CHAPTER 3

FEMALE LABOR PARTICIPATION AND OCCUPATION DECISIONS IN POST-NAFTA MEXICO

Rafael E. De Hoyos[1]

ABSTRACT

The objective of this chapter is to estimate the parameters defining female labor participation and occupation decisions in mexico. Based on a theoretical framework, we use micro data to estimate the wage-participation elasticity in urban Mexico. Consistency between the selectivity-adjusted wages and the multinomial participation equations is achieved via a two-step estimation procedure following Lee (1983). We use the results of our model to test and quantify three hypotheses explaining recent increases in female labor participation in urban mexico. Our results show that the observed 12 percent increase in female labor participation in mexico between 1994 and 2000 is explained by the combination of a negative income shock caused by the 1994–1995 participation; wage differentiaeso crisis, the increase in expected wages taking place in the manufacturing sector during the post-North American Free Trade Agreement (NAFTA) period, and a reduction in female reservation wage.

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INTRODUCTION

Increasing female labor participation is an important aspect that is contributing to the development process in many emerging economies. Identifying the determinants of female labor participation and occupation decisions improves our understanding of the dynamics of labor supply and its interaction with economic development. The objective of the present study is to estimate the determinants of female labor participation and occupation decisions within a structural, utility-maximizing framework, and to use them to explain the recent increase in female participation in the Mexican labor market.

Based on the relationships described by the structural model, the chapter develops a microeconometric model to obtain the determinants of labor participation and occupation decisions. The starting point is a utility-maximizing setting where individuals' choice depends on a set of comparisons between *expected* market wages and a subjective *reservation* wage. Although the agent's choice depends, ultimately, on personal and household characteristics and a subjective valuation of leisure, we estimate the way in which participation reacts to changes in expected wages (participation-wage elasticity). Given that participation/occupation decisions are the outcome of a nonrandom utility-maximizing process, we model *expected* wages taking selectivity into account; therefore, selectivity-adjusted wages and labor participation/occupation functions are estimated using a two-step procedure.

The structural models of labor occupation developed in Heckman and Sedlacek (1985) and Heckman and Honore (1990) are based on Roy's (1951) concept of comparative advantage. These papers show that agents' occupation decisions are not entirely determined by differences in market wages; personal preferences also play a significant role in the *selection* process. These findings, together with the fact that the econometrician only observes market wages and not personal preferences, have led almost all labor supply studies to use reduced-form estimations where wages are substituted by their determinants (i.e., observed personal characteristics within a human capital framework). An exception to this is van Soest (1995) and Gong and van Soest (2002) who develop a model that explicitly links expected wages with labor participation and occupation decisions. Using data for Mexico, Gong and van Soest (2002) find that higher wages have a positive effect on women's participation and their occupational choices.

The present study contributes to our understanding of the determinants of female labor participation in urban Mexico. With respect to previous studies on Mexican labor markets, our approach is novel in two respects: (1) using micro data for several years we uncover the dynamics of intrahousehold female labor participation dependence and (2) the participation and occupation effects of exogenous shocks (currency crisis and liberalizing reforms) are evaluated using microsimulation techniques.

The model is estimated using biannual Mexican household data for the years 1994–2000. This interval allows us to test changes in female labor participation/occupation wage elasticities during a period of liberalizing reforms. Female labor participation in urban Mexico increased by 12 percent between 1994 and 2000, representing a total of more than 700,000 new entrants during the first six years of NAFTA. Given the simultaneity of these two events, it is tempting to infer a causal relationship, explaining the increase in female participation as a result of NAFTA. Our model allows us to create a *hypothetical* economy where the participation/occupation structure is free of "trade-induced" changes in labor market parameters. Hence, using microsimulation techniques, we can quantify how much of the increase in female participation was brought about by changes in expected wages (market conditions affected by trade liberalization) versus changes explained by shifts in structural parameters determining female *reservation wage* function.

