The Role of the Informal Sector in the Early Careers of Less-Educated Workers

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Abstract

Does work experience gained in the informal sector affect the career prospects of less-educated workers? This paper examines two roles that informal sector jobs play in the early stages of a worker’s career: informal jobs may (i) provide the opportunity to accumulate skills, and (ii) act as a screening device that enables employers to learn a worker’s ability. This paper develops a matching model of the informal and formal sectors that can accommodate both roles. Implied hazard rates from informal to formal sectors as a function of tenure are shown to differ depending on whether the dominant role is human capital accumulation or screening. Using the ENOE, a longitudinal employment survey from Mexico, hazard functions are estimated for less-educated workers. The estimated hazard functions suggest that screening plays a more important role in the informal sector than does skill formation in the early stages of a worker’s career. The estimation results also imply that employers would only learn the ability of 14% of their workers after one month of employment. This finding suggests that employers’ capacity to select workers is limited in government employment programs requiring employers to provide permanent positions to a predetermined fraction of workers after a short period of time.

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1 Introduction

The informal sector is an important feature of labor markets in developing countries. This sector, composed of all jobs not complying with labor regulations, occupies a significant portion of these countries’ labor markets. In Latin America and the Caribbean, the fraction of workers employed in the informal sector ranges from 15% to 62% (see Figure 1). Jobs in this sector employ the majority of young unskilled workers usually paying very low wages, not to mention the lack of health and employment insurance enjoyed by workers holding formal sector jobs.

Figure 1: Share of Salaried Workers in Informal Jobs in Latin America and the Caribbean

The presence of large informal sectors has typically been a concern for researchers and policymakers. Some are concerned that the informal sector could be the disadvantaged sector in a segmented labor market (Magnac, 1991; Maloney, 1999; Amaral and Quintin, 2006; Arias and Khamis, 2008). Others are concerned that the informal sector might adversely affect productivity and growth (Loayza, 1996; Schneider and Enste, 2000; Farrell, 2004; Levy, 2007; Fajnzylber, 2007). Whether these concerns are supported by the evidence is still unresolved. However, they have induced policymakers to introduce tighter regulations to reduce or control the size of the informal sector.

Before attempting to restrict the informal sector, it is important to investigate the potential benefits that workers obtain during informal sector employment. Previous studies have found that less-educated workers start their working careers in salaried jobs in the informal sector and move into formal jobs as they grow older (Maloney, 1999; Arias and Maloney, 2006).
We would like to know if informal sector jobs provide some value above and beyond make-shift low-paying work while people wait to find a “good” formal sector job: do these jobs also provide skills or help screen workers to facilitate a transition to higher paying formal sector jobs? If rules designed to reduce the informal sector are implemented, would we lose some valuable worker training or screening? If so, restrictions on informal sector employment should be accompanied by policies that replace the productive functions of these jobs.

We investigate two potential roles that informal sector jobs could play in the early stages of a worker’s career. First, these jobs may provide the opportunity to accumulate skills, making workers more productive and more attractive to formal sector employers. While more-educated workers tend to access greater training opportunities in formal sector employment, less-educated workers may turn to the informal sector to gain work skills. Second, informal sector jobs may serve as a screening device that enables employers to learn a worker’s ability. The lack of compliance with labor regulations, especially firing costs and severance payments, suggests that informal sector employers may be more prone to hire young unskilled workers entering the labor market than are formal sector employers. Hence, an informal sector worker who reveals that he is productive may increase his likelihood of finding a formal sector job.

The role of the informal sector as a provider of training opportunities was first suggested by Hemmer and Mannel (1989) and has been advocated by Maloney (1999) and Arias and Maloney (2007). The role of the informal sector as a screening device is rarely discussed. One exception is Arias and Maloney (2007) who argue that labor regulations and information asymmetries “impede young workers’ entry into the formal sector.” The study presented here contributes to this literature by providing an analytical framework and empirical evidence about these roles of the informal sector.

To determine the relative importance of the training or screening roles of the informal sector, we develop a two-sector matching model to study worker movements from the informal to the formal sector. The model is designed to better understand the labor market dynamics in Mexico, a country with a significant informal labor market. In Mexico, the informal sector is a port of entry to the labor market for less-educated workers. These workers are concentrated in the informal sector in the early stages of their working careers, moving to the formal sector as they age (see Figure 2). Figure 3 shows that the probability of moving from the informal to the formal sector increases during the early stages of workers’ careers.

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1 The evidence presented by Barron et al. (1997) indicates that more educated workers in the U.S. have greater access to on-the-job training (see Table 4.2).

2 Bosch (2006) and Bosch et al. (2007) present evidence that labor regulations affect the patterns of job creation in the formal sector in economies with large informal sectors. Some argue that these regulations disproportionately affect the youth (World Bank 2007, chap. 4).
Figure 2: Distribution of Workers by Employment Sector in Mexico
(a) Years of Education: [0,9)  
(b) Years of Education: [9,12)

Source: Author’s calculations using ENOE I:2005 - IV:2010. A worker is considered informal if he is an employee not enrolled in government health care program. Males not attending school.

Figure 3: Transitions Out of the Informal Sector in Mexico
(a) Years of Education: [0,9)  
(b) Years of Education: [9,12)

Source: Author’s calculations using ENOE I:2005 - IV:2010. Number of transitions relative to the size of the informal sector. A worker is considered informal if he is an employee not enrolled in government health care program. Males not attending school. IS = Informal Sector, FS = Formal Sector, SE = Self-Employed.
The empirical analysis is based on the analytical implications for hazard rates from the informal to the formal sectors derived from the model. It is shown that hazard rates from informal to formal sectors as a function of tenure differ depending on the role of the informal sector: human capital accumulation or screening. On the one hand, if workers accumulate human capital while working in the informal sector, the likelihood of moving into the formal sector increases with informal sector tenure. On the other hand, if workers’ productivities are screened while working in the informal sector, those discovered as highly productive move faster to the formal sector, leaving behind those with low productivity who have difficulties to access formal sector jobs. Thus, the likelihood of moving into the formal sector may initially increase, but it eventually decreases with informal sector tenure.

Using an employment survey from Mexico to obtain measures of duration of employment in the informal sector, we estimate the hazard functions and test the two hypotheses. The estimated hazard is consistent with the implications of the screening model, which indicates that informal sector jobs have an important role by solving the information problem about the abilities of young less-educated workers that are new to the labor market.

Our results give us the means to infer the parameters governing the screening process in one stream of the Bécate training program for the unemployed in Mexico, which is targeted at less-educated youth. One of the streams of Bécate is a mixture of skill formation and worker placement. In this stream, training takes place at the workplace, and the hosting firm must have empty vacancies that need to be filled. The training program lasts for one to three months. At the end of the training program, the firm is committed to hire at least 70% of the participants. Given this short amount of time, it seems likely that the program works more as a screening device than a source of significant skill formation.

Based on the estimated hazard, we can deduce the rate at which an employer learns about a worker’s ability. For workers with less than 12 years of education, the estimates indicate that an employer learns about a worker’s ability at a rate of 14% per month. Consequently, if an employer commits to hire 70% of the program participants, a one or two month program requires the employer to take a gamble on a considerable portion of the program participants, since the employer must bear the firing costs of terminating any unsuitable workers. This highlights the importance of better understanding the role of the informal sector in the design of policy.

The study is organized as follows. In Section 2 we present the baseline model and

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3Bécate was launched in 1984 and was designed to assist individuals with less than 9 years of education between the ages of 16 and 30. Currently, the program has more streams to assist a broader set of workers and needs. Delajara et al. (2006) provides a comprehensive evaluation of the program.

4In this stream of the program, the firm can participate in the selection and recruitment of workers participating in the program.
its implications for hazard rates from the informal to the formal sector. In Section 3, we present models with human capital accumulation and with employer learning, deriving their implications for hazard rates. Once the theoretical implications are described, in Section 4 we describe the data used in the empirical analysis. The details of the estimation follow in Section 5. Section 6 summarizes the empirical results, and Section 7 concludes with some remarks on the results and suggestions for future research.

2 Baseline Model

The labor market is composed of two sectors, a formal sector and an informal sector. Formal sector firms comply with labor regulations represented by a firing cost incurred by firms when jobs are destroyed. The firing cost is assumed to be a wasteful tax as in Mortensen and Pissarides (2003) and Dolado et al. (2005), so no transfer to the worker takes place. Informal sector firms do not comply with labor regulations.

We follow Albrecht et al. (2006, 2009) by assuming that workers differ in their productivity in the formal sector, but they are equally productive in the informal sector. Workers in the formal sector produce \( px \) units per period, where \( p \in \{p_L, p_H\} \), with \( p_H > p_L \), and \( x \) is a measure of match quality. Match quality is a random draw from a known distribution \( G(x) \) with support on \([0, 1]\) that is made when the worker and firm meet; match quality stays constant until the job is destroyed. A fraction \( \phi \) of the workers have the innate productivity \( p_L \) in the formal sector; we refer to these workers as L-skilled and the others as H-skilled. Innate productivity is perfectly observable. All workers in the informal sector produce \( p_I \) units per period. It is assumed that \( p_I \geq z \), where \( z \) is the flow utility in unemployment.

Job destruction in both sectors follows from an idiosyncratic shock that arrives to occupied jobs at Poisson rate \( \delta \). If the job is destroyed in the formal sector, the firm incurs a firing cost \( D \). Jobs are also destroyed due to worker’s death. A worker dies with probability \( \tau \) regardless of the worker’s employment status. Every dead worker is replaced by a new unemployed worker who is L-skilled with probability \( \phi \). Job destructions due to death do not generate firing costs.

Unemployed workers search for jobs in both sectors, and all informal sector workers search for jobs in the formal sector. The number of meetings between workers and firms in the informal sector is \( m(u, v_I) \) and \( m(u + e_I, v_F) \) in the formal sector, where \( u \) and \( e_I \) are the number of workers in unemployment and in informal sector jobs, respectively, \( v_j \) is the number of open vacancies in sector \( j \in \{F, I\} \), and \( m(\cdot, \cdot) \) is the meeting function. The

\footnote{To focus on flows from the informal to the formal sector, we abstract from on-the-job search in the opposite direction and from on-the-job search within each sector.}
meeting function is homogeneous of degree one, concave and increasing in both its arguments. As a result, a job seeker meets a firm in sector \( j \in \{F, I\} \) with probability \( m(\theta_j) = m(1, \theta_j) \), and a firm in sector \( j \) meets a job seeker with probability \( m(\theta_j)/\theta_j \), where \( \theta_I = v_I/u \) and \( \theta_F = v_F/(u + e_I) \) are the measures of market tightness in the informal and the formal labor markets, respectively.

Given the assumptions on productivity in the informal sector, all meetings between an informal sector firm and an unemployed worker lead to job creation. Due to firing costs and to the assumptions on productivity in the formal sector, a job in this sector is created if and only if the match quality is higher than a reservation match quality. The reservation match quality is endogenous and depends on both the skill level and the current employment status of the worker.

The payoffs for workers are:

\[
\begin{align*}
\bar{r}U(p) &= z + m(\theta_I)[W_I(p) - U(p)] + m(\theta_F) \int_{C(p)}^{1} [W_F(s, p) - U(p)] dG(s) \\
\bar{r}W_F(x, p) &= w_F(x, p) + \delta[U(p) - W_F(x, p)] \\
\bar{r}W_I(p) &= w_I(p) + \delta[U(p) - W_I(p)] + m(\theta_F) \int_{Q(p)}^{1} [W_F(s, p) - W_I(p)] dG(s)
\end{align*}
\]

where \( \bar{r} \equiv r + \tau \) and \( r \) is the discount rate. \( U(p), W_F(x, p), \) and \( W_I(p) \) denote the present discounted value of the expected income stream of an unemployed worker, a worker employed in the formal sector, and a worker employed in the informal sector, respectively. Employed workers earn wage \( w_I(p) \) or \( w_F(x, p) \) when they work in the informal or the formal sector, respectively. The reservation match quality for the unemployed is \( C(p) \) and for informal sector workers is \( Q(p) \).

For workers of skill level \( p \), the value of unemployment, \( \bar{r}U(p) \), depends on three main factors. First, unemployed workers receive flow utility \( z \), which can be thought as the utility derived from leisure. Second, if they find an informal sector job, they experience a gain of \( [W_I(p) - U(p)] \), and this happens with probability \( m(\theta_I) \). Third, if they find a formal sector job, they experience a gain of \( [W_F(s, p) - U(p)] \). For unemployed workers, the probability of finding a formal sector job depends on: (i) the probability of meeting a formal sector firm with an empty vacancy, \( m(\theta_F) \), and (ii) the probability that the match is worth forming, i.e. that the match quality randomly drawn is higher than \( C(p) \).

For formal sector workers of skill level \( p \) currently employed with match quality \( x \), the value of formal sector employment, \( \bar{r}W_F(x, p) \), depends on two main factors. First, they

\[\text{We follow}^{6}\text{Dolado, Jansen, and Jimeno (2005) in this job creation mechanism with two worker skill levels, firing cost, and initial random draw determining cut-offs for job creation.}\]
receive wage $w_F(x, p)$. Second, with probability $\delta$ they lose their job and experience a loss of $[U(p) - W_F(x, p)]$.

