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Matteo Bobba
Luca Flabbi
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Matteo Bobba
University of Toulouse Capitole and IZA

Luca Flabbi
University of North Carolina at Chapel Hill and IZA

Santiago Levy
Inter-American Development Bank and IZA

Mauricio Tejada
Universidad Alberto Hurtado

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Labor Market Search, Informality, and On-The-Job Human Capital Accumulation

We develop a search and matching model where firms and workers produce output that depends both on match-specific productivity and on worker-specific human capital. The human capital is accumulated while working but depreciates while searching for a job. Jobs can be formal or informal and firms post the formality status. The equilibrium is characterized by an endogenous steady state distribution of human capital and by an endogenous formality rate. The model is estimated on longitudinal labor market data for Mexico. Human capital accumulation on-the-job is responsible for more than half of the overall value of production and upgrades more quickly while working formally than informally. Policy experiments reveal that the dynamics of human capital accumulation magnifies the negative impact on productivity of the labor market institutions that give raise to informality.

JEL Classification: J24, J3, J64, O17

Keywords: labor market frictions, search and matching, Nash bargaining, informality, on-the-job human capital accumulation

Corresponding author:
Matteo Bobba
Toulouse School of Economics
University of Toulouse Capitole
21 Allée de Brienne
31015 Toulouse
France
E-mail: matteo.bobba@tse-fr.eu

1 Introduction

Most labor markets in medium- and low-income countries are characterized by high levels of informality (see , e.g., La Porta and Shleifer [2014]; Levy and Schady [2013]). Informality refers to the non-compliance with labor market regulations, including the failure to contribute to the social security system. The result is a lower contribution base and the loss of health and retirement benefits for a large portion of the labor force. The advantage is the reduction of the negative employment effects induced by rigid contractual arrangements between firms and workers.

If the presence of informality may be seen as an optimal response to a given institutional context, it is also correlated to other labor market features that may impact overall productivity. A growing literature is focusing on the firm side, showing strong correlations between firm's productivity and formality status and identifying an important channel of the relation in the distortions of firms' investment decisions.[1] The literature focusing on productivity and the worker side is smaller and rarely takes into account human capital accumulation in presence of high informality. In a companion paper [Bobba et al., 2017], we study the issue focusing on human capital accumulation decisions *before* entering the labor market. In this paper, we move our attention to the dynamic of human capital that takes place *after* entering the labor market. In particular, we look at human capital accumulation on-the-job, its possible depreciation while searching for a new job, and whether and how the formality status of the job significantly affects this dynamic. Recent evidence on lower wage profiles over the life-cycle in countries with a large informal sector [Lagakos et al., 2018] suggests that this relation is potentially very relevant.

We develop and estimate a search and matching model where formality status and job search decisions are updated optimally every time the human capital levels change either as a result of upgrading on the job or of downgrading while searching for a new job. We model in detail the structure of social security costs and benefits, allowing for the presence of a "dual" system where formal jobs enjoy benefits financed by payroll contributions while informal workers and labor market searchers receive benefits financed by resources collected outside the labor market. Firms face monetary penalties for hiring informally.

In our environment, workers and employers search for potential partners to enter a job relation. When they meet, they observe a match-specific productivity that contributes to the overall output of the match together with the workers' human capital. Firms optimally

[1]For evidence on informality and firm productivity in Mexico, see Busso et al. [2012]. Studies of firms' investment decisions in the presence of informality include de Paula and Scheinkman [2011]; Ulyssea [2018].

post the formality status for each specific match and wages are determined by bargaining. At a given point in time, each worker can be in one of four possible labor market states: formal employee, informal employee, self-employed, and unemployed. The human capital evolution while participating in the labor market captures the additional productivity that may be acquired on the job (human capital upgrading). This additional productivity may depreciate if not working (human capital downgrading). While working, human capital upgrading may occur at different rates depending on the formality status of the job and on the current human capital level. The process of human capital upgrading and downgrading generates endogenous changes in wages and labor market states. For example, an informal employee who upgrades his human capital may endogenously negotiate a higher wage, a different formality status or quit the job relationship. However, human capital upgrading is not the result of any explicit investment decisions but it is motivated by a learning-by-doing view of human capital evolution[2] where workers may increase their productivity by practicing their skills on the job.

We estimate the model on individual data from Mexico's official labor force survey.[3] We find that human capital accumulation on-the-job is important: in steady state, it is responsible for more than half of the overall value of production. Human capital upgrading is slower while working informally than formally: for first entrants in the labor market, it takes on average 1.4 years to start upgrading their human capital if they work formally and about 2 years to do so if they work informally. We also estimate that the upgrading is harder the higher the level of human capital already acquired on the job. Still, at any human capital level, the probability of upgrading remains higher if working formally. This advantage is partially offset by the size of the upgrade when the shock hits, which is instead on average higher when working informally.

There are two main sources of identification in the data for the parameters governing the human capital dynamics: (i) transitions between jobs and labor market states; (ii) wage growth within and between jobs, conditioning on formality status. In the data set at our disposal, we can observe both of them for a balanced panel of individuals for up to five quarters.

We use the estimated model to perform policy experiments focusing on the two parameters considered crucial in generating the high level of informality observed in Mexico and

[2]For a recent review, see Thompson [2010].

[3]The estimation sample is extracted from Mexico's official labor force survey, the *Encuesta Nacional de Ocupación y Empleo* (ENOE) for the years 2013 and 2014.

other countries in Latin America:[4] the contribution rate paid by formal employees and the level of non-contributory social security benefits received by any non-formal employee. Increasing the contribution rate leads to an increase in informality and a decrease in the stock of human capital. However, the negative impact on aggregate human capital is almost neutralized when the contribution rate increase is paired with a proportional increase in the benefit. Increasing the non-contributory benefit also leads to an increase in informality and a decrease in the stock of human capital but has a different, and major, impact on the selection of workers into formal jobs.

We contribute to the growing empirical literature on equilibrium search models by introducing and quantifying an additional mechanism behind wage growth over the life cycle: on-the-job human capital accumulation. Most estimated search models of the labor market impose constant wages at the same job. The main exceptions include models allowing for on-the-job search and wage renegotiation, such as Cahuc et al. [2006] and Dey and Flinn [2005]. Very few introduce human capital accumulation on-the-job: notable examples are Bagger et al. [2014] and Flinn et al. [2017].

We also contribute to the small literature estimating search models of the labor market in which informality arises endogenously. Meghir et al. [2015] is the only published work to have accomplished this result but it does not allow for human capital accumulation. Within the general literature of search and informality, we are unique in providing a theoretical foundation and an empirical implementation for the possibility of a change in formality status at the *same* job. This is a small but significant empirical regularity which is only studied by the literature focusing on the demand side of the labor market. For example, neither Bosch and Esteban-Pretel [2012], nor Meghir et al. [2015], nor Bobba et al. [2017] can account for this type of labor market transition.

A key result of our policy experiments is that a higher contribution rate not only increases informality but also decreases human capital. This is a direct consequence of taking into account the dynamic of the human capital accumulation: more informality in steady state means lower rate of human capital upgrading over time. This result creates a link with the literature on life-cycle labor supply with learning-by-doing. In policy experiments based on estimated models, Imai and Keane [2004] and Keane [2015] show that higher – respectively, temporary, and, as in our case, permanent – tax rates reduce human capital accumulation by inducing a dynamic feedback loop with labor supply.

[4] For a focus on the payroll contribution, see Albrecht et al. [2009] and Rocha et al. [2017]. For a review on Mexico, see Levy [2008].

The paper is organized as follows. Section 2 describes the data and the institutional context. Section 3 develops and discusses the model. Section 4 describes the identification of the model's parameters with the data at our disposal. Section 5 defines the estimation method and presents the estimation results. Section 6 reports the policy experiments. Section 7 concludes.

2 Context and Data

2.1 Institutional Setting

In Mexico, as in most Latin American countries, there exists a centralized social security registry (called IMSS[5]) were all salaried workers are supposed to be enrolled. This registry records all the contributions made by the firm on behalf of the worker and determines the benefits generated by these contributions. The firm is the agent that the legislation mandates to be responsible to enroll its salaried workers in IMSS. The firm is also responsible to pay fines and past contributions when a worker hired informally is discovered by the enforcing branch of IMSS. The benefits obtained by the salaried workers contributions are bundled in a package that includes health benefits, housing benefits, some day care services, and pensions. Some benefits are directly proportional to the worker's contribution (pensions) while others are not (health benefits). Since the contribution are proportional to wages, this implies redistribution within salaried formal workers. There is no unemployment insurance and thus no flow payments out of wages into an unemployment fund or individual accounts. In Mexico, the rate of the social security contribution is approximately 33 percent of the wage of salaried workers.

Since labor market regulations are imperfectly enforced, non-compliance occurs as a device for firms to save on labor costs. When caught hiring illegally, firms have to pay monetary fines that range between 20-350 daily minimum wages for each non-registered worker.[6] Many firms operate in both the formal and informal sector because they hire workers both legally and illegally.[7] This fact, together with the frequent and significant flow

[5]The acronym stands for *Instituto Mexicano del Seguro Social* (Mexican Social Security Institute).

[6]The exact parameters that IMSS uses to determine which establishments to inspect are confidential. However, according to IMSS officers in charge of inspections, when deciding which firms to inspect they take into account firm size, industry, history of previous violations and notifications made to IMSS by the Ministry of Labor.

[7]Perry et al. [2007] show that in Mexico 50% to 70% of small-medium firms have used both formal and informal contracts simultaneously in a given point in time. Ulyssea [2018] documents that in small formal firms in Brazil 40% percent of workers are informal. At the same time, 52% of all informal workers are

of workers who transit back and forth from formal to informal jobs [Maloney, 1999, 2004; Meghir et al., 2015], is in contrast with a segmented view of the labor market where barriers restrict access to the formal sector. Yet, there is evidence to suggest that the returns to formal and informal jobs are potentially different.[8]

To the extent that there is no firm-worker relationship, labor market regulations do not apply to self-employed workers. For most of the individuals engaged in those activities, the notion of self-employment differs quite fundamentally from its counterpart in high-income countries. It can be mostly ascribed as a "necessity" labor market state whereby individuals who are not matched with firms engage in self-employment activities while also searching for a job [Fields, 1975]. A typical example of such activity is working as a street vendor. Financial barriers to enter into self-employment do not appear as an important obstacle [Bianchi and Bobba, 2013], which is consistent with the fact that unemployment is in general very limited in those labor markets [Feng et al., 2018].

In response to the lack of social security coverage for informal workers, starting from the early 2000s non-contributory programs were launched to expand the coverage of housing subsidies, retirement pensions and day care facilities. Spending in those programs doubled between 2002 and 2013, from 0.8 to 1.65 percent of GDP – a pattern that is in common across many countries with a dual social security system [Frolich et al., 2014].[9] The voluntary, unbundled, and practically free nature of non-contributory programs implies that valuation issues are substantially less complex than in the case of contributory programs. There are no significant regional or quality differences between contributory and non-contributory pension, housing and day care programs; with regards to health, differences have narrowed considerably as a result of a large expansion in the health infrastructure of state governments, which provide services to those not covered by IMSS [Levy, 2008].

employed in large firms that are unlikely to be fully informal.

[8]World-Bank [2019] reports evidence from a variety of countries that the returns to experience for a worker are higher in the formal sector than in the informal sector. In emerging economies, on average, the earnings increase for an additional year of work for informal wage workers is 1.4 percent, whereas it is 1.8 percent for formal wage workers. Also, job training for active workers takes place largely in formal firms. Alaimo et al. [2015] document striking differences between the two sectors in the proportion of workers that during their work life receive on-the-job training.

[9]The corresponding figures for other Latin American countries document even steeper growth rates than Mexico over the same period. For instance, in Chile spending in non-contributory social programs increased from 0.5 percent of GDP in 2002 to 1.5 percent of GDP in 2013. In Argentina, spending increased from 1 percent of GDP to 4 percent of GDP.

2.2 Data

The data is extracted from Mexico's official labor force survey, the *Encuesta Nacional de Ocupación y Empleo* (ENOE). Similar to the US Current Population Survey, the dataset has a panel component – households stay in the sample for five consecutive quarters. In the first quarter of each year, employed individuals are inquired about the date in which they started working with their current employer. We stack together two cohorts of individuals entering in the first quarter of the year 2013 and in the first quarter of 2014, respectively. This information combined with quarterly panel data on wages and labor market status allows us to fully characterize the labor market trajectories for the individuals in our sample (job-to-job transitions, wage growth within and between job spells, as well as changes in the formality status within the same job). Appendix A provides further details about the construction of the longitudinal sample employed in the analysis.[10]

We restrict the sample to nonagricultural, male, private-sector workers between the ages of 20 and 55. We focus our analysis on workers at the mid-range of the skill distribution – i.e. those with at most secondary schooling completed. We thus drop from the sample those who did not complete middle school (i.e. below 9th grade) and those with at least some tertiary education (i.e. some College or more). We consider individuals with at most secondary schooling completed instead of primary or tertiary for three main reasons: (i) they are the most numerous, comprising more than half of the labor force in most Latin American countries, including Mexico [Bobba et al., 2012]; (ii) they are significantly affected by informality (a statement which is true for primary but much less so for tertiary); (iii) they are at a skill level where human capital accumulation on the job is relevant (a statement which is clearly true for tertiary but more questionable for primary).

We define a worker to be an *employee* if he declares (i) being in a subordinate working relationship in their main occupation; and (ii) receiving a wage as a result of that working relationship. We identify the formal or informal status of the job depending on whether the employee reports having access to health benefits through their employers, which is common practice in the literature.[11] We define the *self-employed* workers as those who declare (i) not

[10]The two years under consideration are the most recent available in ENOE at the start of this project. We are forced to merge the two years together to gain sample size. While the overall sample size is not small, some labor market transitions important for the identification of the model are relatively rare: combining two years allows us to compute more credible moments. The Mexican economy was quite stable over the period, so assuming that agents were participating in the same labor market over the two years is not unreasonable.For example, unemployment rate was 4.9% in 2013 and 4.8% in 2014; real GDP growth was, respectively, 1.4% and 2.6%. Source: World Development Indicators (WDI), *The World Bank*.

[11]In the literature on Latin America the informality status of an employee is typically defined in reference to firms' compliance with the social security regulation. See Bobba et al. [2017] for more details on this

being in a subordinate relationship in their main occupation and (ii) having a business by their own. In order to obtain a more homogenous population of self-employed individuals and to be consistent with the "necessity" self-employment we are interested in, we drop those who report having paid employees and those who report having access to contributory health benefits. The entire sub-population of self-employed workers that we consider is thus informal, as opposed to employee workers who can be formal or informal depending on employers' decision to enroll some, none or all of their employees in the social security registries. We define the *unemployed* as those who declare (i) not to be working during the last week; and (ii) being actively searching for a job. Earning distributions are trimmed at the top and bottom 1% in each labor market state (formal employees, informal employees and self-employed).

