \frac{1}{r}\int_{rV}^{\infty}(w + b - rV)f(w)dw \tag{5}$$

Given a wage offer w, a worker accepts the offer and stops searching if the payoff from accepting the offer is at least equal to the payoff from continuing to search; thus, if $\frac{(w+b)}{r} \geq V$ but rejects the offer and continues searching if $\frac{(w+b)}{r} < V$. An individual does not search or drop out of the labor market if $V < 0$. The optimal strategy of the job seeker involves choosing the lowest remuneration she is willing to accept- reservation wage. The reservation wage w^*, is the unique solution to:

$$w^* = rV - b \tag{6}$$

I can further rewrite Equation (5) as:

$$w^* = -c - b + \frac{1}{r}\int_{w^*}^{\infty}(w - w^*)f(w)dw \tag{7}$$

Rearranging terms gives:

$$w^* + b + c = \frac{1}{r}\int_{w^*}^{\infty}(w - w^*)f(w)dw \tag{8}$$

The right side of Equation (8) can be interpreted as the marginal return associated with continued search given an offer that equals the reservation wage. The left side represents the cost of searching during the period when the reservation wage is offered, and it is comprised of two parts. The first part is the marginal opportunity cost of additional search, which is the sum of the value of working at the reservation wage and the subsidy benefit associated with that offer. The second is the marginal direct cost associated with a continued job search.

Equation (8) shows that the reservation wage w^* is set such that the present discounted benefit of search equals the cost of search. The left side of Equation (8) implies that as the subsidy increases, the marginal opportunity cost of search increases, thereby increasing the search cost. Consequently, as the benefits become more generous, it becomes more costly for individuals looking for employment to wait and search for the right job match. The next part of the model derives the relationship between the subsidy level and the reservation wage and the implication of the relationship for job match quality. It also shows how match quality relates to the wages of workers.

4.2 Impact of Wage Subsidies on the Reservation Wage

I derive the impact of a wage subsidy on the reservation wage by differentiating Equation (7),

$$\frac{dw^*}{db} < 0. \tag{9}$$

Equation (9) indicates that increases in the subsidy benefit lower the reservation wage. The intuition behind Equation (9) is that as the wage subsidy becomes more generous and the cost of job searching increases, it becomes more costly for individuals looking for employment to wait and search for the right job match. The increases in the cost of search reduce the net-of-cost benefit of holding out for better opportunities, which incentivizes job seekers to lower their reservation wages. A lower reservation wage implies that job seekers are more likely to be less selective during their search and, therefore, more willing to accept jobs with poor matches they may otherwise not accept. For example, evidence from Krueger and Mueller (2016) suggests that the reservation wage of workers contains useful information about their future decisions as it has more predictive power on whether a worker accepts an offered job.

This paper examines the effects of the increasing generosity of the Earned Income Tax Credit (EITC), a wage subsidy for low- and moderate-income households, on job match quality among single non-college-educated women. Additionally, I investigate the impact of the EITC on starting wages. The underlying hypothesis, based on the predictions from the model, is that the generosity of the EITC may have an unintended consequence of creating worse job matches among eligible job seekers.

Finally, I assume that wages are a function of match quality (m) and firm and worker characteristics (z), with the relationship between wages and match quality characterized by the following Equation:

$$\frac{\partial w(m, z)}{\partial m} > 0. \tag{10}$$

Clearly, Equation 10 implies that conditional on firm and worker characteristics, workers who are mismatched earn lower wages compared to those who are better matched. In my analysis, I further explore whether match quality matters for the wages of single non-college-educated women.

5 Data Sources

The main dataset for this study is the restricted National Longitudinal Survey of Youth 1979 cohort (NLSY79). The NLSY79 is a panel data of individuals aged 14 to 22 when interviewed in 1979. The NLSY79, when weighted, is a nationally representative sample of young men and women born between 1957 and 1964 and living in the United States when the survey began. Respondents were interviewed annually until 1994 and biennially after that. The NLSY79 contains measures of ability endowment for each respondent who took the Armed Services Vocational Aptitude Battery (ASVAB). The ASVAB test was conducted around the beginning of the survey, with 94% of the NLSY79 sample completing the ASVAB test. Additionally, the survey contains detailed labor market information of individuals. During the survey, questionnaires were administered to elicit respondents' social attitudes.

The study uses the 1980-2006 waves of the NLSY79. I use the core civilian sample, a cross-section of 6,111 observations, of which 3,108 were females. Since the population I analyze is more likely to consist of low and moderate-income individuals, I include the supplemental sample of Black, Hispanic or Latino and poor nonblack/non-Hispanic respondents consisting of 5,295 respondents, of which 2,719 were females. I restrict the sample to single women with less than a college degree who reentered the labor market between 1980 and 2006 and took a new job. Subsection A.1 in the appendix shows details of the sample selection process, and Table A1 indicates the number of individuals and observations that remain after each selection process. The final analysis sample consists of 2,047 unique single women (never married, divorced, widowed) and 4,287 observations. I apply the NLSY79 initial sample weight to account for the oversampling of poor households.

Table 1 shows the demographic and labor market information of the entire sample and separately by the number of qualifying children. Women with two or more qualifying children are, on average, older (30 years old), and this is expected because the NLSY79 is a panel dataset, and individuals are likely to have more children as they age. Also, these women are more likely to have a high school degree (53%), have spent fewer years in employment (15.64 years), and have more years out of the labor force (10.31 years). Women with no qualifying children tend to be younger (23 years old), more likely to have some college education (52%), have spent more years in employment (19.53 years), and have fewer years out of the labor force (7.34 years).

[Table 1 about here]

5.1 Ability Endowment of Workers

The ASVAB was administered by the Department of Defense (DoD) to help ASVAB respondents identify and explore careers that are suitable for them in the private, public, or military sectors. The ASVAB consists of a battery of 10 subtests that measure the knowledge and skills of individuals who took the tests. I follow the guidelines of the ASVAB career exploration program to use selected scores on the ASVAB subtests to construct three composite scores that measure the cognitive skill endowments of each worker: *math; verbal; and science/technology/mechanics*.[4] Additionally, the NLSY79 contains attitudinal scales: Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale, and self-reported measures of sociability at age six and adulthood. I use the scores on the attitudinal scales and sociability to obtain a measure of attitudinal social skills that proxy for workers' non-cognitive skill endowment.

5.2 Occupational Skill Requirements

The Department of Labor's O*NET (Occupational Information Network) database provides broad information on job characteristics for over 1000 occupations.[5] The O*NET dataset provides descriptors of the mix of knowledge, skills, and abilities (KSA) required to perform each occupation-specific task content. For each occupation, experts, job analysts, job supervisors, or job incumbents rate the importance and level of each KSA to perform tasks.

Additionally, experts from the ASVAB career exploration program have shown that scores on particular ASVAB tests, to a large extent, relate to the degrees of mastery or competency over certain O*NET KSAs (ASVAB Career Exploration Program 2010). I rely on the O*NET descriptors of KSAs to obtain skill requirements within the NLSY79 occupations by linking the NLSY79 occupations to the O*NET occupations. Since the NLSY uses different classification systems for the occupation and industry of respondents' jobs in certain years, in my analysis, occupation, and industry codes are harmonized using the occupation and industry crosswalk from Guvenen et al. (2020a). Combining the National Longitudinal Survey of Youth 1979 cohort (NLSY79) and the O*NET database to obtain worker abilities and occupation skill requirements to measure the quality of job match for worker-occupation pairs has been used in several papers such as (Guvenen et al. 2020b; Addison, Chen, and Ozturk 2020; Lise and Postel-Vinay 2020).

4. The ASVAB consists of 10 subtests that are designed to measure knowledge and skills in the following areas: *general science; arithmetic reasoning; word knowledge; paragraph comprehension; numerical operations; coding speed; auto and shop information; mathematics; mechanical comprehension; and electronics information*, that measure knowledge and skills.

5. I use the 2007 version of the O*NET after Addison, Chen, and Ozturk (2020). I am grateful to Professor Orgul Ozturk and Liwen Chen for sharing their paper's O*NET data and other files.

5.3 Constructing Worker Skill Endowments and Occupational Skill Requirements.

I follow the ASVAB career exploration program guidelines to construct three ability composite scores from the ASVAB subtests: math, verbal, and science/technological/mechanical (STM) (ASVAB Career Exploration Program 2010). Experts from the ASVAB career exploration program performed factor analysis of the ASVAB and found that the verbal composite composed of *word knowledge* and *paragraph comprehension*, math composite composed of *arithmetic reasoning* and *mathematical knowledge*, and science, technology, and mechanics composed of *general science, mechanical comprehension,* and *electronics information*. I take the averages of these subtests to obtain each corresponding composite score. I adjust the raw scores by age within 3-month birth cohorts because of the age difference between respondents at the time of the test (Addison, Chen, and Ozturk 2020). I convert the resulting scores to percentile ranks, which range between 0 and 1 (for example, a score of 0.9 for a respondent represents a rank in the 90th percentile). Appendix A.2 shows details on how I construct the percentile rank for each ability type.

The NLSY79 data is limited in the number of variables that measure the sociability of individuals. Therefore, I follow Addison, Chen, and Ozturk (2020) and combine the strategy of Deming (2017) and Guvenen et al. (2020b) to construct attitudinal social skills by relying on scores from the following attitudinal measures: (1) Rotter Locus of Control Scale (2) Rosenberg Self-Esteem Scale (3) Sociability at age 6 (4) Sociability in adulthood. The Rotter Locus of Control is an attitudinal scale administered during the 1979 survey to respondents to elicit their feelings about their autonomy in the world and the importance of self-determination rather than chance. The Rosenberg Self-Esteem is also an attitudinal scale that asks questions about feelings about oneself, self-worth, and satisfaction. The study uses the Rosenberg Self-Esteem scores from the 1980 survey in the analysis.

The remaining component of the attitudinal social skill is from the NLSY79 sociability measure at age six and in adulthood, reported through questionnaires administered during the 1985 survey. Respondents report being shy or outgoing by describing themselves based on the following ordinal scale: 1 “Extremely shy," 2 “Somewhat shy," 3 “Somewhat outgoing," 4 “Extremely outgoing." To measure attitudinal social skills, I take averages of the Rotter Locus of Control, the Rosenberg Self-Esteem scores, and sociability measures and scale the resulting score to a unit standard deviation.

An occupation is defined as the combination of knowledge, skills, and abilities (KSA) required to perform tasks that produce outputs. The O*NET database contains descriptors of the knowledge, skills, and abilities required to perform tasks within an occupation successfully. These KSAs provide an overview of the content of an occupation and include cognitive and non-cognitive skills such as attitudinal social skills. Experts from the career exploration program performed several analyses to link the ASVAB factors, math, verbal, and science/technology/mechanics, to the KSAs that describe each of the O*NET occupations. Judges identify 26 KSAs relatable to the ASVAB subtests used to form the ASVAB factors. Another group of industrial/organizational psychologists, psychologists, and psychometricians relate 5 of these KSAs to the verbal factor, 9 KSAs to the math factor, and 16 KSAs to the science/technology/composite (See, ASVAB Career Exploration Program 2010). Hence, I can create an O*NET analog for each of the ASVAB factors. Table A2 shows the link between the ASVAB ability composites and the O*NET KSA composites. For each ability composite from the NLSY79, I average the level ratings of the corresponding KSA descriptors and convert the measures into percentile rank scores. To construct the attitudinal social skills from the O*NET database, I use the six items in the O*NET module on social skills. These six items are coordination, which measures "adjusting actions in relation to others' actions," instructing which measures "teaching others how to do something," negotiation which measures "bringing others together and trying to reconcile differences," persuasion which measures "persuading others to change their minds or behavior," service orientation which measures "actively looking for ways to help people," and social perceptiveness which measures "being aware of others' reactions and understanding why they react as they do." I take averages of these items and convert the resulting measures into percentile rank scores. Details on how the percentile ranking for each ability and skill type is obtained can be found in Appendix subsections A.2 and A.3., respectively.

[Table 2 about here]

Table 2 shows the average percentile ranking of individual skills for the full sample and separately by number of qualifying children. Women with two or more qualifying children, on average, rank higher in attitudinal social ability (0.43 percentile) than in all the other ability types (Verbal: 31st percentile; Math: 28th percentile; STM: 25th percentile). Women with no qualifying children rank higher in verbal ability (58th percentile) than all other ability types even though the difference across all abilities on average except STM is not large (Math: 54th percentile; STM: 45th percentile; attitudinal Social: 53rd percentile). In Appendix Tables B2 and B3, I show the average ability percentile ranking by education and race, respectively. Table B2 shows that, on average, individuals with more years of schooling have higher ability across all ability types. Table B3 reveals that Non-Hispanic Nonblacks, on average, have more ability than other races except in some instances where Blacks have more attitudinal social ability.

[Table 3 about here]

Table 3 shows the correlation between workers' abilities and the correlation between their abilities and skill requirements in their occupation using the analysis sample. The highest ability correlations are between verbal and STM (0.82), verbal and math (0.81), and math and STM (0.79). The correlation between abilities and skill requirements is low, especially between attitudinal social ability and the different skill requirements, but they are all positive. The low correlation reveals the mismatch between worker's abilities and the skills required in their occupations. The positive correlation between worker's abilities and the skills required in their occupation implies workers are more likely to sort into occupations requiring the skills they possess.

5.4 Measuring Match Quality.

Following the literature on multidimensional skill mismatch (Guvenen et al. 2020b; Lise and Postel-Vinay 2020; Addison, Chen, and Ozturk 2020), I calculate skill mismatch for individual i with skill endowment along dimension j; maths; verbal; science/technology/mechanics, attitudinal social and employed in occupation c as the absolute value of the difference between the worker's skill and that required in his occupation. Algebraically, this is specified as follows:

$$m_{ijc} = |A_{ij} - R_{cj}| \tag{11}$$

where A_{ij} represent individual $i's$ percentile-rank score in the ASVAB test along skill dimension j. And R_{cj} denotes the percentile-rank of the O*NET skill requirements in occupation c along skill dimension j. Also, I obtain aggregate mismatch as

$$m_{ic} = \sum_j w_j |A_{ij} - R_{cj}|. \tag{12}$$

The w_j's are weights obtained through a principal component analysis (PCA). The lower the value of m_{ic}, the better skills are matched to their job requirements.

Following Guvenen et al. (2020b), I further decompose the measure of a mismatch as follows:

$$m^{+}_{ic} = \sum_j w_j \max\left[(A_{ij} - R_{cj}), 0\right] \tag{13}$$

$$m_{ic}^{-} = \sum_{j} w_j \min\left[(A_{ij} - R_{cj}), 0\right] \tag{14}$$

where m_{ic}^{+} means an individual is positively matched (over-qualified) and m_{ic}^{-} indicates a worker is negatively matched (under-qualified). I can write the aggregate measure of a mismatch based on Equations 13 and 14 as $m_{ic} = m_{ic}^{+} + |m_{ic}^{-}|$, implying that workers can be either be positively or negatively mismatched. These measures of mismatch are rescaled to a unit standard deviation to allow ease of interpretation of results and used as the outcome variables to test the hypothesis that the EITC may have an unintended consequence of creating worse job matches in an initial job among job seekers eligible for the credit.