Finally, for informal sector workers of skill level $p$, the value of informal sector employment, $\tilde{r}W_I(p)$, depends on three main factors. First, they receive wage $w_I(p)$. Second, with probability $\delta$ they lose their job and experience a loss of $[U(p) - W_I(p)]$. Third, if they find a formal sector job, they experience a gain of $[W_F(s, p) - W_I(p)]$. For informal sector workers, the probability of finding a formal sector job depends on: (i) the probability of meeting a formal sector firm with an empty vacancy, $m(\theta_F)$, and (ii) the probability that the match is worth forming, i.e. that the match quality randomly drawn is higher than $Q(p)$.

The payoffs for firms are:

$$\tilde{r}J_F(x, p) = px - w_F(x, p) + \delta \left[ V_F - D - J_F(x, p) \right] + \tau V_F$$

$$\tilde{r}J_I(p) = p_I - w_I(p) + \left[ \delta + \mu(p) \right] \left[ V_I - J_I(p) \right] + \tau V_I$$

$$rV_F = -k_F + \frac{m(\theta_F)}{\theta_F} \left( E_{X,P}[J_F(x, p)|\phi_U, \phi_I] - V_F \right)$$

$$rV_I = -k_I + \frac{m(\theta_I)}{\theta_I} \left( E_P[J_I(p)|\phi_U] - V_I \right)$$

where $\mu(p) \equiv m(\theta_F)[1 - G(Q(p))]$, $J_F(x, p)$, and $J_I(p)$ denote the present discounted value of the expected profit from an occupied job in the formal and the informal sector, respectively, and $V_j$ denotes the present discounted value of expected profit from a vacant job in sector $j \in \{F, I\}$. Note that (4) incorporates firing costs, (5) incorporates the possibility that the worker moves to the formal sector, and that the value of an open vacancy depends on the recruitment costs, $k_j$, and on the fraction of low-skilled job seekers, given by $\phi_U$ in unemployment and $\phi_I$ in the informal sector.

For a firm in the formal sector matched with a worker of skill level $p$ and current match quality $x$, the value of the filled vacancy, $\tilde{r}J_F(x, p)$, depends on three main factors. First, the firm has a profit of $[px - w_F(x, p)]$. Second, if the job is destroyed, the firm experiences a loss of $[V_F - D - J_F(x, p)]$. Third, if the worker dies, the firm is left with an empty vacancy, and this happens with probability $\tau$.

For a firm in the informal sector matched with a worker of skill level $p$, the value of the filled vacancy, $\tilde{r}J_I(p)$, depends on three main factors. First, the firm has a profit of $[p_I - w_I(p)]$. Second, with probability $\delta$ the jobs is destroyed, and with probability $\mu(p)$ the worker quits in order to take a formal sector job. In both cases, the firm suffers a loss of $[V_I - J_I(p)]$. Third, if the worker dies, the firm is left with an empty vacancy, and this happens with probability $\tau$. 
In both sectors, the value of an open vacancy depends on two main factors. First, it depends on the recruitment costs, \( k_j \), for \( j \in \{ F, I \} \). Second, it depends on the gain from filling the vacancy. This gain depends on the distribution of L-skilled and H-skilled workers that may contact the firm. For informal sector firms, since only unemployed workers contact them, the gain is given by \([E_P[J_I(p)|\phi_U] - V_I]\), where \( E_P[J_I(p)|\phi_U] = \phi_U J_I(p_L) + (1 - \phi_U) J_I(p_H) \). For formal sector firms, since both unemployed and informal sector workers contact them, the gain is given by \([E_X,P[J_F(x,p)|\phi_U,\phi_I] - V_F]\), where:

\[
E_{X,P}[J_F(x,p)|\phi_U,\phi_I] = \phi_U \int_{C(p_L)}^1 J_F(x,p_L)dG(x) + (1 - \phi_U) \int_{C(p_H)}^1 J_F(x,p_H)dG(x)
\]

\[
+ \phi_I \int_{Q(p_L)}^1 J_F(x,p_L)dG(x) + (1 - \phi_I) \int_{Q(p_H)}^1 J_F(x,p_H)dG(x),
\]

where \( \phi_U \) and \( \phi_I \) are the steady state proportion of L-skilled workers in unemployment and in the informal sector, respectively.

Wages in both sectors are determined according to a surplus sharing rule that entitles workers to a fraction \( \beta \) of the match surplus. The match surplus in the informal sector is \( S_I(p) = W_I(p) - U(p) + J_I(p) - V_I \), and in the formal sector is given by \( S_F(x,p) = W_F(x,p) - U(p) + J_F(x,p) - V_F \). The resulting wages are presented in Appendix B.

The decision to create a job in the formal sector depends on the match quality drawn when the worker and the firm meet. If the firm meets with an unemployed worker, both the firm and the worker require \( x \geq C(p) \) to match, where \( C(p) \) is such that \( S_F(C(p),p) = 0 \) for \( p \in \{ p_L, p_H \} \). If the firm meets with a worker in the informal sector, they require \( x \geq Q(p) \), where \( Q(p) \) is such that \( S_F(Q(p),p) = S_I(p) \) for \( p \in \{ p_L, p_H \} \). Using the payoffs and wages, these cut-offs are given by:

\[
C(p) = \frac{\bar{r}U(p)}{p} + \frac{\delta D}{p} \tag{8}
\]

\[
Q(p) = C(p) + \frac{(\bar{r} + \delta)S_I(p)}{p} \tag{9}
\]

where \( p \in \{ p_H, p_L \} \). Note that from (8) and (9) we cannot determine if \( C(p_H) < C(p_L) \) and \( Q(p_H) < Q(p_L) \) without some assumptions on productivity levels in the formal and informal sectors. Lemma 1 provides a sufficient condition that enables us to determine the relative size of the cut-offs.

**Lemma 1.** Let \( g(x) \) be the probability density function of the random variable \( x \) with support
on $[0, 1]$ representing match quality. Let $\eta = \frac{1}{1 - \beta} \left( \frac{p_L}{p_L - z} \right)$. If

$$\forall x \in [0, 1] \quad \left( g(x) - \eta \int_x^1 g(u) du \right) < \eta (\tilde{r} + \delta),$$

then $C(p_H) < C(p_L)$ and $Q(p_H) < Q(p_L)$.

Appendix C.1 presents the proof of Lemma 1. The condition in Lemma 1 is easily satisfied. This condition requires the distribution of match quality to be smooth and without spikes, so that the random draw taken when the worker and firm meet is relevant in the decision to create a job or keep looking for a better match.

After substituting wages and cut-offs in the match surplus in the formal sector, we find that $S_F(x, p) = \frac{p}{\tilde{r} + \delta} (x - C(p))$. Then, given the result in Lemma 1 and that $p_H > p_L$, it follows that $\forall x \in [0, 1]$, $S_F(x, p_H) > S_F(x, p_L)$ and $\partial S_F(x, p_H)/\partial x > \partial S_F(x, p_L)/\partial x$. Figure 4 illustrates this result, and the fact that $C(p_H) < C(p_L)$ and $Q(p_H) < Q(p_L)$. Note that $S_I(p) > 0$ implies that $Q(p) > C(p)$ for $p \in \{p_L, p_H\}$, as a consequence informal sector workers are more selective than unemployed workers when it comes to matching with a formal sector firm.

Figure 4: Reservation Match Quality for Employed and Unemployed Workers

The baseline model produces implications for the hazard rate from the informal to the formal sector. We distinguish between the hazard rate conditional on worker skill level, denoted $\lambda(t|p)$, and the unconditional (or average) hazard rate, denoted $\lambda(t)$; where $t$ is the

\[7\] Notice that if $p_L > p_I$, then $\eta > 1$, since by assumption $p_I \geq z$. The larger $\eta$, the easier for the condition in Lemma 1 to be satisfied.
realization of a random variable $T \geq 0$ measuring duration of employment in the informal sector and $p \in \{p_L, p_H\}$. These results are summarized in Propositions 2 and 3.

**Proposition 2.** Suppose that the condition in Lemma 1 holds. Then, in the baseline model, the hazard rate from the informal to the formal sector conditional on the worker skill level, $\lambda(t|p)$, is constant for each $p \in \{p_L, p_H\}$, and it is higher for H-skilled workers than for L-skilled workers.

**Proof.** In the baseline model, the hazard rate conditional on worker skill is given by $\lambda(t|p) = \mu(p) = m(\theta_F)[1 - G(Q(p))]$, so that $\partial \lambda(t|p)/\partial t = 0$. By Lemma 1, $Q(p_H) < Q(p_L)$, which implies that $\lambda(t|p_H) > \lambda(t|p_L)$.

**Proposition 3.** In the baseline model, the unconditional hazard rate, $\lambda(t)$, is decreasing in duration.

The proof of Proposition 3 follows the arguments of Lancaster (1990) and is presented in Appendix C.2. In this model, the fraction of L-skilled workers in the risk set (i.e. those that have not left the informal sector yet) increases with duration, pushing down the average hazard rate. This fraction increases with duration because H-skilled workers move from the informal to the formal sector at a faster rate than L-skilled workers. Lancaster (1990) calls this a “selection effect.”

## 3 Extensions to the Baseline Model

The baseline model provides an analytical framework that helps us understand the key factors underlying the transitions from the informal to the formal sector. However, this model predicts that the transition rates from the informal to the formal sector remain constant as workers age. Yet, as shown in Figures 2 and 3, this is not the case in the data. Instead, we observe that transition rates increase as workers age (during early stages of the workers’ careers).

We consider two extensions to the baseline model intended to explain this feature in the data. First, we assume that workers can accumulate human capital while working, which increases the chance of finding a formal sector job. Second, we assume that employers gradually learn about workers’ skills. As a result, workers who are found to be H-skilled increase their chances of finding a formal sector job. We implement each extension separately because, as shown below, each mechanism generates opposing implications that would be hard to disentangle in a model with both mechanisms.

We focus on the implications for the hazard rate from the informal to the formal sector. On the one hand, when we assume that a worker can become more productive while in the
informal sector, the longer such a worker stays in this sector, the more likely he is to make a transition into the formal sector. On the other hand, when we assume that a worker’s productivity is gradually learned, those discovered as highly productive move to the formal sector faster, leaving behind those with low productivity levels and hence greater difficulties to access formal sector jobs. Thus, the longer a worker stays in the informal sector, the lower the likelihood that he makes a transition to the formal sector.

3.1 Human Capital Accumulation

First, we extend the baseline model by adding the possibility that workers accumulate skills through learning-by-doing. We follow Rebière (2008) and assume that a L-skilled worker can accumulate skills and become H-skilled with probability $\kappa$. The accumulation of skills can only take place on the job, so the unemployed L-skilled workers cannot become H-skilled. Human capital does not depreciate, but since workers die and are replaced, the model does not converge to a degenerate distribution of skills.

The payoffs for unemployed workers and for vacancies have the same formulation as in the baseline model. The payoffs for employed workers and for filled vacancies now incorporate the possibility of accumulating skills. These are given by:

\[
\begin{align*}
\tilde{r}W_F(x, p) &= w_F(x, p) + \delta [U(p) - W_F(x, p)] + \kappa [W_F(x, p_H) - W_F(x, p)] \\
\tilde{r}W_I(p) &= w_I(p) + \delta [U(p) - W_I(p)] + \kappa [W_I(p_H) - W_I(p)] \\
&\quad + \mu(\theta_F) \int_{Q(p)} [W_F(s, p) - W_I(p)] dG(s) \\
\tilde{r}J_F(x, p) &= px - w_F(x, p) + \delta [V_F - D - J_F(x, p)] + \kappa [J_F(x, p_H) - J_F(x, p)] + \tau V_F \\
\tilde{r}J_I(p) &= p_I - w_I(p) + [\delta + \mu(p)] [V_I - J_I(p)] + \kappa [J_I(p_H) - J_I(p)] + \tau V_I.
\end{align*}
\]

The terms that account for the accumulation of skills disappear when $p = p_H$, so the value functions for H-skilled workers have the same formulation as in the baseline model.

For L-skilled workers in this model, the value of employment increases by the possibility of accumulating human capital, which happens with probability $\kappa$ either in the formal or in the informal sector. The worker’s gain from human capital accumulation is given by $[W_F(x, p_H) - W_F(x, p_L)]$ if the worker is employed in the formal sector, and by $[W_I(p_H) - W_I(p_L)]$ if the worker is employed in the informal sector.
$W_i(p_L)$] if the worker is employed in the informal sector.

Firms with filled vacancies also benefit from the worker’s human capital accumulation. A formal sector firm matched with a L-skilled worker and current match quality $x$ experiences a gain of $[J_F(x, p_H) - J_F(x, p_L)]$ with probability $\kappa$, and an informal sector firm matched with a L-skilled worker experiences a gain of $[J_I(p_H) - J_I(p_L)]$ with probability $\kappa$.