The final sample that we use in our empirical analysis is a balanced panel dataset comprised of 4,936 individuals observed every quarter for five quarters, either starting in the first quarter of 2013 or in the first quarter of 2014. Table 1 and Figure 1 depict the main cross-sectional facts; Table 2 reports statistics on labor market dynamics. The observed patterns are broadly consistent with previous evidence for Mexico and with aggregate evidence from Latin America. First, there is a significant mass of workers in each labor market state: about 60% of workers are employed formally and 35% informally. Among informal workers, 2/3 are employees and 1/3 self-employed. The unemployment rates is around 5%. Second, there is a large overlap between the wage distributions of formal employees and informal employees. Self-employed earnings distributions are approximately in between those of formal and informal employees, with a larger standard deviation. Third, there is a significant amount of transitions between labor market states and formality regimes. Looking at the second row of Table 2, we observe that more than 30% of the informal employees change labor market status after a year. In the case of the most persistent state – formal employee – about 14% change labor market status after a year. Changes of formality status are also significant, with about 20% of informal employees becoming formal after a year. Fourth, and frequently neglected by the literature, changes in formality status may frequently occur at the *same* job. Out of all the informal employees becoming formal within a year, almost 40% of them do so at the same job. Interestingly, the opposite is also taking place: out of the 9% of the formal employees becoming informal, 30% of them do so at the same job. Fifth, transition rates out of unemployment are on average more frequent than those out of self-employment, suggesting different dynamics in the two labor market states. Roughly 81% of the unem-

measure of labor informality in Mexico.

ployed find a job over a period of one year compared with 33% of the self-employed. Also, while the majority of the unemployed transit toward a formal job most of the self-employed transit toward an informal one.

3 Model

3.1 Environment

The model assumes stationarity and continuous time. All agents are subject to a common discount rate ρ and to a common probability of death, modeled as a Poisson process with parameter δ. When an agent dies, a new agent is born as a draw from the initial population of agents.

The labor market is characterized by search frictions: workers and employers search for potential partners to enter a job relation but meetings do not happen instantaneously and they require time. When they meet, they decide if entering the job relationship or continue searching for a new partner. Crucial in the decision is the productivity generated by the specific match of a given worker with a given employer. We model the match-specific productivity as a draw $x \sim G(x)$.[12] Since the productivity is match-specific, it is realized only upon meeting the employer therefore individual workers ex-ante identical may end up either in a formal or informal job. This is our modeling strategy to capture that labor markets in Latin America are not described as segmented between a formal and informal sector but as much more porous, with workers moving back and forth between the two types of jobs and with firms changing the formality status of their job positions.[13]

Workers can be in four labor market states: unemployment, self-employment, informal employment and formal employment. The informal sector is composed by the self-employed and by the informal employees. Agents only receive job offers as employees while unemployed or self-employed.[14] Formality status as an employee is denoted by $f \in \{0, 1\}$, with 1

[12]This is the most commonly used productivity representation in search-matching-bargaining models of the labor market, including our previous Bobba et al. [2017] and Eckstein and Wolpin [1995], Cahuc et al. [2006] and Flinn [2006]. For theoretical foundations, see Wolinsky [1987] and Jovanovic [1979]. For a recent review, see Chapter 4.2 in Keane et al. [2011].

[13]This assumption imposes a restriction because the primitive match-specific productivity is the same for both formal and informal jobs. However, in estimation we allow all the other relevant labor market parameters (mobility parameters and human capital upgrading parameters) to be formality-specific.

[14]We rule out the possibility of receiving employee offers while working as an employee, i.e. there is no on-the-job search while working as a formal or informal employee. The main reason for this modeling assumption is data limitation. A good identification of on-the-job search parameters together with the related renegotiation mechanism requires a longer panel than the one available to us and typically needs

indicating a formal labor contract. Searching status as an agent receiving employee offers is denoted by $s \in \{0, 1\}$, with 1 indicating self-employment.

We focus on the human capital that accumulates and depreciates *while* participating in the labor market. We condition on the human capital accumulated *before* entering the labor market.[15] The human capital evolution while participating in the labor market captures the additional productivity that may be acquired on the job (human capital upgrading). This additional productivity may depreciate if not working (human capital downgrading). Notice that neither process results from explicit investment decisions but it is a result of the worker's labor market state. In other words, choosing the labor market status means also choosing the human capital accumulation process. This approach is consistent with a learning-by-doing view of human capital evolution.[16] While working on the job, the worker has the possibility to practice his skills and to learn, potentially leading to higher productivity. While off the job, the worker has less opportunities to practice his skills and may even loose previously accumulated knowledge, potentially leading to a depreciation of human capital. We let the rate of human capital upgrading depend on the formality status of the job. This flexibility in the specification allow us to empirically study if human capital accumulation on the job is a channel through which the presence of informality imposes costs on the system. We also allow for a flexible specification of rates at which the shocks arrive in order to take into account that human capital upgrading may be harder the higher the level of human capital already acquired on the job.

To these ends, we represent the evolution of human capital in the labor market by assuming a discrete distribution of human–capital–upgrading values $1 = a_1 < ... < a_K < \infty$. The total productivity of the match of a worker with labor market human capital a_k meeting a firm in a match generating productivity x is:

$$y(x, k) = a_k x \tag{1}$$

A worker in such relationship receives a human capital upgrading shocks following a Poisson process with rate $\tau_{f,k}$. When an upgrading shock arrives, the labor market human capital of the workers 'upgrades' to an higher level, from the starting a_k to a new $a_{k'}$ with $k' > k$. A

information from matched employer-employee data as done, for example, in Cahuc et al. [2006] and Bagger et al. [2014]. On top of the lack of a longer panel, we also lack relevant information on the relative short panel we actually observe. Specifically, we observe labor market status only quarterly so we cannot recover precisely the job-to-job transitions timing and the associated wages.

[15]In the empirical analysis, the pre-labor market human capital will be fully described by education. As discussed in Section 2, we focus on individuals with Secondary School education level.

[16]Seminal contributions are Arrow [1962] and Lucas Jr [1993]; for a recent review, see Thompson [2010].

searcher in a labor market state s with labor market human capital a_k receives human capital downgrading shocks following a Poisson process with rate $\gamma_{s,k}$. When a downgrading shock arrives, it decreases the labor market human capital to a lower level of a. Notice the limiting cases: $\tau_{f,K} = 0$ and $\gamma_{s,1} = 0$. Notice also that this human capital is only valuable while working as an employee but has no impact on self-employment income. This assumption is driven by the type of self-employment we are observing on our sample of medium- to low-educated individuals. As we discuss in Section 2.1, self-employment in this education range mainly consists of very low-skill activities such as reselling modest quantity of food, drinks or clothing in public spaces. They are activities requiring some talent that may be heterogeneous in the population but they should be relatively unaffected by the human capital accumulated while working as an employee.

On top of the human capital process, the usual labor market dynamic is taking place. While searching, agents meet employers at the Poisson rate λ_s. While working as employee, matches are terminated at the Poisson rate η_f. Agents have the faculty to accept or reject job offers but they cannot reject a termination: when the shock hits, they have to revert to their optimal searching state. Termination may also occur endogenously, as a result of human capital upgrading.

Formality and searching status are endogenous. The formality status while working as employee (f) is posted by the firm optimally, based on the observed labor market human capital a_k, and the match-specific productivity x. Assuming that the authority to post the formality status is in the hand of the firm is consistent with the institutional setting in Mexico and in most Latin American countries. Specifically, as we mention in Section 2.1, the legislation mandates the firm to be responsible to enroll the worker in the social security registry. It is also the firm that is legally bound to pay fines if this registration does not occur and if the correct amount of contributions is not collected. Conditioning on x, f and k, workers and firms engage in bargaining to determine wages. The searching status (s) is decided by the workers optimally, based on their labor income generated as self-employed: $q \sim R(q)$. q is heterogeneous in the population but time-invariant within individuals. The flow utility while searching as unemployed is homogeneous and denoted by ξ.

We follow previous literature by assuming linear utility.[17] We follow our previous work on Mexico (Bobba et al. [2017]) in defining flow utility as composed by labor income and by a social security benefit component. The social security benefit component depends on the

[17]Search models of the labor market typically assume linear utility. The exception are household (or dual) search model of the labor market, such as Dey and Flinn [2008], Guler et al. [2012] and Flabbi and Mabli [2018].

formality status and includes both the preferences for the the benefit and the monetary input used to provide the benefit. This setting leads to the following four flow utility definitions:

$$\xi \quad + \quad \beta_0 B_0 \tag{2}$$

$$q \quad + \quad \beta_0 B_0 \tag{3}$$

$$w_0(x; k, q) \quad + \quad \beta_0 B_0 \tag{4}$$

$$w_1(x; k, q) \quad + \quad \beta_1 B_1[w_1(x; k, q)] \tag{5}$$

The first flow utility refers to the unemployed: they receive the (dis)utility of being unemployed and searching ξ and the non-contributory benefit B_0, which they value β_0 to the peso. Exactly the same benefit is received in all the other labor market states with the exception of formal employment. Formal employees receive a contributory benefit B_1, which they value β_1 to the peso. We discuss the exact form of this benefit in the next paragraph. On top of the benefits, agents in self-employment receive labor income q and agents working as employees receive the wage $w_f(x; k, q)$.

The benefit B_1 is received only by formal employees and it is a contributory benefit, i.e. the firm contributes to the benefit of each employee by withdrawing at the source a rate t of the employee's wage. This contribution provides two benefits: a proportional benefit, which represents institutions such as a defined contribution retirement plan; and a fixed benefit, which represents institutions such as health benefits. The contributions to the first benefit is a proportion ϕ of the total contribution. Formally, the benefit B_1 is defined as:

$$B_1[w_1(x; q, h)] \equiv \phi t w_1(x; k, q) + b_1 \tag{6}$$

where b_1 is the notation we use for the fixed benefit. As discussed in more detail in our previous work on Mexico (Bobba et al. [2017]), the system has important distributional effects. Since the collection of contributions is proportional to wages and b_1 is equal for all formal employees, the system implies redistribution from high-wage earners to low-wage earners within the formal sector.

The employers side of the model is very stylized. Employers post vacancy at no cost and earn revenues equal to the match-specific productivity, scaled by the worker's human capital. The labor costs include wages and social security contribution when hiring formally. They include wages and the probability as well as the monetary penalties of being caught when hiring informally. This setting leads to the following two flow profit definitions:

$$\pi_1(x;k,q) = y(x,k) - (1+t)w_1(x;k,q) \tag{7}$$
$$\pi_0(x;k,q) = y(x,k) - w_0(x;k,q) - cy(x,k) \tag{8}$$

The linear specification of the cost function for hiring informally is meant to capture the notion that imperfect enforcement creates a size-dependent distortion in the economy: larger firms face a significantly higher probability of being audited (see for example de Paula and Scheinkman [2011]; Ulyssea [2018]). The same empirical literature also points out that the larger firms are also the more productive firms. Since our model cannot incorporate firm size, we can only match the evidence by imposing a positive correlation between productivity and the cost of informality.

3.2 Wages and Formality Status

Before discussing the determination of wages and formality status, we introduce the notation for the value functions. The value functions definition is provided in Section 3.3. On the workers' side, we denote the searching states with V_s and the employee states with E_f; on the firms' side, we denote the value of a filled vacancy with F_f. Since we assume there is no cost of posting and keeping the vacancy open, we do not introduce notation for the value of an unfilled vacancy.[18]

The formality status decision is taken by the firm upon observing the labor market human capital a_k, the outside option $V_s(k,q)$, the match-specific productivity x and with the knowledge that wages will be set by bargaining. The decision involves comparing the value of filling the vacancy hiring formally or informally. The endogenous formality status f is therefore determined as:

$$f \equiv f(x;k,q) = \begin{cases} 1 & \text{if } F_1(x;k,q) \geq F_0(x;k,q) \\ 0 & \text{otherwise} \end{cases}$$

Note that throughout the paper we simplify notation by dropping the dependence of f on $(x;k,q)$.

Wages are set by bargaining upon observing the labor market human capital a_k, the outside option $V_s(k,q)$, the match-specific productivity x and the formality status posted by

[18] A foundation for this result may be given by assuming free-entry of firms together with congestion effects, as in Bobba et al. [2017] and Flinn and Mullins [2015]. For a more complete discussion, see Pissarides [2000].

the firm f. We assume the axiomatic Nash-bargaining solution leading to:

$$w_f(x;k,q) = \arg\max_w \left[E_f(x;k,q) - V_s(k,q)\right]^{\alpha} \left[F_f(x;k,q)\right]^{(1-\alpha)} \tag{9}$$

The solution is a quite involved analytical expression that we report in the Appendix (equations B.1 and B.2). But the interpretation is the usual one: wages are a linear combination of productivity y and the outside option $V_s(k,q)$. The higher the worker's bargaining coefficient α, the more weight is given to productivity in determining wages.

3.3 Value Functions

Assume an individual searching in the labor market with human capital a_k, and potential self-employment income q. This agent will receive two possible shocks: meeting an employer and incurring human capital downgrading. The value of this state can be written in recursive form as follows:

$$\begin{aligned} (\tilde{\rho} + \lambda_s + \gamma_{s,k})V_s(k,q) &= (1-s)\xi + sq + \beta_0 B_0 \\ &+ \lambda_s \int_x \max\{(1-f)E_0(x;k,q) + fE_1(x;k,q), V_s(k,q)\} dG(x) \\ &+ \gamma_{s,k} \sum_{k'=1}^{k-1} \max\{V_0(k',q), V_1(k',q)\} \Pr[k'|k], \end{aligned} \tag{10}$$

where to simplify the notation we define $\tilde{\rho} \equiv \rho + \delta$. The first row represents the flow value, which is a function of the searching state (either unemployment or self-employment). When workers meet an employer, a match-specific productivity x is drawn and they receive either a formal or informal employee offer. The worker then decides if accepting the offer or not by maximizing over the two possible value function. When the worker receives a human capital downgrading shock, he moves to the lower level $a_{k'}$ and decides if continue searching in the current state – being that unemployment or self-employment – or switch to the other state. Note that the formality status f is endogenous and posted by the firm, as we show in Section 3.2.

When an agent is working as an employee, two shocks are possible: termination and human capital upgrading. The value of the employee state in recursive form is therefore:

$$
\begin{aligned}
(\tilde{\rho}+\eta_f+\tau_{f,k})E_f(x;k,q) &= w_f(x;k,q)+(1-f)\beta_0 B_0+fB_1[w_1(x;k,q)] \\
&+ \tau_{f,k}\sum_{k'=k+1}^{K}\max\left\{\begin{array}{c}(1-f)E_0(x;k',q)+fE_1(x;k',q),\\ \max\{V_0(k',q),V_1(k',q)\}\end{array}\right\}\Pr[k'|k] \\
&+ \eta_f\max\{V_0(k,q),V_1(k,q)\}
\end{aligned}
\tag{11}
$$

The first row represents the flow value, which is a function of the wage and the formality–status–specific benefit (either B_0 or B_1). The second row shows that when the worker upgrades the labor market human capital, the formality status and the searching state are both updated optimally. This generates an interesting dynamic usually ignored in the literature: formality status may change *within* the same employer and job termination may occur *endogenously*. Finally, the third row shows that when the match is exogenously terminated, the agent has to go back to the searching state.

The value functions for the demand side of the market are as follows. Employers post vacancies and search for workers to fill them. The value of a filled job is consistent with the worker's side and defined as:

$$
\begin{aligned}
(\tilde{\rho}+\eta_f+\tau_{f,k})F_f(x;k,q) &= (1-f)\pi_0(x;k,q)-f\pi_1(x;k,q) \\
&+ \tau_{f,k}\sum_{k'=k+1}^{K}\max\{F_0(x;k',q),F_1(x;k',q),0\}\Pr[k'|k]
\end{aligned}
\tag{12}
$$

The flow value is defined by the firm's profit, defined in equation (7) and (8). A filled job is subject to the same shocks we discussed for the worker's side: a termination shock η_f, which sends the firm back to a value of zero, and a human capital upgrading shock $\tau_{f,k}$. When the human capital upgrading shock hits, the employer enters a new negotiation with the worker and decides optimally the formality regime and whether or not keeping the worker.