The chapter is organized in the following way. In the next section, we develop the model, stressing the necessary assumptions to identify the parameters in our empirical strategy. Third section shows the results of the model using Mexican household data for the period 1994–2000. In fourth section, we carry out a microsimulation analysis to test the impact of exogenous changes in parameters on the employment and the occupation structure. Finally, a summary and conclusions are shown in the last section.

THE MODEL

Theoretical Framework

Following Heckman (1974), we assume that an agent's participation decision is determined by the difference between market wages and a reservation wage function (what Heckman calls shadow prices of female time). Heckman develops a model for the binomial choice problem; however, it can easily be extended to a multinomial one. Define a reservation wage, w_{ij}^{*}, as the minimum wage required to observe individual

i working in occupation j. Such a reservation wage will be determined by the agent's personal and household characteristics and preferences:

$$w^*_{ij} = w^*_j(\boldsymbol{X}_i, \boldsymbol{Z}_i) \quad \forall\ j = 1 \ldots J \tag{1}$$

where $\boldsymbol{X}_i$ and $\boldsymbol{Z}_i$ are vectors of personal and household characteristics of individual i, respectively. Instead of having a single reservation wage function for each individual (as in Heckman's model), we have J of them, that is, as many as the number of remunerated choices (occupations). The J reservation wages derived from the assumption that occupations have different characteristics, apart from monetary ones, that have a value for the individuals making them a function of personal preferences. Allowing for different reservation wages across choices is justified on the basis of differences in observable characteristics (e.g., working conditions) and unobservable ones (e.g., an individual preference for a particular occupation) across occupations. Therefore, individuals attach a different personal valuation to each occupation. A well-documented example of this is the institutional rigidities present in the labor market, where the lack of working hours flexibility can be substituted by occupational choices (see Deaton & Muellbauer, 1980, p. 86). The utility valuation given to the different occupational characteristics is captured – indirectly – by vectors $\boldsymbol{X}_i$ and $\boldsymbol{Z}_i$. On the other hand, expected market wages, following conventional human capital theory, are defined by the well-known function $\hat{w}_{ij} = \boldsymbol{X}_i\hat{\boldsymbol{\beta}}_j$, where w_{ij} is the log of hourly wages.

Once a reservation (w^*) and an expected market wage ($\hat{w}$) are defined for each occupation and each individual, agents' choices will be based on a series of pair comparisons between $\hat{w}_j$ and w^*_j. The utility-maximizing choice will depend not merely on the level of these two components but also on the difference between them, (i.e., $\hat{w}_{ij} - w^*_{ij}$). In this framework, the conventional reservation wage (i.e., whether an individual decides to work or not) is defined implicitly by the same set of pair comparisons. An individual participates in the labor market as long as one of the differences $\hat{w}_{ij} - w^*_{ij}$ is positive, but the final occupational choice will be the one which maximizes the gap between them. There is an implicit *utility* function embedded in this maximizing process that can be defined as follows:

$$V_{ij} = V(\hat{w}_{ij} - w^*_{ij}), \ \forall j \tag{2}$$

Notice that while V_{ij} is defined by elements $\hat{w}$ and w^*, reservation wages will depend, in turn, on individual preferences; *utility* is thus ultimately defined by monetary income, a personal valuation of it and individual preferences.[2]

A reduced form of (2) takes into account the fact the we do not observe w_{ij}^* and hence we can only include the observable components that determine reservation wages, that is, $\boldsymbol{X}_i$ and $\boldsymbol{Z}_i$. Assuming that *utility*, $V(\cdot)$, is a linear function of its arguments and adding a random component, it can be defined as follows:

$$V_{ij} = \lambda \hat{w}_{ij} - (\boldsymbol{X}_i \gamma'_j + \boldsymbol{Z}_i \gamma_j) + \eta_{ij} \tag{3}$$