Wages are determined by the surplus sharing rule. The resulting wages for this model are presented in Appendix [3]. The reservation match qualities for unemployed and employed workers are determined in terms of the match surplus in the formal sector. That is, $S_F(C(p), p) = 0$ and $S_F(Q(p), p) = S_I(p)$. In this model the cut-offs are given by:

\begin{align}
C(p) &= \frac{\bar{r}U(p)}{p} + \frac{\delta D}{p} - \kappa \left( \frac{U(p_H) - U(p)}{p} \right) - \kappa \left( \frac{S_F(C(p), p_H)}{p} \right) \\
Q(p) &= C(p) + \left( \frac{\bar{r} + \delta}{p} \right) S_I(p) - \kappa \left( \frac{S_F(Q(p), p_H) - S_I(p) - S_F(C(p), p_H)}{p} \right)
\end{align}

where the terms that account for the accumulation of skills disappear when $p = p_H$. Note that the direct effect of human capital accumulation is to reduce the cut-offs for L-skilled workers; this effect is picked up by the negative terms in both (14) and (15). An indirect effect of human capital accumulation increases the cut-offs for L-skilled, because both the value of unemployment and the match surplus in the informal sector increase.

Obtaining results similar to those in Lemma [4] is much more complicated with the inclusion of human capital accumulation. Consider environments which satisfy the following conditions:

**Condition 1.** $\forall x \in [0, 1], S_F(x, p_H) > S_F(x, p_L)$.

**Condition 2.** $\forall x \in [0, 1], S_F(x, p_H) - S_F(x, p_L) > S_I(p_H) - S_I(p_L)$.

These two conditions impose complementarities between the production technology in the formal sector and worker skills. Condition [1] implies that formal sector firms have a strict preference for H-skilled workers. If satisfied, then $C(p_H) < C(p_L)$. Condition [2] implies that the marginal value of skills is higher in the formal sector than in the informal sector. If satisfied, then $Q(p_H) < Q(p_L)$. These two implications can be easily verified in Figure [4].

If Conditions [1] and [2] are satisfied, the human capital model preserves the same ranking in cut-offs as in the baseline model. With this, we can derive similar implications for the conditional and unconditional hazard rates. These results are summarized in Propositions [4] and [5].
Proposition 4. Suppose that Conditions 1 and 2 are satisfied. Then, in the model with human capital accumulation, the hazard rate from the informal to the formal sector conditional on worker’s initial skill level, \( \lambda(t|p) \), is constant for H-skilled workers and increasing for L-skilled workers.

Proof. The conditional hazard rate for H-skilled workers is \( \lambda(t|p_H) = \mu(p_H) \), which is constant with respect to duration, \( t \). Next, for L-skilled workers, the conditional hazard rate is given by \( \lambda(t|p_L) = (1-\kappa)^t \mu(p_L) + [1 - (1 - \kappa)^t] \mu(p_H) \). Then: \( \partial \lambda(t|p)/\partial t = (1-\kappa)^t \ln(1-\kappa) [\mu(p_L) - \mu(p_H)] > 0 \), which is positive because \( \mu(p_L) < \mu(p_H) \) and \( \kappa \in (0, 1) \).

When workers accumulate skills while working in the informal sector, the increase in productivity derived from the accumulation of skills facilitates access to job opportunities in the formal sector. Consequently, the likelihood of moving from the informal to the formal sector for L-skilled workers increases with tenure in the informal sector, resulting in an increasing hazard for L-skilled workers.

Proposition 5. Suppose that Conditions 1 and 2 are satisfied. Let \( \phi_I \) be the probability that \( p = p_L \) in the informal sector. Then, in the model with human capital accumulation, the unconditional hazard rate, \( \lambda(t) \), is:

(i) increasing if: \( -\ln(1-\kappa) > (1-\phi_I) [\mu(p_H) - \mu(p_L)] \)

(ii) U-shaped otherwise.

The proof of Proposition 5 follows the arguments of Lancaster (1990) and is presented in Appendix C.2. This Proposition states that when \( \kappa \) is large, the higher transition rate to the formal sector of H-skilled workers does not increase the fraction of L-skilled in the risk set, because L-skilled workers accumulate skills at a faster rate. As such, the hazard rate is increasing in duration. In contrast, if \( \kappa \) is not very large, it takes some time for the L-skilled to accumulate skills, and the higher transition rate of the H-skilled results in a higher fraction of L-skilled in the risk set. In this case, the hazard rate is initially decreasing. However, eventually L-skilled workers accumulate skills, so the fraction of L-skilled in the risk set decreases, resulting in an increasing hazard for higher durations.

3.2 Employer Learning (Screening)

In this extension of the baseline model, we abstract from human capital accumulation. Instead, we assume that when workers enter the labor market, their skill level (or type) is not known, but it is eventually revealed while they are working. We refer to these workers as
“newcomers.” We assume that neither the worker nor the employer knows the newcomer’s type, and that once the type is revealed, everybody can observe the worker’s skill level, as in Farber and Gibbons (1996). The revelation process is a stochastic process such that the worker’s skill is revealed with probability $\sigma$.

All newcomers start unemployed, and it is common knowledge that a fraction $\phi$ of them are L-skilled. Newcomers also follow a reservation match quality strategy when facing formal sector job opportunities, taking informal sector opportunities as they arrive. When the worker’s type is revealed in a formal sector job, the job could be destroyed if the current match quality is below the reservation match quality for that worker’s type.

Let $C$ be the reservation match quality for unemployed newcomers, and $Q$ be the reservation match quality for newcomers holding an informal sector job. In the current study we focus on cases that satisfy the following condition:

**Condition 3.** $C(p_H) < C < C(p_L)$ and $Q(p_H) < Q < Q(p_L)$.

If Condition 3 holds, then all formal sector workers found to be H-skilled keep their job. On the contrary, a formal sector worker found to be L-skilled with match quality $x < C(p_L)$ loses his job, in which case the firm incurs firing costs. If the worker is found to be L-skilled but match quality is $x > C(p_L)$, then the worker keeps his job.

The payoffs and the reservation match quality for L-skilled and H-skilled workers have the same formulation as that in the baseline model. Let $\bar{p} \equiv \phi p_L + (1 - \phi) p_H$ reflect the expected formal sector productivity for newcomers. Given Condition 3 holds, the payoffs for newcomers are given by:

\begin{align*}
(16) \bar{r}U &= z + m(\theta_I)[W_I - U] + m(\theta_F) \int_C [W_F(s) - U] dG(s) \\
(17) \bar{r}W_F(x) &= w_F(x) + \delta[U - W_F(x)] + \sigma(1 - \phi)W_F(x, p_H) \\
&\quad \quad + \sigma \phi \left[\Gamma_L(x)U(p_L) + (1 - \Gamma_L(x))W_F(x, p_L)\right] - \sigma W_F(x) \\
(18) \bar{r}W_I &= w_I + \delta[U - W_I] + m(\theta_F) \int_Q [W_F(s) - W_I] dG(s) \\
&\quad \quad + \sigma \phi W_I(p_L) + \sigma(1 - \phi)W_I(p_H) - \sigma W_I \\
(19) \bar{r}J_F(x) &= \bar{p}x - w_F(x) + \delta[V_F - D - J_F(x)] + \sigma(1 - \phi)J_F(x, p_H) \\
&\quad \quad + \sigma \phi \left[\Gamma_L(x)[V_F - D] + (1 - \Gamma_L(x))J_F(x, p_L)\right] - \sigma J_F(x) + \tau V_F \\
(20) \bar{r}J_I &= p_I - w_I + [\delta + \bar{\mu}][V_I - J_I] + \sigma \phi J_I(p_L) + \sigma(1 - \phi)J_I(p_H) - \sigma J_I + \tau V_I
\end{align*}
where $\bar{\mu} \equiv m(\theta_F)[1 - G(Q)]$, and $\Gamma_L(x) = 1\{x < C(p_L)\}$.

For unemployed newcomers, the value of unemployment, $\bar{r}U$, depends on three main factors. First, unemployed newcomers receive flow utility $z$. Second, if they find an informal sector job, they experience a gain of $[W_I - U]$, and this happens with probability $m(\theta_I)$. Third, if they find a formal sector job, they experience a gain of $[W_F(s) - U]$. For unemployed newcomers, the probability of finding a formal sector job depends on: (i) the probability of meeting a formal sector firm with an empty vacancy, $m(\theta_F)$, and (ii) the probability that the match is worth forming, i.e. that the match quality randomly drawn is higher than $C$.

For newcomers employed in the formal sector with current match quality $x$, the value of formal sector employment, $\bar{W}_F(x)$, depends on three main factors. First, they receive wage $w_i(x)$. Second, they experience a loss of $[U - W_F(x)]$ if the job is destroyed, which happens with probability $\delta$. Third, with probability $\sigma$, their skill level is revealed, in which case they might keep or lose their job. On the one hand, if a worker is found to be H-skilled, then the worker keeps his job and experiences a gain of $[W_F(x, p_H) - W_F(x)]$. On the other hand, if the worker is found to be L-skilled, then two things may happen: (i) if the current match quality is higher than $C(p_L)$, then the worker keeps his job, but experiences a loss of $[W_F(x, p_L) - W_F(x)]$, and (ii) if the current match quality is lower than $C(p_L)$, then the worker loses his job and experiences a loss of $[U(p_L) - W_F(x)]$.

By comparison, for formal sector firms matched with a newcomer with current match quality $x$, the value of the filled vacancy, $\bar{r}J_F(x)$, depends on three main factors. First, the firm has profit $[\bar{p}x - w_F(x)]$. Second, with probability $\delta$ the job is destroyed and the firm suffers a loss of $[V_F - D - J_F(x)]$. Third, with probability $\sigma$ the worker’s skill level is revealed, and then the firm may keep the worker or let him go. If the worker is found to be H-skilled, the firm keeps the worker, and experiences a gain of $[J_F(x, p_H) - J_F(x)]$. If the worker is found to be L-skilled, two things can happen: (i) if the current match quality is higher than $C(p_L)$, then the firm keeps the worker, but suffers a loss of $[J_F(x, p_L) - J_F(x)]$, and (ii) if the current match quality is lower than $C(p_L)$, then the firm has to let the worker go, suffering a loss of $[V_F - D - J_F(x)]$.

For newcomers employed in the informal sector, the value of informal sector employment, $\bar{r}W_I$, depends on four main factors. First, newcomers receive wage $w_i$. Second, if the job is destroyed, they suffer a loss of $[U - W_I]$. Third, if they find a formal sector job, they experience a gain of $[W_F(s) - W_I]$. For newcomers employed in the informal sector, the probability of finding a formal sector job depends on: (i) the probability of meeting a formal sector firm with an empty vacancy, $m(\theta_F)$, and (ii) the probability that the match is worth forming, i.e. that the match quality randomly drawn is higher than $Q$. Fourth, if their skill level is revealed, then they experience a gain of $[W_I(p_H) - W_I]$ if they are found to be
H-skilled, and a loss of $[W_I(p_L) - W_I]$ if they are found to be L-skilled.

By comparison, for informal sector firms matched with a newcomer, the value of the filled vacancy, $\tilde{r} J_I$, depends on four main factors. First, the firm has profit $[p_I - w_I]$. Second, with probability $\delta$ the job is destroyed. Third, with probability $\bar{\mu}$ the worker quits to take a formal sector job. In any of these two situations, the firm suffers a loss of $[V_I - J_I]$. Fourth, if the worker skill level is revealed, then the firm experiences a gain of $[J_I(p_H) - J_I]$ if the worker is found to be H-skilled, and a loss of $[J_I(p_H) - J_I]$ if the worker is found to be L-skilled.

Wages for this model are presented in Appendix B. Given Condition 3, reservation match qualities for newcomers are:

$$C = \frac{\tilde{r} U}{\bar{p}} + \frac{\delta D}{\bar{p}} + \frac{\sigma \phi D}{\bar{p}} - \frac{\sigma [\phi U(p_L) + (1 - \phi)U(p_H) - U]}{\bar{p}} - \frac{\sigma (1 - \phi)S_F(C, p_H)}{\bar{p}}$$

$$Q = \frac{\tilde{r} U}{\bar{p}} + \frac{\delta D}{\bar{p}} + \frac{\Gamma_L(Q) \sigma \phi D}{\bar{p}} - \frac{\sigma [\phi U(p_L) + (1 - \phi)U(p_H) - U]}{\bar{p}}$$

$$- \frac{[1 - \Gamma_L(Q)] \sigma \phi S_F(C, p_L)}{\bar{p}} - \frac{\sigma (1 - \phi)S_F(Q, p_H)}{\bar{p}} + \frac{(\tilde{r} + \delta + \sigma) S_I}{\bar{p}}.$$
Proposition 7. Suppose that the condition in Lemma 1 and Condition 3 hold. Let $\phi$ be the probability that $p = p_L$ in the labor market. Then, in the model with employer learning, the unconditional hazard rate, $\lambda(t)$, is:

(i) decreasing if $\overline{\mu} > \phi \mu(p_L) + (1-\phi) \mu(p_H)$

(ii) hump-shaped otherwise.

The proof of Proposition 7 follows the arguments of Lancaster (1990) and is presented in Appendix C.2. Proposition 7 states that the shape of the unconditional hazard function initially depends on whether the hazard rate of newcomers is higher or lower than the average hazard rate of workers with revealed types. Cases (i) and (ii) compare these two hazard rates. Eventually, as more worker types are revealed, the hazard function decreases with duration due to selection, as in the baseline model.