[Table 4 about here]

Table 4 presents the averages of total mismatch and by skill type for the entire sample, as well as by the number of qualifying children. The table reveals that, on average, women without qualifying children tend to have a higher level of mismatch compared to those with qualifying children. Tables 1 and 2 show that women with more children are more likely to have less education and lower levels of abilities, respectively. This pattern may explain why mismatches fall with the number of qualifying children. The mismatch pattern is consistent with findings in the literature that mismatch is more prevalent among highly educated workers (Addison, Chen, and Ozturk 2020; Guvenen et al. 2020b). Even though the value of mismatch is higher for workers with less number of children, mismatch is observed across all groups. Appendix Tables B4 and B5 show mismatch by education and race, respectively. Table B4 indicates that, on average, mismatch increases with education, while Table B5 reveals that, on average, Non-Hispanic Nonblacks individuals experience greater mismatches than individuals from other racial groups.

6 Identification and Empirical Strategy

I provide an intent-to-treat estimate of how increases in the generosity of the Earned Income Tax Credit (EITC) impact occupational skill mismatch among single non-college-educated women. I leverage the rich set of variations in the EITC benefit arising from several federal and state-level changes between 1980-2006 to simulate changes in the EITC generosity within that period (See similar approach in, Lim and Michelmore 2018; Michelmore and Pilkauskas 2021; Michelmore, Strauss, and Wiemers 2024). The sample period for my analysis covers the federal EITC expansions under the Tax Reform Act of 1986 and the Omnibus Reconciliation Acts of 1990 and 1993, which differentially affected families based on factors such as the number of qualifying children in the household.

I use a sample of non-college-educated unmarried women (never married/single, divorced, widowed) aged 25 to 45 in the 1979 Current Population Survey Annual Social and Economic Supplement (CPS-ASEC) to simulate the EITC benefit. Using the following steps, I obtain the average EITC benefit for the analysis sample. (1) I fix the distribution of earnings and demographics to the 1979 CPS-ASEC values. (2) I inflate earnings to their nominal values in each year between 1980 and 2006 using the Social Security Administration (SSA) national average wage index.[6] (3) Using the National Bureau of Economic Research (NBER) TAXSIM [7] tax calculator, I compute the federal and state EITC benefits for each year and individual in the CPS-ASEC sample. (4) I adjust the EITC benefits to their 2007 values using the SSA national average wage index. (5) I also obtain the total EITC benefit, which is a combination of the federal and state EITC benefits. (6) I aggregate the dataset to obtain the EITC benefits at the federal level, which varies by year and number of qualifying children (use 1, 2, 3 or more because the NBER tax calculator allows detailed information on up to 3 dependent) and state level which differs by year, number of children, and state of residence. (7) I match the average federal, state, and total EITC to the NLSY79 sample.

In my analysis, I use the average total EITC as the main explanatory variable. Figure 4 shows the variation in the average total EITC benefit.

[Figure 4 about here]

One benefit of using the average total EITC benefit a family is eligible to receive is that the actual total EITC benefit, which is based on family income, may be correlated with other factors that affect the outcome variables. Regarding state EITC policy, there may be concerns that state adoption of the policy and changes in the benefit level may be correlated with state economic conditions and demographic characteristics. As mentioned by Michelmore and Pilkauskas (2021) and Michelmore, Strauss, and Wiemers (2024), using a national sample to calculate state EITC benefits helps to address the endogeneity of state demographic characteristics to state EITC benefits.

I examine the impact of changes in the EITC generosity on mismatches by estimating models of the following form:

$$m_{i,c,k,s,t} = \beta_0 + \beta_1 AverageEITC_{k,s,t} + \beta_2 X_{i,k,s,t} + \beta_3 \Gamma_{s,t} + \beta_4 \bar{A}_i + \beta_5 \bar{R}_c + \delta_s + \tau_t + \epsilon_{i,c,k,s,t} \tag{15}$$

where $m_{i,c,k,s,t}$ is the size of a mismatch for individual i, employed in occupation c, with k number of EITC qualifying children, residing in state s and at time t. I model skill mismatch

6. https://www.ssa.gov/oact/cola/AWI.html

7. https://taxsim.nber.org/taxsim35/

in an initial job as a function of the EITC generosity, $AverageEITC_{k,s,t}$, the average EITC benefit in thousands of dollars available to households with k number of EITC qualifying children in state s in tax year t. $\mathbf{X}_{i,k,s,t}$ is a vector of controls that include labor market experience and its square, indicators for the number of children; education and its square; a race dummy, physical health, and one-digit level occupation and industry dummies. Evidence from the literature suggests that women who engage in intermittent labor force participation tend to earn lower wages than their counterparts who do not; for example, see Hotchkiss and Pitts (2005). To account for the impact of intermittency on match quality via wages, I include controls for years out of the labor force (intermittency) and its square,

Additionally, I include $\Gamma_{s,t}$ as controls for state-year-level characteristics such as the state unemployment rate, state minimum wage, State AFDC/TANF benefit for a 3-person family, and State FS/SNAP benefit for a 3-person family. These controls account for the potential endogeneity of state economic conditions to state EITC policies.[8] state fixed effects, δ_s, controls for time-invariant state-specific characteristics that may affect the state EITC generosity. Year fixed effects, τ_t controls for national economic conditions. Additional controls include Micro/Metropolitan unemployment rate and an indicator for whether an individual resides in a Standard Metropolitan Statistical Area.

The term $\bar{A}_i$ measures the average ability of a worker i across all dimensions, and $\bar{R}_c$ is the average skill requirement in occupation c. Due to potential autocorrelation when pooling all cross-sections of the NLSY79 waves during the analysis period, I cluster standard errors at the state level to ensure a consistent estimator.

The key parameter of interest is β_1, which captures the effect of an increase in EITC generosity on skill mismatch in an initial job among workers who are more likely to be eligible for the EITC.

Additionally, I examine the relationship between the EITC generosity and initial wage by estimating the following model:

$$\begin{aligned} \text{In}w_{i,k,s,t} = {} & \alpha_0 + \alpha_1 AverageEITC_{k,s,t} + \alpha_2 X_{i,k,s,t} + \alpha_3 \Gamma_{s,t} + \alpha_4 \bar{A}_i + \alpha_5 \bar{R}_c + \delta_s + \tau_t \\ & + \varepsilon_{i,k,s,t}, \end{aligned} \tag{16}$$

for individual i, $\text{In}w_{i,k,s,t}$ is the measure of the log hourly wage associated with the initial job. All controls are defined as before.

The literature has shown that mismatch matters for the wages of workers. For example, Bowlus (1995), using a sample of males from the NLY79, finds that the labor market internalizes mismatching through lower starting wages. I perform an additional analysis by

8. I obtain these measures from University of Kentucky Center for Poverty Research. (2023, Feb.)

investigating whether mismatch matters for the starting wages of single non-college-educated women.

In the analysis, I estimate models of the following form for the relationship between match quality and starting wage:

$$\begin{aligned}\text{In}w_{i,c,s,t} = {} & \psi_0 + \psi_1 m_{i,c,s,t} + \psi_2 X_{i,s,t} + \psi_3 \Gamma_{s,t} + \psi_4 \bar{A}_i + \psi_5 \bar{R}_c + \delta_s + \tau_t \\ & + \varepsilon_{i,c,s,t},\end{aligned} \tag{17}$$

such that for an individual i, $\text{In}w_{i,c,s,t}$ is the starting wage. $\Gamma_{s,t}$ is a vector of controls that include state unemployment rate and state minimum wage. I define all other controls as before.

7 Results

Table 5 presents the results for the relationship between the EITC generosity and occupational skill mismatch. In the first three columns, I focus on total mismatch as the outcome variable. The first column includes year, state, and number of children fixed effects, and the results reveal a significant impact of the EITC on mismatch. In the second column, I include additional controls, such as factors that may be correlated with human capital accumulation and local area economic conditions. The magnitude of the coefficients is slightly attenuated by making these adjustments. Following a $\$1,000$ increase in the average EITC benefit at the household size, state, and year level, there is an increase in mismatch by a 14% of a standard deviation among single non-college-educated women, which represents a one percentage point reduction compared to the estimates in column 1. In column 3, I add controls for experience and time out of the labor force, and I do not observe a significant change in the magnitude of the estimate compared to the previous column. In the next three columns, I explore positive mismatch as the outcome variable. Including more controls reveals changes in magnitude similar to changes in the results in the previous columns when additional controls were added. Estimates from the regressions in all three columns show a statistically significant effect of the EITC on positive mismatch-overqualification. For instance, in column 6, which includes the full set of controls, a $\$1,000$ increase in the average EITC benefit at the household size, state, and year level leads to overqualification among single non-college-educated women by a 10% of a standard deviation.

[Table 5 about here]

The remaining set of columns examines the effect of the EITC on negative mismatch. None of the estimates from the different regressions for this analysis reveal a statistically significant effect of the EITC on underqualification. These findings indicate that the EITC contributes to mismatching among single women, and much of the mismatch is attributable to workers being overqualified for their jobs, which is consistent with the prediction of my model that the EITC may lead to poor match quality among job seekers eligible for the benefit. My preferred specifications are the regressions, which include the full set of controls. [9] In all, as the EITC benefit becomes more generous, single women tend to take up jobs that utilize less of the skills they possess.

I further explore the mismatch effect by splitting the full analysis sample into different subsamples: workers with a high school degree or less, those with some college education, and all mothers. I look at the different effects by education because the means of mismatch by education in Table B4 shows that mismatch is more pronounced among workers with more education. I also restrict the sample to all mothers to examine the mismatch effect in order to be consistent with other EITC papers that generally focus on single mothers. Table 6 provides the results from this analysis. I find evidence of a statistically significant effect of the EITC on mismatch among single women with some college education and all mothers when using total and positive mismatch as outcomes. Interestingly, the coefficients of the EITC for single women with some college education more than double in their effects on mismatch compared to the results from the preferred specification in 5. These results suggest that much of the mismatch associated with EITC generosity is concentrated among single women with some level of college education.

[Table 6 about here]

In Tables 7, I repeat the analysis above, focusing this time on the source of mismatch by decomposing the mismatch measures by skill type. Table 7 Panel A reveals a significant impact of the EITC on total mismatch along the math, verbal, and STM dimensions. I find no evidence of a statistically significant effect of the EITC on attitudinal social skill mismatch. It can be seen in Panel B that most of the mismatch by skill type is caused by workers being overqualified.

[Table 7 about here]

Focusing on the subsamples in Table 8, I observe that much of the effect of the EITC on mismatch by skill type is concentrated among single women with some college education. These workers are more likely to be mismatched and overqualified in the math, verbal, and

9. I present results for my preferred specification for the remaining analyses. Other detailed results are available on request.

STM dimensions, with most of the coefficients more than doubling that in Table 7. However, the total mismatch results are not significant in the STM dimension. Mothers also tend to be mismatched and overqualified in math, verbal, and STM dimensions. I find no evidence of a mismatch in most of the skill dimensions among those with a high school degree or less, except along the STM dimension.

[Table 8 about here]

Next, I investigate whether the EITC has an impact on the starting wages of workers. The expectation is that increases in the EITC will lead to a reduction in the starting wages of workers because of the prediction of my model. Table 9 shows the results from this analysis. As expected, increases in the EITC lead to lower starting wages in all the regressions. For example, the results in column 1 show that a $\$1,000$ increase in the EITC generosity reduces starting wages by 4.2%. However, most of the results are not significant, except among mothers. I explain the non-significance of my results as potentially due to power issues.

[Table 9 about here]

Since the literature has shown that mismatch matters for the wages of workers, I examine the relationship between the different mismatch outcomes and the starting wage for the full sample and separately for the subsamples. In Table 10, I focus on the effect of total, positive, and negative mismatch on the starting wage. The first panel shows that individuals who are mismatched by one standard deviation above the mean earn 3%(2×1.5 less than those who are one standard deviation below the mean; however, none of the estimates using the subsample are statistically significant. Results in Panel B show that the labor market penalizes workers who are either overqualified or underqualified in their jobs through a lower starting wage. For instance, in column 1, workers who are overqualified by one standard deviation above the mean earn 18%(8.8×1.5) less than those who are one standard deviation below the mean. These results suggest that the labor market internalizes mismatch by lowering the starting wage of workers, which is consistent with the findings from Bowlus (1995). Examining the impact of mismatch by skill type on starting wages in Table 11 reveals no significant effects.

[Tables 10 and 11 about here]

In conclusion, the EITC leads to skill mismatch among single non-college-educated women, lowers their starting wage, and mismatches affect the wages of single non-college-educated women. Next, I perform different robustness checks to test the sensitivity of my results to various concerns that may arise in some of my analyses.

7.1 Robustness Check: Staggered Rollout of State EITC Policy

There are concerns about using a two-way fixed effects (TWFE) estimator when the timing of treatment differs across states (Goodman-Bacon 2021). States that adopted the EITC policy early may be different from those that implemented it later. To address this concern, I repeat my analysis using the entire sample, exploiting the federal variation in the EITC benefit, which is less sensitive to this TWFE problem. Results comparing the mismatch effects between the main specification and this specification are shown in Appendix B Tables B6 and B7. There is no compelling difference between these two specifications, which is consistent with the findings from Michelmore, Strauss, and Wiemers (2024). A comparison between the specifications for the starting wage equation is shown in Table B8. The two sets of results are not significantly different in terms of the magnitude of the coefficients, significance, and the direction of the effects. These findings show that my results are robust to the TWFE problem of having a staggered rollout of the EITC policy across states.

7.2 Robustness Check: Sociability Measure

In my analysis, I construct a measure of attitudinal social skills using the Rotter Locus of Control Scale, Rosenberg Self-Esteem Scale, Sociability at age 6, and sociability in adulthood. However, there may be concerns about the validity of this measure of attitudinal social skill and whether its components align with the elements used to construct the attitudinal social skills from the O*NET. Therefore, I check whether my results are sensitive to excluding attitudinal social skills from the aggregate measure of mismatch. The results are available in Table B9. Estimates obtained by excluding the attitudinal social skills are similar to those from the main specification.