3.4 Equilibrium

3.4.1 Definition

First entrants in the labor market start at the lowest level of human capital a_1. This level is a lower bound and it does not depreciate. Based on q, they decide if start searching for an employee job as unemployed ($s=0$) or self-employed ($s=1$). They decide based on the following maximization:

$$\max_s \{V_0(1,q), V_1(1,q)\}$$

where $V_s(1,q)$ is the value of searching for an employee job (equation 10). Since $V_1(1,q)$ is increasing in q faster than $V_0(1,q)$, there exists a unique:

$$q^*(1) : V_0(1, q^*(1)) = V_1(1, q^*(1)) \tag{13}$$

Only agents with $q < q^*$ search as unemployed, whereas agents with $q \geq q^*$ search at lower intensity while working as self-employed.

After accepting employee offers, workers start to accumulate human capital, upgrading from a_1 to a_2 to potentially any a_k up to a_K. Once they go back to a searching state with a generic a_k, that value may depreciate and may affect the searching status decision. The searching status decision is updated using the same reservation value rule based on the generic $q^*(k)$.

A worker with searching status s, labor market human capital a_k, and potential self-employment income q observes a match-specific productivity value x when meeting an employer. The employer observes the same information and knows the wage determination process. Based on this information, posts a formality status f. The worker observes the formality status, bargains with the firm leading to the wage schedule defined in (9), and decides if accepting the match or not. The firm is deciding if completing the match or not, too. Both firm and worker will arrive to the same optimal decision thanks to the no disagreement result implied by Nash bargaining. Since the outside option for both agents are constant in x while the value of the match is increasing in x, the optimal decision rule will again be a reservation decision rule. The reservation value is defined by:

$$x_f^*(k,q) : F_f(x_f^*; k, q) = 0 \quad \Longleftrightarrow \quad E_f(x_f^*; k, q) = V_s(k,q) \tag{14}$$

For any $x \geq x_f^*$, the match is realized.

The formality status is posted by the firm following the optimal decision rule described in Section 3.2. As shown in Bobba et al. [2017], this decision is also characterized by a reservation value property based on x. The indifference point is determined as:

$$\tilde{x}(k,q) : F_1(\tilde{x}; k, q) = F_0(\tilde{x}; k, q) \tag{15}$$

For any $x \geq \tilde{x}(k,q)$, the firm is posting a formal job ($f = 1$); for any $x < \tilde{x}(k,q)$, the firm is posting an informal job ($f = 0$).

Notice that $\tilde{x}(k, q)$ is determined by equating the firm's value functions because the formality status is posted by the firm. If formality posting were done by the worker or if formality status were part of a joint bargaining game with the wage, the threshold values would be different. Intuitively, firms and workers value formality at the margin differently because firms pay full value for the benefit but workers value the benefit at less (or more) than full value due to the preference parameters β_0 and β_1.

With the optimal decision rules in place, the equilibrium is defined by the set of value functions that satisfies equations (10)–(12), once the optimal decision rules – including the optimal determination of wages and formality status – are taken into account. The equilibrium also determines steady state values for the measures of workers in each labor market state and for the distribution of human capital. We solve the model numerically by value function iteration. Appendix B.2 provides a detailed description of our procedure.

3.4.2 Discussion

We highlight some features of the equilibrium that are useful to understand both the empirical implications of the model and the identification strategy with the data at our disposal.

A first crucial decision concerns the formality status. When firms post a formal job instead of an informal job, they trade-off the cost $tw_1(x; k, q)$ of contributing to maintain formal status with the cost $cy(x, k)$ of covering for the risk of being discovered hiring informally and having to pay a fine. The workers also face a trade-off when accepting to work formally: they are willing to give up some monetary wage in exchange for better benefits ($B_1 > B_0$). The combination of these two mechanisms, together with the determination of wages through bargaining, implies that the value function of a filled formal job is more sensitive to x than the value function on an unfilled formal job, generating the unique (for each k, q) reservation value $\tilde{x}(k, q)$ defined in equation (15). Exactly at $\tilde{x}(k, q)$, the formal wage is lower than the informal wage because the benefit is higher in the former than in the latter. This is true also in a neighborhood around $\tilde{x}(k, q)$ which is more or less large depending on the willingness to pay for the additional benefits, on the difference between contributory and non-contributory benefits and on the cost of informality c. For example, the higher the valuation of the formal benefit (the β_1), the larger the portion of wage the worker is willing to give up to work formally.[19]

[19] We discuss in detail this feature of the equilibrium in our previous contribution Bobba et al. [2017] where we also provide a graphical interpretation of the result.

Another important dynamics concerning the formality status is how it is affected by the human capital process. In other words, is the reservation value $\tilde{x}(k, q)$ increasing or decreasing in k? The answer is that the impact of the human capital upgrading process on $\tilde{x}(k, q)$ is ambiguous. The source of the ambiguity is that human capital upgrading is valuable under both formality statuses. The impact on both value functions $F_1(x; k, q)$ and $F_0(x; k, q)$ is therefore positive but in a non-linear way since wages are determined by bargaining and human capital upgrading also changes the outside options. Looking at equation (15) – which defines $\tilde{x}(k, q)$ – this means that both the left hand side and the right hand side will increase as a result of human capital upgrading. At different points of the support of the match-specific distribution $G(x)$, one or the other will increase more, leading to an increase or a decrease of $\tilde{x}(k, q)$.

The second crucial decision is about accepting an employee job or not. The relevant reservation value is now $x^*_f(k, q)$, defined in equation (14). It is again unique (for each k, q) but it differs by formality status. In the most typical configuration, the reservation value to accept an informal job is lower than the one to accept a formal job, i.e. $x^*_0(k, q) < x^*_1(k, q)$. When this is the case, the support of the match-specific productivity x is divided in three regions: the first for $x \in [0, x^*_0(k, q))$, the second for $x \in [x^*_0(k, q), \tilde{x}(k, q))$, and the third for $x \in [\tilde{x}(k, q), +\infty)$. This creates the following behavior: for low enough productivity (first region) the agent continues searching, for intermediate values of productivity (second region) the agent accepts to work informally, for high enough productivity the agent accepts to work formally.[20] Unlike the previous case, the impact of the human capital updating process on $x^*_f(k, q)$ is now unambiguous: since both value functions for a filled job increase in k while the value function for an unfilled vacancy does not depend on k, the $x^*_f(k, q)$ are decreasing in k. The economics intuition is straightforward, for given x, a higher k means a higher multiplicative factor in generating the overall productivity y (equation 1) and therefore firms and workers will be more willing to accept the match.

The final crucial decision is about looking for an employee job as an unemployed or as a self-employed. The relevant reservation value is now defined over the labor income generated as self-employed, q. The reservation value is denoted by $q^*(k)$ and it is defined by equating the value of the two searching states (see equation (13) for an example with $k = 1$). The trade-off in this case is between receiving more employee offers by searching full-time (unemployment) and receiving less offers but earning income while searching (self-employment). Neither search efficacy nor self-employment income are affected by human

[20]There is only another possible configuration: $x^*_0(k, q) > x^*_1(k, q)$. In this case, the agent will only accept formal jobs. See Proposition 1 in Bobba et al. [2017].

capital and therefore the impact of k on $q^*(k)$ works only through the continuation (or option) values. The impact is positive on the continuation values of both searching states leading to a situation similar to the one observed about the formality status: the impact is ambiguous and transitions between unemployment and self-employment are possible in both directions.

3.5 Empirical Implications

The equilibrium just described is able to capture the main characteristics of a labor market with high informality, such as many markets in Latin America, including Mexico (see Section 2).

First, the model equilibrium can generate a positive mass of workers in each labor market state and produce the significant amount of transitions between formality and informality. Transitions between formality and informality can take place not only when agents change job but also within the same job. The human capital upgrading process is the reason why a worker may change formality status within the same job. For example, worker i with human capital a_k may have accepted a job working informally as an employee because the match-specific productivity x_i was:

$$x_0^*(k,q) \leq x_i < \tilde{x}(k,q)$$

While in the informal job, he may receive a human capital upgrading shock, moving him from a_k to $a_{k'}$, with $k' > k$. The upgrading may be such that the new reservation value to work formally is now lower than the match-specific productivity x_i:

$$\tilde{x}(k',q,h) \leq x_i$$

since it is possible that $\tilde{x}(k',q,h) < \tilde{x}(k,q)$. As a result, the worker will remain in the same job but at the same time will change his formality status from informal to formal. Notice that, as discussed in Section 3.4.2, the impact of the human capital upgrading process on $\tilde{x}(k,q)$ is ambiguous and therefore both transitions from informal to formal and from formal to informal may take place at the same job. If $\tilde{x}(k,q)$ decreases, the worker may transit from informal to formal; if $\tilde{x}(k,q)$ increases, the worker may transit from formal to informal.

Second, the model is able to generate wage distributions in line with the data. The data show two main features: average wages of formal employees are on average higher than average wages of informal employees but there is a lot of wage dispersion within each formality status, so that the two distribution significantly overlap. As we mentioned in Section 3.4.2, both results are a direct consequence of the property of the equilibrium. The equilibrium implies, for given k, q, a ranking in the support of the match specific distribution: this ranking generates the differences in average wages by formality status. At the same time, the equilibrium implies that the mapping from productivity to wages is mediated by the parameters governing benefits and institutional costs associated with the choice of the formality status. The trade-offs involved in this mapping generate the overlap.

Third, the model is able to generate wage growth not only across jobs – as common in related literature – but also within jobs. The reason is the renegotiation process taking place when the human capital upgrading occurs. Assume a worker i with match-specific productivity x_i and human capital level a_k upgrades his human capital while working as a formal employee to $a_{k'}$, with $k' > k$. Further assume that x_i is such that $\tilde{x}(k', q_i) < x_i$. Then the worker will remain matched with the same employer and with the same formality status but his wage will increase from $w_1(x_i; k, q_i)$ to $w_1(x_i; k', q_i)$. These wage changes are observed in our data and are essential in the identification of the human capital upgrading shocks.

4 Identification

The model is characterized by the following parameters set:

$$\{\rho, \delta, \tau_{f,k}, \gamma_{s,k}, \lambda_s, \eta_f, \xi, \alpha\} \tag{16}$$

and by the following distributions:

$$\{G(x), R(q)\} \tag{17}$$

In addition, we have to define the support of the human capital dynamics: $\{a_k\}_{k=1}^{K}$ and the set of parameters that characterizes the institutional setting: $\{\beta_0, B_0, \phi, t, \beta_1, b_1, c\}$. We split the identification discussion in two parts. We first focus on the preferences for social security benefits, the cost to firms of hiring informally along with the usual search, matching and bargaining parameters. In the second part we consider the identification of the parameters describing the novel feature of our model: the human capital dynamic while working in the labor market.

4.1 Labor Market Parameters

Starting with the institutional parameters, we set $\{\phi, t\}$ at the values present in Mexico during the surveying period of our sample. The parameters are stable over the entire decade that include our two years and they are respectively equal to 0.55 and 0.33.[21] The non-contributory benefit B_0 is calibrated from aggregate data following the same procedure described in Bobba et al. [2017] and it is equal to 4.27 pesos per hour for the year 2013. The portion of the contributory benefit that is distributed equally across all the formal employee after collecting their individual contributions (b_1) is estimated from the data by assuming that the formal system runs a balanced budget. Denoting with i a generic observation in our sample, the estimator is:

$$\hat{b}_1 = t(1 - \phi) \sum_{i \in N_{E_1}} \frac{w_1(i)}{N_{E_1}} \tag{18}$$

where N_{E_1} denotes the set of formal employees.

With the institutional parameters in place, Bobba et al. [2017] proposes an identification strategy for β_0, β_1 and c. It builds upon observing the large overlap in accepted wages between formal and informal employees and providing an explanation for such overlap based on the model. The intuition is that at the reservation value $\tilde{x}$ – and in a small enough neighborhood around it – workers accept lower wages to work formally than informally because they receive higher non-monetary benefits. The amount of this overlap is driven by the preference and quantity of the benefits and by the cost of informality c. Adding this observation to the quasi-random roll-out of a non-contributory social program (the *Seguro Popular* program) concludes the identification strategy we proposed there.[22] In the current setting, we cannot rely on the differential roll-out of the *Seguro Popular* program because at the time of our surveying period virtually everybody was covered by that program. Moreover, adding the human capital dynamic on the job weakens the separate identification of the preference parameters, β_0 and β_1, from the cost parameter of offering an informal job, c. Under the assumption that preferences for social security benefits are stable over the nine years that separate the data of the two papers, we have chosen to calibrate the preferences with the point estimates obtained in Bobba et al. [2017]. With the preference in place, we can use the overlap of the accepted wage distributions for formal and informal employees to identify c.

We exploit classic results from Flinn and Heckman [1982] to identify the labor market

[21] See Appendix C in Bobba et al. [2017] for more details on the institutional sources of these values.

[22] For a more detailed and more formal discussion of this identification strategy, see Section 4 of Bobba et al. [2017].

parameters $\{\rho, \lambda_s, \eta_f, \xi, \alpha\}$ and the match-specific distribution $G(x)$. They show that by assuming a recoverable distribution for $G(x)$, the entire set of parameters – up to two restrictions – is identified from observing accepted wages and transitions between labor market states.[23] The recoverable distribution we assume for $G(x)$ is a lognormal with parameters that we denote $\{\mu_x, \sigma_x\}$.[24] The two restrictions refer to the parameters $\{\rho, \xi\}$ and α. Flinn and Heckman [1982] show that the first two parameters are only jointly identified. We follow previous literature by setting ρ to 5% a year and recovering ξ by exploiting the equilibrium equation (10). Flinn and Heckman [1982] do not provide an identification strategy for α because they impose a sharing rule that splits productivity equally between worker and employer. We lack the demand side information necessary to identify α and we therefore choose to assume symmetric Nash bargaining which leads to a value of α equal to 0.5.[25] In addition to the inter-temporal discount rate, we also have to identify δ, the Poisson parameter describing the death shock. Since the risk of death is constant in the model, we can identify it by the average duration of the (labor market) lives of our sample.

The same recoverability condition necessary and sufficient to identify $G(x)$ from accepted wage distributions can be applied to identify $R(q)$ from observed self-employed labor income. The observed distribution of q is a truncation of the primitive $R(q)$ at the reservation value $q^*(1)$. If we assume a recoverable distribution, the primitive can be identified from its truncation. We assume a lognormal distribution with parameters that we denote $\{\mu_q, \sigma_q\}$.

4.2 Human Capital Parameters

We finally consider the parameters describing the novel feature of our model: the human capital dynamic while working in the labor market. The dynamic is characterized by human capital upgrading on the job and by human capital downgrading while searching. Both processes are characterized by shocks moving agents over the support $\{a_k\}_{k=1}^K$. We do not have direct information about events that may change human capital on the job, such as training, specific knowledge acquisition, or testing of skills. To identify the process, we can only rely on standard labor market dynamics, i.e. wages and transitions. Given this data

[23] In their original contribution, Flinn and Heckman [1982] use durations to describe labor market dynamic. Using transitions across labor market states (both across and within jobs), as we do in our estimation procedure, does not change the source of identification; it just describes in a different way the dynamic over labor market states.

[24] Virtually all the search-matching-bargaining literature assume log-normality, from the seminal Eckstein and Wolpin [1995] to our recent Bobba et al. [2017].