where η_{ij} is a stochastic component. We are implicitly assuming that, controlling for differences in $\boldsymbol{X}_i$ and $\boldsymbol{Z}_i$, the marginal utility of monetary income, λ, is constant across individuals and occupations; therefore, λ is a scalar parameter.[3] Since $\hat{w}_i$ is fully determined by $\boldsymbol{X}_i$, a major problem with Eq. (3) is that we cannot identify both sets of parameters, λ and γ'_j, at the same time. Changes in $\boldsymbol{X}_i$ will have a double and simultaneous effect, on the one hand on expected market wages and, on the other, on reservation wages. To tackle this problem, as an alternative to (3), we define a less flexible but more parsimonious version of the *utility* function. Substitute the reduced-form version of the expected (log) wage function ($\boldsymbol{X}_i \hat{\boldsymbol{\beta}}_j$) into (3):

$$V_{ij} = \lambda(\boldsymbol{X}_i \hat{\boldsymbol{\beta}}_j) - (\boldsymbol{X}_i \gamma'_j + \boldsymbol{Z}_i \boldsymbol{\gamma}_j) + \eta_{ij} \tag{4}$$

Simplify:

$$V_{ij} = (\lambda - \gamma'_j / \hat{\boldsymbol{\beta}}_j) \boldsymbol{X}_i \hat{\boldsymbol{\beta}}_j - \boldsymbol{Z}_i \boldsymbol{\gamma}_j + \eta_{ij} \tag{5}$$

Define $\delta_j = (\lambda - \gamma'_j / \hat{\boldsymbol{\beta}}_j)$:

$$V_{ij} = \delta_j \hat{w}_{ij} - \boldsymbol{Z}_i \boldsymbol{\gamma}_j + \eta_{ij} \tag{6}$$

Notice that the wage-participation parameter, δ_j, will be positive if and only if $\lambda^* \hat{\boldsymbol{\beta}}_j > \gamma'_j$. Therefore, $(\lambda^* \hat{\boldsymbol{\beta}}_j)$ and (γ'_j) can be interpreted as the substitution and income effects of changes in personal endowments $\boldsymbol{X}_i$, respectively. Participation will increase as a result of higher expected wages as long as the substitution effect is larger than the income effect, or, in other words, as far as the marginal utility of monetary income is larger than the increase in reservation wages. Eq. (6) allows the marginal utility of fitted wages, $\hat{w}_{ij}$, to differ across choices, capturing the unobservable effects deriving from the reservation wage function (γ'_j) and the remunerations of personal characteristics across occupations $(\hat{\boldsymbol{\beta}}_j)$. Moreover, the first element of $\boldsymbol{Z}_i$ is a column of ones (i.e., there is a different intercept for each occupation), accounting for the utility effects of occupation-specific attributes such as working conditions or working hours flexibility. Based on specification (6), individual i will choose occupation j if and only if:

$$V_{ij} > \max_{m \neq j}\{V_{im}\} \;\; \forall j \tag{7}$$

Framework (1)–(7) combines Heckman's (1974) reservation wage concept and McFadden's (1974) multinomial utility maximization criteria. Unifying both approaches helps us understand the dynamic processes that might lie behind the data we observe. Our focus solely on participation and occupation decisions rather than endogenizing hours of work is based on the institutional rigidities present in many developing countries, where working hours are not freely chosen.[4]

Empirical Strategy

This section elaborates on the aspects that we have to take into account in order to obtain a set of equations that are suitable for estimation. The advantage of having a structural model behind the estimations is that we can interpret the parameters in a way that is consistent with the theoretical framework.

From (3) we know that a change in one of the elements of $\boldsymbol{X}_i$ will have a double – and possibly opposing – effect on the probability of participating in the labor market. On the one hand, an increase in $\boldsymbol{X}_i$ will tend to increase the agent's expected wage and this might have a positive effect on participation. On the other hand, the same increase in $\boldsymbol{X}_i$ can rise the agent's reservation wage and hence reduce his or her participation probability. Although we do not observe this second effect, we could estimate a specification like (3) and try to identify both effects. However, as we have already pointed out, we cannot identify the parameters on $\hat{w}_{ij}$ and $\boldsymbol{X}_i$ simultaneously. Furthermore, even using a parsimonious specification like (6) and a simple empirical strategy like the one developed in McFadden's (1974), the interpretation of δ_j is not straightforward. Given the normalization assumption that is necessary to estimate the probability of participation and occupation based on the criteria described in (7), allowing the parameters on expected wages to vary across outcomes will be misleading in terms of our theoretical model. Say that we normalize by making the parameters of outcome "not active" equal to 0. For every possible occupation, we will have an expected wage, but the interpretation of the parameters for all of them would be in terms of the base category (not active). In terms of our structural model, an increase in the expected wage in occupation j does not have an effect on the probability of participating in occupation j' *relative to being not active*; therefore, there is no basis for including all J expected wages as if they were characteristics of the individuals. Instead of allowing expected wages to enter (6) as if they were characteristics of the individuals, we restrict δ_j to be the same for all occupations (δ). Thus, we interpret expected wages as an outcome's *attribute* rather than a characteristic of the individuals.[5]