7.3 Robustness Check: Trends

Given that my analysis focuses on women, there may be concerns that my estimates just reflect changes in mismatch over time that differ across women based on the number of children. To examine if this is the case, I include a number of children-specific linear trends as an additional control in my specification. The results of this analysis are in Appendix B Tables B10 to B18. The result in Table B10 column 2 reveals that the coefficient on total mismatch becomes less significant when the additional control is included, but in column 5, the effect on positive mismatch is quite robust. The results in columns 2, 5, and 8 of Table B11 for those with a high school degree or less show that the estimates do not significantly change when I include the number of children-specific linear trends. I find that the estimates in Tables B12 and B13 for those with some college and all mothers, respectively, are consistent with that from the main analysis even though in some cases, the estimates are fairly large. This pattern is almost similar to what I observe in Tables B14 to B17 when I consider mismatch by skill type. The results for the wage equations in columns 2, 5, 8, and 11 of Table B18 are not significantly different when compared to the corresponding results from the main specifications. Results from including state-specific linear trends in this new specification do not change the main message that increases in the EITC generosity lead to mismatch due to workers being overqualified for their jobs.

7.4 Robustness Check: Multiple Observations of Individuals

To account for multiple observations of individuals in my analysis, I repeat my analysis for the full sample using a Random Effects estimator to leverage the within- and between-individual variation. The results from this exercise, reported in Appendix Section B Tables B19 to Table B22, show that mismatch estimates from the Random Effects estimator are generally smaller in magnitude than those from the Ordinary Least Squares (OLS), but they tend to be more statistically significant. Again, the results from this analysis do not change the finding that increases in the EITC lead to mismatch and lower starting wages among workers, and mismatch negatively affects starting wages.

8 Conclusion

Using exogenous changes in the generosity of the EITC benefits, I show that increases in the EITC generosity increase occupational skill mismatch among single non-college-educated women. I find that the mismatch effect is mainly due to workers being overqualified for their jobs, and the impacts are highly concentrated among single women with some level of college education. I document a negative impact of the EITC on the starting wage of workers even though these effects are not statistically significant. I also investigate whether mismatches impact the starting wages of these workers. Results reveal that mismatched workers have a lower starting wage, which is consistent with findings from earlier literature. These findings emphasize that increases in the EITC generosity lead to workers taking up jobs that utilize less of their skills, and the mismatch hurts their starting wages. Knowing these effects is important for policymakers to understand that the effort to reduce welfare dependency by using wage subsidies to promote employment may lead to unintended consequences such as lower starting wages and poor match quality. Although this analysis does not have sufficient power to assess the persistence of the mismatch and the long-term costs of the poor match quality, the results in this paper open an avenue for future research in these areas.

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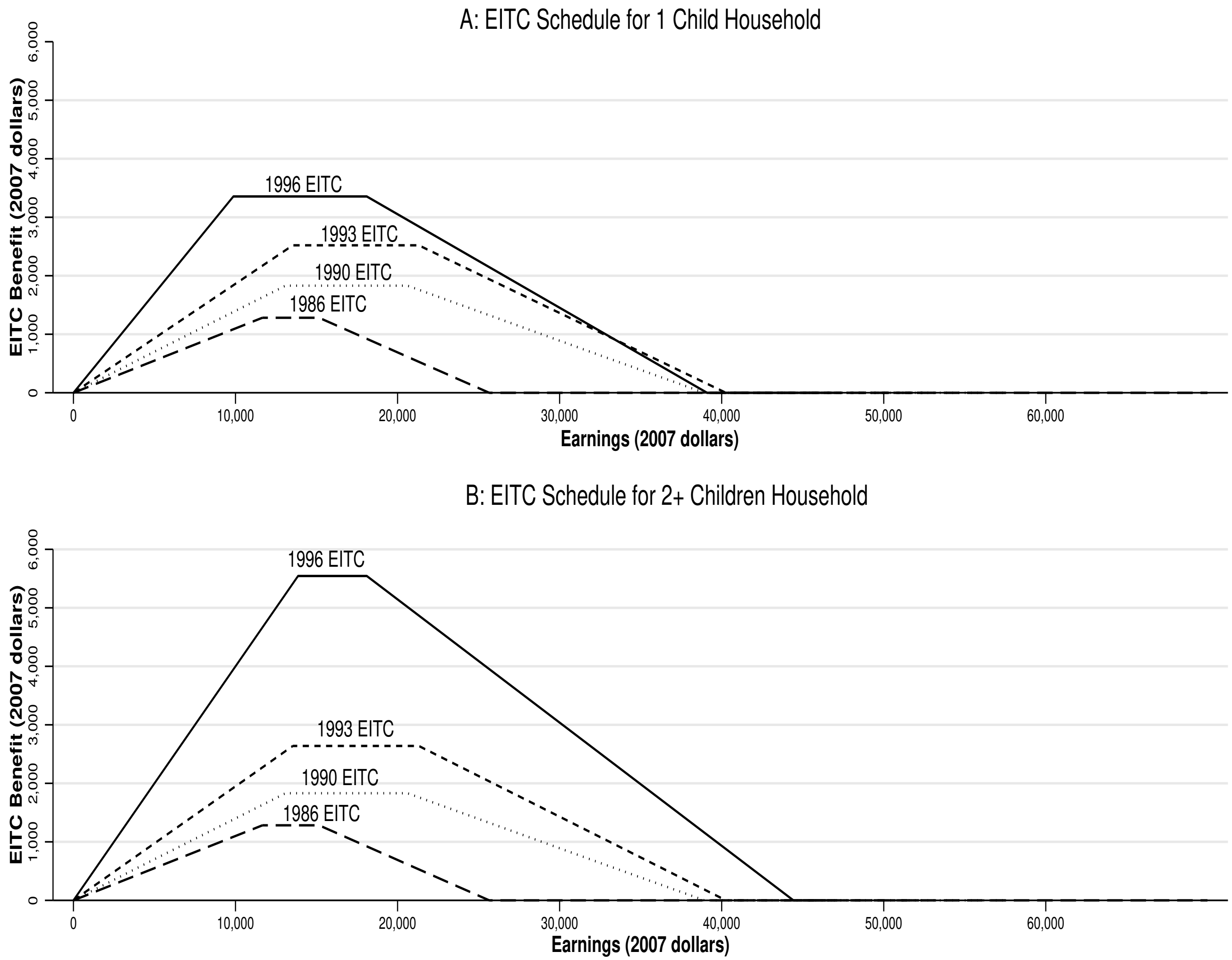
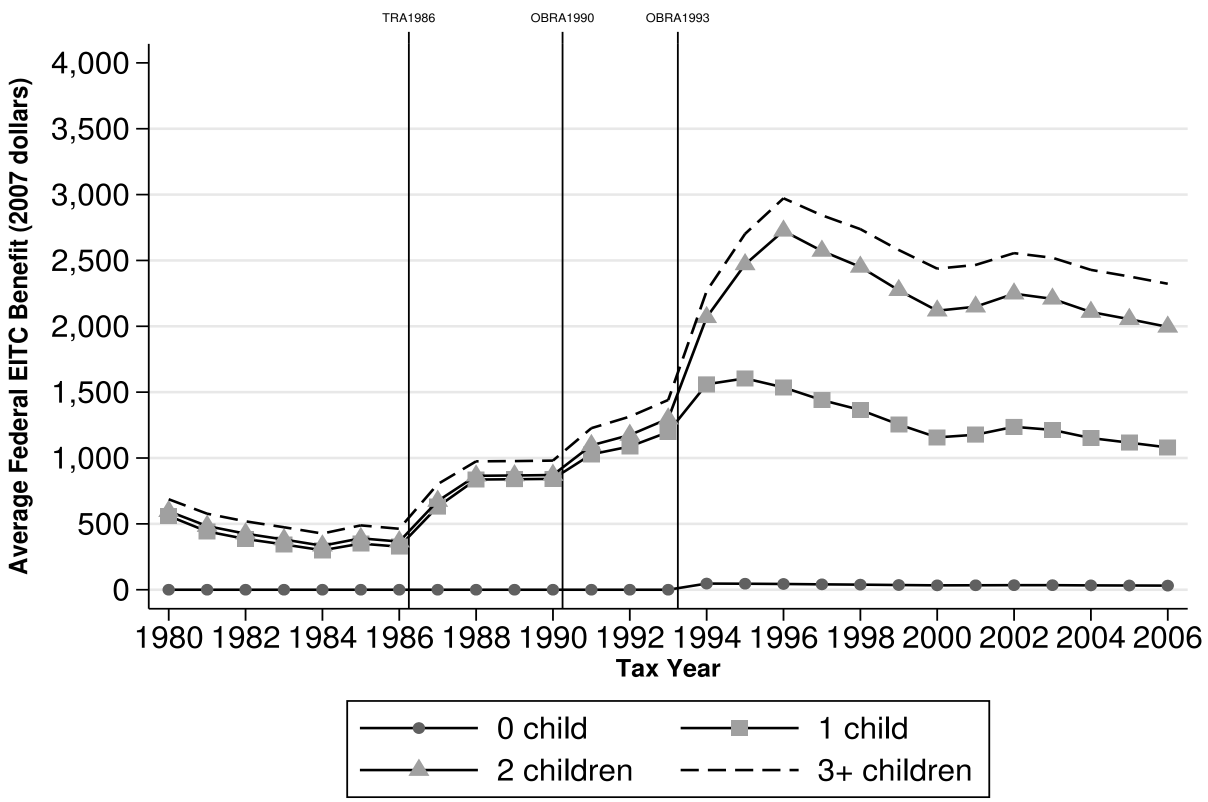
Figure 1. Federal EITC Parameters



Notes: EITC Benefit schedule for different sized households in selected tax years using federal EITC parameters from the Tax Policy Center.

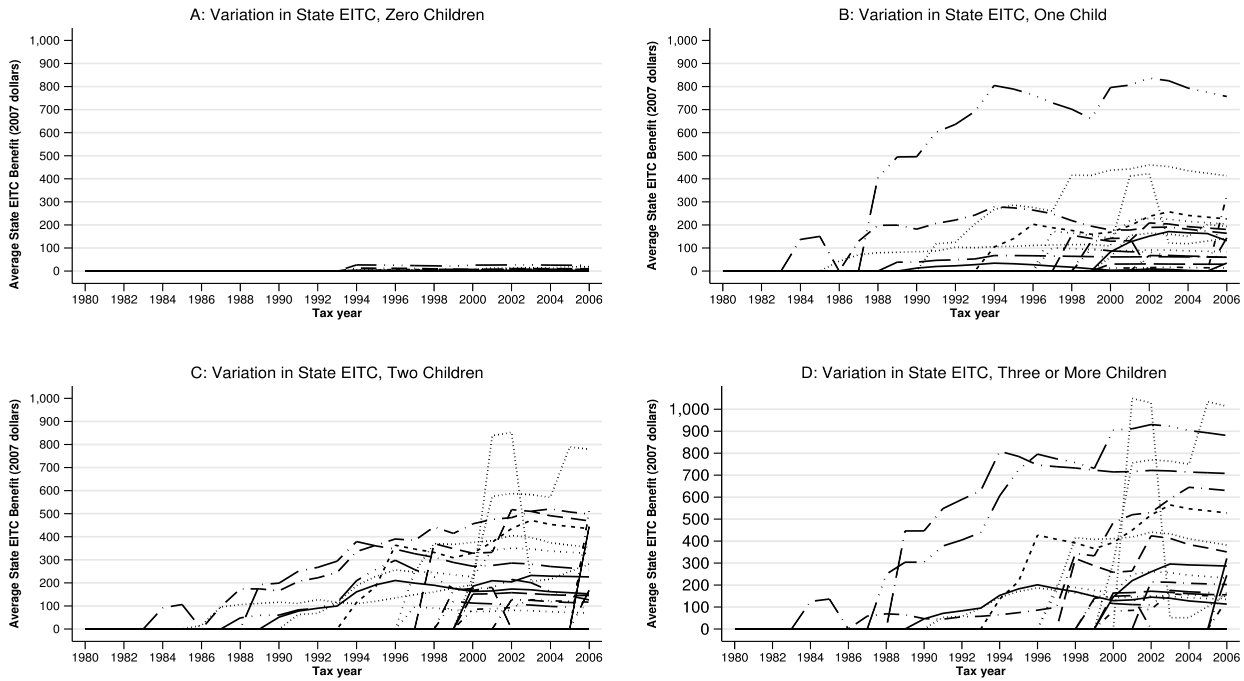
Figure 2. Variation in the Federal EITC benefit



Source: Current Population Survey Annual Social and Economic Supplement (CPS-ASEC) 1979.

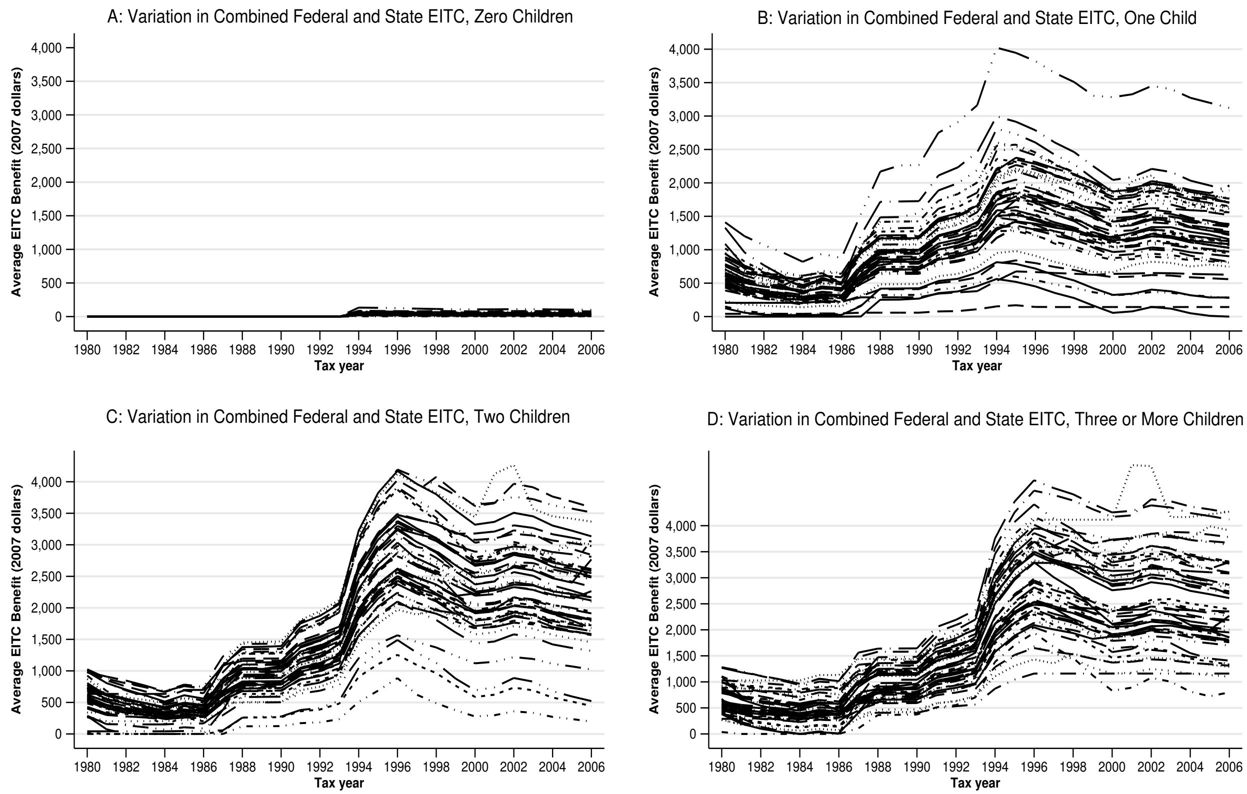
Notes: This figure shows the Variation in the simulated federal EITC benefit for households of different sizes using the CPS-ASEC 1979 survey and the National Bureau of Economic Research's TAXSIM tax calculator. The sample is constricted by restricting the 1979 CPS-ASEC sample to single women aged 25-45 with less than a College degree. Lines depict the average federal EITC in tax years between 1980-2006 for households with 0, 1, 2, or 3+ qualifying EITC children based on tax liabilities from the NBER TAXSIM tax calculator. See the main text for details on how the simulated EITC is obtained.