[25] Recent works setting α using a similar strategy include Flabbi and Moro [2012] and Borowczyk-Martins et al. [2018].

limitation, we do not attempt to estimate the support $\{a_k\}_{k=1}^{K}$. Instead, we follow Flinn et al. [2017] by imposing an upper and lower bound for the support of the a_k distribution and we discretize the resulting range in equal intervals. The breakpoints generated by the intervals define the different a_k. After some robustness checks, we have set the upper bound at $a_K = 5.5$ and we have divided the support in 10 discrete intervals. The lower bound has a natural normalization at $a_1 = 1$. This means that the productivity on the job of first entrants is equal to the actual match-specific productivity x. The productivity of agents with level of human capital equal to the midpoint of the support is equal to three times their match-specific productivity draw. The maximum productivity boost is equal to 5.5 times the match-specific productivity.

Given the support, we can propose an identification strategy for the parameters characterizing the shocks: the Poisson rates $\tau_{f,k}$ and $\gamma_{s,k}$. The human capital upgrading shock is governed by $\tau_{f,k}$ and has three important consequences for the labor market dynamic on the job. First, it induces wage renegotiation: as a result of human capital upgrading, the surplus increases and the wage of a worker at the same job increases. Second, the formality status may change as a result of the renegotiation since – as detailed in Section 3.5 – the reservation values are all dependent on the human capital level of the worker. A formality status change on the job is therefore additional valuable information to identify the occurrence of an upgrading shock. Third, the renegotiation may lead neither to a wage change nor to a formality regime change but to a labor market status change, i.e. firm and worker may agree to dissolve the match and go back to search. Transitions between labor market states is the final piece of information useful to identify the shock, albeit it is less valuable than the other two because transitions out of the employee state may also be induced by an exogenous termination shock.

In the data at our disposal, we can observe the rich labor market dynamic just described. We can see how wages evolve within the same job, we can observe transitions between labor market states and we can observe changes in formality status within the same job. We can therefore directly use this information to identify the frequency of the human capital upgrading shock. Even if this information is relatively rich, it remains limited: we observe individuals only at quarterly intervals and only for five quarters. We have therefore decided to impose a functional form that is very parsimonious in terms of parameters but still maintains enough flexibility to describe the process. We propose the following specification for the arrival rate of the human capital upgrading shock:

$$\tau_{f,k} \equiv \begin{cases} \tau_{f,1} a_k^{\tau_{f,2}} & \text{if } 1 \leq k < K \\ 0 & \text{if } k = K \end{cases}$$

The functional form reduces the number of parameters from (K-1) to 2 for each formality status f.[26] Even if clearly restrictive, the proposed specification allows to capture that human capital upgrading is more likely when starting from a lower level of human capital than from a value closer to the upper bound. A positive $\tau_{f,1}$ combined with a negative $\tau_{f,2}$ implies that the probability to upgrade at a low a_k is higher than at a high a_k. This is consistent with decreasing returns in human capital accumulation and it is actually what we find in estimation *without* imposing any sign constraints. Another important dimension of the human capital upgrading shock is the extent of the upgrading. In terms of our parameterization, it is equivalent to ask how much higher is k' with respect to the starting k. Wage growth and formality status changes within the same job are valuable information to identify this dynamic: longer 'jumps' imply more wage growth and a higher probability to change formality status. As we will show in Section 5.3, the second event is not infrequent in our data, in particular when looking at switches from informal to formal within the same job. The additional flexibility allowed by different jump's lengths for given upgrading shock is crucial in matching this dimension of the data.[27] Still, both the arrival rate and the upgrading shock can potentially contribute to this dynamic therefore we keep a tight parametrization in estimating the distribution of the jumps' length: let m be the size of the jump in the human capital grid, we assume that $m \sim Q_f(x; \nu_f)$ with $Q_f(\cdot)$ being a negative exponential distribution with parameter ν_f. In Appendix B.2, we provide additional details on how we

[26]The unknown parameters in the most flexible specification are (K-1) because – as shown in the second row – $\tau_{f,K}$ is zero by definition (no additional upgrading can take place when reaching the upper bound of the human capital distribution).

[27] Even if our proposed model environment can account for the whole labor market dynamic just described, there could be other explanations for it. A prominent one is the presence of on-the-job search together with a renegotiation mechanism determining wages when offers on the job are received, a mechanism we rule out due to data limitation (see footnote 14). Dey and Flinn [2005], Cahuc et al. [2006] and a number of follow-up papers propose a renegotiation mechanism where a new firm and the incumbent firm engage in Bertrand competition for the services of the worker. In so doing, firms may transfer some surplus to the worker increasing her wage even within the same job. However, an on-the-job search model with renegotiation will have difficulty in generating changes in formality status. Without human capital accumulation, the reservation value for switching between formal and informal is fixed. Formally, in our model the reservation value $\tilde{x}$ is a function of both k and q (equation 15), without human capital accumulation it is only a function of q. As a result, either the incumbent firm and worker match is within the match range for informal job or it is within the range for formal job: the presence of a new firm bidding for the services of the worker does not change this result.

implement the truncation and discretization of this distribution in the simulations used in estimation.

In the case of the human capital downgrading shock, the amount of information that we have from the data is much more limited because – as common in most standard labor market data – we do not observe much about the searching process. Specifically, we only observe durations and transitions over the searching states but we do not observe either the number or the amount of offers actually received. The impact of the downgrading shock during search is to make workers more willing to accept jobs. We should then observe impacts on durations and transition rates. However, this is the same information that is identifying arrival rates of offers so we need additional information to separately identify the downgrading shock. The additional information we use is comparing if the optimal decision rules change between different search episodes for the *same* individual. As mentioned, our panel is short – five quarters – so we only rarely see two or more search episodes for the same individual. However, we see a significant number of individuals quitting their job, searching, and finding another job all within our observation window. Comparing wages accepted in a previous job with wages accepted in a job following a search period is informative about the shocks received during the search episode in between. For example, if wages accepted in the following period are systematically lower than those in the previous period, it is very likely that a downgrading shock has occurred. If, for same length of search, this is more likely the case while searching as unemployed than as self-employed, then the depreciation shock should be more frequent in the first searching state than in the second. Finally, a downgrading shock may also induce a change in searching state. While this is relatively rare in the data, it is very valuable in terms of identification because it signals a depreciation shock has taken place with probability one (of course conditioning on the model).

In conclusion, comparisons of wages before and after a search period and changes of searching states for the same individual is the information we use to identify the downgrading shock. However, only the change in searching state unequivocally identifies a depreciation shock. The wage information is also driven by different draws of the match-specific productivity x. As a result, we propose the most parsimonious specification possible by assuming that the downgrading shocks only depend on the searching state s:

$$\gamma_{s,k} \equiv \begin{cases} \gamma_s & \text{if } 1 < k \leq K \\ 0 & \text{if } k = 1 \end{cases}$$

and that the downgrading length is fixed to one step: every time that a downgrading shock is received, human capital moves from the starting a_k to a_{k-1}. The second row of the equation simply states that no additional depreciation can take place at the lower bound of the human capital distribution.

5 Estimation

5.1 Method

We estimate the parameters of the model using the Method of Simulated Moments (MSM).[28] To define the estimator, we introduce the following notation: Θ is the parameter vector; m_N is an appropriately chosen set of sample moments derived from our sample of size N; $M_R(\Theta)$ is the set of the same moments derived from a simulated sample of size R, extracted from the steady state equilibrium realized at the parameter vector Θ. We set R at 5,000, which is slightly larger than the sample size N, in order to gain more precision in capturing those labor market transitions that are relatively rare. W is a symmetric, positive-definite weighting matrix that we introduce to harmonize the different scales of the moments and to weight them according to their sampling variability. We thus build W by replacing the diagonal of an identity matrix with the bootstrapped sample variances of the sample moments. We are now ready to define the estimator as:

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \; [M_R(\Theta) - m_N]' \, W^{-1} \, [M_R(\Theta) - m_N] \, , \tag{19}$$

We choose the moments to be used in the quadratic form (19) in order to capture the data features described in Section 4. We match the proportion of workers in each labor market state in a given point in time (we choose the first quarter) and the transitions rates obtained by observing agents one year apart in order to describe the distribution over labor market states and the dynamics between them (see Tables 1 and 2). From working as either a formal or informal employee in the first quarter, the worker may end up in the fifth quarter in one of the following six possible states: working formally at the same job, working formally at a different job, working informally at the same job, working informally at a different job, working as self-employed, and being unemployed. From the search states of self-employment or unemployment, the agent may end up in the fifth quarter in one of the four labor market

[28]The method is commonly used to estimate highly nonlinear models with value functions solved numerically such as ours. For the asymptotic properties of the MSM estimator defined in (19), see Pakes and Pollard [1989] and Newey and McFadden [1994]. For applications similar to ours, see Bobba et al. [2017], Flinn et al. [2017], Flabbi and Moro [2012], and Dey and Flinn [2008].

states: formal employee, informal employee, unemployed and self-employed.

We use mean and standard deviation of employees' wages and self-employment labor income in a given point in time (we choose the first quarter) in order to describe the wage information. We add wage growth on the job and across jobs one year apart, taking into account if there is an episode of search longer or shorter than a quarter when changing job. To describe the overlap between the accepted wages in formal and informal jobs, we follow the procedure proposed in Flabbi and Moro [2012] and Bobba et al. [2017]. We build quintiles over the distribution of accepted wages for formal workers and for each interval, we compute mean wages of formal and informal employees; and the proportion of employees in informal jobs earning a wage in that interval. The complete set of 62 sample moments and the corresponding simulated moments and weights used in the quadratic form (19) are reported in Appendix C.2. All wage-related moments are computed unconditionally on the labor market state in order to guarantee a smoother and well-defined quadratic form during the optimization procedure. To ease the discussion and interpretation, we report in Table C.3 the mean and standard deviation of wages and self-employed income conditional on the labor market state.

Finally, to asses the reliability of our estimator, we performed a Monte Carlo procedure where we compare the point estimates obtained by applying our estimation procedure on the original data with the point estimates obtained by applying the same estimation procedure on synthetic data generated by known parameters. We find them close enough to lend credibility to our estimation method. Details and results are reported in Appendix C.1.

5.2 Results

The estimated parameter values are reported in Table 3. The differences in arrival rates between the unemployed and the self-employed are very large, explaining in part the observed persistency in the self-employment state and the high-turnover in the unemployment state. Taking into account the endogenous acceptance probability, these rates translate in unemployed workers accepting a job after on average 3.8 months while self-employed workers do so in 3.2 years. The estimated parameters of the job destruction rates imply average durations of 17 months in informal jobs and of 31 months in formal jobs. Although we don't directly observe employment durations in our sample, these numbers are broadly comparable with existing estimates from Mexico and other Latin American countries (see, e.g. Alaimo et al. [2015]). They confirm the presence of high turnover and churning in labor markets characterized by high informality rates, causing workers to change jobs frequently (and to transit often between formal and informal employment). Out of those total destruction rates, 95.7 percent are due to exogenous separations between firms and workers and 4.3 percent are due to endogenous quits following human capital updating. The majority of workers do not quit as a result of human capital updating because their employee status is renegotiated: both the formality status and the wage may change to reflect the higher productivity generated by the human capital increase. Our estimates imply that 67 percent of workers remain at the same firm after receiving a human capital shock.

The estimated values of the parameters of the match-specific productivity distribution $\{\mu_x, \sigma_x\}$ and the self-employed earning distribution $\{\mu_q, \sigma_q\}$ are smaller in magnitudes when compared with the previous estimates on Mexico obtained by Bobba et al. [2017]. A portion of the difference is explained by differences in the data on employees' wages and self-employed incomes across the time periods considered in the analysis. The rest is explained by allowing human capital accumulation in our model. The total productivity of the match between a worker and a firm is augmented by the worker's human capital (equation (1)) while in Bobba et al. [2017] had to be fully explained by the primitive match-specific productivity. Also, the model allows for transitions between the two searching states, unemployment and self-employment, which affect the value of self-employment in equilibrium. In terms of scale, the primitive match-specific productivity has both higher mean and higher standard deviation than the productivity in self-employment.

The estimates for the arrival rates of the human capital downgrading shocks $\{\gamma_0, \gamma_1\}$ imply that on average individuals who are unemployed depreciate their stock of human capital every half a year. The depreciation rate is much lower during spells of self-employment: approximately 1.8 years. The estimated values for the arrival rates of the human capital upgrading shocks $\{\tau_{f,1}, \tau_{f,2}\}$ reveal concave patterns in the expected time of arrival of these shocks, which are depicted in Figure 2. The interpretation is that the probability of human capital upgrading when possessing a low level of human capital is higher than when possessing a level of human capital which is already closer to the upper bound. In this case too, we estimate systematic differences between formal and informal employees. The rate of human capital upgrading is estimated to be slower while working informally than formally at any level of human capital. For individuals at the lower bound of the human capital support, it takes about 1.4 years to start upgrading their human capital if they work formally and about 2 years if they work informally. At the average value of the distribution of human capital ($\bar{a} = 2.34$, see Figure 3), it takes about 5.2 years to upgrade while working formally and 20 years to upgrade while working informally. This advantage in the human capital accumulation process while working formally is partially offset by the size of the upgrade when the shock hits. As the estimated values for the parameters ν_0 and ν_1 show, the average size is larger while working formally. At the same time, large jump while working informally are more likely to lead to a change in formality status. The final result of the upgrading and downgrading human capital process in equilibrium is the steady state distribution reported in Figure 3: while more than 20% of workers does not have human capital that increase the match-specific productivity ($a_k = 1$), the majority of them possess some positive human capital, covering the entire support. For example, about 15% of them will double the productivity of the match-specific productivity when working as employees ($a_k = 2$).

Table 4 reports some statistics on productivity and human capital implied by these estimates. The average worker's productivity (second column) increases steeply with the level of human capital. This is partially due to selection over the match-specific productivity and to the effect of a higher level of human capital. The relative contribution of human capital on overall productivity is presented in the third column[29] and it is estimate at about 60% in the overall sample, with a value of about 62% when working formally and a value of about 50% when working informally. The relative contribution of human capital is monotonically increasing in its level, reaching more than 80% at the upper bound.

The estimate of the cost of hiring informally – the parameter c – is roughly 5 percent of job productivity. This parameter captures all the costs associated with hiring informally, including the probability and penalty of getting caught. While the estimated cost is economically important – at the mean productivity of the realized informal matches it is approximately 0.85 pesos per hour – it is still lower than the cost of hiring formally. As a comparison, the payroll tax rate applied to the formal wage that corresponds to the same productivity level would be 3.26 pesos per hour.[30] It is not obvious to compare our estimated c to actual fines levied since the parameter captures both the probability of being audited and the monetary fines to be paid conditional on being audited. While the first is available in the legislation (and it is the value mentioned in Section 2.1), the second is much harder to observe. There are some statistics on the number of audits but the universe of firms that should be used to

[29]The relative contribution of on-the-job human capital on overall productivity is calculated as follows. Recall from the model that the total productivity of the match of a worker with labor market human capital a_k meeting a firm in a match generating productivity x is: $y(x, k) = a_k x$. Let e_i be an indicator variable denoting the employee status (both formal and informal) for individual i in the simulated data, then the Average Value of Production can be expressed as $S(y) = \frac{1}{\sum_i e_i} \sum_i y_i$, while the average value of the match-specific productivity is given by $S(x) = \frac{1}{\sum_i e_i} \sum_i x_i$. The contribution of human capital can be then written as $1 - \frac{S(x)}{S(y)}$.