Whether case (i) or (ii) arises depends on: a) the mixture of H-skilled and L-skilled workers in the population, summarized by $\phi$; b) the location of $Q$ with respect to $Q(p_L)$ and $Q(p_H)$; and c) the properties of the distribution of match quality, $G(x)$. Note that $Q$ is not determined by $Q(\phi p_L + (1-\phi)p_H)$, and so we cannot raise conclusions in terms of the properties of $Q(\cdot)$, defined in equation (9). Even so, case (i) is more likely to occur if $\overline{G}(x) \equiv [1-G(x)]$ is concave (or $G(x)$ convex), so that the convex combination $\phi \overline{G}(Q(p_L)) + (1-\phi) \overline{G}(Q(p_H))$ is lower than $\overline{G}(Q)$. In contrast, case (ii) is more likely to arise if $\overline{G}(Q(x))$ is convex (or $G(x)$ concave), so that the convex combination of $\overline{G}(Q(p_L))$ and $\overline{G}(Q(p_H))$ is higher than $\overline{G}(Q)$.

3.3 Understanding the Role of the Informal Sector in the Early Careers of Less-educated Workers

We are now in a position to assess the role of the informal sector in the early stages of the careers of less-educated workers. The implications derived earlier suggest estimating the hazard function from the informal to the formal sector to determine whether human capital accumulation or screening/learning are important in the informal sector. We estimate these

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9Simulation exercises assuming that $G(\cdot)$ is uniform indicate that whether case (i) or (ii) arises is mainly determined by the fraction of L-skilled workers in the population, $\phi$. These exercises show that $\phi$ is the main determinant of the location of $Q$ with respect to $Q(p_L)$ and $Q(p_H)$. The larger $\phi$ is, the closer $Q$ is to $Q(p_L)$, and the more likely that case (ii) arises. Intuitively, when $\phi$ is large, formal sector employers treat “newcomers” as if they were L-skilled. As a result, both “newcomers” and L-skilled workers in the informal sector move to the formal sector at similar rates, whereas H-skilled in the informal sector move at faster rates. Hence, for short spells (low $t$) the hazard increases when the first “newcomers” see their skill level being revealed because H-skilled have a faster exit rate than both “newcomers” and L-skilled.
hazard functions using data from an employment survey from Mexico. In the next section, we describe the data, the sample, and some details of the variables used in estimation.

4 Data: The ENOE

We use a household survey from Mexico called the Occupation and Employment Survey, ENOE (its acronym in Spanish). The ENOE is a rotating panel where households are visited five times during 12 months, one visit every three months. Every three months, 20% of the sample is replaced. Although information from each family member is recorded, this information is provided by only one member; the respondent is not necessarily the same individual on each visit.

The ENOE records the demographics of each family member (e.g. education, age, marital status), and information on the main and secondary jobs of family members older than 12 years of age. Job information includes working hours, earnings, fringe benefits, job position, firm size, industry, occupation and job tenure. The job tenure information is only recorded in the long form of the ENOE, which is answered at least once during the five visits to the household. For further details about the ENOE see INEGI (2005, 2007).

4.1 Sample

To focus on less-educated workers, we restrict the sample to individuals not currently attending school and with less than 12 years of education. To focus on young workers, our sample only includes workers between the ages of 16 and 25. Age 16 is the minimum age at which a worker can be hired according to Mexican Labor Law (see Congress, 1970), and age 25 is the age at which transitions from the informal to the formal sector plateau (see Figures 2 and 3). Our sample only includes male workers because women may have different reasons for joining the informal sector, e.g. job flexibility to balance work and child rearing (Arias and Maloney, 2007).

We divide our sample of less-educated workers into two groups based on completion of the mandatory level of education in Mexico, which is 9 years. In one group, we include less-educated workers who failed to complete the mandatory level of education, and in the other those who completed the mandatory level of education but who failed to complete high school (i.e. 12 years). Since the mandatory level of education in Mexico could be compared to junior high school in the U.S., we refer to the first group as junior high school dropouts, and the second as junior high school graduates.

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In Mexico, compulsory education comprises primary school (grades 1 to 6) and junior high school (grades...
Table 1 presents the sample summary statistics. For the purpose of this table, the group of junior high school dropouts is further divided into two groups. Junior high school graduates represent 63% of the sample. Workers in all three groups are mainly concentrated in small firms, but the junior high school graduates have the highest percentage in large firms. Also, note that the two groups of junior high school dropouts are mainly concentrated in the construction industry, while graduates are mainly concentrated in the services industry. Finally, note that graduates are more likely to have a parent working in a formal sector job. Firm size, industry, and family head employment status could be important determinants of the probability of moving from the informal to the formal sector.

4.2 Identification of Informal Salaried Workers

When a worker is hired in Mexico, it is the employer’s responsibility to register the worker in the IMSS or the ISSSTE. These institutions provide a bundle of benefits to their affiliates. For example, the bundle offered by IMSS includes: health insurance, day-care services for children, life insurance, disability pensions, work-risk pensions, sports and cultural facilities, retirement pensions, and housing loans (Levy, 2007). Both the worker and the employer must pay fees to fund these institutions, but the portion paid by the employer is much higher than that paid by the worker. If the firm is caught not complying with these regulations, it incurs a penalty.

Once a worker is registered in the IMSS or the ISSSTE the work relationship must abide by the labor regulation in Mexico. This means that the employer will incur firing costs if the work relationship is terminated.

The questionnaire of the ENOE does not ask the individual whether he is a formal or an informal worker. Instead, the survey asks the individual if his job gives him access to medical services provided by: the IMSS, the ISSSTE, the military hospital, the PEMEX hospital, or any other hospital (i.e. private hospital). We consider a worker to belong to the formal sector if he is an employee and his job gives him access to any kind of medical services: from IMSS, ISSSTE, military, PEMEX, or private; and to belong to the informal sector if he is an employee and his job does not give him access to any of these services. Note that the self-employed are not included in our definition of the informal sector.

7 to 9). In terms of our labeling, note that some of the individuals in the junior high school dropout group may not have even started junior high school.

11IMSS is the acronym in Spanish for the Mexican Institute of Social Security and ISSSTE is the acronym in Spanish for the Institute of Security and Social Services for the State’s Workers.

12PEMEX is the state-owned petroleum company in Mexico. Both, military and PEMEX workers, have access to medical services independent of IMSS or ISSSTE. Workers that have access to private medical services are usually hired formally, and even though they do not use the medical service of IMSS, they are registered at the IMSS, and could use it if desired.
4.3 Measuring Duration in the Informal Sector

Duration of employment in the informal sector is obtained using two different sampling schemes: flow sampling and stock sampling. In the flow sample, we include individuals who enter the informal sector during a fixed period of time, namely the 12 months in which the ENOE follows households. In the stock sample, we include individuals who are already in the informal sector at a given point in time, namely the month of the visit in which the household answered the long form of the ENOE. The date of the visit in which the long form is answered is used as the stock sampling date because the long form records the starting date of the current job. The starting date is either recorded as: (i) the exact month, if the job started in the current or the previous calendar year, or (ii) the year, if the job started before the previous calendar year.

Duration of employment in the informal sector is defined as the length of time that passes between the point in time in which the respondent enters the informal sector and the point in time in which the respondent moves from the informal to the formal sector. Duration is right-censored if the respondent is still employed in the informal sector at the time of the last interview. Duration of employment for individuals who leave the informal sector but do not enter the formal sector is also treated as right-censored.

Given that the household is visited every three months, the point in time of the transition from the informal to the formal sector either is known to be: (i) the exact month, or (ii) contained in a 3-month interval. The second case can arise in two situations: (i) if the respondent made such transition without changing jobs, or (ii) if the respondent changed jobs, but the visit to the household following that transition did not use the long form questionnaire, and so the starting time of the new job was not recorded.

Consequently, combining the two different formats in which the starting time and the transition time are recorded, duration from the stock sample is either known to the exact number of months or contained within some interval. On the other hand, all duration measures from the flow sample are interval-censored. This is because the starting time is never exactly known, but only known within three months (the time between interviews). Thus, whether the point in time of the transition is known to the month or within a 3-month interval does not change the fact that the completed duration will be only known within an interval.

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13 We include in this sample individuals who enter the informal sector after the first but before the fourth visits. Those who made a transition between the fourth and fifth visits are not included, because we are not able to follow them after the fifth visit.

14 We include in this sample informal sector workers whose long form interview took place in the first, second, third, or fourth visits. If an individual answered the long form for more than one visit, we use the first one as the stock sampling date.
Table 2 describes the distribution of formats in which duration in the informal sector is recorded in the sample. The most frequent intervals are 6-month for the flow sample, and 3-month and 15-month for the stock sample. This is a result of the frequency in which the household is visited. The numbers in the table also reveal the fact that the sample is subject to a high degree of right-censoring. Sixty percent of the spells in the sample are right-censored. Table 3 describes the source of censoring in the sample. Among those censored observations, 52% are due to the respondent being employed in the informal sector at the time of the last interview, 29% are due to the respondent moving out of the informal sector to another work status, such as self-employment, and 20% are due to the respondent becoming unemployed.

To summarize, let $T_i$ be the duration of employment in the informal sector for respondent $i$. We either observe $T_i$ up to the exact number of months, or an interval $(L_i, R_i]$ such that $T_i \in (L_i, R_i]$. Similarly, let $C_i$ be the censoring time for respondent $i$. Then, for censored observations we only know that $T_i > C_i$, or that $(L_i, R_i] = (C_i, \infty)$. Notice that because different respondents have different starting dates, the intervals $(L_i, R_i]$ may overlap for different respondents. As a result, we cannot use the techniques of discrete time duration analysis (e.g. Prentice and Gloeckler 1978; Meyer 1990; Han and Hausman 1990). We must instead work with interval-censored data (e.g. Finkelstein 1986; Sun 2006).

Finally, some of the spells in the sample have starting times on a date before the individual reaches age 16. Individuals who started their informal sector jobs before age 16 may delay their transition to the formal sector owing to legislative restrictions, and not for the reasons stipulated in the model. We adjust the duration measure of these individuals by subtracting from their duration the number of months worked before age 16, and create an indicator variable for them, which is included in the covariates. In this way, all job spells measure the time that the individuals were “at risk” of making a transition to the formal sector. About 2% of the spells in the sample are adjusted because of their pre-age 16 starting point.

Table 4 summarizes the duration data generated from the ENOE. For this table, we impute interval-censored duration measures with the midpoint in the interval. Note that the mean duration of employment in the informal sector is lower for junior high school graduates. In fact, the distribution of duration for junior high school graduates first-order-stochastically dominates that of the dropouts, suggesting that graduates move to the formal sector at a

\footnote{In the flow sample, both the point in time in which the individual enters the informal sector and the point in time in which the individual moves to the formal sector can be only known within a 3-month interval, which results in a 6-month interval. This turns out to be the most frequent case in the sample. In the flow sample, the starting time of the job is either known to the month or within a 12-month interval, and the point in time of the transition to the formal sector can be known within a 3-month interval, which results in a 3-month or in a 15-month interval. These are the two most frequent cases in the sample.}
faster rate than the dropouts.

Before proceeding with the estimation, it is important to mention that the implications from the models derived in the previous sections are in terms “sector spells.” However, in the estimation below we will be using measures of “job spells.” Given that we cannot follow the individual since the first time they entered the labor market, we have to work with the spell of the last job held by the individual. To the extent that the individual held other informal jobs before the current informal job, we would be underestimating the length of the sector spells, or in other words, the sector spells would be left-censored. It is in our advantage, however, that we are working with a sample of young workers, and so we should expect that the job spells should be similar to the sector spells.

5 Estimation

5.1 Likelihood Function

The likelihood function is defined in terms of the hazard function, which is conditioned on a set of time-invariant covariates, \( x \). The inclusion of covariates is very important in the presence of right-censoring in order to make valid inference. The right-censoring mechanism must satisfy the assumption of independent censoring (Kalbfleisch and Prentice, 1980). In terms of duration of employment in the informal sector, independent censoring requires that, conditional on \( x \), an individual’s duration is not censored because such individual has an unusually high (or low) probability of moving to the formal sector.

In the ENOE, because all households are visited exactly five times, censoring as a result of the individual working in the informal sector during the last visit satisfies independent censoring. But we must be cautious with the duration of employment of individuals whose transition to the formal sector is not observed because they moved to another state (e.g. self-employment). The duration of employment of these individuals is right-censored, but the assumption of independent censoring could be violated if they were systematically more (or less) likely to make a transition to the formal sector.

To that end, in our covariates we include variables that also explain why these individuals move to another state before moving to the formal sector. The covariates include industry, firm size, educational attainment, government’s financial support to self-employment, marital status, condition of employment of the family head, and dummies for different starting years.

\(^{16}\)Kalbfleisch and Prentice (1980) define a censoring scheme as independent if “the probability of censoring at time \( t \) depends only on the covariate \( x \), the observed pattern of failures and censoring up to time \( t \) in the trial, or on random processes that are independent of the failure times in the trial.” In the case of duration of employment in the informal sector, failure is defined as a transition from the informal to the formal sector.
As mentioned before, we use time-invariant covariates, although some of these covariates are in nature time-varying and could explain why some informal sector workers are more or less likely to make a transition to the formal sector. In particular, the covariates for marital status and firm size may vary over time and are important determinants of the transition from the informal to the formal sector. It is possible that during the time that the worker was employed in the informal sector his marital status changed from single to married, and so the increase in the demand for medical services associated with marriage could affect how fast the individual moves to the formal sector. Similarly, firms that are expanding might have an increased demand for formal sector jobs, or vice versa for a firm that is contracting. Levenson and Maloney (1998) find that, in the case of Mexico, firms treat formality as a “normal” input, and so its demand increases with the firm’s expansion.