Figure 3. Variation in State EITC benefit



Notes: This figure shows the variation in the simulated state EITC benefit for households of different sizes using the CPS-ASEC 1979 survey and the National Bureau of Economic Research's TAXSIM tax calculator. The sample is constricted by restricting the 1979 CPS-ASEC sample to single women aged 25-45 with less than a College degree. Each line represents a state and the average EITC benefits available within tax years 1980-2006 for households with 0, 1, 2, or 3+ qualifying children based on tax liabilities from the NBER TAXSIM tax calculator. See the main text for details on how the simulated EITC is obtained.

Figure 4. Variation in Total EITC benefit



Notes: This figure shows the variation in the simulated average federal and state EITC benefit for households of different sizes using the CPS-ASEC 1979 survey and the National Bureau of Economic Research's TAXSIM tax calculator. The sample is constricted by restricting the 1979 CPS-ASEC sample to single women aged 25-45 with less than a College degree. Each line shows the combined average federal and state EITC benefits in tax years between 1980-2006 for households with 0, 1, 2, or 3+ qualifying children based on federal and state tax liabilities from the NBER TAXSIM tax calculator. See the main text for details on how the simulated EITC is obtained.

Table 1. Sample and Geographic Characteristics

	All Sample	No Qualifying Child	One Qualifying Child	Two or more Qualifying Children
Age at date of interview	24.92	23.15	27.28	29.96
	(6.21)	(5.33)	(6.68)	(5.58)
Number of Children	0.56	0.00	1.00	2.50
	(0.96)	(0.00)	(0.00)	(0.74)
Share Less Than High School	0.16	0.10	0.20	0.27
Share High School	0.44	0.38	0.55	0.53
Share Some College	0.40	0.52	0.25	0.20
Share White	0.42	0.53	0.30	0.22
Share Black	0.42	0.30	0.55	0.62
Share Hispanic	0.17	0.17	0.15	0.16
Fraction in SMSA	0.58	0.53	0.62	0.65
Total Employment (mean)	18.42	19.53	16.57	15.64
	(6.64)	(6.46)	(6.57)	(6.23)
Total Employment (median)	19.02	20.79	17.17	15.08
Total Out of the Labor Force (mean)	8.16	7.34	9.43	10.31
	(5.94)	(5.83)	(5.98)	(5.60)
Total Out of the Labor Force (median)	7.21	5.65	8.48	10.46
Physical health rank	0.50	0.53	0.44	0.44
	(0.31)	(0.31)	(0.31)	(0.29)
Simulated EITC Benefit (2007 dollars)	336.85	2.71	710.97	1,366.01
	(656.22)	(10.13)	(465.34)	(895.30)
State Unemployment rate	7.39			
	(2.39)			
Metropolitan/Micropolitan Unemployment rate	7.85			
	(3.33)			
State Minimum Wage	3.44			
	(0.84)			
State AFDC/TANF benefit for a 3-Person Family ($)	349.11			
	(144.60)			
State FS/SNAP benefit for a 3-Person Family ($)	225.76			
	(54.39)			
Observations	4,287	2,524	841	922

Notes: The sample includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey who reentered the labor market between 1980 and 2006 and took a new job. The sample is weighted using the initial sampling weight to account for the oversampling of Black, Hispanic or Latino and poor nonblack/non-Hispanic respondents in the NLSY79 supplemental samples. The full sample consists of 2,047 unique individuals and 4,287 observations. Education is defined using the highest grade completed. Total employment (out of the labor force) is defined as the number of years employed (out of the labor force) from 1978 to 2006 using the NLSY79 weekly files. SMSA is a dummy variable that equals one if an individual resides in a Standard Metropolitan Statistical Area and zero otherwise. Physical health denotes the rank scores-ranging from 0 to 1- of an individual's physical health. This measure is constructed from the SF-12 Physical Component Score (PCS) in the NLSY79 database. The NLSY79 SF-12 PCS provides a summary measure of individual health status at age 40 in selected survey years. See the main text for details on the simulated EITC benefit. State Minimum Wage, AFDC/TANF, and FS/SNAP represent nominal dollar values.

Table 2. Means and Standard Deviations of Individual Skill Rank

	Full Sample	**No Qualifying Child**	**One Qualifying Child**	**Two or more Qualifying Children**
Math Percentile Rank	0.46	0.54	0.31	0.28
	(0.29)	(0.29)	(0.23)	(0.20)
Verbal Percentile Rank	0.50	0.58	0.36	0.31
	(0.30)	(0.29)	(0.26)	(0.23)
STM Percentile Rank	0.39	0.45	0.29	0.25
	(0.26)	(0.26)	(0.21)	(0.20)
Social Percentile Rank	0.50	0.53	0.43	0.43
	(0.29)	(0.29)	(0.27)	(0.27)
Observations	4,287	2,524	841	922

Notes: This table represents the average percentile ranking of individual ability along different dimensions. Standard deviations are in brackets. Percentile scores on selected ASVAB subtests are used to construct the Math, Verbal, STM (Science/Technology/Mechanics) composites and converted to percentile rankings. Social ability is constructed as a composite of the following attitudinal measures from the NLSY79: Rotter locus of control scale, Rosenberg self-esteem scale, sociability at age six, and sociability in adulthood. The sample used to calculate the averages include single non-college educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. The full sample consists of 2,047 unique individuals and 4,287 observations. The sample is weighted using the initial NLSY79 sampling weight.

Table 3. Correlation between Individual Ability Rank and the Rank of Occupational Skill Requirement

N=4,287	**Individual's Ability**				**Occupational Skill Requirement**			
Individual's Ability	Math	Verbal	STM	Social	Math	Verbal	STM	Social
Math	1	0.81	0.79	0.30	0.24	0.25	0.10	0.20
Verbal	0.81	1	0.82	0.32	0.23	0.25	0.10	0.20
STM	0.79	0.82	1	0.25	0.22	0.22	0.14	0.18
Social	0.30	0.32	0.25	1	0.13	0.15	0.05	0.13

Notes: This table represents the correlation between individual ability and the skills required within occupations. STM refers to Science/Technology/Mechanics. The sample used to obtain the correlations included single non-college educated women aged 19 to 49 between 1979 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between the analysis period and took a job not previously held. The sample consists of 2,047 unique individuals and 4,287 observations. The sample is weighted using the initial NLSY79 sampling weight.

Table 4. Means and Standard Deviations of Mismatch

	Full Sample	**No Qualifying Child**	**One Qualifying Child**	**Two or more Qualifying Children**
Total Mismatch	1.76	1.92	1.50	1.36
	(1.08)	(1.14)	(0.90)	(0.80)
Math Skill Mismatch	1.39	1.55	1.12	1.00
	(1.09)	(1.15)	(0.89)	(0.85)
Verbal Skill Mismatch	1.42	1.54	1.23	1.07
	(1.07)	(1.12)	(0.93)	(0.85)
STM Skill Mismatch	1.36	1.45	1.19	1.12
	(1.01)	(1.04)	(0.92)	(0.90)
Social Skill Mismatch	1.44	1.50	1.36	1.30
	(1.01)	(1.03)	(0.95)	(0.97)
Observations	4,287	2,524	841	922

Notes: Total mismatch is computed as the weighted average of mismatch along the Math, Verbal, STM, and Social dimensions. Weights are obtained through a principal component analysis. The sample used to obtain the correlations include single non-college educated women aged 19 to 49 between 1979 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between the analysis period and took a job not previously held. The sample consists of 2,047 unique individuals and 4,287 observations. The sample is weighted using the initial NLSY79 sampling weight.

Table 5. Effect of the EITC on Skill Mismatch in an Initial Job

N=4,287	Total Mismatch			Positive Mismatch			Negative Mismatch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$AverageEITC_{k,s,t}$	0.2331***	0.1444***	0.1310**	0.2425***	0.1118***	0.1039***	0.0639	-0.0155	-0.0105
	(0.0520)	(0.0503)	(0.0519)	(0.0668)	(0.0274)	(0.0283)	(0.0823)	(0.0509)	(0.0510)
Year Fixed Effects.	X	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X
Demographic, Human Capital and Occupation Requirements Controls.		X	X		X	X		X	X
Experience and Intermittency Controls.			X			X			X

Notes: This table shows the effect of the EITC benefit on skill mismatch using the full analysis sample. The dependent variable in the regressions across all columns is a mismatch scaled to a unit standard deviation. The analysis sample across all columns includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. The sample consists of 2,047 unique individuals and 4,287 observations. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of dollars for clear interpretation of estimates. Additional controls in all regressions except Columns 1, 4, and 7 include physical health rank, an indicator for whether an individual resides in a Standard Metropolitan Statistical Area, Metro/Micropolitan Unemployment rate, State unemployment rate, the maximum TANF and SNAP benefit for a three-person family, occupation and industry dummies at the one-digit level. The full set of controls are in Columns 3, 6, and 9 and include year fixed effects, State fixed effects, number of children fixed effects, education and its square, race dummy, the average skill of a worker, average skill requirement, experience and its square, intermittency and its square, and the additional controls. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the State level and are in brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table 6. Effect of the EITC on Skill Mismatch in an Initial Job, Subsample.

	Total Mismatch			Positive Mismatch			Negative Mismatch		
	High School and Less	Some College	All Mothers	High School and Less	Some College	All Mothers	High School and Less	Some College	All Mothers
$AverageEITC_{k,s,t}$	0.07107	0.3311***	0.1475**	0.0471	0.2308***	0.1119***	-0.0189	-0.0722	-0.0191
	(0.0487)	(0.1087)	(0.0710)	(0.0281)	(0.0507)	(0.0411)	(0.0300)	(0.0917)	(0.0392)
Observations	2,581	1,706	1,763	2,581	1,706	1,763	2,581	1,706	1,763

Notes: This table shows the effect of the EITC benefit on skill mismatch for different subsamples. The dependent variable in the regressions across all columns is a mismatch scaled to a unit standard deviation. Subsamples are obtained by splitting the analysis sample into different groups. All regressions include the full set of controls discussed in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the State level and are in the brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table 7. Effect of the EITC on Skill Mismatch in an Initial Job by Skill Type

N=4,287	Math	Verbal	STM	Social
Panel A. Total Mismatch				
$AverageEITC_{k,s,t}$	0.1334**	0.1234**	0.1092**	-0.0571
	(0.0561)	(0.0487)	(0.0488)	(0.0723)
Year Fixed Effects. X	X	X	X	
State Fixed Effects.	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X
Panel B. Positive Mismatch				
$AverageEITC_{k,s,t}$	0.1459***	0.0804***	0.1102***	-0.0638
	(0.0378)	(0.0300)	(0.0330)	(0.0536)
Year Fixed Effects.	X	X	X	X
State Fixed Effects.	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X
Panel C. Negative Mismatch				
$AverageEITC_{k,s,t}$	0.0326	-0.0480	-0.0026	-0.0210
	(0.0509)	(0.0343)	(0.0390)	(0.0561)
Year Fixed Effects.	X	X	X	X
State Fixed Effects.	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X

Notes: This table shows the effect of the EITC benefit on skill mismatch by skill type. The analysis sample across all columns includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. The sample consists of 2,047 unique individuals and 4,287 observations. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. All regressions include the full set of controls discussed in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the state level and are in the brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table 8. Effect of the EITC on Skill Mismatch in an Initial Job by Skill Type, Subsample

	Math			Verbal			STM			Social		
	High School and Less	Some College	All Mothers	High School and Less	Some College	All Mothers	High School and Less	Some College	All Mothers	High School and Less	Some College	All Mothers
Panel A. Total Mismatch												
$Average EITC_{k,s,t}$	0.0339	0.4218***	0.0981	0.0826	0.2670**	0.1392**	0.1007**	0.1761	0.1296**	-0.0628	-0.0362	0.0365
	(0.0524)	(0.0917)	(0.0887)	(0.0572)	(0.1065)	(0.0610)	(0.0490)	(0.1098)	(0.0596)	(0.0740)	(0.1236)	(0.1071)
Full set of controls.	X	X	X	X	X	X	X	X	X	X	X	X
Panel B. Positive Mismatch												
$Average EITC_{k,s,t}$	0.0272	0.4230***	0.1030*	0.0574	0.1328**	0.1047**	0.0896**	0.1755***	0.1123***	-0.0597	-0.1342	0.0160
	(0.0341)	(0.0668)	(0.0605)	(0.0351)	(0.0647)	(0.0437)	(0.0347)	(0.0624)	(0.0378)	(0.0591)	(0.1061)	(0.0791)
Full set of controls.	X	X	X	X	X	X	X	X	X	X	X	X
Panel C. Negative Mismatch												
$Average EITC_{k,s,t}$	-0.0065	0.0458	0.0176	-0.0268	-0.1644	-0.0335	-0.0150	-0.0065	-0.0225	-0.0061	-0.1659	-0.0269
	(0.0429)	(0.0952)	(0.0558)	(0.0384)	(0.0989)	(0.0415)	(0.0358)	(0.0931)	(0.0523)	(0.0579)	(0.1199)	(0.0838)
Full set of controls.	X	X	X	X	X	X	X	X	X	X	X	X
Observations	2,581	1,706	1,763	2,581	1,706	1,763	2,581	1,706	1,763	2,581	1,706	1,763

Notes: This table shows the effect of the EITC benefit on skill mismatch by skill type for different subsamples. Subsamples are obtained by splitting the analysis sample into various groups. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. The full set of controls is described in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the state level and are in the brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table 9. Regressions for the EITC and Starting Wage