Before estimating the model, we need one further assumption. The random components of (6), η_{ij}, can follow many distributions, for example, normal, poisson, extreme value or a combination of various distributions (logit kernel or mixed logit). For simplicity, we assume that η_{ij} are i.i.d. with extreme value distribution. With all our assumptions at hand, the probability that agent i will choose occupation s is defined as follows:

$$\Pr(i = s) = \frac{\exp[\delta \hat{w}_{is} + \mathrm{Z}_i \gamma_s]}{\sum_{j=1}^{J} \exp[\delta \hat{w}_{ij} + \boldsymbol{Z}_i \gamma_j]} \tag{8}$$

Eq. (8) combines *attributes* of the occupations, $\hat{w}_{ij}$, with *characteristics* of the individual $\boldsymbol{Z}_i$, in other words it is a generalized multinomial model combining McFaddens conditional logit and the multinomial logit (MNL).[6] According to Maddala (1983) "…the main difference between the McFadden logit model and the MNL model [considered here] is that the McFadden model considers the effects of choice characteristics on the determinants of choice probabilities as well, whereas the MNL model [considered here] makes the choice probabilities dependent on individual characteristics only" (p. 42). Specification (8) is a combination of a conditional and an MNL with $\hat{w}_{ij}$ varying across individuals and occupations and $\boldsymbol{Z}_i$ varying only across individuals.[7]

Selectivity and Expected Wages

Let us define the log of hourly wages net of taxes, w_i, as a linear function of formal years of schooling, years of schooling interacting with a dummy variable for higher education, experience, experience squared, and a regional dummy variable.[8] These variables plus a constant are the elements of $\boldsymbol{X}_i$. We allow for different parameters across occupations, estimating a separate wage equation for each of them assuming that their residuals are only related via the selection criteria (7). Our working age population is defined as women between 12 and

65 years old without a physical impediment to work and not being full-time students. Women within this classification face the following set of choices: (i) to participate in the labor market as self-employed or informal worker,[9] (ii) work in the manufacturing sector, (iii) work in other formal sectors, or (iv) not to participate in the labor market at all (not active).[10]

As we have already specified, the workers observed in each sector are not the outcome of a random process, indeed they follow criteria (7). Therefore, to estimate parameters that are valid for the whole population, the wage equations in each of the three remunerated sectors have to account for selectivity. Following (8), we can obtain the conditional probabilities of labor participation for each sector and, given a parameterization rule, include them in the wage equation to control for selectivity.[11] The problem is that, as we can see from (8), the conditional probabilities obtained from the MNL, $\Pr(\cdot)$, are themselves a function of expected wages; therefore, we have the following simultaneous equation model:

$$\hat{w}_{ij} = w[\boldsymbol{X}_i, \Pr(\hat{w}_{ij}, \boldsymbol{Z}_i)] \tag{9}$$