For the stock sample, we can only observe changes in the covariates after the first interview, but we do not observe any changes before the first interview. For workers in the stock sample, we use the value of the covariate at the interview in which the long form of the ENOE was used. Although we can observe changes in the covariates for workers in the flow sample, in order to be consistent, we also fix the covariates for workers in this sample. For workers in the flow sample, we use the value of the covariate at the interview in which the informality status of the worker changed from not being informal to being an informal sector worker.

Interval-censoring also imposes a requirement in order to make inference, which is very similar to the one for right-censoring. Kalbfleisch and Prentice define this requirement as independent interval censoring. Let $0 < C_{i1} < C_{i2} < \cdots < C_{im} < \infty$ be the visiting dates for individual $i$. Independent interval censoring requires that: “having observed that the individual is [in the informal sector] at time $C_{ij-1}$, the timing of the next [visit] is distributed independently of the time of the [transition to the formal sector]” (Kalbfleisch and Prentice, 1980, page 79). Since the household visits are scheduled every three months, this assumption is also satisfied in the ENOE. The assumption would be violated if the next visit is determined to be sooner (or later) depending on the probability that the individual moves from the informal to the formal sector.

Now, recall that 60% of the duration measures are from the stock sample (see Tables 2 and 3). It is known that stock sampling introduces a sample selection problem because long durations are more likely to be sampled than short durations (Wooldridge, 2002). This problem, known as length-biased sampling (Kiefer, 1988), is easily addressed by including the starting time of the job spell in the likelihood, or more precisely the length of time that passes between the start of the job and the stock sampling date, which is known as the elapsed duration. Thus, in order to account for this sampling bias, we include the elapsed duration
in the likelihood function.

Let $T$ be a nonnegative random variable denoting the duration of employment in the informal sector, and let $t$ be a particular value of $T$. Let $\lambda(t|x)$ be the hazard function of $T$, $S(t|x)$ be the survivor function, which is defined in terms of the hazard function as $S(t|x) = \exp\{-\int_0^t \lambda(s|x)ds\}$, and let $f(t|x)$ be the density of $T$, which is defined as $f(t|x) = \lambda(t|x)S(t|x)$. Given that both censoring mechanisms are independent, the contribution of a right-censored observation to the likelihood is $\Pr(T_i > C_i|x) = S(C_i|x)$, and the contribution of an interval-censored observation is $S(L_i|x_i) - S(R_i|x_i)$. Let $e_i$ be the elapsed duration of individual $i$, then the likelihood function is given by:

\[
L(\theta|x_i) = \prod_{\{i|\Upsilon_i=1\}} \frac{f(t_i|x_i)^{d_i}S(t_i|x_i)^{(1-d_i)}}{S(e_i|x_i)} \prod_{\{i|\Upsilon_i=0\}} \frac{S(L_i|x_i) - S(R_i|x_i)}{S(e_i|x_i)}
\]

where $\Upsilon_i$ is an indicator for interval-censoring ($\Upsilon_i = 1$ if uncensored, $\Upsilon_i = 0$ if interval-censored), and $d_i$ is an indicator for right-censoring ($d_i = 1$ if uncensored, $d_i = 0$ if right-censored).

Finally, as explained in the previous section, job starting times in the stock sample are either known up to the month, or up to the year. The likelihood function (23) assumes that we know $e_i$ or, equivalently, that we know the starting time. However, for some respondents, all we know is that this starting time is included in a 12-month interval, if the job started before the previous calendar year.

In order to overcome the coarseness of starting times, we performed a Monte Carlo analysis to explore different alternatives to impute the starting time when this information is interval-censored. A brief description of the Monte Carlo analysis is presented in Appendix D. The Monte Carlo analysis follows Cano-Urbina (2012), in which the author explores three methods to impute the elapsed duration were explored, using the: 

(i) lower bound of the interval, (ii) upper bound of the interval, and (iii) midpoint of the interval. The simulation results indicate that, for the case of duration data obtained from surveys like the ENOE, using the midpoint in the interval outperforms the alternatives.

### 5.2 Hazard Function

To estimate the hazard, instead of imposing the functional form implied by each model, we estimate a flexible hazard function. Widely used parametric models such as the Weibull or the Log-logistic impose restrictions on the shape of the hazard (see Wooldridge 2002, chap. 20). For this reason, our main results rely on the estimation of a piecewise constant hazard, which allows more flexibility in the shape of the hazard function. We assume a proportional
hazards model \( \lambda(t|x_i) = \exp(x_i'\rho)\lambda_0(t) \), where:

\[
(24) \quad \lambda_0(t) = \lambda_m, \quad a_{m-1} \leq t < a_m, \quad \lambda_m > 0, \quad m = 1, 2, \ldots, M
\]

and \( \{a_0, a_1, \ldots, a_M\} \) are known break points that define \( M + 1 \) intervals \([a_0, a_1), [a_1, a_2), \ldots, [a_{M-1}, a_M), [a_M, \infty)\) that may contain \( t \). We set \( a_0 = 0 \), and choose the other break points using the distribution of \( T \). The distribution of \( T \) is divided into six quantiles, so that \( M = 6 \), with break points determined by the quantiles\(^{17}\)

The survivor function is given by:

\[
(25) \quad S(t|x_i) = \exp\left\{-\exp(x_i'\rho) \left[ \sum_{k=1}^{I(t)-1} \lambda_k \left( a_k - a_{k-1} \right) + \lambda_{I(t)} \left( t - a_{I(t)-1} \right) \right] \right\}
\]

where \( I(t) \) is such that \( a_{I(t)-1} \leq t < a_{I(t)} \), i.e. \( t \) is contained in the \( I(t)^{th} \) interval.

We estimate the hazard function for the whole sample and for two mutually exclusive education groups. The break points for each of these samples are:

<table>
<thead>
<tr>
<th>Education Group</th>
<th>months</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>[0, 12)</td>
<td></td>
<td>3.0</td>
<td>4.5</td>
<td>6.0</td>
<td>12.0</td>
<td>24.0</td>
</tr>
<tr>
<td>[0, 9)</td>
<td></td>
<td>3.0</td>
<td>4.5</td>
<td>7.0</td>
<td>12.0</td>
<td>24.0</td>
</tr>
<tr>
<td>[9, 12)</td>
<td></td>
<td>3.0</td>
<td>3.5</td>
<td>6.0</td>
<td>11.0</td>
<td>24.0</td>
</tr>
</tbody>
</table>

6 Results

6.1 Piecewise Constant Hazard Function

We maximize the likelihood function in equation (23) using all of the elements discussed in the previous section. The estimation results for the whole sample and for junior high school dropouts and graduates are summarized in Table 5. Figure 5 depicts the estimated baseline hazard with the 95% pointwise confidence intervals. The plot of the baseline hazard in Figure 5 depicts the hump-shaped pattern predicted by the model with employer learning. Note that this pattern holds for the whole sample, and for the junior high school dropouts and graduates\(^{18}\).

Even though both junior high school dropouts and graduates show signs of employer

---

\(^{17}\)To avoid ties in the quantiles, the break points are the quantiles of \( \bar{T}_i = (L_i + R_i)/2 \).

\(^{18}\)A similar estimation exercise was performed using only interval-censored weekly duration measures instead of using monthly duration measures. The estimation results indicate the same hump-shaped pattern in the hazard function for the three education groups.
learning, those who completed the mandatory level of education have a higher hazard rate at all times. In terms of Proposition 7, this result indicates that the proportion of L-skilled workers is higher among dropouts than among graduates as one might expect.\footnote{Alternatively, there could be more than two worker skill levels, with some of them concentrated in one education group, e.g. the highest concentrated in group of graduates and the lowest concentrated in the group of dropouts. Note that we could extend the models to a continuum of worker types, as in Albrecht et al. (2006, 2009). This would yield similar results to those derived above.}

Estimated effects of the covariates in Table \ref{tab:results} are fairly similar for the whole sample and for junior high school graduates and dropouts. The estimation results for the whole sample show that graduation from primary school (grade 6) has little effect on the hazard rates, but graduation from secondary school (grade 9) has a significant effect. This is consistent with Arias and Maloney (2007) who claim that “graduation to formal salaried work is unlikely for youth who drop out of school before completing at least a full course of secondary education” (Arias and Maloney, 2007, page 62).

Not surprisingly, one of the most important covariates is the size of the firm. The higher the firm size, the higher the hazard rate from the informal to the formal sector. There are two potential explanations for this result. On the one hand, many of the transitions could be happening within the same employer. Alternatively, it could be that larger firms have a larger network and as a result expose workers’ skills to other employers more than small firms do.

Industry does not play a big role in explaining the hazard rate from the informal to the formal sector. Married workers have higher hazard rates than single workers, consistent with the incremental demand for health services when individuals form their own families. And when the family head works in the formal sector, the individual also has a higher hazard rate, which could also be the result of the individual having access to a larger network of formal sector employers.\footnote{In Mexico, dependents of workers registered in the IMSS can only use the medical services of this institution up to age 18. The coverage can be extended if the dependent is attending school, which is not the case in our sample.} Notice that the estimates for these covariates are larger for junior high school dropouts than for the graduates.

Finally, note that a hump-shaped hazard rules out the baseline model. The baseline model predicts constant hazard rates conditional on worker skill level, which in turn implies that the unconditional survivor function is a mixture of exponential distributions. Based on comments made by Chamberlain (1980), Heckman, Robb, and Walker (1990) argue that “all mixtures of exponentials models have nonincreasing hazards.” The pointwise confidence intervals for our estimated hazard imply that the hazard is increasing for short spells, thereby ruling out the baseline model (with any arbitrary number of worker types)\footnote{Using the estimated hazard function, and following the procedure suggested by Chamberlain, we conclude}.
6.2 Parametric Hazard Functions

As a robustness check, we estimated two widely used parametric hazards, the Weibull and the Log-logistic hazard models. We are mainly interested in the estimation result from the Log-logistic model. The Weibull is characterized by the hazard function:

\[ \lambda(t) = \varphi \alpha t^{\alpha-1} \]

and the Log-logistic by:

\[ \lambda(t) = \frac{\varphi \alpha t^{\alpha-1}}{1 + \varphi t^\alpha}, \]

where \( \varphi = \exp(x'\rho) \) is the most common choice in empirical applications. The shape of the hazard function in each case is determined by the parameter \( \alpha \), as summarized in the following table:

<table>
<thead>
<tr>
<th>( \alpha )</th>
<th>Weibull</th>
<th>Log-logistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha &lt; 1 )</td>
<td>Decreasing</td>
<td>Decreasing from ( \infty ) at ( t = 0 ), to 0 as ( t \to \infty )</td>
</tr>
<tr>
<td>( \alpha = 1 )</td>
<td>Constant</td>
<td>Decreasing from ( \varphi ) at ( t = 0 ), to 0 as ( t \to \infty )</td>
</tr>
<tr>
<td>( \alpha &gt; 1 )</td>
<td>Increasing</td>
<td>Increasing from 0 at ( t = 0 ), to a single maximum ( T^* ), and then approaches 0 as ( t \to \infty )</td>
</tr>
</tbody>
</table>

When \( \alpha > 1 \) in the Log-logistic, the maximum occurs at \( T^* = \left[ (\alpha - 1)/\varphi \right]^{1/\alpha} \) (see Lancaster, 1990, chap. 3).

The estimated hazards for these two models are presented in Table 6. The estimated coefficients for the covariates in the Weibull hazard are very similar to the ones in the piecewise constant hazard, since both of these are proportional hazards models. For the Log-logistic model, they are not identical but have the same pattern across the groups of dropouts and graduates from junior high school. Given the restrictions of the Weibull hazard, the estimates suggest a monotonically decreasing hazard, but the Log-logistic suggests a hump-shaped hazard. More importantly, the predicted maximum in the Log-logistic hazard function is very similar to the maximum we have in the piecewise constant hazard in Figure 5.

Likewise, a similar estimation exercise was performed using only interval-censored weekly duration measures, instead of using monthly duration measures. The estimation results yield very similar estimates for \( \alpha \) in both the Weibull and the Log-logistic hazard functions.

\(^{22}\) Likewise, a similar estimation exercise was performed using only interval-censored weekly duration measures, instead of using monthly duration measures. The estimation results yield very similar estimates for \( \alpha \) in both the Weibull and the Log-logistic hazard functions.

\(^{22}\) That the survivor function for the data in this study cannot be generated by a mixture of exponentials. For a description of the rejection criterion and the procedure see Chamberlain (1980) or Heckman et al. (1990).
6.3 Unobserved Heterogeneity

The models developed in the previous sections are based on the premise that there are two worker skill levels, which are not observable to the econometrician. For each model, we develop predictions based on the average (or unconditional) hazard function, which effectively integrates over any unobserved heterogeneity. In fact, changes in unobserved types over time play an important role in driving patterns of the average hazard functions used to identify the different models. An advantage of our approach is that it is based on the estimation of the average hazard function, and so it does not require us to specify a particular distribution for the unobserved heterogeneity.