	Full Sample	High School and Less	Some College	All Mothers
$AverageEITC_{k,s,t}$	-0.0418	-0.0478	-0.0205	-0.1049**
	(0.0304)	(0.0327)	(0.0535)	(0.0510)
Worker Ability (Mean)	0.2326***	0.1987**	0.2764**	0.2564***
	(0.0699)	(0.0913)	(0.1044)	(0.0813)
Occupation requirement (Mean)	0.0058	-0.1673***	0.3018***	-0.0571
	(0.0373)	(0.0493)	(0.0692)	(0.0767)
Physical Health	0.1095***	0.1284***	0.0993***	0.1230***
	(0.0243)	(0.0322)	(0.0344)	(0.0394)
State Unemployment Rate	0.0007	0.0008	0.0005	0.0110
	(0.0075)	(0.0099)	(0.0150)	(0.0178)
Metro Unemployment Rate	-0.0149***	-0.0161**	-0.0143	-0.0213***
	(0.0041)	(0.0080)	(0.0094)	(0.0072)
State Minimum Wage	0.0308	0.0185	0.0620	0.0145
	(0.0266)	(0.0343)	(0.0395)	(0.0387)
AFDC/TANF Benefit for a 3-Person Family	0.0004	0.0008	0.0002	-0.0007
	(0.0005)	(0.0007)	(0.0010)	(0.0006)
FS/SNAP Benefit for a 3-Person Family	0.0123***	0.0114***	0.0192***	0.0114***
	(0.0017)	(0.0017)	(0.0041)	(0.0032)
Intermittency	-0.0174	-0.0438*	0.0355*	-0.0185
	(0.0158)	(0.0222)	(0.0202)	(0.0171)
$Intermittency^2 \times 100$	0.1098**	0.1500*	-0.0302	0.1683**
	(0.0524)	(0.0799)	(0.0795)	(0.0723)
Experience	0.0314***	0.0097	0.0751***	0.0299**
	(0.0103)	(0.0155)	(0.0140)	(0.0129)
$Experience^2 \times 100$	-0.0101	0.0066	-0.0518	-0.0182
	(0.0354)	(0.0528)	(0.0700)	(0.0549)
Observations	4,129	2,490	1,639	1,706

Notes: This table shows the regressions for the EITC benefit and starting wage. The dependent variable in the regressions across all columns is the natural log of the starting wage. The full sample includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. Subsamples are obtained by splitting the full sample into different groups. The starting wage is adjusted for inflation using 2007 dollars. Additional controls in regressions across all columns are year-fixed effects, state-fixed effects, number of children fixed effects, an indicator for whether an individual resides in a Standard Metropolitan Statistical Area, education and its square, race dummy, and occupation and industry dummies at the one-digit level. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the State level and are in brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table 10. Mismatch and Starting Wage

	Full Sample	High School and Less	Some College	All Mothers
Panel A.				
Total Mismatch	-0.0151*	-0.0036	0.0063	0.0060
	(0.0089)	(0.0166)	(0.0135)	(0.0223)
Full set of controls	X	X	X	X
Panel B.				
Positive Mismatch	-0.0877***	-0.0757**	-0.0679**	-0.0904
	(0.0158)	(0.0334)	(0.0289)	(0.0546)
Negative Mismatch	-0.0545***	-0.0589**	-0.0847***	-0.0855***
	(0.0164)	(0.0244)	(0.0237)	(0.0270)
Full set of controls	X	X	X	X

Notes: This table shows regressions for the different measures of mismatch and the starting wage. Each panel represents a different set of regression. The dependent variable in the regressions across all columns is the natural log of the starting wage. The full sample includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. Each subsample is obtained by splitting the full sample into different groups. The starting wage is adjusted for inflation using 2007 dollars. All regressions include the full set of controls in Table 9, excluding AFDC/TANF Benefit for a 3-person Family and FS/SNAP Benefit for a 3-person Family. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the State level and are in brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table 11. Mismatch and Starting Wage by Skill Type

	Full Sample	High School and Less	Some College	All Mothers
Math Mismatch	-0.0095	-0.0134	0.0042	0.0203
	(0.0123)	(0.0205)	(0.0217)	(0.0187)
Verbal Mismatch	0.0002	0.0116	0.0085	-0.0060
	(0.0154)	(0.0183)	(0.0172)	(0.0223)
STM Mismatch	-0.0079	-0.0195	-0.0069	-0.0298
	(0.0126)	(0.0160)	(0.0205)	(0.0251)
Social Mismatch	0.0084	-0.0013	0.0310	0.0147
	(0.0104)	(0.0120)	(0.0197)	(0.0125)
Math Ability	0.1243	0.0900	0.1240	0.1140
	(0.0776)	(0.0802)	(0.1368)	(0.0971)
Verbal Ability	0.0574	0.1318	-0.0854	0.2284
	(0.0857)	(0.1230)	(0.1204)	(0.1453)
STM Ability	-0.0098	-0.0764	0.0960	-0.1846
	(0.0943)	(0.1398)	(0.1279)	(0.1756)
Social Ability	0.1090**	0.1427**	0.0351	0.1190
	(0.0449)	(0.0660)	(0.0838)	(0.0734)
Math Occupational requirement	0.1286	0.2025	0.1395	0.1340
	(0.0912)	(0.1674)	(0.1530)	(0.2148)
Verbal Occupational requirement	0.0006	-0.1834	0.3014	-0.4215*
	(0.1277)	(0.1449)	(0.1952)	(0.2191)
STM Occupational requirement	0.4898***	0.5780***	0.3622***	0.7085***
	(0.0921)	(0.1425)	(0.0981)	(0.2060)
Social Occupational requirement	-0.5359***	-0.7351***	-0.2624	-0.3687**
	(0.1197)	(0.1297)	(0.1628)	(0.1431)
Full set of controls	X	X	X	X
Observations	4,129	2,490	1,639	1,706

Notes: This table shows the results of regressions for mismatch by skill type and the starting wage. Each panel represents a different set of regression. The dependent variable in the regressions across all columns is the natural log of the starting wage. The full sample includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. Each subsample is obtained by splitting the full sample into different groups. The starting wage is adjusted for inflation using 2007 dollars. All regressions include the full set of controls in Table 9, excluding AFDC/TANF Benefit for a 3-person Family and FS/SNAP Benefit for a 3-person Family.The average ability and occupational skill requirement are replaced by the specific ability and skill type. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the State level and are in brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Appendix

A Data

A.1 Sample Selection

I use the 1980-2006 waves of the NLSY79 for my analysis. The NLSY79 work history file provides week-by-week information on respondents' jobs and labor force statutes from January 1, 1978. The weekly panel offers the number of jobs held in a given week or the labor force status if the week was not associated with employment. From the weekly panel, I can observe each job an individual reports after reentering the labor market. I restrict the sample to women in the female cross-sectional and supplementary sample who reentered the labor market within the analysis period. I retain in my sample women whose reentry job is not previously held and has valid occupation and industry information. Since I need scores on the ASVAB subtests and sociability measures to obtain the skill endowment of workers, I drop women with invalid ASVAB scores and sociability measures. I exclude women who are under 19 years old to avoid having individuals in the sample who are more likely to be claimed as dependents for tax benefits. My analysis focuses on single women, so I exclude those who are either married or separated. I further restrict the sample to single women with less than a college degree, as these women are more likely to be eligible for the EITC. I do not include individuals who are new entrants because, on average, new entrants are more mismatched (Lise and Postel-Vinay 2020).

Additionally, individuals who reenter the labor market have some experience and may know where to search in the labor market compared to new entrants. Re-entrants may also have skills from their previous jobs, so the measures of mismatch may be less accurate. Finally, I exclude women who have missing values in any of the key variables. Table A1 shows the sample process and the remaining individuals and observations after each step. The final sample consists of 2,047 unique women and 4,287 observations.

Table A1. NLSY79 Sample Selection

Criterion for Selecting Sample	Remaining Individuals	Remaining Observations
Reentry job in the female cross-sectional and supplementary sample	5,404	27,677
Keep if job is an initial one	5,026	16,427
Drop if occupation and industry information is not valid	5,025	16,409
Drop if ability measures are not valid	4,822	15,879
Have valid sociability measures	4,493	14,968
Older than 19 years	4,292	13,057
Exclude those who are either Married or Separated	2,901	6,546
Have less than a college degree	2,720	5,717
Drop if newly entering the labor market	2,618	5,454
Keep if not missing key variables	2,047	4,287

Notes: This table represents the different criteria used to select the main analysis sample from the NLSY79 dataset.

A.2 ASVAB Skills

I follow the approach of Addison, Chen, and Ozturk (2020) to obtain the percentile ranks of the ability composite scores by taking the following steps.[10] (1) For each ability type- Math, Verbal, STM- I take the averages of the corresponding subtests based on the ASVAB career exploration program guideline mentioned in the main text to obtain a composite score. (2) I divide the NLSY79 into 20 age groups with 3-month birth intervals. Since the NLSY79 is a cohort of individuals born between January and March 1957 through December 31, 1964, the youngest age group are individuals born between January and March 1957, with the oldest group being those born between October and December 1964. (3) I then construct weights for each ability type by summing up the ASVAB weights of all individuals within the age group who have non-missing composite scores. (4) I rescale the composite scores to have a unit standard deviation. (5) For each ability type, I use the composite scores to rank individuals with non-missing scores relative to others within their age group. (6) After this, I obtain the weights for each rank on an ability type within an age group by adding up the ASVAB weights of all individuals who rank equal to or less than that rank position. (7) I obtain the percentile ranks of individuals for each ability type by dividing the outputs from step (6), the weight associated with the individual's ability rank within their age group, by the output

10. I thank Professor Orgul Ozturk and Liwen Chen for their assistance with the NLSY79 ASVAB weights and creating the weighted composites.

from step (2), the total weights corresponding with the ability type within the age group. The resulting percentile ranks range between 0 and 1 (for example, a score of 0.9 for a respondent represents a rank in the 90th percentile).

A.3 O*NET Skills

For each Math, Verbal, and STM composite from the NLSY79, I adopt the same strategy as Addison, Chen, and Ozturk (2020) to create an O*NET analog by taking the following steps. (1) Construct the O*Net composite for each skill type by averaging the level ratings of the KSA descriptors that correspond with that skill composite in the ASVAB. Table A2 shows the link between the ASVAB ability composites and the O*NET Skill composites. (2) Rescale the resulting composite to have a unit standard deviation. (3) I obtain total weights by summing the 2007 employment weights across all Three-Digit Level CPS occupations. (4) For each type of skill, I obtain the rank position of each Three-Digit Level CPS Occupation with non-missing scores relative to others using the composite scores. (5) I then compute the weights associated with each rank position for each skill type by summing the employment weights of all Three-Digit Level CPS occupations that rank equal to or less than that rank position. (6) I obtain the percentile rank for each Three-Digit Level CPS occupation by dividing the outputs from step (5) by that from step (3). (7) I average over the 1990 Occupation Classification Codes that map to the same code in the Three-Digit Level CPS Occupation Classification.

Table A2. O*NET KSAs Related to ASVAB Test Composite

ASVAB Verbal Composite		**O*NET Verbal Composite**	
WK	Word Knowledge	Ability	Inductive Reasoning
PC	Paragraph Comprehension	Ability	Written Comprehension
		Ability	Oral Comprehension
		Knowledge	English Language
		Skill	Reading Comprehension
ASVAB Math Composite		**O*NET Math Composite**	
AR	Arithmetic Reasoning	Ability	Deductive Reasoning
MK	Math Knowledge	Ability	Inductive Reasoning
		Ability	Written Comprehension
		Ability	Number Facility
		Ability	Mathematical Reasoning
		Ability	Information Ordering
		Knowledge	Mathematics
		Skill	Science
		Skill	Mathematics
ASVAB Science and Technical Composite		**O*NET Science and Technical Composite**	
GS	General Science	Ability	Deductive Reasoning
MC	Mechanical Comprehension	Ability	Inductive Reasoning
EI	Electronics Information	Ability	Written Comprehension
		Knowledge	Mechanical
		Knowledge	Biology
		Knowledge	Computers and Electronics
		Knowledge	Engineering and Technology
		Knowledge	Chemistry
		Knowledge	Physics
		Knowledge	Building and Construction
		Skill	Technology Design
		Skill	Science
		Skill	Installation
		Skill	Trouble Shooting
		Skill	Equipment Selection
		Skill	Operation and Control

Source: ASVAB Career Exploration Program: Theoretical and Technical Underpinnings of the Revised Skill Composites and OCCU-Find

Notes: This table shows the link between the ASVAB composite score and the O*NET KSA Composite.

B Additional Tables and Robustness Checks

Table B1. State EITC Parameters

State	Years	Percentage of Federal Benefit	Credit Type
Colorado[1]	1999	8.5	R
"	2000-01	10	R
Delaware	2006	20	NR
District of Columbia	2000	10	R
"	2001-2004	25	R
"	2005-2006	35	R
Illinois	2000-2002	Min (5%, State tax rate)	NR
"	2003-2006	5	R
Indiana[2]	1999-2002	3.4%(12000-total income)	R
"	2003-2006	6	R
Iowa	1990	5	NR
"	1991	6	NR
"	1992-2006	6.5	NR
Kansas	1998-2001	10	R
"	2002-2006	15	R
Maine	2000-2002	5	NR
"	2003-2005	4.92	NR
"	2006	5	NR
Maryland	1987+	50	NR
"	1998-1999	10	R
"	2000	15	R
"	2001-02	16	R
"	2003	18	R
"	2004-06	20	R
Massachusets	1997-2000	10	R
"	2001-2006	15	R
Minnesota[3]	n/a	n/a	n/a
Nebraska	2006	8	R
New Jersey[4]	2000	10	R
"	2001	15	R
"	2002	17.5	R
"	2003-2006	20	R
New York	1994	7.5	R
"	1995	10	R
"	1996-1999	20	R
"	2000	22.5	R
"	2001	25	R
"	2002	27.5	R
"	2003+	30	R
Oklahoma	2002-2006	5	R
Oregon	1997-2005	5	NR
"	2006	5	R
Rhode Island	2001	25.5	NR
"	2002	25	NR
"	2003-2006	25	Non-Refundable part
"	2003 and 2004	5	Refundable part
"	2005	10	Refundable part
"	2006	15	Refundable part
Vermont	1988	23	R
"	1989-1993	28	R
	1994-1999	25	R
"	2000-2006	32	R
Virginia[5]	2006	20	NR
Wisconsin[6]	1984 and 1985	30	NR
"	1989-1993	5/25/75	R
"	1994	12/63/18.8	R
"	1995	4/16/50	R
"	1996-2006	4/14/43	R

Source: https://taxsim.nber.org/state-eitc.html
Notes: This table shows states with an EITC program between 1980 and 2006 and the rules for the credit.