To solve the simultaneity, we estimate (9) following a two-step procedure.[12] In the first step, we estimate $\Pr(\cdot)$ using a reduced form of it with expected wages being substituted by its determinants $\boldsymbol{X}_i$: $\Pr(\boldsymbol{X}_i, \boldsymbol{Z}_i)$, where $\boldsymbol{X}_i$ captures, in an indirect fashion, the wage effects on $\Pr(\cdot)$. In the second step, the conditional probabilities $\Pr(\boldsymbol{X}_i, \boldsymbol{Z}_i)$ are included in the wage equations based on the results by Lee (1983). Define z_i as a vector containing $\boldsymbol{X}_i$ and $\boldsymbol{Z}_i$; selectivity-adjusted wage equations are estimated in the following way (we exclude the individual subindex for clarity):

$$w_s = \boldsymbol{X}\beta_s + \sigma_s\rho_s\left(\frac{\phi(H_s(z\gamma_s))}{F_s(z\gamma_s)}\right) + \varepsilon_s \tag{10}$$

where $\sigma_s\rho_s$ are parameters capturing the covariance between the wage and selection equations; $H_s(z\gamma_s)$ is a transformation of the MNL index, $z\gamma_s$, into a standard normal distribution; ϕ is the standard normal density function and $F_s(z\gamma_s)$ is the marginal distribution of the MNL residuals. Since the wage equations and the conditional probabilities from the selection equation share vector $\boldsymbol{X}$, the identifying variables or exclusion restrictions in Eq. (10) are contained in $\boldsymbol{Z}$ (instruments). We define $\boldsymbol{Z}$ bearing in mind that its components must affect reservation wages but not market wages. In the case of female laborers, $\boldsymbol{Z}$ includes the number of children in the household (less than 7-year-old); a dummy variable equal to 1 if the woman is not head of the household and the head is active; the income of all other household members and its quadratic form. As has been argued in Attanasio, Low, and Sánchez-Marcos (2004), female labor participation is closely linked to household income variability and economy-wide shocks. To take this into account, the last element of $\boldsymbol{Z}$ is a measure of the variation in all other household members' income.[13] All these variables are expected to have a significant effect on female reservation wages without affecting their expected market remuneration.

Estimation of informal sector "wages" using specification (10) implicitly assumes that this sector is *complete*, and therefore it remunerates the marginal productivity of labor as the outcome of personal characteristics. Marcouiller, Ruiz, and Woodruff (1997) find that returns to personal characteristics in the Mexican informal sector behave quite like those in the formal sector. The same study and those by Maloney (1999) and Gong, van Soest, and Villagomez (2000) suggest that, controlling for personal characteristics, the informal sector in Mexico is a desirable destination rather than an inferior forced option. As it was mentioned in the theoretical section, the different occupations can have certain attributes valued by agents. A special feature that is present in the informal sector that might have an advantage over its formal counterpart is the flexibility in working hours. To account for this occupational *attribute*, we include the standard deviation of working hours ($\tilde{h}$) in each sector as a determinant of participation and occupation. A note of caution is necessary at this point. Notice that $\tilde{h}$ will only vary across occupations but not between individuals. The same can be said about the intercept in (6) – the first element of $\boldsymbol{Z}$. Therefore, including $\tilde{h}$ and allowing for a different intercept for each occupation will result in perfect multicollinearity. To avoid this problem, our estimations assume that the intercept for the informal sector equation is equal to 0. In other words, all particular attributes attached to the informal sector (apart from $\hat{w}$) will be captured by $\tilde{h}$.

Finally, the structural participation and occupation function is estimated using a *generalized* MNL[14] including the exponential of the fitted values of the wage Eq. (10), $\hat{W}$, $\tilde{h}$, and $\boldsymbol{Z}_i$ as regressors:[15]

$$\text{Prob}(i = s) = \frac{\exp[\delta \hat{W}_{is} + \varphi \tilde{h}_s + \text{Z}_i \gamma_s]}{\sum_{j=1}^{J} \exp[\delta \hat{W}_{ij} + \varphi \tilde{h}_j + \boldsymbol{Z}_i \gamma_j]} \tag{11}$$

Although rather standard, the empirical strategy described in this section is well-suited for answering the question in hand: what explains the increase in female labor participation observed in post-NAFTA Mexico? Other more sophisticated models such as van Soest (1995), exploiting variations in hours worked, would add little – if any – to our understanding of the factors behind the increase in female labor participation in Mexico. Additionally, as it will become clear from fifth section, estimating Eq. (11) will allow us to quantify the relative importance of three possible explanations behind the increase in female labor participation: (a) the negative income effect brought about by the 1995 economic crisis; (b) a positive substitution effect (increase in relative wages) after 1996, explained by the increase in female labor demand in the manufacturing sector; and (c) changes in female reservation wage functions favoring participation.