[30]Notice that these are only direct costs, i.e. they do not take into account that through bargaining firms are able to partially transfer them to the workers, as seen in the equilibrium wage schedules (9).

compute a probability based on frequency is not obvious [Levy, 2018].

Finally, the flow value of being an unemployed searcher ξ is estimated to be negative. A negative value was expected in order to generate enough wage dispersion in accepted wages [Hornstein et al., 2011].

5.3 Model Fit

Tables C.3-C.4 in the Appendix report the complete set of moments targeted by the MSM estimator. When compared to the data, the distribution over the four labor market states in the simulated data tend to understate the share of formal employees and to overstate slightly the share of self-employed and unemployed workers. The match is quite good on means and standard deviations of the accepted wages and of the self-employment incomes – with differences in the 10-15% range.

A peculiar and relevant feature of Mexico's and other labor markets with high informality is the substantial overlap in the formal and informal accepted wage distributions. We are able to replicate the overlap in the data quite well, both in terms of the proportions of informal employees in each quintile and in the mean accepted wages by quintiles. This result is achieved by two model features. First, the endogenous mapping between match-specific productivity and wages implied by bargaining. Second, the flexibility introduced by allowing the self-employment state to be a searching state, with heterogenous productivity levels that are pinned down by the (observed) income generated while in self-employment.

The moments describing the yearly transitions between labor market states both within and across jobs are all qualitatively replicated, most of them are also quantitatively matched with reasonable precision. An original feature of our model is the ability to generate formality status transition within the same job. These transitions are observed in the data in both directions, i.e. we observe workers becoming formal when they started the year in the same job working informally but we also observe the opposite. As explained in Section 3.5, the model provides theoretical foundations for both events and the estimated model is able to generate such transitions. However, we underestimate the proportion of both of them, in particular the transition from formal to informal in the same job.

In spite of the limited longitudinal dimension of the available data, wage growth rates both within and across jobs are quite close to the data. This is quite remarkable since the process of human capital accumulation is the only possible source of variation in wages within the same job that is embedded in the model.

6 Policy Experiments

Our model incorporates the structure of the social security system implemented by several countries in response to the lack of coverage for informal workers. The resulting 'dual system' is characterized by contributory benefits – governed by a payroll contribution rate, a benefit level increasing in wages and a redistributive component – and non-contributory benefits. To evaluate the impact of this complex system of incentives and disincentives, we use the estimated model to generate counterfactual labor markets where the crucial policy parameters take different values. The counterfactual labor markets are characterized by new steady state equilibria where labor market outcomes and human capital levels are endogenously determined. We focus on changes in two policy parameters: the payroll contribution rate in formal jobs t and the per-capita level of the non-contributory social benefits B_0. These two parameters are considered crucial in generating the high level of informality observed in Mexico and other LAC countries since they directly affect the differential between benefits and costs of working formally.[31]

The policy experiments procedure works as follows. For each value of the policy parameter, we find and compute the new equilibrium holding fixed the other institutional parameters and setting the structural parameters at the point estimates reported in Table 3. We simulate labor market careers for 5,000 individuals. Figures 4 and 5 display relevant statistics from the resulting simulated data.

6.1 Policy Experiment 1: Contribution Rate

In the first experiment, we vary the contribution rate t in a wide neighborhood around the benchmark level (from 10% to 70%, where the benchmark level is 33%). We run the experiments under two different scenarios. In the first scenario, labelled "Not Revenue Neutral", we keep all the other institutional parameters to their benchmark value. These include the redistributive component of the social security benefits for formal employees, b_1. It is the redistributive component because it is distributed equally among all the formal employees even if those with higher wages contribute more due to the proportional contribution rate (see Equation 6). In this scenario, we can isolate the impact of the policy lever we are changing (t) but we loose a link between contributions and benefits. For example, if the change in t ends up increasing the proportions of formal workers, the revenue generated by

[31] For a focus on the payroll contribution, see Albrecht et al. [2009] and Rocha et al. [2017]. For a review on Mexico, see Levy [2008]. For similar experiments in an environment with endogenous schooling choice, see our companion paper Bobba et al. [2017].

their additional contribution may or may not be enough to cover for all of them receiving the benchmark benefit b_1. For this reason, in the second scenario, labelled "Revenue Neutral", we adjust the value of b_1 according to the endogenous wages and proportion of formal workers in the counterfactual economy so that the contributions can pay for the benefits (see equation 18).

Figure 4 reports simulation results on labor market outcomes computed at the various contribution rates over the range. We denote the benchmark value of t with a vertical dashed line in all Panels. As the contribution rate in a formal job increases, Panel (a) shows that the share of informal employees in the labor force increases substantially in the "Not Revenue Neutral" scenario. The mechanism is straightforward: formality becomes more costly and only a portion of the benefit (retirement) increases while the other portion (health) remains constant. As a result, workers and firms prefer to realize informal matches. In the "Revenue Neutral" case, instead, the proportion remains roughly constant because while formality becomes more costly both components of the contributory benefit increase. It is not exactly constant – and it is actually lower for high enough values of the contribution – because of the redistributive component: As the rate increases, the worker who is marginal between formality and informality receives higher transfers from the better paid formals through a higher b_1.[32]

This dynamic has a direct link with the amount of human capital accumulated in the economy, as shown in Panel (b). Since we estimate that the probability of receiving a human capital upgrading shock is higher for formal employees, the aggregate human capital roughly follows the behavior of the proportion of formal employees: decreasing in the "Not Revenue Neutral" case; more or less constant in the "Revenue Neutral" case. The first scenario is consistent with recent results from the literature on life-cycle labor supply with learning-by-doing. This literature shows that not only higher tax rates decrease labor supply today but also induce a dynamic feedback loop by affecting human capital accumulation. Even a transitory tax rate increase may therefore have permanent impacts: a higher tax rate today decreases labor supply today, but a lower labor supply today reduces human capital tomorrow, affecting labor supply tomorrow even if the tax rate goes back to its original value [Imai and Keane, 2004]. Closer to our experiments are the permanent tax changes impacts

[32] Both the location of the inflection point and the elasticity of the relative proportion of formal or informal employees in the economy depend on parameters. In our companion paper [Bobba et al., 2017], we find a qualitatively similar behavior but much higher elasticities. The small dip in overall human capital observed for high values of t in Panel (b) of Figure 4 is due to an increase in self-employment with respect to informal employment (see Figure D.1 in the Appendix). Since in self-employment human capital actually depreciates, the aggregate human capital decreases.

estimated by Keane [2015], who shows that permanent tax changes can have larger current effects on labor supply than transitory tax changes. In our model, the impact is not so much on the overall reduction of labor supply but on the overall reduction of formal work since the alternative to (formal) labor is not leisure but either informal work (either as employee or as self-employed) or search. Conditioning on these differences (and of course the lack of a life-cycle component) both the overall and feedback effects found in this literature are reflected in our results. Looking at Panels (b) and (c), we observe that both aggregate human capital and formal employees' average wages significantly decrease as the contribution rate increases. However, this happens only in the first scenario because, as mentioned above, in the second "Revenue Neutral" scenario the worker who is marginal between formality and informality is compensated by the added benefit.

When looking at wages in Panels (c) and (d), it is also useful to recall that in our Nash-bargaining context the impact of the contribution rate is highly non-linear. First, it does impact the wage schedule through three channels: a direct channel, an equilibrium channel and a policy channel. The direct channel, as discussed in Section 3.2 and shown in equation (B.1) in the Appendix, is that the contribution rate enters directly in the wage equation because bargaining implies that firms can partially pass-through the cost of the tax to the worker. The equilibrium channel is that the contribution rate affects the value of participating in the market which itself enter the wage schedule (B.1) as the value of the worker's outside option. Finally, in the revenue neutral case, the policy channel is at work because a higher contribution rates means a higher benefit that in turn allows workers to give up more wage when working formally. Second, the contribution rate impacts the average wages of formal and informal employees because it affects who is becoming a formal or informal employee, i.e. the selection over the match-specific productivity value x. Since wages are proportional to x, a higher threshold value between formality and informality (the $\tilde{x}(k, q)$ defined in equation 15) means that formal employees are more positively selected in terms of productivity and therefore everything else equal earn higher wages.

All these components generate the highly heterogenous impact we see on average formal and informal wages when comparing the two scenarios. If in both cases a higher contribution rate decreases average formal wages and increases average informal wages, the two elasticities are quite different. Formal wages are more sensitive to contribution rate changes in the "Revenue Neutral" scenario while the opposite is true for informal wages. The main reason for this difference is that in the "Not Revenue Neutral" scenario the selection into formal jobs is more positive and partially offsets the wage drop on formal wages induced by the direct and equilibrium effects mentioned above.

In conclusion, the experiments generate some expected results: informality increases and human capital decreases when the contribution rate increases. However, they also show that these expected results are very sensitive to the design of the policy: if the contribution rate increase is paired with a proportional increase in the benefit (a "revenue neutral" experiment), the negative impact on aggregate human capital is almost neutralized while the increase in informality is limited to the increase in self-employment (see Figure D.1 in the Appendix).

6.2 Policy Experiment 2: Non-contributory Benefit

In the second experiment, we vary the non-contributory benefit B_0. Again, we perform the experiment in a wide neighborhood around the benchmark level: from 0 to 8. Figure 5 reports simulation results on labor market outcomes computed at the various contribution rates over the range. We denote the benchmark value of B_0 with a vertical dashed line in all Panels. An increase in B_0 can predict the impact of current policy proposals in Mexico and other Latin American countries that are focusing on broadening the coverage of current non-contributory benefits [Levy, 2018].

Panels (a) and (b) report the expected results: as more resources are given to informal employees at no cost, their share in the labor market increases. Since human capital upgrading shocks arrive faster while working formally, the human capital accumulation slows down and the aggregate level of human capital in steady state decreases. The impact can be quite substantial. For example, the increase in benefit from the inception of the *Seguro Popular* program in 2002 to our period of observation in 2013 has been of about 2 and half pesos per hour (from 1.82 to 4.27). Such an increase would be associated in our experiments with a drop in aggregate human capital of about 5 percentage points. In addition, an increase in the non-contributory benefit is by definition not budget neutral because the benefit is not paid by any contribution. The fiscal cost is therefore increasing in B_0 and relative to GDP is increasing at a higher rate because the overall productivity of the labor market decreases due to the lower human capital.[33]

Panels (c) and (d) generate results that are less obvious but that become clear when recalling the discussion of Section 6.1. A higher non-contributory benefit has a very different impact on the average wage for formal and informal employees: the first increases, while

[33] In Figure D.3 of the Appendix, we report the cost of providing B_0 relative to the overall value of production: for example, if the benefit were to double from current values, the relative cost would increase almost three times.

the second remains quite stable. As it was the case for the contribution rate t, the non-contributory benefit B_0 impacts average wages through multiple channels: the direct impact on the wage schedule, the equilibrium impact through the value of the outside option, and the selection impact through the reservation value $\tilde{x}(k, q)$. The net results are the ones shown in the two Panels. Panel (c) shows an increase in the average wage for formal employee because they are increasingly more positively selected over productivity.[34] Panel (d) shows a stable wage for informal employees because the positive impact of better selection over productivity is compensated by the workers's willingness to accept lower wages in exchange for higher benefits.

In conclusion, the experiments confirm that an increase of the non-contributory benefit would increase informality and decrease human capital accumulation. However, they also show that it is important to look at labor market states distribution and to take into account selection when interpreting wage impacts.

7 Conclusions

We study how the different rate of human capital accumulation in formal and informal jobs impact labor market outcomes. Recognizing that formality status and labor market states are endogenous choices interacting with the human capital dynamic on the job, we develop a search and matching model where firms and workers produce output that depends both on match-specific productivity and on worker-specific human capital. Worker-specific human capital accumulates on-the-job in a learning-by-doing fashion and depreciates while searching. This setting is able to generate a very rich dynamic: not only produces a mixture of formal and informal jobs with overlapping wage distributions but also allows for changes in formality status both between and within jobs; not only generates wage growth following a job change but also produces wage growth on-the-job as a result of human capital accumulation.

We propose and implement an identification strategy for the structural parameters of the model using standard and representative labor market data for Mexico, an economy sharing a significant informality rate with many other middle income countries. Specifically, the parameters of the human capital accumulation and depreciation process are identified by exploiting the panel dimension of the data where the same individual is interviewed every quarter for five consecutive quarters. The crucial information we use to identify the human

[34] As reported in Figure D.2 of the Appendix, the proportion of formal employees decreases since the reservation value $\tilde{x}(k, q)$ increases.

capital process are wage changes within and between jobs and transitions between labor market states.

The estimation results show that the probability of human capital upgrading is lower when working informally than formally. For individuals at the lower bound of the human capital support, it takes on average 1.4 years to start upgrading their human capital if they work formally and about 2 years if they work informally. This advantage in the human capital accumulation process while working formally is partially offset by the size of the upgrade when the shock hits since the extent of the upgrade is on average larger when working informally than formally. The relative contribution of human capital to overall productivity is estimated to be substantial: it is about 60% in the overall sample, reaching more than 80% for workers with the highest level of human capital.

We use the estimated model to perform policy experiments where we change the two parameters that are considered crucial in generating the high level of informality observed in Mexico: the payroll contribution rate in formal jobs and the per-capita level of the non-contributory social benefits. In the first case, we perform the experiments under two scenarios: in the first, we simply change the contribution rate keeping all the other policy parameters at benchmark; in the second, we impose a "revenue neutral" constraint where we adjust the value of the benefit according to the increase or decrease in the amount collected by the contribution. Results are significantly different under the two scenarios. If in the first we find the expected increase in informality and decrease in human capital when the contribution rate increases, in the second we find that the negative impact on aggregate human capital is almost eliminated. The experiments varying the level of the non-contributory social benefits show that an increase in the benefit leads to a decrease in human capital accumulation because it increases the proportion of workers employed in informal jobs.

In conclusion, this paper focusing on human capital accumulation after entering the labor market reinforces the results we found in a companion paper focusing on human capital accumulation before entering the labor market [Bobba et al., 2017]. Labor market informality results from optimal reactions to specific features of the labor market. But the presence of an informal labor market state may magnify the negative impact that such features have on labor market outcomes. In this paper, the channel generating this negative externality is the endogenous accumulation of human capital on the job.

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Tables and Figures

Table 1: Descriptive Statistics, Cross-Section

Labor Market State	Proportions	Mean Hourly Wages	SD Hourly Wages
Formal Employees	0.597	24.525	12.406
Informal Employees	0.262	18.857	9.975
Self-employed	0.090	22.521	16.650
Unemployed	0.051	.	.

NOTE: Data extracted from the first quarters of 2013 and 2014 of the Mexican labor force survey (N=4,936). Wages for employees and incomes for self-employed individuals are reported in Mexican pesos (exchange rate: 1 US dollars $\approx$ 13.5 Mex. pesos in 2014). The Formal status of the job is defined according to whether or not workers report having access to health care through their employers.

Table 2: Yearly Transition Rates

LMK State Q5:	Formal Employees		Informal Employees		Self-empl.	Unempl.
Job change:	(No	Yes)	(No	Yes)		
LMK State Q1:						
Formal Employee	86.43		9.16		1.12	3.29
	(57.50	28.93)	(2.78	6.38)		
Informal Employee	19.66		68.96		6.50	4.88
	(7.51	12.15)	(37.54	31.42)		
Self-employed	6.55		26.19		64.79	2.48
Unemployed	43.48		29.25		8.70	18.58

NOTE: Stacked panel of individuals who were followed for five quarters starting in the first quarters of 2013 and 2014 of the Mexican labor force survey (N=24,680). The Formal status of the job is defined according to whether or not workers report having access to health care through their employers..