Table B2. Means and Standard Deviations of Individual Skill Rank by Education

	Full Sample	**No Qualifying Child**	**One Qualifying Child**	**Two or more Qualifying Children**
Less than High School	N=678	N=263	N=167	N=248
Math Percentile Rank	0.20	0.23	0.19	0.17
	(0.17)	(0.17)	(0.16)	(0.16)
Verbal Percentile Rank	0.21	0.25	0.19	0.18
	(0.18)	(0.19)	(0.16)	(0.18)
STM Percentile Rank	0.18	0.21	0.19	0.15
	(0.17)	(0.18)	(0.19)	(0.14)
Social Percentile Rank	0.34	0.35	0.30	0.34
	(0.26)	(0.29)	(0.20)	(0.26)
High School	N=1,903	N=953	N=461	N=489
Math Percentile Rank	0.36	0.39	0.32	0.29
	(0.23)	(0.24)	(0.22)	(0.19)
Verbal Percentile Rank	0.41	0.46	0.38	0.33
	(0.26)	(0.27)	(0.25)	(0.22)
STM Percentile Rank	0.33	0.35	0.31	0.28
	(0.22)	(0.22)	(0.21)	(0.21)
Social Percentile Rank	0.44	0.46	0.42	0.43
	(0.28)	(0.28)	(0.27)	(0.27)
Some College	N=1,706	N=1,308	N=213	N=185
Math Percentile Rank	0.62	0.67	0.40	0.37
	(0.27)	(0.25)	(0.24)	(0.22)
Verbal Percentile Rank	0.66	0.70	0.48	0.42
	(0.25)	(0.23)	(0.28)	(0.25)
STM Percentile Rank	0.51	0.55	0.33	0.30
	(0.25)	(0.24)	(0.20)	(0.21)
Social Percentile Rank	0.60	0.61	0.55	0.52
	(0.27)	(0.26)	(0.28)	(0.26)

Notes: This table represents the average percentile ranking of individual ability by education. Education is defined using the highest grade completed. Standard deviations are in brackets. Percentile scores on selected ASVAB subtests are used to construct the Math, Verbal, STM (Science/Technology/Mechanics) composites and converted to percentile rankings. Social ability is constructed as a composite of the following attitudinal measures from the NLSY79: Rotter locus of control scale, Rosenberg self-esteem scale, sociability at age six, and sociability in adulthood. Subsamples are obtained by splitting the analysis sample into different groups. Each sample is weighted using the initial sampling weight to account for the oversampling of Black, Hispanic or Latino and poor nonblack/non-Hispanic respondents in the NLSY79 supplemental samples.

1. Colorado's EITC started in 1999 and was contingent on a surplus from state revenue. The benefit was paid out from 1999 to 2001. In 2015, the credit was made permanent through legislation.

2. Indiana's EITC benefits were available between 1999-2002 period for families with dependents.

3. Minnesota has a different EITC schedule, which is available at https://taxsim.nber.org/eitc_MN.pdf.

4. New Jersey's EITC benefits were available between 2000-2006 for families with dependents and annual gross income not more than 20,000

5. Virginia's benefit for families is a minimum of the EITC and a credit available for low-income individuals.

6. Wisconsin's credit was repealed in the tax year 1986 and reinstated in 1989. The state has had separate benefit rules for families since 1989. The percentages shown correspond to the number of dependents, respectively, of 1, 2, and 3 or more.

Table B3. Means and Standard Deviations of Individual Skill Rank by Race

	Full Sample	**No Qualifying Child**	**One Qualifying Child**	**Two or more Qualifying Children**
Non-Hispanic Non-Black	N=1,781	N=1,327	N=251	N=203
Math Percentile Rank	0.53	0.59	0.38	0.36
	(0.28)	(0.28)	(0.23)	(0.20)
Verbal Percentile Rank	0.59	0.64	0.44	0.44
	(0.27)	(0.26)	(0.26)	(0.22)
STM Percentile Rank	0.47	0.51	0.37	0.37
	(0.24)	(0.25)	(0.21)	(0.20)
Social Percentile Rank	0.51	0.55	0.40	0.41
	(0.29)	(0.29)	(0.27)	(0.27)
Black	N=1,791	N=757	N=460	N=574
Math Percentile Rank	0.25	0.31	0.22	0.20
	(0.20)	(0.21)	(0.18)	(0.17)
Verbal Percentile Rank	0.26	0.32	0.24	0.19
	(0.22)	(0.25)	(0.21)	(0.17)
STM Percentile Rank	0.17	0.21	0.17	0.13
	(0.15)	(0.17)	(0.15)	(0.12)
Social Percentile Rank	0.48	0.50	0.47	0.46
	(0.27)	(0.27)	(0.27)	(0.26)
Hispanics	N=715	N=440	N=130	N=145
Math Percentile Rank	0.32	0.36	0.27	0.22
	(0.24)	(0.26)	(0.22)	(0.18)
Verbal Percentile Rank	0.35	0.39	0.31	0.26
	(0.26)	(0.27)	(0.25)	(0.19)
STM Percentile Rank	0.25	0.28	0.20	0.20
	(0.20)	(0.21)	(0.17)	(0.18)
Social Percentile Rank	0.41	0.43	0.42	0.34
	(0.27)	(0.29)	(0.23)	(0.25)

Notes: This table represents the average percentile ranking of individual ability along different dimensions. Standard deviations are in brackets. Percentile scores on selected ASVAB subtests are used to construct the Math, Verbal, STM (Science/Technology/Mechanics) composites and converted to percentile rankings. Social ability is constructed as a composite of the following attitudinal measures from the NLSY79: Rotter locus of control scale, Rosenberg self-esteem scale, sociability at age six, and sociability in adulthood. Subsamples are obtained by splitting the analysis sample into different groups. Each sample is weighted using the initial sampling weight to account for the oversampling of Black, Hispanic or Latino and poor nonblack/non-Hispanic respondents in the NLSY79 supplemental samples.

Table B4. Means and Standard Deviations of Mismatch by Education

	Full Sample	**No Qualifying Child**	**One Qualifying Child**	**Two or more Qualifying Children**
Less than High School	N=678	N=263	N=167	N=248
Aggregate Mismatch	1.24	1.23	1.30	1.20
	(0.74)	(0.64)	(0.87)	(0.76)
Math Skill Mismatch	0.90	0.88	0.96	0.87
	(0.78)	(0.65)	(0.86)	(0.86)
Verbal Skill Mismatch	0.92	0.86	1.08	0.86
	(0.74)	(0.66)	(0.81)	(0.77)
STM Skill Mismatch	1.10	1.12	1.06	1.11
	(0.94)	(0.97)	(0.96)	(0.87)
Social Skill Mismatch	1.25	1.34	1.16	1.19
	(0.93)	(0.93)	(0.88)	(0.97)
High School	N=1,903	N=953	N=461	N=489
Aggregate Mismatch	1.58	1.68	1.51	1.38
	(0.92)	(0.95)	(0.89)	(0.80)
Math Skill Mismatch	1.17	1.25	1.11	0.99
	(0.92)	(0.96)	(0.87)	(0.81)
Verbal Skill Mismatch	1.29	1.38	1.21	1.12
	(0.96)	(1.01)	(0.91)	(0.85)
STM Skill Mismatch	1.25	1.31	1.20	1.11
	(0.91)	(0.92)	(0.89)	(0.89)
Social Skill Mismatch	1.41	1.44	1.40	1.35
	(1.00)	(1.03)	(0.94)	(0.97)
Some College	N=1,706	N=1,308	N=213	N=185
Aggregate Mismatch	2.08	2.17	1.68	1.49
	(1.19)	(1.22)	(0.92)	(0.82)
Math Skill Mismatch	1.74	1.83	1.29	1.16
	(1.20)	(1.22)	(0.95)	(0.93)
Verbal Skill Mismatch	1.67	1.74	1.40	1.18
	(1.16)	(1.18)	(1.03)	(0.88)
STM Skill Mismatch	1.53	1.58	1.27	1.17
	(1.09)	(1.11)	(0.96)	(0.96)
Social Skill Mismatch	1.53	1.55	1.44	1.32
	(1.04)	(1.04)	(1.03)	(0.97)

Notes: This table represents the averages of skill mismatch by education. Education is defined using the highest grade completed. Subsamples are obtained by splitting the analysis sample into different groups. Each sample is weighted using the initial sampling weight to account for the oversampling of Black, Hispanic or Latino and poor nonblack/non-Hispanic respondents in the NLSY79 supplemental samples.

Table B5. Means and Standard Deviations of Mismatch by Race

	Full Sample	**No Qualifying Child**	**One Qualifying Child**	**Two or more Qualifying Children**
Non-Hispanic Non-Black	N=1,781	N=1,327	N=251	N=203
Aggregate Mismatch	1.93	2.04	1.64	1.48
	(1.13)	(1.17)	(0.95)	(0.81)
Math Skill Mismatch	1.55	1.67	1.23	1.09
	(1.15)	(1.18)	(0.96)	(0.92)
Verbal Skill Mismatch	1.56	1.64	1.37	1.22
	(1.11)	(1.15)	(0.97)	(0.86)
STM Skill Mismatch	1.46	1.53	1.26	1.17
	(1.02)	(1.05)	(0.90)	(0.86)
Social Skill Mismatch	1.49	1.53	1.40	1.32
	(1.02)	(1.03)	(0.97)	(0.96)
Black	N=1,791	N=757	N=460	N=574
Aggregate Mismatch	1.32	1.39	1.32	1.22
	(0.80)	(0.81)	(0.82)	(0.76)
Math Skill Mismatch	0.96	1.01	0.96	0.88
	(0.79)	(0.82)	(0.76)	(0.76)
Verbal Skill Mismatch	1.03	1.11	1.02	0.92
	(0.83)	(0.86)	(0.81)	(0.81)
STM Skill Mismatch	1.08	1.09	1.11	1.04
	(0.94)	(0.94)	(0.96)	(0.92)
Social Skill Mismatch	1.36	1.43	1.31	1.30
	(1.00)	(1.05)	(0.94)	(0.99)
Hispanics	N=715	N=440	N=130	N=145
Aggregate Mismatch	1.43	1.48	1.28	1.43
	(0.84)	(0.86)	(0.69)	(0.90)
Math Skill Mismatch	1.13	1.17	0.99	1.11
	(0.87)	(0.89)	(0.75)	(0.92)
Verbal Skill Mismatch	1.12	1.19	1.01	1.01
	(0.89)	(0.90)	(0.86)	(0.84)
STM Skill Mismatch	1.15	1.16	0.98	1.30
	(0.95)	(0.96)	(0.85)	(0.98)
Social Skill Mismatch	1.26	1.26	1.30	1.24
	(0.94)	(0.94)	(0.92)	(0.97)

Notes: This table represents the averages of skill mismatch by racial group. Subsamples are obtained by splitting the analysis sample into different groups. Each sample is weighted using the initial sampling weight to account for the oversampling of Black, Hispanic or Latino and poor nonblack/non-Hispanic respondents in the NLSY79 supplemental samples.

Table B6. Robustness Check: Relationship between the EITC Benefit and Skill Mismatch in an Initial Job, Federal Variation in the EITC.

N=4,287	Total Mismatch		Positive Mismatch		Negative Mismatch	
	Main Specification	Federal variation Only	Main Specification	Federal variation Only	Main Specification	Federal variation Only
$AverageFEDEITC_{k,t}$	0.1310**	0.1324**	0.1039***	0.1068***	-0.0105	-0.0080
	(0.0519)	(0.0497)	(0.0283)	(0.0249)	(0.0510)	(0.0400)
Year Fixed Effects.	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X
Demographic, Human Capital and Occupation Requirements Controls.	X	X	X	X	X	X
Experience and Intermittency Controls.	X	X	X	X	X	X
Full set of control	X	X	X	X	X	X

Notes: This table shows the relationship between the EITC benefit and skill mismatch in an initial job using the federal variation in the EITC benefit. The dependent variable in the regressions across all columns is mismatch scaled to a unit standard deviation. The analysis sample across all columns includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. The full sample consists of 2,047 unique individuals and 4,287 observations. The average federal EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. The full set of controls is described in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the State level and are in the brackets. ***, **, * denote significance levels at the 0.01, 0.05 and 0.1, respectively

Table B7. Robustness Check: Relationship between the EITC Benefit and Skill Mismatch in an Initial Job by Skill Type, Federal Variation in the EITC.

N=4,287	Math Mismatch		Verbal Mismatch		STM Mismatch		Social Mismatch	
	Main Specification	Federal variation Only	Main Specification	Federal variation Only	Main Specification	Federal variation Only	Main Specification	Federal variation Only
Panel A. Total Mismatch								
$AverageFEDEITC_{k,t}$	0.1334**	0.1718***	0.1234**	0.1203**	0.1092**	0.1096	-0.0571	-0.1284
	(0.0561)	(0.0558)	(0.0487)	(0.0470)	(0.0488)	(0.0748)	(0.0723)	(0.0792)
Year Fixed Effects.	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X
Panel B. Positive Mismatch								
$AverageFEDEITC_{k,t}$	0.1459***	0.1829***	0.0804***	0.0800***	0.1102***	0.1123**	-0.0638	-0.1278**
	(0.0378)	(0.0432)	(0.0300)	(0.0262)	(0.0330)	(0.0498)	(0.0536)	(0.0539)
Year Fixed Effects.	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X
Panel C. Negative Mismatch								
$AverageFEDEITC_{k,t}$	0.0326	0.0345	-0.0480	-0.0444	-0.0026	-0.0008	-0.0210	-0.0219
(0.0509)	(0.0633)	(0.0343)	(0.0383)	(0.0390)	(0.0503)	(0.0561)	(0.0721)	
Year Fixed Effects.	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X

Notes: This table shows the relationship between the EITC benefit and skill mismatch by skill type in an initial job using the federal variation in the EITC benefit. The dependent variable in the regressions across all columns is mismatch by the corresponding skill type scaled to a unit standard deviation. The analysis sample across all columns includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. The full sample consists of 2,047 unique individuals and 4,287 observations. The average federal EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. The full set of controls is described in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the state level and are in the brackets. ***, **, * denote significance levels at the 0.01, 0.05 and 0.1, respectively

Table B8. Robustness Check: Regressions for the Relationship between the EITC Benefit and Starting Wage, Federal Variation in the EITC.