DATA

The model described in second section is estimated using Mexican household survey data (ENIGH) for households located in urban areas (communities with 15,000 inhabitants or more) for the years 1994, 1996, 1998, and 2000, respectively. Between 1994 and 1996, Mexico experienced great macroeconomic turbulence as a result of the Peso crisis that erupted in December 1994. In 1994, the country embarked on a free trade agreement with Canada and the United States. The years between 1996 and 2000 were a time of economic recovery, with high rates of growth mainly boosted by manufacturing exports. All these changes could have had a significant impact on female labor participation and occupation decisions.

To summarize the most important changes taking place in the Mexican female labor market, in Fig. 1 we show the percentage change in labor participation and the time trend in real wages.[16] Female labor participation increased during the period of analysis with the proportion of active women rising from 41.6 percent in 1994 to 46.6 percent in 2000, representing a 12 percent increase in a period of only six years. An increase of 5 percentage points might seem to be a small change, but when we consider the number of total women entering the labor market during those years, the increase is far from being trivial. An increase in female participation of 5 percentage points of the 1994 female working age population represents a total of 707,993 female laborers entering the market over and above the effects due to demographic trends.[17] Of the total amount, around 338,794 of the new entrants took place in the manufacturing sector, 244,684 new laborers went into other formal sectors, and 124,514 ended up in the informal sector. During these period, the manufacturing sector absorbed most of the new female entrants into the labor marker despite its relatively small size in