Table 3: Estimates of the Model Parameters

	Coefficient	Standard Error
Estimated Parameters		
$\lambda_{\{s=0\}}$	0.5051	0.0015
$\lambda_{\{s=1\}}$	0.0782	0.0006
$\eta_{\{f=0\}}$	0.0573	0.0001
$\eta_{\{f=1\}}$	0.0317	0.0001
μ_x	1.6835	0.0062
σ_x	1.0099	0.0001
μ_q	1.5733	0.0068
σ_q	0.9464	0.0019
$\gamma_{\{s=0\}}$	0.1617	0.0003
$\gamma_{\{s=1\}}$	0.0472	0.0004
$\tau_{\{f=0\},1}$	0.0460	0.0001
$\tau_{\{f=0\},2}$	-2.9775	0.0167
$\tau_{\{f=1\},1}$	0.0576	0.0002
$\tau_{\{f=1\},2}$	-1.6230	0.0031
c	0.0514	0.0005
$\nu_{\{f=0\}}$	0.4958	0.0014
$\nu_{\{f=1\}}$	1.3988	0.0015
ξ	-8.9533	0.0245
Predicted Values		
$E(x)$	8.9664	0.0032
$SD(x)$	11.9388	0.0057
$E(q)$	7.5473	0.0036
$SD(q)$	9.0853	0.0088
Loss Function	3665	
Number of Individuals per quarter	4939	
Number of Observations (5 quarters)	24695	

NOTE: Bootstrap standard errors reported. For the definition of the parameters, see Section 3.1 and Section 4.

Table 4: Output and Contribution of Human Capital

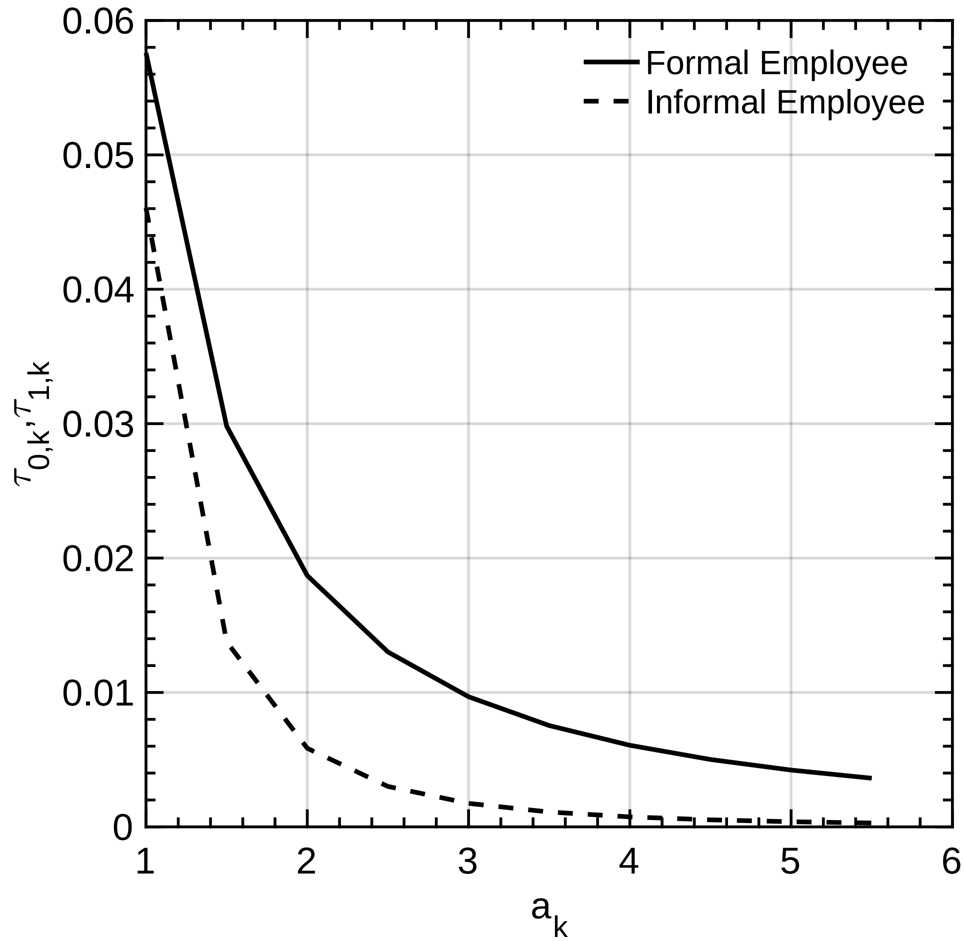
	Proportion Over All Employees	Average Value of Production	Contribution of Human Capital
All Employees	1.0000	42.8322	0.6052
By Formality Status			
Formal Employees	0.6965	54.0746	0.6171
Informal Employees	0.3035	17.0267	0.5183
By Human Capital Level			
a_1	0.1172	16.6469	0.0000
a_2	0.1350	26.9492	0.3333
a_3	0.1668	33.3405	0.5000
a_4	0.1882	41.7311	0.6000
a_5	0.1558	50.2172	0.6667
a_6	0.1131	59.6796	0.7143
a_7	0.0589	63.2288	0.7500
a_8	0.0351	77.0307	0.7778
a_9	0.0200	85.4184	0.8000
a_{10}	0.0100	112.4372	0.8182

NOTE: Simulated samples of 5,000 worker-level observations for each quarter based on the estimates reported in Table 3. Let e_i be an indicator variable denoting the employee status (both formal and informal) for individual i in the simulated data, then the Average Value of Production can be expressed as $S(y) = \frac{1}{\sum_i e_i} \sum_i y_i$, while the average value of the match-specific productivity is given by $S(x) = \frac{1}{\sum_i e_i} \sum_i x_i$, and the Contribution of Human Capital can be expressed as $1 - \frac{S(x)}{S(y)}$.

Figure 1: Observed Wages, Density Functions

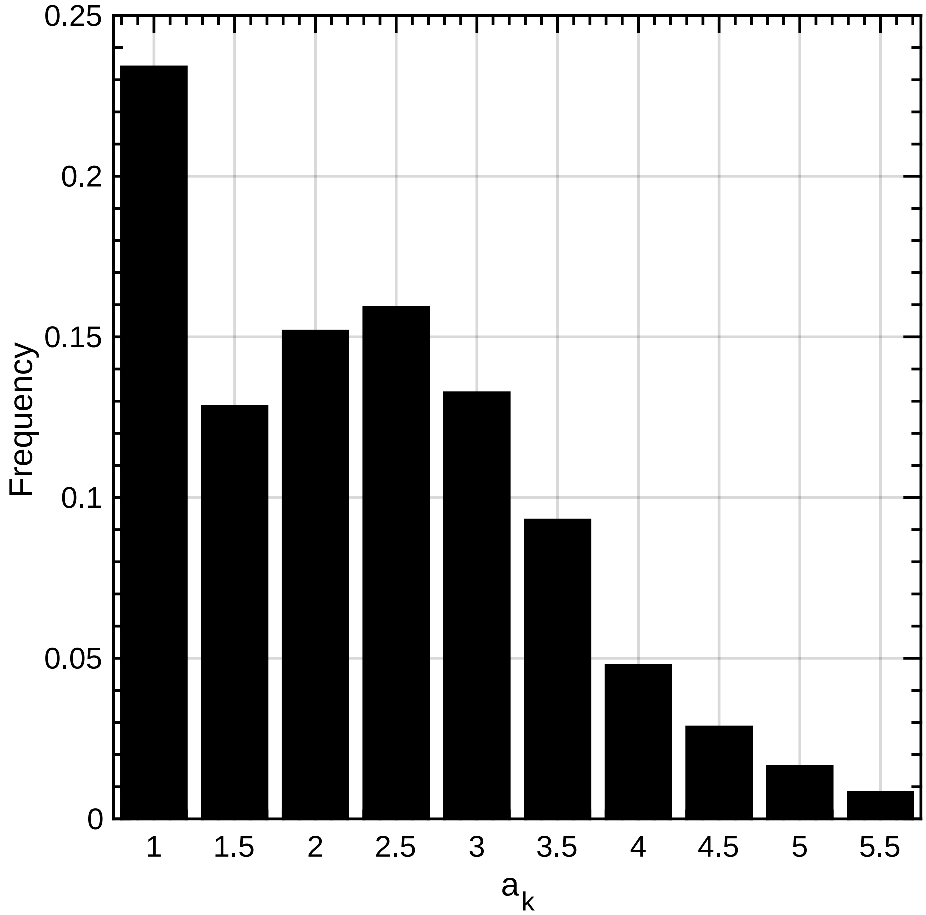
NOTE: Data extracted from the first quarters of 2013 and 2014 of the Mexican labor force survey (N=4,936). Wages for employees are reported in Mexican pesos (exchange rate: 1 US dollars $\approx$ 13.5 Mex. pesos in 2014). The Formal status of the job is defined according to whether or not workers report having access to health care through their employers.

Figure 2: Distribution of Arrival Rates of Human Capital Upgrading Shocks



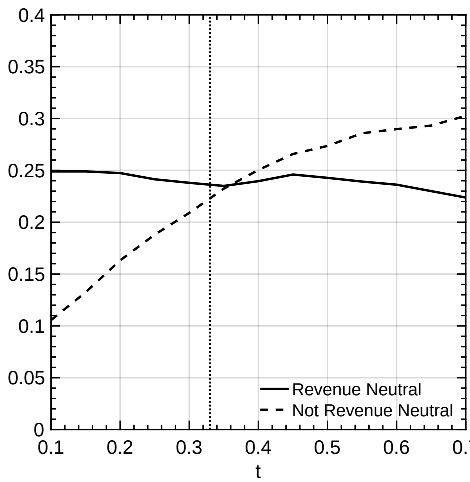
NOTE: Figure based on the estimates reported in Table 3.

Figure 3: Distribution of Human Capital

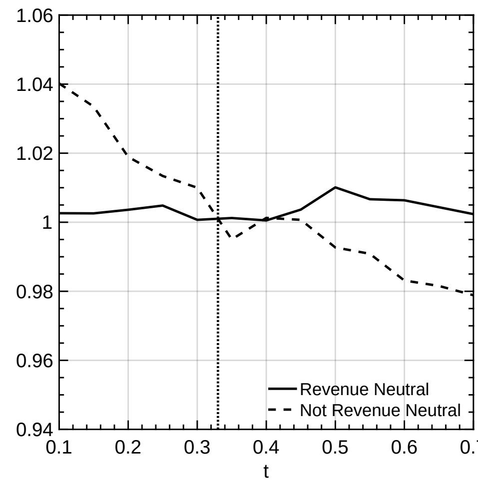


NOTE: Figures based on the estimates reported in Table 3.

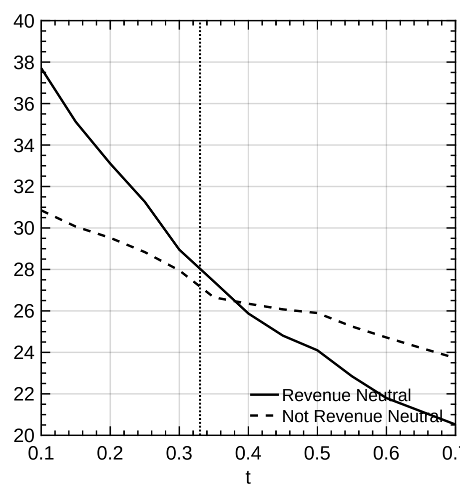
Figure 4: Impacts of Policy 1 – Changes in the Contribution Rate t



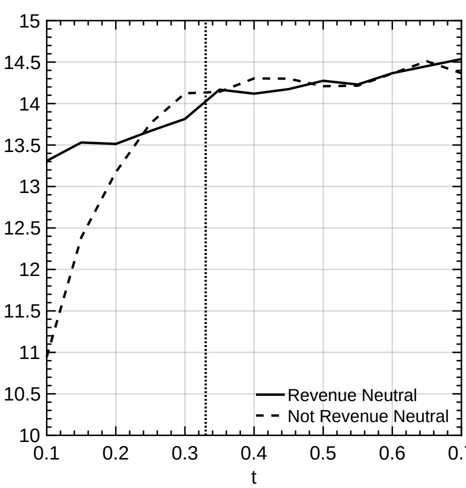
(a) Share of Informal Employees



(b) Aggregate Human Capital (Benchmark = 1)



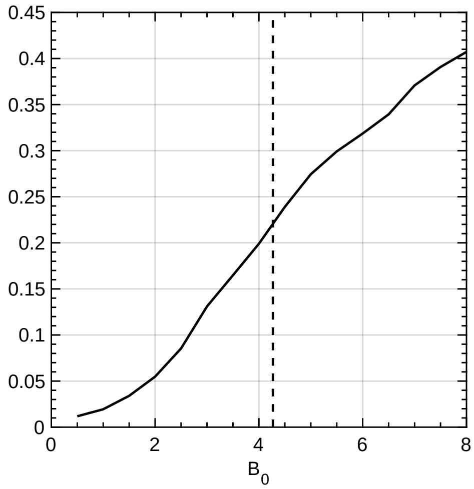
(c) Mean Wages Formal



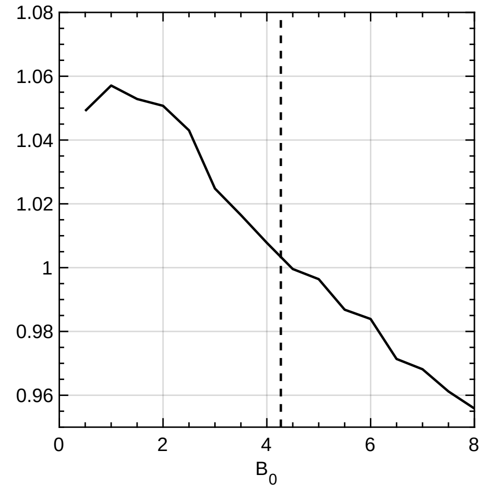
(d) Mean Wages Informal

NOTE: Simulated samples of 5,000 worker-level observations for each quarter based on the estimates reported in Table 3. The vertical lines are set at the institutional values for the Mexican labor market in 2013-2014. See Table C.2 for details. Wages are hourly and reported in Mexican pesos (exchange rate: 1 US dollars ≈ 13.5 Mex. pesos in 2014).