N=4,129	Main Specification	Federal Variation Only
$AverageFEDEITC_{k,t}$	-0.0418	-0.0314
	(0.0304)	(0.0394)
Worker Ability (Mean)	0.2326***	0.2323***
	(0.0699)	(0.0701)
Occupation requirement (Mean)	0.0058	0.0061
	(0.0373)	(0.0372)
Physical Health	0.1095***	0.1097***
	(0.0243)	(0.0244)
State Unemployment Rate	0.0007	0.0010
	(0.0075)	(0.0075)
Metro Unemployment Rate	-0.0149***	-0.0149***
	(0.0041)	(0.0041)
State Minimum Wage	0.0308	0.0299
	(0.0266)	(0.0268)
AFDC/TANF Benefit for 3-Person Family	0.0004	0.0004
	(0.0005)	(0.0005)
FS/SNAP Benefit for 3-Person Family	0.0123***	0.0120***
	(0.0017)	(0.0017)
Intermittency	-0.0174	-0.0171
	(0.0158)	(0.0159)
$Intermittency^2 \times 100$	0.1098**	0.1097**
	(0.0524)	(0.0529)
Experience	0.0314***	0.0312***
	(0.0103)	(0.0102)
$Experience^2 \times 100$	-0.0101	-0.0075
	(0.0354)	(0.0348)
Full set of controls	X	X

Notes: This table shows the relationship between the EITC benefit and starting wage using the federal variation in the EITC. The dependent variable in the regressions across all columns is the natural log of the starting wage. The starting wage is adjusted for inflation using 2007 dollars. The analysis sample across all columns includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. The sample includes 2,010 unique individuals and 4,129 observations. All regressions include the full set of controls discussed in Table 9. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the State level and are in the brackets. ***, **, * denote significance levels at the 0.01, 0.05 and 0.1, respectively

Table B9. Robustness Check: Relationship between the EITC Benefit and Skill Mismatch in an Initial Job, Social Skills Excluded.

N=4,287	Total Mismatch		Positive Mismatch		Negative Mismatch	
	Main Specification	Sociability Excluded	Main Specification	Sociability Excluded	Main Specification	Sociability Excluded
$AverageEITC_{k,s,t}$	0.1310**	0.1278**	0.1039***	0.0870***	-0.0105	-0.0337
	(0.0519)	(0.0486)	(0.0283)	(0.0245)	(0.0510)	(0.0340)
Year Fixed Effects.	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X
Demographic, Human Capital and Occupation Requirements Controls.	X	X	X	X	X	X
Experience and Intermittency Controls.	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X

Notes: This table shows the relationship between the EITC benefit and skill mismatch in an initial job, excluding social skills in the aggregate measure of mismatch. The dependent variable in the regressions across all columns is the total mismatch scaled to a unit standard deviation. The analysis sample across all columns includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. The sample consists of 2,047 unique individuals and 4,287 observations. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. All regressions include the full set of controls discussed in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the State level and are in the brackets. ***, **, * denote significance levels at the 0.01, 0.05 and 0.1, respectively

Table B10. Robustness Check: Relationship between the EITC Benefit and Skill Mismatch in an Initial Job with Number of Children and State Linear Trends.

N=4,287	Total Mismatch			Positive Mismatch			Negative Mismatch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$AverageEITC_{k,s,t}$	0.1310**	0.1569	0.1543	0.1039***	0.1208**	0.1241**	-0.0105	-0.0178	-0.0099
	(0.0519)	(0.1081)	(0.1200)	(0.0283)	(0.0529)	(0.0569)	(0.0510)	(0.0754)	(0.0865)
Year Fixed Effects.	X	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X
Additional controls:									
Number of Children Linear Trend		X	X		X	X		X	X
State Linear Trend			X			X			X

Notes: This table shows the relationship between the EITC and skill mismatch in an initial job with the number of children and state-specific linear trends as additional controls. The analysis sample across all columns includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. The sample consists of 2,047 unique individuals and 4,287 observations. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. The full set of controls is discussed in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the State level and are in the brackets. ***, **, * denote significance levels at the 0.01, 0.05 and 0.1, respectively

Table B11. Robustness Check: Relationship between the EITC Benefit and Skill Mismatch in an Initial Job with Number of Children and State Linear Trends, High School and Less.

N=2,581	Total Mismatch			Positive Mismatch			Negative Mismatch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$AverageEITC_{k,s,t}$	0.0710	0.0702	0.0530	0.0471	0.0529	0.0475	-0.0189	-0.0097	0.0035
	(0.0487)	(0.0933)	(0.1092)	(0.0281)	(0.0470)	(0.0526)	(0.0300)	(0.0630)	(0.0764)
Year Fixed Effects.	X	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X
Additional controls:									
Number of Children Linear Trend		X	X		X	X		X	X
State Linear Trend			X			X			X

Notes: This table shows the relationship between the EITC benefit and skill mismatch in an initial job with the number of children and state-specific linear trends as additional controls. The dependent variable in the regressions across all columns is mismatch scaled to a unit standard deviation. The subsample is obtained by restricting the analysis sample to women whose highest degree completed is high school or less. The subsample consists of 1,251 unique individuals and 2,581 observations. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. The full set of controls is discussed in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the State level and are in the brackets. ***, **, * denote significance levels at the 0.01, 0.05 and 0.1, respectively

Table B12. Robustness Check: Relationship between the EITC Benefit and Skill Mismatch in an Initial Job with Number of Children and State Linear Trends, Some College.

N=1,706	Total Mismatch			Positive Mismatch			Negative Mismatch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$AverageEITC_{k,s,t}$	0.3311***	0.4691***	0.5638***	0.2308***	0.2985***	0.3414***	-0.0722	-0.1430	-0.1967
	(0.1087)	(0.1619)	(0.1789)	(0.0507)	(0.0866)	(0.1088)	(0.0917)	(0.1324)	(0.1395)
Year Fixed Effects.	X	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X
Additional controls:									
Number of Children Linear Trend		X	X		X	X		X	X
State Linear Trend			X			X			X

Notes: This table shows the relationship between the EITC benefit and skill mismatch in an initial job with the number of children and state-specific linear trends as additional controls. The dependent variable in the regressions across all columns is mismatch scaled to a unit standard deviation. The subsample is obtained by restricting the analysis sample to women with some level of college education. The subsample consists of 949 unique individuals and 1,706 observations. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. The full set of controls is discussed in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the State level and are in the brackets. ***, **, * denote significance levels at the 0.01, 0.05 and 0.1, respectively

Table B13. Robustness Check: Relationship between the EITC Benefit and Skill Mismatch in an Initial Job with Number of Children and State Linear Trends, All Mothers.

N=1,763	Total Mismatch			Positive Mismatch			Negative Mismatch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$AverageEITC_{k,s,t}$	0.1475**	0.1682**	0.1474	0.1119***	0.1250**	0.1121**	-0.0191	-0.0256	-0.0187
	(0.0710)	(0.0818)	(0.0882)	(0.0411)	(0.0514)	(0.0546)	(0.0392)	(0.0451)	(0.0513)
Year Fixed Effects.	X	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X
Additional controls:									
Number of Children Linear Trend		X	X		X	X		X	X
State Linear Trend			X			X			X

Notes: This table shows the relationship between the EITC benefit and skill mismatch in an initial job with the number of children and state-specific linear trends as additional controls. The dependent variable in the regressions across all columns is mismatch scaled to a unit standard deviation. The subsample is obtained by restricting the analysis to only mothers. The subsample consists of 872 unique individuals and 1,763 observations. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. The full set of controls is discussed in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the State level and are in the brackets. ***, **, * denote significance levels at the 0.01, 0.05 and 0.1, respectively

Table B14. Robustness Check: Relationship between the EITC Benefit and Skill Mismatch in an Initial Job by Skill Type, Number of Children and State Linear Trends.

N=4,287	Math Mismatch			Verbal Mismatch			STM Mismatch			Social Mismatch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Total Mismatch												
$AverageEITC_{k,s,t}$	0.1334**	0.1128	0.1178	0.1234**	0.1823*	0.1857	0.1092**	0.1011	0.0938	-0.0571	0.0139	-0.0049
	(0.0561)	(0.1080)	(0.1186)	(0.0487)	(0.1015)	(0.1132)	(0.0488)	(0.0691)	(0.0796)	(0.0723)	(0.1121)	(0.1217)
Year Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X	X	X	X
Additional controls:												
Number of Children Linear Trend		X	X		X	X		X	X		X	X
State Linear Trend			X			X			X			X
Panel B. Positive Mismatch												
$AverageEITC_{k,s,t}$	0.1459***	0.1391**	0.1472**	0.0804***	0.1141**	0.1240**	0.1102***	0.1163**	0.1279***	-0.0638	-0.0356	-0.0747
	(0.0378)	(0.0600)	(0.0648)	(0.0300)	(0.0557)	(0.0607)	(0.0330)	(0.0474)	(0.0461)	(0.0536)	(0.0889)	(0.1000)
Year Fixed Effects.	X	X	X	X	X	X	X	XX	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X	X	X	X
Additional controls:												
Number of Children Linear Trend		X	X		X	X		X	X		X	X
State Linear Trend			X			X			X			X
Panel C. Negative Mismatch												
$AverageEITC_{k,s,t}$	0.0326	0.0509	0.0561	-0.0480	-0.0778	-0.0678	-0.0026	0.0127	0.0328	-0.0210	-0.0781	-0.1145
	(0.0509)	(0.0895)	(0.1032)	(0.0343)	(0.0785)	(0.0895)	(0.0390)	(0.0635)	(0.0717)	(0.0561)	(0.0674)	(0.0740)
Year Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X	X	X	X
Additional controls:												
Number of Children Linear Trend		X	X		X	X		X	X		X	X
State Linear Trend			X			X			X			X

Notes: This table shows the relationship between the EITC benefit and skill mismatch by skill type in an initial job. The analysis sample across all columns includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. The sample consists of 2,047 unique individuals and 4,287 observations. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. The full set of controls is described in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the state level and are in the brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table B15. Robustness Check: Relationship between the EITC Benefit and Skill Mismatch in an Initial Job by Skill Type with Number of Children and State Linear Trends, High School and Less.

N=2,581	Math Mismatch			Verbal Mismatch			STM Mismatch			Social Mismatch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Total Mismatch												
$AverageEITC_{k,s,t}$	0.0339	0.0193	-0.0048	0.0826	0.1087	0.1186	0.1007**	0.0632	0.0285	-0.0628	-0.0211	-0.0188
	(0.0524)	(0.0951)	(0.1111)	(0.0572)	(0.1073)	(0.1198)	(0.0490)	(0.0631)	(0.0742)	(0.0740)	(0.1128)	(0.1224)
Year Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X	X	X	X
Additional controls:												
Number of Children Linear Trend		X	X		X	X		X	X		X	X
State Linear Trend			X			X			X			X
Panel B. Positive Mismatch												
$AverageEITC_{k,s,t}$	0.0272	0.0381	0.0252	0.0574	0.0626	0.0824	0.0896**	0.0862*	0.0682	-0.0597	-0.0544	-0.0724
	(0.0341)	(0.0581)	(0.0675)	(0.0351)	(0.0565)	(0.0599)	(0.0347)	(0.0494)	(0.0578)	(0.0591)	(0.0878)	(0.0949
Year Fixed Effects.	X	X	X	X	X	X	X	XX	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X	X	X	X
Additional controls:												
Number of Children Linear Trend		X	X		X	X		X	X		X	X
State Linear Trend			X			X			X			X
Panel C. Negative Mismatch												
$AverageEITC_{k,s,t}$	-0.0065	0.0301	0.0442	-0.0268	-0.0543	-0.0385	-0.0150	0.0221	0.0409	-0.0061	-0.0581	-0.0905
	(0.0429)	(0.0719)	(0.0893)	(0.0384)	(0.0775)	(0.0921)	(0.0358)	(0.0586)	(0.0638)	(0.0579)	(0.0801)	(0.0975)
Year Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X	X	X	X
Additional controls:												
Number of Children Linear Trend		X	X		X	X		X	X		X	X
State Linear Trend			X			X			X			X

Notes: This table shows the relationship between the EITC benefit and skill mismatch by skill type in an initial job with the number of children and state-specific linear trends as additional controls. The subsample is obtained by restricting the analysis sample to women whose highest degree completed is a high school degree or less. The subsample consists of 1,251 unique individuals and 2,581 observations. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. The full set of controls is described in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the state level and are in the brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table B16. Robustness Check: Relationship between the EITC Benefit and Skill Mismatch in an Initial Job by Skill Type with Number of Children and State Linear Trends, Some College Degree.

N=1,706	Math Mismatch			Verbal Mismatch			STM Mismatch			Social Mismatch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Total Mismatch												
$Average EITC_{k,s,t}$	0.4218***	0.4972***	0.5419***	0.2670**	0.3956**	0.4939**	0.1761	0.2895*	0.3644**	-0.0362	0.0532	0.1130
	(0.0917)	(0.1430)	(0.1478)	(0.1065)	(0.1525)	(0.1876)	(0.1098)	(0.1558)	(0.1747)	(0.1236)	(0.1746)	(0.1815)
Year Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X	X	X	X
Additional controls:												
Number of Children Linear Trend		X	X		X	X		X	X		X	X
State Linear Trend			X			X			X			X
Panel B. Positive Mismatch												
$Average EITC_{k,s,t}$	0.4230***	0.4654***	0.4675***	0.1328**	0.2241**	0.2675*	0.1755***	0.1965	0.2508*	-0.1342	-0.0652	-0.0060
	(0.0668)	(0.0977)	(0.1100)	(0.0647)	(0.1000)	(0.1354)	(0.0624)	(0.1250)	(0.1474)	(0.1061)	(0.1646)	(0.1725)
Year Fixed Effects.	X	X	X	X	X	X	X	XX	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X	X	X	X
Additional controls:												
Number of Children Linear Trend		X	X		X	X		X	X		X	X
State Linear Trend			X			X			X			X
Panel C. Negative Mismatch												
$Average EITC_{k,s,t}$	0.0458	0.0045	-0.0542	-0.1644	-0.2033	-0.2719	-0.0065	-0.1076	-0.1317	-0.1659	-0.1830	-0.1735
	(0.0952)	(0.1403)	(0.1510)	(0.0989)	(0.1526)	(0.1675)	(0.0931)	(0.1064)	(0.1172)	(0.1199)	(0.1628)	(0.1668)
Year Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X	X	X	X
Additional controls:												
Number of Children Linear Trend		X	X		X	X		X	X		X	X
State Linear Trend			X			X			X			X

Notes: This table shows the relationship between the EITC benefit and skill mismatch by skill type in an initial job with the number of children and state-specific linear trends as additional controls. The subsample is obtained by restricting the analysis sample to women with some level of college education. The subsample consists of 949 unique individuals and 1,706 observations. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. The full set of controls is described in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the state level and are in the brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table B17. Robustness Check: Relationship between the EITC Benefit and Skill Mismatch in an Initial Job by Skill Type with Number of Children and State Linear Trends, All Mothers.