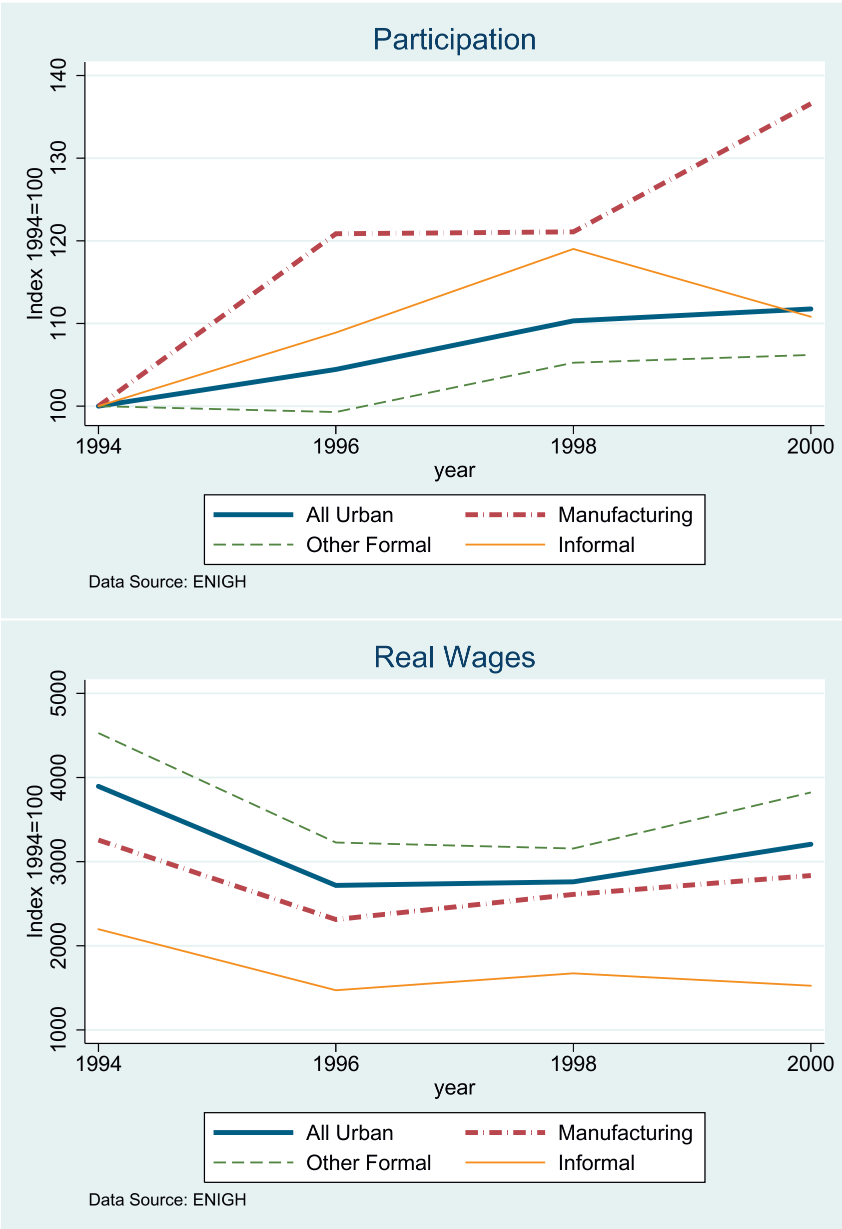

Fig. 1. Female Participation and Real Wages.

the economy (17 percent of the total economy in 1994). As we can see from the upper part of Fig. 1, these changes translated into an increase in the proportion of total female laborers in the manufacturing sector.

After the Peso crisis (1994–1995), real average wages for women working in urban areas decreased 30 percent. Although urban areas average wages remained practically unchanged between 1996 and 1998, wages in the manufacturing sector rose 13 percent during the same period. Manufacturing wages kept rising between 1998 and 2000, time during which wages in other formal sectors began to recover. Real wages in the informal sector showed no constant trend, with a positive change between 1996 and 1998 and an unexpected negative shift between 1998 and 2000.

In Fig. 2, we show the average years of schooling and average age for urban women within working age. We find that, on average, the level of formal education rose steadily between 1994 and 2000. Despite this overall increase, the average education of female workers in the manufacturing sector, as opposed to the increase experienced in all the other sectors, decreased between 1994 and 1996 and remained below the 1994 level throughout the period. The large increase in female participation, together with a decrease in the average educational level observed in the manufacturing sector, makes us suspect that during the years after NAFTA this sector was absorbing the relatively unskilled female laborers who were entering the labor market. This could be a sign that the boom in the manufacturing sector after the Peso devaluation and the enactment of NAFTA made many unskilled Mexican women more likely to participate in the labor market. Finally, the lower right part of Fig. 2 shows that entrants into the informal sector were younger, on average, than the incumbents.

Despite the opposite trends in real wages between the periods 1994–1996 and 1996–2000, participation in the manufacturing sector always showed positive shifts. The explanation for the increasing participation in the manufacturing sector during the period 1994–1996 might be different from the explanation behind the increase during 1996–2000. Perhaps women's participation between 1994 and 1996 was a response to the large negative income effect brought about by the Peso crisis; on the other hand, during the recovery period 1996–2000, increases in participation could be explained by the rise in real wages in the manufacturing sector.

A third hypothesis explaining the observed increase in female labor participation is related to changes in women's *willingness* to work. Changes in female *shadow price of leisure*, for example, reductions in "reservation wage," could have played a significant role in female labor participation decisions. For example, in a relatively traditionalist society like the Mexican