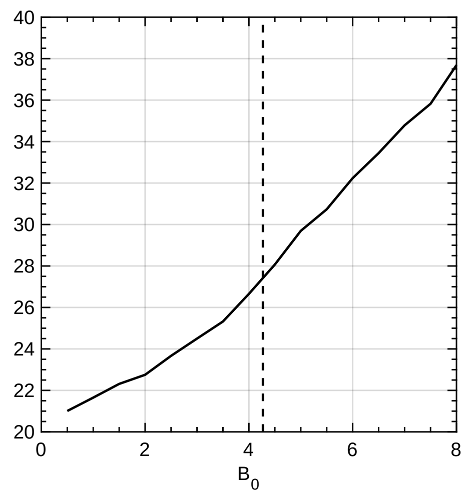
Figure 5: Impacts of Policy 2 – Changes in the Non-Contributory Benefit B_0



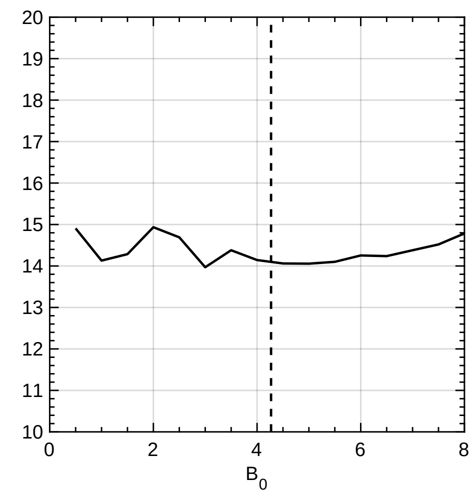
(a) Share of Informal Employees



(b) Aggregate Human Capital (Benchmark = 1)



(c) Mean Wages Formal



(d) Mean Wages Informal

Note: Simulated samples of 5,000 worker-level observations for each quarter based on the estimates reported in Table 3. The vertical lines are set at the institutional values for the Mexican labor market in 2013-2014. See Table C.2 for details. Wages are hourly and reported in Mexican pesos (exchange rate: 1 US dollars ≈ 13.5 Mex. pesos in 2014).

Appendix

A Data

A.1 Sample Selection

Table A.1 shows descriptive statistics on relevant variables as we move from the original sample to the estimation sample. We focus on cross-sectional statistics because many relevant longitudinal statistics are not available in the overall sample. Specifically, transition probabilities are affected by attrition and employment durations are left censored; the only reliable statistics are the on-going unemployment durations, which we present in the Table. In Column 1, we report the raw data of the Mexican labor market survey (ENOE) for two stacked cohorts of male workers entering in the first quarter of the year 2013 and in the first quarter of the year 2014 who are interviewed for up to five consecutive quarters. In Column 2, the same average characteristics are displayed for the sub-set of male workers with secondary education, while in Column 3 we further restrict the sample to the remaining selection criteria detailed in Section 2.2 of the paper. Finally, in Column 4, we consider only those individuals from the sample of Column 3 that we can track longitudinally for five consecutive quarters. This is the estimation sample used throughout the analysis of the paper.

When compared to the nationally-representative figures of Column 1, the selected sample features a similar wage ranking across the three labor market states, albeit a higher proportion of formal workers and a lower share of self-employed individuals. In terms of education, Column 1 included workers that are both more skilled (College graduate or more) and less skilled (primary education only) than our sample. The first group dominates on average wages, in particular for formal employees, leading to higher average wages in Column 1 than in all the other Columns. There are some but not major differences in both labor market proportions and earnings between Column 3 and Column 4, indicating that the underlying determinants of sample attrition are largely idiosyncratic. We will return to this last point in some detail below (see point a). In conclusion, there are some important differences between our estimation sample and a nationally representative sample but these differences are mainly due to focusing on our specific education group. Within this education group, the main difference between a nationally representative sample and our estimation sample is the proportion of self-employed. It results from our focus on the "necessity" self-employment state as described in the paper (Section 2.1).

Table A.1: Descriptive Statistics Across Different Samples

	(1) Original Sample	(2) Restricted Education	(3) Restricted All	(4) Balanced Panel
Proportions:				
Formal Employees	.396	.448	.548	.599
Informal Employees	.300	.302	.287	.265
Self-Employed	.258	.202	.109	.089
Unemployed	.045	.048	.057	.047
Mean Wages: (Hourly)				
Formal Employees	33.1	26.3	24.2	23.9
Informal Employees	20.3	19.6	18.8	18.3
Self-Employed	30.6	31.1	24.2	23.0
Mean Duration (months)				
Unemployed	1.83	1.65	1.59	1.56
Sample Size:				
First quarter	184,209	62,071	23,882	4,936
Overall	542,378	183,825	64,732	24,680

NOTE: Wages and Incomes figures are reported in Mexican pesos (exchange rate: 10 Mex. pesos $\approx$ 1 US dollars in 2005). The formality status of the job is defined according to whether or not workers report having access to health care through their employers.

A.2 Attrition Analysis

Given the definition of our estimation sample, the overall attrition rate in the sample of column 3 of Table A.1 is defined as the probability that a given individual has at least one missing survey round out five consecutive quarterly rounds. The overall attrition rate is 26%. We have checked whether this attrition rate varies systematically across the same labor market outcomes considered in Table A.1 by running a regression over the sample of column 3 and controlling for an indicator variable for whether or not the observation is eliminated due to attrition. Results reported in Table A.2 show that the OLS coefficient of the attrition indicator variable is significantly different from zero only on the labor market proportion of unemployed workers. It results from the fact that unemployed workers have a slightly higher attrition rate (31% instead of 26%). Taken together, we think the table shows attrition does not significantly alter the composition of the longitudinal sample used in the analysis.

Table A.2: Sample Attrition and Labor Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log Earnings (Hourly)			Labor Market Proportions			
	F	I	SE	U	F	I	SE
Attrition (1=yes)	-0.011	0.036	0.025	-0.004	-0.016	0.013	0.006
	(0.018)	(0.028)	(0.081)	(0.002)	(0.011)	(0.013)	(0.009)
Mean Dep. Var.				0.055	0.575	0.274	0.096
Number of Obs.	9251	4418	1542	16099	16099	16099	16099
Number of Clusters	1861	1248	572	2756	2756	2756	2756

NOTE: OLS estimates. Fixed effects at the Municipality×Sector (4-digit) included but not reported. Standard errors clustered at the Municipality×Sector level are reported in parenthesis.

A.3 Job Spells

We use two sets of information to infer status transitions within jobs. The first is the information about the formality status and the second is the information about job spells in the same job.

The first information is provided in the data set in the same way as the general information on formality status we use in the paper. As mention in Section 2.2, we identify the formal or informal status of the job depending on whether the employee reports having access to health benefits through their employers. This definition has strong foundation in the literature and it is reported for all the employees in each quarter of the ENOE sample.

The second information is provided through a question on the starting date of the job. In the last quarter of the survey, i.e. at the end of the observation window, individuals are asked when they started their current job. If the job started within the last two year, the precise starting date (month and year) is reported. If the job started more than two years before, the exact date is not asked but the fact that the job started more than two years before is recorded. When the precise starting date is recorded, we build continuous job spells by simply using the starting date and the observation of labor market status in each quarter.

When only the fact that the job started more than two years before is recorded, it is in principle equally straightforward to extract the information relevant for us. Since these agents are employed at the end of the observation period, since the observation period is one year and they declare to have started the current job more than two years before, they should have been at the same job for the entire observation period. In terms of the relevant information for status transition within job, we could then simply assign them to one job spell in the same job over the one year we observe them. However, some further investigation on the data has led to use a more conservative definition of same-job spell for this group. We have found that some individuals belonging to this group report episodes of search over the period (about 4%) and others report big differences in the economic sector they are working in (about 30% change sector at the NAICS 1-digit level). Both pieces of information are in principle consistent with working at the same job but they are not very credible to us. In the first case, we would have to assume that the worker is losing the job, has one or more episodes of search and then goes back exactly at the same job. In the second case, we would have to assume that the worker is employed in a firm operating in a given sector in one quarter and in another sector in the following quarter. While firms may operate in different sectors, we find it hard to believe that the same job in the same firm is transferred between sectors as different as the NAICS 1-digit.[35] We find it more plausible that the change of sector signals an actual change of job and that any job found after an episode of search is effectively a different job that the one held before searching. In conclusion, we have decided to assign the workers in this group as working in the same job only if, over two consecutive quarters of observation:

1. they are continuously employed, and

[35] 1-digit sectors are very aggregated. In our sample they include the following 8 categories of economic activities, with the relative frequencies in parenthesis: mining and construction (13%), manufacturing (28%), trade, transportation, postal and warehousing services (31%), financial, insurance, real-estate, and business-related services (7%), education and health services (2%), cultural, temporary accommodation, and food and beverage preparation services (8%), other services, except government activities (7%), legislative, governmental and justice administration activities (4%).

2. they operate in the same NAICS 1-digit sector.

Finally, for all the individuals who were either unemployed or self-employed at the time the question was asked and who were employed at some point in the previous year we consider the NAICS definition of the economic sector of the firm (at the 1-digit level). We have therefore assigned those individuals to the same job spell according to the rules [1] and [2] defined above.

B Additional Material on the Model

B.1 Wages

Wages are set by bargaining upon observing the labor market human capital a_k, the outside option $V_s(k, q)$, the match-specific productivity x and the formality status posted by the firm f. We assume the axiomatic Nash-bargaining solution reported in equation (9). The resulting analytical expression for wages of employees hired formally and informally are:

$$
\begin{aligned}
w_1(x;k,q) = {} & \alpha(1+t)^{-1}\left[y(x,k)+\tau_{1,k}\sum_{k'=k+1}^{K}\max\{F_0(x;k',q),F_1(x;k',q),0\}\Pr[k'|k]\right] \\
& + (1-\alpha)(1+\beta_1\tau t)^{-1}\Big[(\tilde{\rho}+\tau_{1,k})V_s(k,q)-\beta_1 b_1 \\
& -\tau_{1,k}\sum_{k'=k+1}^{K}\max\left\{\begin{array}{c}(1-f)E_0(x;k',q)+fE_1(x;k',q),\\ \max\{V_0(k',q),V_1(k',q)\}\end{array}\right\}\Pr[k'|k]\Big]
\end{aligned}
\tag{B.1}
$$

$$
\begin{aligned}
w_0(x;k,q) = {} & \alpha\left[(1-c)y(x,k)+\tau_{0,k}\sum_{k'=k+1}^{K}\max\{F_0(x;k',q),F_1(x;k',q),0\}\Pr[k'|k]\right] \\
& + (1-\alpha)\Big[(\tilde{\rho}+\tau_{0,k})V_s(k,q)-\beta_0 B_0 \\
& -\tau_{0,k}\sum_{k'=k+1}^{K}\max\left\{\begin{array}{c}(1-f)E_0(x;k',q)+fE_1(x;k',q),\\ \max\{V_0(k',q),V_1(k',q)\}\end{array}\right\}\Pr[k'|k]\Big]
\end{aligned}
\tag{B.2}
$$

B.2 Numerical Solution and Simulation

We solve the model using value function iteration. We discretize the state space by using a grid of 100 equally spaced points in the interval $[0, 150]$ for both x and y. The human capital distribution is already assumed discrete over 10 equally spaced points in the interval $[1, 5.5]$.

Since a match can change the formality status or a worker can decide to search for a new job when receiving an upgrading shock, all the value functions are dependent on each other and therefore the value function iteration is performed as a block. Specifically, we guess $V_s(k,q)$, $E_0(x;k,q)$, $E_1(x;k,q)$, $F_0(x;k,q)$ and $F_1(x;k,q)$ over the grid points in the state space and then we jointly iterate the Bellman's equations (10) to (12) (using the definitions of wages and profits) until convergence is achieved on these value functions. To approximate the integral in equation (10), we discretize the distribution $G(x)$ over the grid points of x (using the midpoint intervals between the grid points as support) and we compute the expected value as in a discrete probability distribution.

Finally, to compute the probability of jumping to any higher level of human capital starting in a given k, we use a discretized truncated negative exponential distribution. In particular, let m be the size of the jump in the human capital grid and assume that $m \sim Q_f(x;\nu_f)$ with $Q_f(\cdot)$ a negative exponential distribution with parameter ν_f. Given that in our model $m \in [1,K]$, we define the truncated distribution as:

$$Q^T(m) = \frac{Q(m) - Q(0.5)}{Q(K+0.5) - Q(0.5)}$$

Then the discrete approximation of the probability of jumping m steps can be computed as:

$$\Pr[m = j|k] = \begin{cases} Q^T(j+0.5) & j = 1 \\ Q^T(j-0.5) - Q^T(j+0.5) & j = 2, ..., K-k-1 \\ 1 - Q^T(j-0.5) & j = K-k \end{cases}$$

The maximum K is adjusted to account for the number of steps that are left in the human capital support.

We simulate the model constructing labor market careers. To characterize all the optimal decisions involved in the dynamics of each career, we use direct comparisons between the solved value functions. Since we discretize the state space, we use linear interpolation to approximate the value functions and wages off the grid. We simulate 5,000 individual careers for 540 months. Each individual is assigned a potential self-employment income q drawn from $R(q)$ and starts his career searching for a job with an initial human capital level equal to a_1. The lifetime duration is drawn from a negative exponential distribution with rate δ. The optimal decision in the search state with respect to being unemployed or self-employed is made comparing $V_0(k,q)$ and $V_1(k,q)$ given k and q. In the search state, individuals meet firms and receive downgrading shocks. The durations of these events are draws from negative exponential distributions with rates λ_s and $\gamma_{s,k}$, respectively. If the meeting with a firm occurs first, a productivity x is drawn and firms and individuals decide whether to complete the match and at what wage and formality status. If the match is realized, the individual leaves the searching state with a human capital level of a_k and if not, the searching process continues. If a downgrading shock hits, a new search process starts for the same individual but with human capital a_{k-1}. While working as employees, individuals receive termination and upgrading shocks. As before, we simulate a competing risk model where the durations of these events are draws from negative exponential distributions. In this case, the rates are η_f and $\tau_{f,k}$, respectively. If the termination shock arrives first, the individual starts a new search process with human capital a_k. On the contrary, if the upgrading shock arrives first, then the individual is upgraded to $a_{k'}$ and an optimal decision is made regarding whether to remain in the match and at what wage and formality status. This process continues until the arrival of the termination shock, which sends the agent back to search. Once the lifetime is complete, the individual dies and he is replaced by a new individual that starts his career with q potential self-employment income and with a_1 human capital level.

As time passes in the simulation, the distributions of the labor market states and the human capital levels stabilize, which means that the model has reached the steady state invariant distributions. For estimation, we use a panel of five quarters extracted from a time window in which these distributions are in steady state.

To minimize the quadratic form (19) in the Simulated Method of Moments we use the downhill simplex (Nelder-Mead) algorithm. In each iteration of the simplex algorithm, the quadratic form is evaluated by solving and simulating the model, a procedure that is computationally very intensive. In particular, the simulation of career paths procedure is the most computationally intensive task in the process of estimation. On top of that, because the simplex method is a derivative free optimization algorithm, it requires a nontrivial number of evaluations of the quadratic form before obtaining convergence. To make the computation more efficient, the value function iteration is fully vectorized and the simulation procedure is parallelized. To have a sense of the computational burden, in a 28 core Intel(R) Xeon(R) CPU with 2.60 GHz one round of solution and simulations takes approximately 3 minutes (one quadratic form evaluation), while the complete estimation process takes roughly 500 evaluations of the quadratic form and around 26 hours.

Finally, the weighting matrix is constructed using the bootstrapped variance of the chosen moments in the quadratic form, being the bootstrap samples random samples (with replacement) of individuals of the size equal to the number of total individual in the database. Additionally, the standard errors of the estimators are also calculated using these bootstrapped samples. We use the estimated parameters in the simplex algorithm in each bootstrap iteration. In turn, to check the overall reliability of the estimator we use a Monte Carlo exercise. In particular, using the estimated parameters, the model is simulated generating a database and the estimation procedure, with the same initial values of the parameters as the original estimation, is applied to the generated database.

C Additional Material on the Estimation

C.1 Monte Carlo Experiment

To asses the reliability of our estimator we performed the following Monte Carlo procedure. In the first step, using the estimated parameters of the model, we solved and simulated the model to generate a 5 quarter balanced panel of synthetic data. In the second step, we applied our estimation procedure to the synthetic data. In this step, we keep the same values of the original estimation for all the convergence criteria of the simplex algorithm and the initial values of the minimization process. Due to time constraints we performed just one replication of this Monte Carlo procedure. Table C.1 compares the point estimates obtained by applying our estimation procedure on the original data with the point estimates obtained by applying the same estimation procedure on the synthetic data. We find them close enough to lend some credibility to our estimation method.