N=1,763	Math Mismatch			Verbal Mismatch			STM Mismatch			Social Mismatch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Total Mismatch												
$AverageEITC_{k,s,t}$	0.0981	0.0945	0.0563	0.1392**	0.1810**	0.1648*	0.1296**	0.1448**	0.1656**	0.0365	0.0354	0.0003
	(0.0887)	(0.0934)	(0.0927)	(0.0610)	(0.0774)	(0.0839)	(0.0596)	(0.0619)	(0.0662)	(0.1071)	(0.1448)	(0.1597)
Year Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X	X	X	X
Additional controls:												
Number of Children Linear Trend		X	X		X	X		X	X		X	X
State Linear Trend			X			X			X			X
Panel B. Positive Mismatch												
$AverageEITC_{k,s,t}$	0.1030*	0.1082	0.0945	0.1047**	0.1438**	0.1272**	0.1123***	0.1379***	0.1629***	0.0160	-0.0479	-0.0993
	(0.0605)	(0.0649)	(0.0647)	(0.0437)	(0.0575)	(0.0581)	(0.0378)	(0.0466)	(0.0518)	(0.0791)	(0.1159)	(0.1270)
Year Fixed Effects.	X	X	X	X	X	X	X	XX	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X	X	X	X
Additional controls:												
Number of Children Linear Trend		X	X		X	X		X	X		X	X
State Linear Trend			X			X			X			X
Panel C. Negative Mismatch												
$AverageEITC_{k,s,t}$	0.0176	0.0304	0.0628	-0.0335	-0.0323	-0.0349	-0.0225	-0.0121	-0.0084	-0.0269	-0.1292	-0.1619
	(0.0558)	(0.0657)	(0.0735)	(0.0415)	(0.0529)	(0.0637)	(0.0523)	(0.0668)	(0.0682)	(0.0838)	(0.1030)	(0.1139)
Year Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X	X	X	X	X
Additional controls:												
Number of Children Linear Trend		X	X		X	X		X	X		X	X
State Linear Trend			X			X			X			X

Notes: This table shows the relationship between the EITC benefit and skill mismatch by skill type in an initial job with the number of children and state-specific linear trends as additional controls. The subsample is obtained by restricting the analysis sample to only mothers. The subsample consists of 1,763 unique individuals and 872 observations. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. The full set of controls is described in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the state level and are in the brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table B18. Regressions for the Relationship between the EITC Benefit and Initial Wage with Number of Children and State Linear Trends as Additional Controls.

	N=4,129 Full Sample			N=2,490 High School and Less			N=1,639 Some College			N=1,706 All Mothers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$AverageEITC_{k,s,t}$	-0.0418	-0.0686	-0.0975**	-0.0478	-0.0456	-0.0750	-0.0205	-0.0573	-0.1192	-0.1049**	-0.0924	-0.1381*
	(0.0304)	(0.0432)	(0.0467)	(0.0327)	(0.0527)	(0.0609)	(0.0535)	(0.0950)	(0.0989)	(0.0510)	(0.0640)	(0.0772)
Worker Ability (Mean)	0.2326***	0.2309***	0.2070***	0.1987**	0.1973**	0.1609	0.2764**	0.2769**	0.2376**	0.2564***	0.2563***	0.2515***
	(0.0699)	(0.0717)	(0.0736)	(0.0913)	(0.0930)	(0.0991)	(0.1044)	(0.1054)	(0.0963)	(0.0813)	(0.0813)	(0.0826)
Occupation requirement (Mean)	0.0058	0.0048	-0.0040	-0.1673***	-0.1674***	-0.1591***	0.3018***	0.3019***	0.2557***	-0.0571	-0.0567	-0.0525
	(0.0373)	(0.0377)	(0.0373)	(0.0493)	(0.0491)	(0.0473)	(0.0692)	(0.0694)	(0.0719)	(0.0767)	(0.0765)	(0.0732)
Physical Health	0.1095***	0.1091***	0.1109***	0.1284***	0.1281***	0.1184***	0.0993***	0.0995***	0.0949**	0.1230***	0.1237***	0.1149***
	(0.0243)	(0.0241)	(0.0248)	(0.0322)	(0.0322)	(0.0322)	(0.0344)	(0.0339)	(0.0356)	(0.0394)	(0.0391)	(0.0395)
State Unemployment Rate	0.0007	0.0007	0.0044	0.0008	0.0010	0.0166	0.0005	0.0011	-0.0108	0.0110	0.0110	0.0117
	(0.0075)	(0.0075)	(0.0106)	(0.0099)	(0.0099)	(0.0156)	(0.0150)	(0.0149)	(0.0251)	(0.0178)	(0.0178)	(0.0177)
Metro Unemployment Rate	-0.0149***	-0.0149***	-0.0165***	-0.0161**	-0.0161*	-0.0198**	-0.0143	-0.0145	-0.0163*	-0.0213***	-0.0213***	-0.0213***
	(0.0041)	(0.0041)	(0.0042)	(0.0080)	(0.0080)	(0.0092)	(0.0094)	(0.0094)	(0.0091)	(0.0072)	(0.0072)	(0.0075)
State Minimum Wage	0.0308	0.0315	0.0233	0.0185	0.0170	0.0074	0.0620	0.0611	0.0397	0.0145	0.0136	0.0049
	(0.0266)	(0.0267)	(0.0302)	(0.0343)	(0.0341)	(0.0407)	(0.0395)	(0.0389)	(0.0469)	(0.0387)	(0.0393)	(0.0400)
AFDC/TANF Benefit for 3-Person Family	0.0004	0.0004	0.0003	0.0008	0.0008	0.0004	0.0002	0.0002	0.0008	-0.0007	-0.0007	-0.0007
	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0006)	(0.0007)	(0.0007)
FS/SNAP Benefit for 3-Person Family	0.0123***	0.0126***	0.0104***	0.0114***	0.0118***	0.0130***	0.0192***	0.0205***	0.0197***	0.0114***	0.0116***	0.0107***
	(0.0017)	(0.0018)	(0.0016)	(0.0017)	(0.0016)	(0.0019)	(0.0041)	(0.0036)	(0.0029)	(0.0032)	(0.0032)	(0.0029)
Intermittency	-0.0174	-0.0172	-0.0152	-0.0438*	-0.0444*	-0.0418*	0.0355*	0.0361*	0.0399*	-0.0185	-0.0191	-0.0175
	(0.0158)	(0.0155)	(0.0155)	(0.0222)	(0.0222)	(0.0214)	(0.0202)	(0.0199)	(0.0203)	(0.0171)	(0.0167)	(0.0172)
$Intermittency^2 \times 100$	0.1098**	0.1083**	0.1047*	0.1500*	0.1537*	0.1269	-0.0302	-0.0396	-0.0759	0.1683**	0.1724**	0.1520*
	(0.0524)	(0.0517)	(0.0536)	(0.0799)	(0.0794)	(0.0799)	(0.0795)	(0.0907)	(0.0832)	(0.0723)	(0.0698)	(0.0797)
Experience	0.0314***	0.0314***	0.0349***	0.0097	0.0095	0.0099	0.0751***	0.0743***	0.0764***	0.0299**	0.0299**	0.0299**
	(0.0103)	(0.0102)	(0.0094)	(0.0155)	(0.0157)	(0.0142)	(0.0140)	(0.0139)	(0.0150)	(0.0129)	(0.0128)	(0.0122)
$Experience^2 \times 100$	-0.0101	-0.0086	-0.0239	0.0066	0.0065	0.0011	-0.0518	-0.0484	-0.0511	-0.0182	-0.0194	-0.0343
	(0.0354)	(0.0350)	(0.0374)	(0.0528)	(0.0523)	(0.0486)	(0.0700)	(0.0691)	(0.0701)	(0.0549)	(0.0532)	(0.0580)
Year Fixed Effects	X	X	X	X	X	X	X	X	X	X	X	X
State Fixed Effects	X	X	X	X	X	X	X X	X	X	X	X	
Number of Children Fixed Effects	X	X	X	X	X	X	X	X	X	X	X	X
Full Sets of Controls	X	X	X	X	X	X	X	X	X	X	X	X
Additional Controls												
Number of Children Linear Trend		X	X		X	X		X	X		X	X
State Linear Trend			X			X			X			X

Notes: This table shows the relationship between the EITC benefit and the starting wage with the number of children and state-specific linear trends as additional controls. The dependent variable in the regressions across all columns is the natural log of the starting wage. The starting wage is adjusted for inflation using 2007 dollars. The full set of controls is described in Table 9. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are clustered at the State level and are in the brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table B19. Robustness Check: Relationship between the EITC Benefit and Skill Mismatch in an Initial Job, Random Effects Regression.

N=4,287	Total Mismatch		Positive Mismatch		Negative Mismatch	
	OLS	Random Effect	OLS	Random Effect	OLS	Random Effect
$AverageEITC_{k,s,t}$	0.1310**	0.0998***	0.1039***	0.0664***	-0.0105	-0.0066***
	(0.0519)	(0.0001)	(0.0283)	(0.0000)	(0.0510)	(0.0001)
Year Fixed Effects.	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X

Notes: This table shows the relationship between the EITC benefit and skill mismatch in an initial job. The dependent variable in the regressions across all columns is mismatch scaled to a unit standard deviation. The analysis sample across all columns includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. The full sample consists of 2,047 unique individuals and 4,287 observations. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. All regions include the full set of controls discussed in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are in the brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table B20. Robustness Check: Relationship between the EITC Benefit and Skill Mismatch in an Initial Job by Skill Type, Random Effects Regression.

N=4,287	Math Mismatch		Verbal Mismatch		STM Mismatch		Social Mismatch	
	OLS	Random Effects		OLS	Random Effects	OLS	Random Effects	
Panel A. Total Mismatch								
$AverageEITC_{k,s,t}$	0.1334**	0.0934***	0.1234**	0.0977***	0.1092**	0.0874***	-0.0571	-0.0510***
	(0.0561)	(0.0001)	(0.0487)	(0.0001)	(0.0488)	(0.0001)	(0.0723)	(0.0001)
Year Fixed Effects.	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X
Panel B. Positive Mismatch								
$AverageEITC_{k,s,t}$	0.1459***	0.0724***	0.0804***	0.0466***	0.1102***	0.0867***	-0.0638	-0.0283***
	(0.0378)	(0.0001)	(0.0300)	(0.0000)	(0.0330)	(0.0001)	(0.0536)	(0.0001)
Year Fixed Effects.	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X
Panel C. Negative Mismatch								
$AverageEITC_{k,s,t}$	0.0326	0.0218***	-0.0480	-0.0447***	-0.0026	0.0056***	-0.0210	0.0004***
	(0.0509)	(0.0001)	(0.0343)	(0.0001)	(0.0390)	(0.0001)	(0.0561)	(0.0001)
Year Fixed Effects.	X	X	X	X	X	X	X	X
State Fixed Effects.	X	X	X	X	X	X	X	X
Number of Children Fixed Effects.	X	X	X	X	X	X	X	X
Full set of controls	X	X	X	X	X	X	X	X

Notes: This table shows the relationship between the EITC benefit and skill mismatch by skill type in an initial job. The analysis sample across all columns includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. The full sample consists of 2,047 unique individuals and 4,287 observations. The average EITC benefit is adjusted to real 2007 dollars and rescaled to be in thousands of 2007 dollars for clear interpretation of estimates. The full set of controls is described in Table 5. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are in the brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table B21. Robustness Check: Relationship between the EITC Benefit and Starting Wage, Random Effects Regression.

N=4,129	OLS	Random Effects
$AverageEITC_{k,s,t}$	-0.0418	-0.0339***
	(0.0304)	(0.0000)
Worker Ability (Mean)	0.2326***	0.2357***
	(0.0699)	(0.0001)
Occupation requirement (Mean)	0.0058	0.0092***
	(0.0373)	(0.0001)
Physical Health	0.1095***	0.1131***
	(0.0243)	(0.0001)
State Unemployment Rate	0.0007	-0.0004***
	(0.0075)	(0.0000)
Metro Unemployment Rate	-0.0149***	-0.0141***
	(0.0041)	(0.0000)
State Minimum Wage	0.0308	0.0268***
	(0.0266)	(0.0000)
AFDC/TANF Benefit for 3-Person Family	0.0004	0.0003***
	(0.0005)	(0.0000)
FS/SNAP Benefit for 3-Person Family	0.0123***	0.0105***
	(0.0017)	(0.0000)
Intermittency	-0.0174	-0.0149***
	(0.0158)	(0.0000)
$Intermittency^2 \times 100$	0.1098**	0.1094***
	(0.0524)	(0.0001)
Experience	0.0314***	0.0329***
	(0.0103)	(0.0000)
$Experience^2 \times 100$	-0.0101	-0.0080***
	(0.0354)	(0.0001)
Full Sets of Controls	X	X

Notes: This table shows the relationship between the EITC benefit and starting wage. The dependent variable in the regressions across all columns is the natural log of the starting wage. The starting wage is adjusted for inflation using 2007 dollars. The analysis sample across all columns includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. The full sample consists of 2,010 unique individuals and 4,129 observations. The full set of controls is described in Table 9. Regressions are weighted using the NLYS79 initial sampling weight. Standard errors are in the brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.

Table B22. Relationship between Mismatch and Starting Wage, Random Effects Regression.

N=4,129	OLS	Random Effects
Panel A.		
Mismatch	-0.0151*	-0.0161***
	(0.0089)	(0.0000)
Panel B.		
Positive Mismatch	-0.0877***	-0.0972***
	(0.0158)	(0.0000)
Negative Mismatch	-0.0545***	-0.0579***
	(0.0164)	(0.0000)
Panel C.		
Math Mismatch	-0.0095	-0.0086***
	(0.0123)	(0.0000)
Verbal Mismatch	0.0002	0.0015***
	(0.0154)	(0.0000)
STM Mismatch	-0.0079	-0.0104***
	(0.0126)	(0.0000)
Social Mismatch	0.0084	0.0060***
	(0.0104)	(0.0000)
Math Ability	0.1243	0.1263***
	(0.0776)	(0.0001)
Verbal Ability	0.0574	0.0536***
	(0.0857)	(0.0001)
STM Ability	-0.0098	-0.0059***
	(0.0943)	(0.0001)
Social Ability	0.1090**	0.1088***
	(0.0449)	(0.0001)
Math Occupational requirement	0.1286	0.1198***
	(0.0912)	(0.0002)
Verbal Occupational requirement	0.0006	0.0432***
	(0.1277)	(0.0002)
STM Occupational requirement	0.4898***	0.4737***
	(0.0921)	(0.0001)
Social Occupational requirement	-0.5359***	-0.5482***
	(0.1197)	(0.0001)
Full Sets of Controls	X	X

Notes: This table shows the relationship between the different measures of mismatch and the starting wage. Each panel represents a different set of regression. The dependent variable in the regressions across all columns is the natural log of the starting wage. The starting wage is adjusted for inflation using 2007 dollars. The analysis sample across all columns includes single non-college-educated women aged 19 to 49 between 1980 and 2006 in the NLSY79 survey with valid test scores and non-missing attitudinal measures who reentered the labor market between 1980 and 2006 and took a job not previously held. The sample consists of 2,010 unique individuals and 4,129 observations. All regressions include the same standard set of controls in Table 9, excluding AFDC/TANF Benefit for a 3-person Family and FS/SNAP Benefit for a 3-person Family. However, in Panel C, the average ability and occupational skill requirement are replaced by the specific ability and skill type. Regressions are weighted using the NLSY79 initial sampling weight. Standard errors are in the brackets. ***, **, * denote significance levels at 0.01, 0.05, and 0.1, respectively.