6.4 A Final Comment on Testing the Implications

Notice that the implications of the three theoretical models presented in Propositions 3, 5, and 7 are defined in terms of duration of employment in the informal sector from the time the worker entered the labor market. However, the duration measures used in the estimation of the hazard functions are with respect to the last job of the individual. To the extent that the individual experienced previous job spells in the informal sector, we are underestimating this measure. On the other hand, the fact that we are working with a sample of young individuals suggests that the underestimation is not very severe. A similar estimation was performed using a younger sub-sample, which included only individuals ages 16 to 20. The estimation results from this exercise are very similar and the hump-shape observed in the estimated hazard function persists. These results yield further support to the suggestion that underestimation of the duration of employment in the informal sector does not severely affect our results and conclusions.

6.5 Screening in Bécate Training Program

In this section we use the estimated piecewise constant hazard to infer the parameters governing the employer learning process. Knowledge of these parameters gives us the means to evaluate Bécate’s screening program introduced in Section 1. In terms of the employer learning model, we want to know how fast employers learn about their workers’ abilities. This information is obtained using the model-generated hazard and the estimated hazard. The unconditional hazard in the employer learning model is a function of five parameters, \((\bar{\mu}, \mu(p_L), \mu(p_H), \sigma, \phi)\); while the piecewise constant hazard is a function of seven parameters, \((\lambda_1, \ldots, \lambda_6, \rho)\). We use the estimated parameters \((\hat{\lambda}_1, \ldots, \hat{\lambda}_6, \hat{\rho})\) to infer the value of the parameters of the employer learning model.
Let \( \nu(t) \equiv \lambda_M(t; \tilde{\mu}, \mu(p_L), \mu(p_H), \sigma, \phi) - \lambda_{PW}(t; \hat{\lambda}_1, \ldots, \hat{\lambda}_6, \hat{\rho}), \) for \( t = 0, 1, \ldots, T \), denote the residual between the model generated hazard, \( \lambda_M(\cdot) \), and the estimated piecewise constant hazard, \( \lambda_{PW}(\cdot) \). To get the parameters governing the employers’ learning process, we look for the vector \( (\bar{\mu}, \mu(p_L), \mu(p_H), \sigma, \phi) \) that minimizes the sum of squared residuals. The details of the optimization algorithm are explained in Appendix E.

The estimated and the model-generated hazards are shown in Figure 6. The resulting parameters indicate that employers learn their workers’ abilities at a rate of \( \sigma = 0.1478 \) per month, and that the proportion of L-skilled workers in the population is \( \phi = 0.4833 \). Then, at the end of a three-month \( \text{Bécate} \) program, employers know the skill level of about 51% of the recruited workers, where 48% of these workers are expected to be L-skilled. The firm will be happy to hire those workers identified as H-skilled, but must also fulfill its promise to take 70% of the workers recruited for the program. This implies that the firm must take a gamble in hiring 44% of the original number of workers whose skill level is still unknown. However, since 48% of these workers are expected to to be L-skilled, the firm will end up hiring 21% of the original number of workers that are L-skilled. If the firm does not have a good match quality with these L-skilled workers, it will incur firing costs.

Note that the numbers we are getting from this exercise on the \( \text{Bécate} \) program are at the aggregate level. It must be the case that in some industries, the learning rate is very high, and for other industries it is very low. \( \text{Bécate} \) is a voluntary program, and so the firms that participate in the program must be firms with high learning rates. The authorities must consider this if the goal is to increase the number and types of firms participating in the program.

7 Final Remarks

The present study asks whether work experience in the informal sector can affect the career prospects of less-educated workers. The analysis focuses on two potential roles of informal sector jobs: accumulation of skills and screening of workers’ ability. In the traditional queuing model of the informal sector with heterogenous workers’ abilities, the hazard rate from the informal into the formal sector decreases with duration of informal sector employment. This study shows that, when informal sector jobs also enable workers to accumulate skills or employers to screen workers’ abilities, the shape of the hazard function can be different from that predicted by the traditional queuing model. Human capital accumulation implies an increasing or U-shaped hazard due to the accumulation of skills (and the fact that more skilled workers leave the informal sector faster). Screening can generate a hump-shaped hazard if workers with observable ability leave (on average) faster than informal sector entrants.
resulting in an increasing hazard; eventually, as more skilled workers leave faster, the hazard decreases with duration. These differences in the predicted hazard suggests a procedure to decide which role of informal sector jobs is more important.

The hazard function was estimated using an employment survey from Mexico. The estimated hazard reflects the hump-shaped pattern predicted by the screening model, indicating that informal sector jobs play an important role by screening young less-educated workers new to the labor market. Furthermore, the estimation results reject the traditional queuing model with heterogeneous workers' abilities, indicating that informal sector jobs provide some value above and beyond make-shift work while waiting to find a formal sector job.

Notice that this conclusion could break down if there is a third sector to which discouraged workers move, i.e. nonparticipation. If discouraged informal sector workers move to nonparticipation, and those workers moving out are mainly L-skilled workers, then the proportion of H-skilled workers would increase, pushing the average hazard function up; since H-skilled leave the informal sector at a faster rate, the proportion of H-skilled would decrease, pulling the average hazard function down. This alternate mechanism would produce a similar hump-shape pattern without employer learning. The question is whether young workers entering the labor market are discouraged and move to nonparticipation during the first years of their careers, which depends on the outside options of these workers. These outside options could be limited in developing countries like Mexico.

The employment survey used in this study is a rotating panel with a periodic follow-up, and so a significant fraction of the duration measures are interval-censored. In addition, for a good share of the spells the starting time is only known to fall within a twelve-month interval. These features of the data required the application of techniques for interval-censored failure time data, and a Monte Carlo study to investigate several alternatives for overcoming coarseness of the starting time of job spells. The latter follows Cano-Urbina (2012).

The parameters characterizing the employer learning process were inferred to determine how fast employers learn about their workers' abilities. The exercise suggests that employers learn about their workers' abilities at a much slower rate than that required by a government employment program, Bécate. This finding highlights the importance of a firm's involvement in the recruitment of workers participating in the program. In this way firms can minimize expected firing costs by recruiting candidates with a good match quality. Firm participation in the selection of candidates is allowed in the current format of Bécate.
References


Table 1: Summary Statistics by Education Group

<table>
<thead>
<tr>
<th>Variable</th>
<th>[0, 6)</th>
<th>[6, 9)</th>
<th>[9, 12)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>21.18</td>
<td>20.48</td>
<td>20.75</td>
</tr>
<tr>
<td>Married</td>
<td>0.18</td>
<td>0.16</td>
<td>0.15</td>
</tr>
<tr>
<td>Monthly Earnings†</td>
<td>3385.70</td>
<td>3578.19</td>
<td>3424.24</td>
</tr>
<tr>
<td>Minimum Wage‡</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zone A</td>
<td>0.09</td>
<td>0.11</td>
<td>0.14</td>
</tr>
<tr>
<td>Zone B</td>
<td>0.12</td>
<td>0.15</td>
<td>0.15</td>
</tr>
<tr>
<td>Zone C</td>
<td>0.79</td>
<td>0.74</td>
<td>0.71</td>
</tr>
<tr>
<td>Firm Size</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-5</td>
<td>0.64</td>
<td>0.61</td>
<td>0.60</td>
</tr>
<tr>
<td>6-20</td>
<td>0.25</td>
<td>0.27</td>
<td>0.25</td>
</tr>
<tr>
<td>21+</td>
<td>0.11</td>
<td>0.13</td>
<td>0.15</td>
</tr>
<tr>
<td>Industry</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construction</td>
<td>0.45</td>
<td>0.33</td>
<td>0.23</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.21</td>
<td>0.21</td>
<td>0.20</td>
</tr>
<tr>
<td>Commerce</td>
<td>0.12</td>
<td>0.15</td>
<td>0.21</td>
</tr>
<tr>
<td>Services</td>
<td>0.22</td>
<td>0.31</td>
<td>0.36</td>
</tr>
<tr>
<td>Family Head Status§</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Formal Sector Job</td>
<td>0.10</td>
<td>0.16</td>
<td>0.22</td>
</tr>
<tr>
<td>Self-employed</td>
<td>0.13</td>
<td>0.11</td>
<td>0.12</td>
</tr>
<tr>
<td>Unemployed</td>
<td>0.02</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Entrepreneur</td>
<td>0.06</td>
<td>0.07</td>
<td>0.09</td>
</tr>
<tr>
<td>Out of Labor Force</td>
<td>0.08</td>
<td>0.10</td>
<td>0.08</td>
</tr>
<tr>
<td>Number of Obs.</td>
<td>304</td>
<td>1,415</td>
<td>3,113</td>
</tr>
</tbody>
</table>

†Average monthly earnings in Mexican Pesos as of the 2nd half of December 2010. ‡Minimum wage by zone: A > B > C. §Employment status of the family head, when the family head is different from the individual in the sample.
### Table 2: Distribution of Duration Data in the Sample (Number of Observations)

<table>
<thead>
<tr>
<th>Type of Interval</th>
<th>Type of Sample</th>
<th>Flow</th>
<th>Stock 1†</th>
<th>Stock 2‡</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-month</td>
<td></td>
<td>0</td>
<td>134</td>
<td>0</td>
<td>134</td>
</tr>
<tr>
<td>2-month</td>
<td></td>
<td>2</td>
<td>13</td>
<td>0</td>
<td>15</td>
</tr>
<tr>
<td>3-month</td>
<td></td>
<td>91</td>
<td>679</td>
<td>0</td>
<td>770</td>
</tr>
<tr>
<td>4-month</td>
<td></td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>5-month</td>
<td></td>
<td>23</td>
<td>0</td>
<td>0</td>
<td>23</td>
</tr>
<tr>
<td>6-month</td>
<td></td>
<td>670</td>
<td>0</td>
<td>0</td>
<td>670</td>
</tr>
<tr>
<td>7-month</td>
<td></td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>12-month</td>
<td></td>
<td>0</td>
<td>0</td>
<td>19</td>
<td>19</td>
</tr>
<tr>
<td>14-month</td>
<td></td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>15-month</td>
<td></td>
<td>0</td>
<td>0</td>
<td>257</td>
<td>257</td>
</tr>
<tr>
<td>16-month</td>
<td></td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Right-censored</td>
<td></td>
<td>1,199</td>
<td>1,284</td>
<td>566</td>
<td>3,049</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>1,995</td>
<td>2,115</td>
<td>851</td>
<td>4,961</td>
</tr>
</tbody>
</table>

†Workers with job start in the current or previous calendar year. ‡Workers with job start before the previous calendar year.

### Table 3: Censoring in the Sample (Number of Observations)

<table>
<thead>
<tr>
<th>Type of Sample</th>
<th>Flow</th>
<th>Stock 1†</th>
<th>Stock 2‡</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncensored</td>
<td>796</td>
<td>831</td>
<td>285</td>
<td>1,912</td>
</tr>
<tr>
<td>Unemployed</td>
<td>224</td>
<td>314</td>
<td>57</td>
<td>595</td>
</tr>
<tr>
<td>Another risk§</td>
<td>412</td>
<td>279</td>
<td>185</td>
<td>876</td>
</tr>
<tr>
<td>Still working in IS§</td>
<td>563</td>
<td>691</td>
<td>324</td>
<td>1,578</td>
</tr>
<tr>
<td>Total</td>
<td>1,995</td>
<td>2,115</td>
<td>851</td>
<td>4,961</td>
</tr>
</tbody>
</table>

§Mainly composed by self-employment, but also includes unpaid family work, entrepreneurship, and out of the labor force. †Workers with job start in the current or previous calendar year. ‡Workers with job start before the previous calendar year.

### Table 4: Summary Statistics of Duration Data in Weeks

<table>
<thead>
<tr>
<th>Years of Education</th>
<th>Complete Duration</th>
<th>Elapsed Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[0, 6)</td>
<td>[6, 9)</td>
</tr>
<tr>
<td>Mean</td>
<td>15.3</td>
<td>14.2</td>
</tr>
<tr>
<td>25th pctile</td>
<td>3.0</td>
<td>3.5</td>
</tr>
<tr>
<td>50th pctile</td>
<td>7.0</td>
<td>7.5</td>
</tr>
<tr>
<td>75th pctile</td>
<td>15.0</td>
<td>16.0</td>
</tr>
</tbody>
</table>

Note: For the purposes of getting these summary statistics, we imputed the interval-censored duration data using the midpoint in the interval.
Table 5: Estimated Piecewise Constant Hazard