Table C.1: Monte Carlo Experiment

Parameter	Real Data	Synthetic Data
$\lambda_{\{s=0\}}$	0.5051	0.5072
$\lambda_{\{s=1\}}$	0.0782	0.0810
$\eta_{\{f=0\}}$	0.0573	0.0594
$\eta_{\{f=0\}}$	0.0317	0.0325
μ_x	1.6835	1.6902
σ_x	1.0099	1.0098
μ_q	1.5733	1.5805
σ_q	0.9464	0.9462
$\gamma_{\{s=0\}}$	0.1617	0.1588
$\gamma_{\{s=1\}}$	0.0472	0.0455
$\tau_{\{f=0\},1}$	0.0460	0.0455
$\tau_{\{f=0\},2}$	-2.9775	-2.9461
$\tau_{\{f=1\},1}$	0.0576	0.0586
$\tau_{\{f=1\},2}$	-1.6230	-1.6400
c	0.0514	0.0496
$\nu_{\{f=0\}}$	0.4958	0.4960
$\nu_{\{f=1\}}$	1.3988	1.4022
ξ	-8.9533	-9.0456

C.2 Complete Estimation Results

Table C.2: Fixed Parameters

Parameter	Value	Source
α	0.5000	Symmetric Bargaining case [Binmore et al., 2006]
β_0	0.9082	Bobba et al. [2017]
β_1	0.6705	Bobba et al. [2017]
B_0	4.2700	Updated from Bobba et al. [2017]
ϕ	0.5500	Levy [2008]
t	0.3300	Anton et al. [2012]
b_1	4.5470	Based on average observed wages (see equation 18)
ρ	0.0500	Flinn and Heckman [1982]; Eckstein and van den Berg [2007]
δ	0.0013	Based on average life of 65 years

Table C.3: Matched Moments: Cross-Section

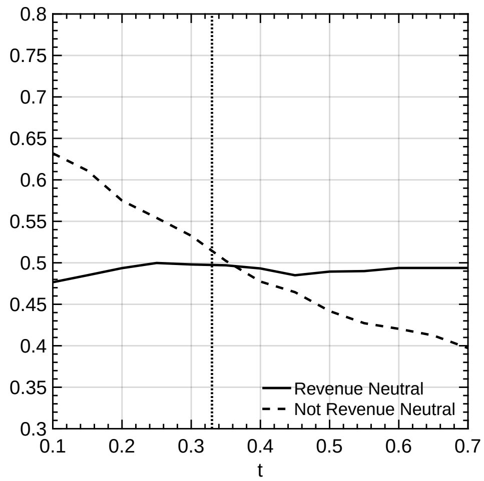
Moments	Simulated	Data	Weight
Proportions:			
Formal Employee	0.518	0.597	144.99
Informal Employee	0.224	0.262	161.05
Self-Employed	0.163	0.090	248.09
Unemployed	0.095	0.051	324.51
Wages and Income:			
Formal Employee: Mean	27.018	24.525	4.78
Formal Employee: SD	18.042	12.406	4.26
Informal Employee: Mean	14.316	18.857	7.33
Informal Employee: SD	8.139	9.975	3.89
Self-Employed: Mean	18.155	22.521	8.61
Self-Employed: SD	13.217	16.650	1.77
Quintiles - Proportions:			
Informal Employee - Q1	0.592	0.401	55.67
Informal Employee - Q2	0.174	0.247	60.04
Informal Employee - Q3	0.127	0.159	69.81
Informal Employee - Q4	0.091	0.118	88.63
Quintiles - Mean Wages:			
Formal Employee - Q1	12.000	12.517	7.03
Formal Employee - Q2	16.990	17.560	6.29
Formal Employee - Q3	22.433	21.708	5.67
Formal Employee - Q4	29.950	27.158	3.39
Informal Employee - Q1	8.860	11.620	6.49
Informal Employee - Q2	16.831	17.386	5.33
Informal Employee - Q3	22.219	21.444	4.29
Informal Employee - Q4	29.400	27.096	2.47

Table C.4: Matched Moments: Dynamics

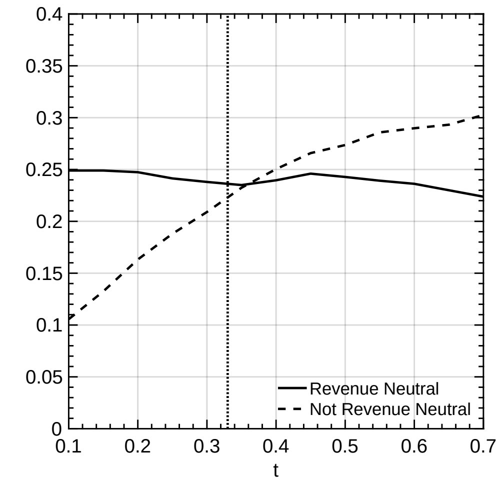
Moments	Model	Data	Weight
Transition Probabilities (Yearly):			
Formal → Formal (Same Job)	0.667	0.575	111.02
Formal → Formal (New Job)	0.138	0.289	120.20
Formal → Informal (Same Job)	0.003	0.028	328.69
Formal → Informal (New Job)	0.069	0.064	220.70
Formal → Self-Employment	0.025	0.011	527.15
Formal → Unemployment	0.098	0.033	300.31
Informal → Formal (Same Job)	0.032	0.075	142.92
Informal → Formal (New Job)	0.180	0.122	109.33
Informal → Informal (Same Job)	0.471	0.375	75.15
Informal → Informal (New Job)	0.129	0.314	78.87
Informal → Self-Employment	0.066	0.065	142.15
Informal → Unemployment	0.122	0.049	168.98
Self-Employment → Formal	0.067	0.065	83.04
Self-Employment → Informal	0.098	0.262	47.43
Self-Employment → Self-Employment	0.833	0.648	43.84
Self-Employment → Unemployment	0.001	0.025	133.74
Unemployment → Formal	0.451	0.435	31.99
Unemployment → Informal	0.334	0.292	36.91
Unemployment → Self-Employment	0.015	0.087	57.04
Unemployment → Unemployment	0.200	0.186	40.36
Wage Growth Rates Within Jobs (Yearly):			
Formal Employee: Mean	0.058	0.083	82.88
Informal Employee: Mean	0.091	0.071	44.64
Wage Growth Rates Within Jobs by Quintiles (Yearly):			
Formal Employee: Mean - Q1	0.105	0.440	29.86
Formal Employee: Mean - Q2	0.067	0.176	41.39
Formal Employee: Mean - Q3	0.042	0.070	42.31
Formal Employee: Mean - Q4	0.040	-0.032	48.73
Informal Employee: Mean - Q1	0.335	0.441	18.25
Informal Employee: Mean - Q2	0.090	0.108	21.89
Informal Employee: Mean - Q3	0.033	0.009	21.69
Informal Employee: Mean - Q4	0.021	-0.021	21.18
Wage Growth Rates Between Jobs:			
Less than a Quarter:			
Formal Employee: Mean	0.107	0.115	55.59
Informal Employee: Mean	0.112	0.129	35.92
More than a Quarter:			
Formal Employee (with Unemployment in Between): Mean	0.087	0.025	74.97
Informal Employee (with Unemployment in Between): Mean	0.033	0.023	73.74
Formal Employee (with Self-Employment in Between): Mean	0.001	0.003	136.42
Informal Employee (with Self-Employment in Between): Mean	0.006	0.029	54.99

D Additional Material on the Policy Experiments

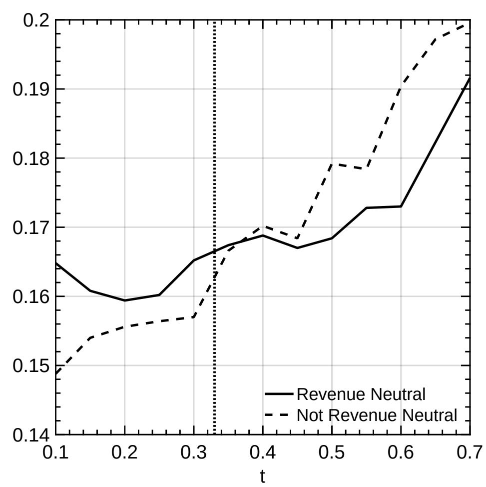
Figure D.1: Impacts of Policy 1 – Employment Status



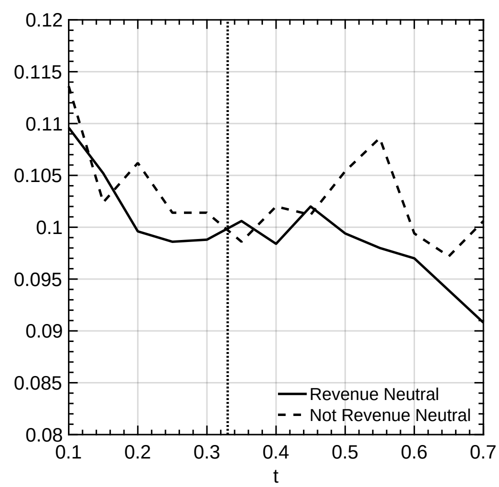
(a) Share of Formal Employees



(b) Share of Informal Employees



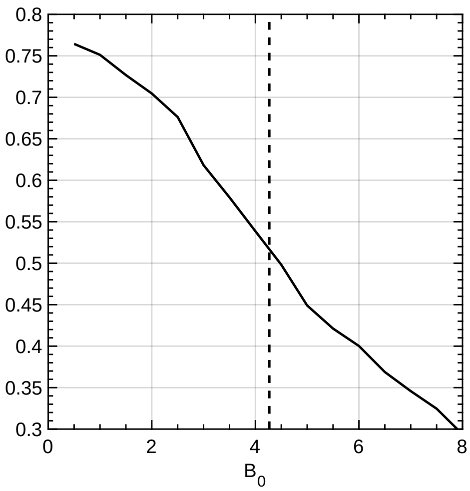
(c) Share of Self-Employed



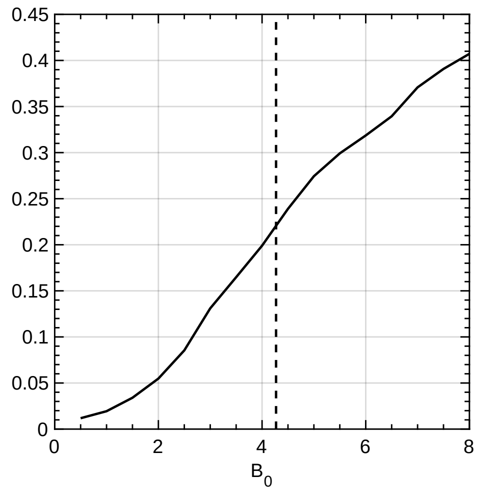
(d) Share of Unemployed

NOTE: Simulated samples of 5,000 worker-level observations for each quarter based on the estimates reported in Table 3. The vertical lines are set at the institutional values for the Mexican labor market in 2013-2014. See Table C.2 for details.

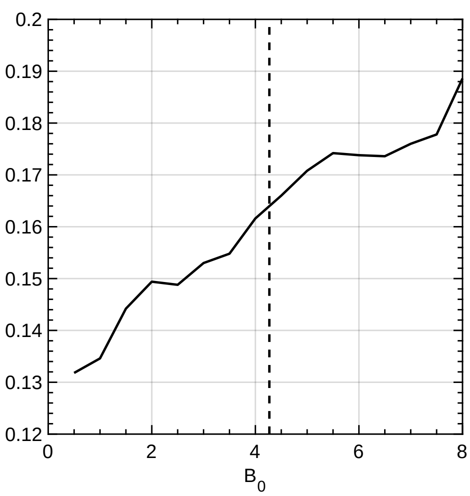
Figure D.2: Impacts of Policy 2 – Employment Status



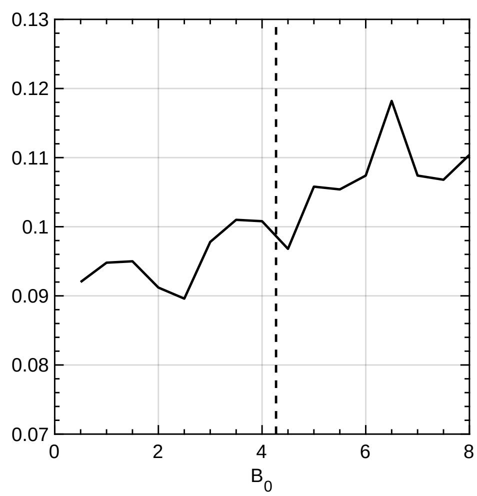
(a) Share of Formal Employees



(b) Share of Informal Employees



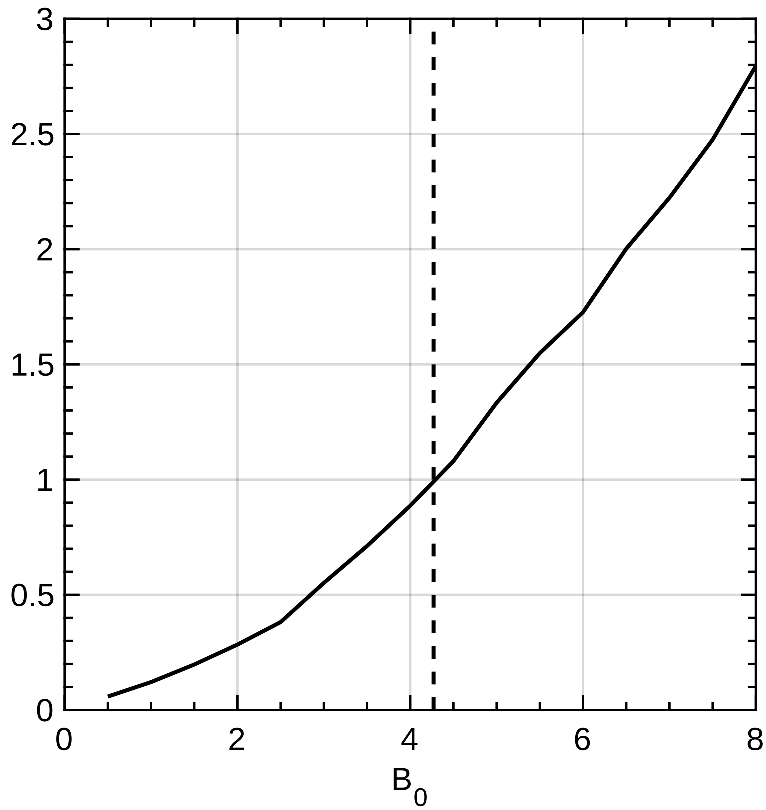
(c) Share of Self-Employed



(d) Share of Unemployed

NOTE: Simulated samples of 5,000 worker-level observations for each quarter based on the estimates reported in Table 3. The vertical lines are set at the institutional values for the Mexican labor market in 2013-2014. See Table C.2 for details.

Figure D.3: Impacts of Policy 2 – Fiscal Cost



NOTE: Table Reports the ratio (Total Cost for B_0)/(Value of Production). Benchmark = 1. Simulated samples of 5,000 worker-level observations for each quarter based on the estimates reported in Table 3. The vertical lines are set at the institutional values for the Mexican labor market in 2013-2014. See Table C.2 for details.