<table>
<thead>
<tr>
<th>Years or Education</th>
<th>[0, 12)</th>
<th>[0, 9)</th>
<th>[9, 12)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm size 6-20</td>
<td>0.4315</td>
<td>0.4390</td>
<td>0.4297</td>
</tr>
<tr>
<td></td>
<td>(0.0553)</td>
<td>(0.0978)</td>
<td>(0.0675)</td>
</tr>
<tr>
<td>Firm size 21+</td>
<td>0.7777</td>
<td>0.9284</td>
<td>0.7225</td>
</tr>
<tr>
<td></td>
<td>(0.0622)</td>
<td>(0.1127)</td>
<td>(0.0751)</td>
</tr>
<tr>
<td>Commerce Ind</td>
<td>0.2740</td>
<td>0.1316</td>
<td>0.3170</td>
</tr>
<tr>
<td></td>
<td>(0.0740)</td>
<td>(0.1429)</td>
<td>(0.0875)</td>
</tr>
<tr>
<td>Services Ind</td>
<td>0.0139</td>
<td>0.1722</td>
<td>-0.0353</td>
</tr>
<tr>
<td></td>
<td>(0.0653)</td>
<td>(0.1176)</td>
<td>(0.0790)</td>
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<tr>
<td>Construction Ind</td>
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<tr>
<td></td>
<td>(0.0706)</td>
<td>(0.1187)</td>
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<tr>
<td>Graduate Grade 6</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.1066)</td>
<td>(0.1076)</td>
<td></td>
</tr>
<tr>
<td>Graduate Grade 9</td>
<td>0.2915</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0544)</td>
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<td></td>
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<tr>
<td>Married</td>
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<tr>
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<td>Family Head FS</td>
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<td>(0.0554)</td>
<td>(0.1058)</td>
<td>(0.0650)</td>
</tr>
<tr>
<td>$\lambda_1$</td>
<td>0.0223</td>
<td>0.0270</td>
<td>0.0296</td>
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<tr>
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<td>(0.0075)</td>
<td>(0.0055)</td>
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<td>$\lambda_2$</td>
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<td></td>
<td>(0.0293)</td>
<td>(0.0434)</td>
<td>(0.0916)</td>
</tr>
<tr>
<td>$\lambda_3$</td>
<td>0.0671</td>
<td>0.0495</td>
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<td>(0.0149)</td>
<td>(0.0216)</td>
</tr>
<tr>
<td>$\lambda_4$</td>
<td>0.0379</td>
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<td>(0.0084)</td>
</tr>
<tr>
<td>$\lambda_5$</td>
<td>0.0387</td>
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<td>0.0543</td>
</tr>
<tr>
<td></td>
<td>(0.0055)</td>
<td>(0.0085)</td>
<td>(0.0069)</td>
</tr>
<tr>
<td>$\lambda_6$</td>
<td>0.0320</td>
<td>0.0364</td>
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</tr>
<tr>
<td></td>
<td>(0.0041)</td>
<td>(0.0062)</td>
<td>(0.0048)</td>
</tr>
</tbody>
</table>

Log likelihood: -3,838.71 -1,344.01 -2,478.97
Number of Obs.: 4,961 1,825 3,136

The omitted industry is Manufactures and the omitted firm size is 1-5 employees. The covariates also include: (i) a variable summarizing the number of self-employment scholarships approved in the state of residence relative to the size of the state’s labor market, (ii) three dummies for the year of start of the IS-Job (1997-2004, 2005-2006, 2007-2008, 2009-2010), the first category is omitted, and (iii) a dummy for adjusted duration measures. Standard errors in parenthesis.
Table 6: Estimated Weibull and Log-logistic Hazards

<table>
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<tr>
<th></th>
<th>Weibull</th>
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<th>Log-Logistic</th>
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<td>Years or Education</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0, 12)</td>
<td>[0, 9)</td>
<td>[9, 12)</td>
<td>[0, 12)</td>
</tr>
<tr>
<td>Firm size 6-20</td>
<td>0.4347</td>
<td>0.4725</td>
<td>0.4170</td>
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</tr>
<tr>
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<td>(0.0549)</td>
<td>(0.0974)</td>
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<td>(0.0953)</td>
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<td>Firm size 21+</td>
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<td>(0.0615)</td>
<td>(0.1121)</td>
<td>(0.0739)</td>
<td>(0.1135)</td>
</tr>
<tr>
<td>Commerce Ind</td>
<td>0.2875</td>
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<tr>
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<td>(0.0734)</td>
<td>(0.1422)</td>
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<td>(0.1313)</td>
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<td>Services Ind</td>
<td>0.0133</td>
<td>0.2019</td>
<td>-0.0492</td>
<td>-0.0006</td>
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<td>(0.0649)</td>
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<td>(0.0700)</td>
<td>(0.1185)</td>
<td>(0.0871)</td>
<td>(0.1206)</td>
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<tr>
<td>Graduate Grade 6</td>
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<td>0.1639</td>
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<tr>
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<td>(0.1063)</td>
<td>(0.1073)</td>
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<td>(0.1684)</td>
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<tr>
<td>Graduate Grade 9</td>
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<td></td>
<td>0.5403</td>
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<td>(0.0541)</td>
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<tr>
<td>Married</td>
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<td>Family Head FS</td>
<td>0.2676</td>
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<td>(0.1053)</td>
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<tr>
<td>α</td>
<td>0.8630</td>
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<td>0.8539</td>
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<td>(0.0294)</td>
<td>(0.0451)</td>
</tr>
<tr>
<td>T*</td>
<td></td>
<td></td>
<td>5.73</td>
<td>5.96</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-4,022.24</td>
<td>-1,385.59</td>
<td>-2,626.72</td>
<td>-4,011.19</td>
</tr>
<tr>
<td>Number of Obs.</td>
<td>4,961</td>
<td>1,825</td>
<td>3,136</td>
<td>4,961</td>
</tr>
</tbody>
</table>

The omitted industry is Manufactures and the omitted firm size is 1-5 employees. The covariates also include: (i) a variable summarizing the number of self-employment scholarships approved in the state of residence relative to the size of the state’s labor market, (ii) three dummies for the year of start of the IS-Job (1997-2004, 2005-2006, 2007-2008, 2009-2010), the first category is omitted, and (iii) a dummy for adjusted duration measures. $T^*$ was computed using $x = \ddot{x}$. Standard errors in parenthesis.
Figure 5: Piecewise Constant Baseline Hazard with 95% Pointwise Confidence Interval

(a) Years of Education: [0,12)

(b) Years of Education: [0,9)

(c) Years of Education: [9,12)
APPENDIX

A Wage Imputations

The information on earnings and working hours collected by the ENEU refers to the job held during the week previous to the interview, which is called the reference week. However, if the respondent did not attend work during the reference week, this information is missing. This section explains the methodology and criteria used in this paper to impute the respondent’s earnings and working hours when they are missing.

If the respondent was absent from work during the reference week, but stated to have a job, then the ENEU proceeds to determine why the respondent did not attend work. Some of the reasons why the respondent might have been absent from work are: vacation, sickness and recovery, strike, lack of production inputs, and work season ended. In such cases, the ENEU collects information on usual earnings and usual working hours. The information on usual earnings and usual working hours is used in this paper to impute the missing earnings and working hours only when the respondent declared to be absent from work due to vacation or due to sickness and recovery. Then, this information is used to compute a measure of usual hourly earnings, which in turn is used to impute the missing hourly earnings.

Finally, only those measures of usual earnings that satisfy certain criteria are used to impute the missing hourly earnings. The criteria is to compare the measure of usual hourly earnings against hourly earnings from the previous and subsequent interviews, and to impute missing hourly earnings whenever the measure of usual hourly earnings are within one
standard deviation from the previous, or the subsequent, measure of hourly earnings. The standard deviation is obtained with respect to the hourly earnings observations of each respondent. About 1% of the measures of hourly earnings in the final sample are the imputed hourly earnings.

As mentioned in the description of the sample, the top and bottom 1% of the hourly earnings are dropped from the sample. Only after the top and bottom 1% are dropped are missing hourly earnings imputed.

Appendix for Chapter ??

B Wages in the Model

The surplus sharing rule implies that:

\[ w_F(x, p) \text{ is such that: } W_F(x, p) - U(p) = \frac{\beta}{1 - \beta} [J_F(x, p) - V_F] \]

\[ w_I(p) \text{ is such that: } W_I(p) - U(p) = \frac{\beta}{1 - \beta} [J_I(p) - V_I] \]

where in equilibrium, free entry implies that \( V_F = 0 \) and \( V_I = 0 \).

Wages in the Baseline Model:

\[ w_F(x, p) = \beta(px - \delta D) + (1 - \beta)\bar{r}U(p) \]

\[ w_I(p) = \beta p_I + (1 - \beta) \left( \bar{r}U(p) - \beta m(\theta_F) \int_{Q(p)} S_F(s, p)dG(s) \right) \]

Wages in the Human Capital Model:

\[ w_F(x, p) = \beta(px - \delta D) + (1 - \beta) \left( \bar{r}U(p) - \kappa[U(p_H) - U(p)] \right) \]

\[ w_I(p) = \beta p_I + (1 - \beta) \left( \bar{r}U(p) - \kappa[U(p_H) - U(p)] - \beta m(\theta_F) \int_{Q(p)} S_F(s, p)dG(s) \right) \]

Wages in the Learning Model:

\[ w_F(x) = \beta \left( \bar{p}x - \delta D - \sigma \phi \Gamma_L(x)D \right) + (1 - \beta) \left( \bar{r}U - \sigma [\phi U(p_L) + (1 - \phi)U(p_H) - U] \right) \]

\[ w_I = \beta p_I + (1 - \beta) \left( \bar{r}U - \sigma [\phi U(p_L) + (1 - \phi)U(p_H) - U] - \beta m(\theta_F) \int_{Q} S_F(x)dG(x) \right) \]
C Proofs

C.1 Proof of Lemma 1

Note that \( S_I(p) = \frac{J_I(p)}{1 - \beta} \). In the proof we replace \( S_I(p) \) with \( \frac{J_I(p)}{1 - \beta} \) in (11). Consider the following result which proves to be useful in the proof of Lemma 1.

Lemma 8. An upper bound for \([Q(p) - C(p)]\) is \( \tilde{r} + \delta \left( \frac{p_t - z}{p} \right) \).

Proof. First, note that:

\[
J_I(p) = \frac{1 - \beta}{\tilde{r} + \delta + \mu(p)} \left( p_t - \tilde{r}U(p) + m(\theta_F) \int_{Q(p)}^1 [W_F(x, p) - U(p)]dG(x) \right) < \frac{1 - \beta}{\tilde{r} + \delta + \mu(p)} \left( p_t - \tilde{r}U(p) + m(\theta_F) \int_{C(p)}^1 [W_F(x, p) - U(p)]dG(x) \right) = \frac{1 - \beta}{\tilde{r} + \delta + \mu(p)} \left( p_t - z - m(\theta_I) \left[ W_I(p) - U(p) \right] \right) = \frac{1 - \beta}{\tilde{r} + \delta + \mu(p)} \left( p_t - z - m(\theta_I) \frac{\beta}{1 - \beta} J_I(p) \right)
\]

And so, \( J_I(p) < \frac{1 - \beta}{\tilde{r} + \delta + \mu(p) + \beta m(\theta_I)} (p_t - z) \). Since \( Q(p) - C(p) = \left( \frac{\tilde{r} + \delta}{p} \right) \frac{J_I(p)}{1 - \beta} \), the result follows.

Next, we proceed to prove Lemma 1.

Proof. Note that once we substitute equilibrium wage equations and use the surplus sharing rules to substitute for unknown value functions, equations (11), (15), and (19) represent a system of three equations with three unknowns and one parameter:

(28) \( F(\tilde{r}U, C, Q; p) = 0. \)

Note that we treat \( \Omega = (\delta, p_t, m(\theta_I), m(\theta_F), r, z, D, \beta) \) as given because \( \Omega \) does not change when the parameter \( p \) changes. Linearizing (28), we get:

\[
(1 - A)d(\tilde{r}U) + (N + AK)dC + (A(L - E))dQ - (AH + M)dp = 0
\]
\[\frac{1}{p}d(\tilde{r}U) + dC + \frac{C}{p}dp = 0\]
\[Bd(\tilde{r}U) + (BK - 1)dC + (1 + B(L - E))dQ - \left( BH - \frac{Q - C}{p} \right) dp = 0\]
where:

\[ A = \frac{m_I \beta}{\bar{r} + \delta + \mu(p)}, \quad K = \frac{\mu(p)\beta}{\bar{r} + \delta} p, \]

\[ B = \frac{\bar{r} + \delta}{p(\bar{r} + \delta + \mu(p))}, \quad L = \frac{m_F \beta}{\bar{r} + \delta} p(Q - C)g(Q), \]

\[ E = m_F g(Q) \frac{J}{1 - \beta}, \quad M = \frac{m_F \beta}{\bar{r} + \delta} \int_1^{x-C} (x - C) dG(x), \]

\[ H = \frac{m_F \beta}{\bar{r} + \delta} \int_1^{x-C} (x - C) dG(x), \quad N = \frac{m_F \beta}{\bar{r} + \delta} p[1 - G(C)]. \]

Note that for ease of exposition we denoted \( m(\theta_j) = m_j \) for \( j \in \{F,I\} \). By the Implicit Function Theorem and using Cramer’s rule, we can derive \( dC/dp \), which is given by:

\[
\frac{dC}{dp} = \frac{A(L - E)(Q - C) + pB(L - E)(M - C) + pA(H - C) + p(M - C)}{p[(L - E)(BN + A + pB) + AK + Ap + N + p]}.
\]

It is straightforward to show that all the terms in the numerator, except for the second one, are negative. Ignore the third term, which we know is negative, then adding the first, second, and fourth terms in the numerator, and after some algebra, we get:

\[
p \left( \frac{\delta D + z}{p} \right) \left[ \frac{m_F(1 - \beta)}{\bar{r} + \delta + \mu(p)}(Q - C)g(Q) - 1 \right] - \frac{m_I \beta}{\bar{r} + \delta} p(Q - C)
\]

which is negative if the term in square brackets is negative. Using Lemma 8 to bound the term in square brackets from above we get:

\[
\left[ \frac{m_F(1 - \beta)}{\bar{r} + \delta + \mu(p)}(Q - C)g(Q) - 1 \right] < \left( \frac{\bar{r} + \delta}{\bar{r} + \delta + \mu(p)} \right) \left( \frac{(1 - \beta)m_F g(Q)}{\bar{r} + \delta + \mu(p) + m_I \beta} \right) \left( \frac{p_I - z}{p} \right) - 1.
\]

Notice that because \( \mu(p) > 0 \), we can further bound the term on the right hand side of the inequality from above. Then, a sufficient condition for the numerator to be negative is that:

\[
\left( \frac{(1 - \beta)m_F g(Q)}{\bar{r} + \delta + \mu(p) + m_I \beta} \right) \left( \frac{p_I - z}{p} \right) < 1.
\]

Let \( \eta = \frac{1}{1 - \beta} \left( \frac{p_L}{p_I - z} \right) \). Rearranging this condition we get:

\[
m_F \left( g(Q) - \eta [1 - G(Q)] \right) < \eta(\bar{r} + \delta) + \eta m_I \beta.
\]

Finally, since \( m_I > 0, m_F < 1 \), and \( Q \in [0,1] \), a stronger condition that does not depend on endogenous variables is:

\[
(CDN \ 1) \ \forall x \in [0,1] \quad \left( g(x) - \eta \int_x^1 g(u) du \right) < \eta(\bar{r} + \delta)
\]
Since the third term is negative, (CDN 1) is a sufficient condition for the numerator to be negative. Now, we focus on the denominator of \( dC/dp \). It is straightforward to show that \((L - E)(BN + A + pB) < 0\), and using Lemma 8 again, we can bound from above the absolute value of the this term:

\[
\left| (L - E)(BN + A + pB) \right| < g(Q) \frac{m_F(1 - \beta)(p_I - z)}{\bar{r} + \delta + \mu(p)} + m_I \beta \left[ \frac{m_F \beta [1 - G(Q)] + \bar{r} + \delta}{\bar{r} + \delta} \right].
\]

The other term in the denominator is positive and it is given by:

\[
(AK + Ap + N + p) = p \left[ \left( \frac{m_I \beta}{\bar{r} + \delta + \mu(p)} \right) \left( \frac{\mu(p) \beta}{\bar{r} + \delta} \right) + \frac{m_I \beta [1 - G(C)]}{\bar{r} + \delta} + 1 \right].
\]

Next, we compare (29) and (30). Using the sufficient condition (CDN 1) we can show that \( p > g(Q) \frac{m_F(1 - \beta)(p_I - z)}{\bar{r} + \delta + \mu(p)} + m_I \beta \), so the outer term is higher for (30). Finally, it is straightforward to show that the term in square brackets is also higher in (30) than the term in square brackets in (29), so that the denominator is positive. As a result, \( dC/dp < 0 \).

Now, we apply the Implicit Function Theorem and use Cramer’s rule again to derive \( dQ/dp \), which is given by:

\[
\frac{dQ}{dp} = \frac{pB[H(N + p) - M(K + p) + C(K - N)] + p[(M - Q) + A(H - Q)] + (N + AK)(C - Q)}{p[(L - E)(BN + A + pB) + AK + Ap + N + p]}.
\]

We already proved that under certain parameter conditions the denominator of \( dQ/dp \) is positive. Then it just remain to show that the numerator is negative. It is straightforward to show that the second and third terms of the numerator are negative. To show that the first term is negative, note that \( M > H \) so:

\[
pB[H(N + p) - M(K + p) + C(K - N)] < pB[M(N + p) - M(K + p) + C(K - N)]
= pB[MN - MK + C(K - N)]
= pB(N - K)[M - C]
< 0
\]

where the last inequality from the fact that \( C > M \). As a result, \( dQ/dp < 0 \). And this completes the proof.

\[\square\]

C.2 Proofs of the Shape of the Unconditional Hazard Rates

Before proving Propositions 3, 5, and 7, consider the following result about the unconditional hazard rate. The proof of Lemma 9 follows the arguments of Lancaster (1990, chap. 4).

**Lemma 9.** Let \( \lambda(t|p) \) be the hazard rate conditional on worker skill level, and \( \lambda'(t|p) = \partial \lambda(t|p)/\partial t \). Let \( \phi_I \) be the probability that \( p = p_I \) in the informal sector. Then, the uncondi-
tional hazard rate and its derivative are given by:

\[ \lambda(t) = \gamma(t)\lambda(t|p_L) + [1 - \gamma(t)]\lambda(t|p_H) \]

\[ \lambda'(t) = \gamma'(t)[\lambda(t|p_L) - \lambda(t|p_H)] + \gamma(t)\lambda'(t|p_L) + [1 - \gamma(t)]\lambda'(t|p_H) \]

where \( \gamma(t) = \frac{1}{1 + \eta(t)} \), \( \eta(t) = \left( \frac{1 - \phi_t}{\phi_t} \right)e^{-\left[\Lambda(t|p_H) - \Lambda(t|p_L)\right]} \), \( \Lambda(t|p) = \int_0^t \lambda(s|p)ds \), and \( \eta'(t) = \eta(t)[\lambda(t|p_L) - \lambda(t|p_H)] \).

\[ \phi_t = 1 - \phi_t \]

**Proof.** The conditional survivor function is given by \( S(t|p) = e^{-\Lambda(t|p)} \). Then, the unconditional survivor function is given by \( S(t) = \phi_t e^{-\Lambda(t|p_L)} + (1 - \phi_t)e^{-\Lambda(t|p_H)} \), and the unconditional hazard is given by \( \lambda(t) = -d\ln S(t)/dt \), then by the First Fundamental Theorem of Calculus:

\[ \lambda(t) = \frac{\phi_t \lambda(t|p_L)e^{-\Lambda(t|p_L)} + (1 - \phi_t)\lambda(t|p_H)e^{-\Lambda(t|p_H)}}{\phi_t e^{-\Lambda(t|p_L)} + (1 - \phi_t)e^{-\Lambda(t|p_H)}} = \gamma(t)\lambda(t|p_L) + [1 - \gamma(t)]\lambda(t|p_H) \]

and

\[ \gamma(t) = \frac{\phi_t e^{-\Lambda(t|p_L)}}{\phi_t e^{-\Lambda(t|p_L)} + (1 - \phi_t)e^{-\Lambda(t|p_H)}} = \frac{1}{1 + \eta(t)} \]

\[ \eta(t) = \left( \frac{1 - \phi_t}{\phi_t} \right)e^{-\left[\Lambda(t|p_H) - \Lambda(t|p_L)\right]} \],

so that \( \eta(t) > 0 \). \( \lambda'(t) \) is straightforward and applying the First Fundamental Theorem of Calculus again we have:

\[ \eta'(t) = \eta(t)[\lambda(t|p_L) - \lambda(t|p_H)] \].

\[ \square \]

**C.2.1 Proof of Proposition 3**

**Proof.** From Lemma 9 and Proposition 2 we have that:

\[ \eta'(t) = \eta(t)[\mu(p_L) - \mu(p_H)] < 0, \]

\[ \gamma'(t) = -\gamma(t)^2\eta(t)[\mu(p_L) - \mu(p_H)] > 0, \text{ and} \]

\[ \lambda'(t) = \gamma'(t)[\mu(p_L) - \mu(p_H)] < 0. \]

\[ \square \]

**C.2.2 Proof of Proposition 5**

**Proof.** From Lemma 9 and Proposition 4 we have that:

\[ \eta'(t) = \eta(t)(1 - \kappa)^f[\mu(p_L) - \mu(p_H)] < 0, \]

\[ \gamma'(t) = -\gamma(t)^2\eta(t)(1 - \kappa)^f[\mu(p_L) - \mu(p_H)] > 0, \text{ and} \]

\[ \square \]
\[
\lambda'(t) = \gamma(t)(1 - \kappa)^t \left[ \mu(p_L) - \mu(p_H) \right] \left[ \ln(1 - \kappa) - \gamma(t) \eta(t)(1 - \kappa)^t \right],
\]
where each term in the square brackets is positive. However, the first term in the square brackets is constant while the second one decreases with time. To see this, define \( \Phi(t) = \gamma(t) \eta(t)^i = \eta(t)(1 - \kappa)^i \), then it is easy to check that
\[
\Phi'(t) = \eta'(t) \left[ (1 - \kappa)^i + \frac{\eta(t)(1 - \kappa)^i \ln(1 - \kappa)}{1 + \eta(t)} \right] < 0
\]
where negativity follows from \( \eta'(t) < 0 \) and \( \kappa \in (0, 1) \). Evaluating \( \Phi(t) \) at \( t = 0 \) we find that \( \Phi(0) = 1 - \phi_I \), therefore:

(i) if \( \ln(1 - \kappa)/[\mu(p_L) - \mu(p_H)] > (1 - \phi_I) \), then the term in square brackets is always positive, and

(ii) if \( \ln(1 - \kappa)/[\mu(p_L) - \mu(p_H)] < (1 - \phi_I) \), then the term in square brackets is initially negative, but becomes eventually positive, so that \( \lambda(t) \) decreases initially, but eventually increases.

C.2.3 Proof of Proposition 7

Proof. From Lemma 9 and Proposition 6 we have that
\[
\eta'(t) = \eta(t) [1 - (1 - \sigma)^t] \left[ \mu(p_L) - \mu(p_H) \right] < 0
\]
\[
\gamma'(t) = -\gamma(t)^2 \eta(t) [1 - (1 - \sigma)^t] \left[ \mu(p_L) - \mu(p_H) \right] > 0, \quad \text{and}
\]
\[
\lambda'(t) = -\gamma(t)^2 \eta(t) [1 - (1 - \sigma)^t] \left[ \mu(p_L) - \mu(p_H) \right]^2
+ (1 - \sigma)^t \ln(1 - \sigma) \left[ \bar{\mu} - \phi \mu(p_L) - (1 - \phi) \mu(p_H) \right].
\]
Note that in the definition of \( \eta(t) \) in Lemma 9, \( \phi \) replaces \( \phi_I \). Inspection of \( \lambda'(t) \) reveals that for low values of \( t \), the second term dominates but it is eventually overtaken by the first term, much more faster the higher \( \sigma \) is. Next, evaluating \( \lambda'(t) \) at \( t = 0 \), we find
\[
\lambda'(0) = \ln(1 - \sigma) \left[ \bar{\mu} - \phi \mu(p_L) - (1 - \phi) \mu(p_H) \right].
\]
Therefore, if the term in square brackets is:

(i) Positive, then the hazard is monotonically decreasing.

(ii) Negative, then the hazard increases initially, but eventually decreases.

D Imputing Interval-Censored Elapsed Duration

In the Monte Carlo experiment, the duration data is generated taking into account the features of the ENOE, primarily: (i) only individuals with job start before the previous
calendar year have interval elapsed duration, (ii) the complete duration from the stock sample is interval-censored.

To construct one stock sample, we made repeated draws from spells until all individuals accumulated enough duration to reach certain point in time, which represents the moment at which the stock sample is taken. The spell in which an individual reaches the stock sampling point is taken as that individual’s duration of employment. We assumed that the individuals’ duration has a Weibull-Gamma distribution, and tried six different parameter sets to cover cases with positive, negative and no duration dependence, as well as cases with and without unobserved heterogeneity. We only simulate stock sample data.

We tried three imputation methods. Let \( \tilde{E}_i \) be the imputed duration, then we tried: (i) \( \tilde{E}_i = E_i^L \), (ii) \( \tilde{E}_i = E_i^R \), and (iii) \( \tilde{E}_i = (E_i^L + E_i^R)/2 \). The simulation exercise shows that using either \( E_i^L \) or \( E_i^R \) yields very poor results, and that using the midpoint in the interval yields the best results. We also tried a random draw from the interval using the uniform distribution in the interval, but the results are very similar to those using the midpoint. Thus, we use this midpoint imputation method for estimation.

### E Minimization Algorithm to Find Parameters of the Employer Learning Model

The estimated hazard suggest starting values for \( (\bar{\mu}, \mu(p_L), \mu(p_H)) \). In particular, by Condition 3 \( Q(p_H) < Q < Q(p_L) \), and so \( \mu(p_L) < \bar{\mu} < \mu(p_H) \). This is because at \( t = 0 \) the hazard must equal \( \bar{\mu} \) and for longer durations the hazard must equal \( \mu(p_L) \). However, the estimated hazard in Figure 5 suggests that \( Q \approx Q(p_L) \). Then, we set \( \mu(p_L) = 0.99 \cdot \bar{\mu} \), so that \( \mu(p_L) \) is arbitrarily close to, but below \( \bar{\mu} \), and use \( \exp(\tilde{x}'\hat{\beta})\hat{\lambda}_1 = 0.03 \) as a starting value for \( \bar{\mu} \).

Similarly, we know that \( \mu(p_H) \) must be higher than the maximum of the hazard function, then we use \( \exp(\tilde{x}'\hat{\beta})\hat{\lambda}_2 = 0.3 \) as a starting value for \( \mu(p_H) \). The estimated hazard does not provide much information to select starting values for \( (\sigma, \phi) \). Hence we use different starting values given by \{0.1, 0.3, 0.5, 0.7, 0.9\} for each parameter. This gives a total of 25 different starting values, in all cases we use \( T = 50 \). For all starting values, the resulting vector of parameters is: \( \bar{\mu} = 0.05 \), \( \mu(p_L) = 0.0495 \), \( \mu(p_H) = 1.0 \), \( \phi = 0.4833 \), and \( \sigma = 0.1478 \).