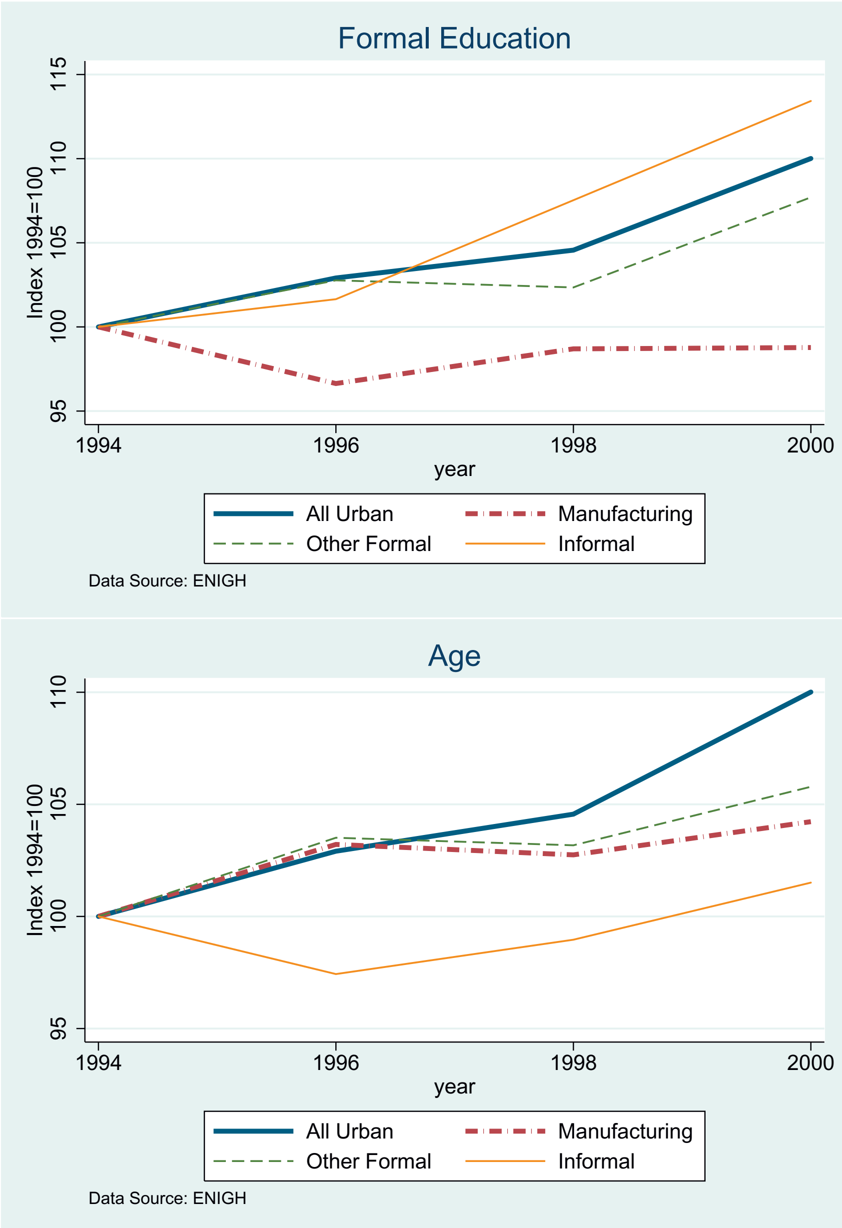

Fig. 2. Years of Schooling and Age.

one, female labor participation still depends on the husband's labor status; that is, if the husband (head of the household) is working, the probability of observing an active spouse is lower than if the head was not active. If this type of *dependency*, or any other factor affecting the female reservation wage function, is changing throughout the period in a way that favors participation, then we could conclude that the observed increase in female labor participation in Mexico between 1994 and 2000 can be explained by three effects: (a) the negative income effect brought about by the crisis; (b) a positive substitution effect (increase in relative wages) after 1996, explained by the increase in female labor demand in the manufacturing sector; and (c) changes in female reservation wage functions favoring participation. To be able to test these hypotheses and quantify their effects, a structural model linking exogenous income effects, market wages, and female *dependency* with labor participation decisions will be estimated. If hypotheses (a)–(c) are true, the data should support the following statements: income effects are positive, that is, female labor participation probability decreases as household income rises; wage-participation elasticity is positive; and finally, the female reservation wage is decreasing over time. To test the validity of these statements, in the following sections we show the model estimates and, based on this, we quantify the effects of our three main hypotheses using microsimulation analysis.

EMPIRICAL ESTIMATES OF THE STRUCTURAL MODEL

This section presents the estimation results for the selectivity-adjusted wages (10) and the participation and occupation Eq. (11) for the years 1994, 1996, 1998, and 2000, respectively.[18] Given the large amount of results, the tables with the wage equation's estimates for each sector are placed in Appendix C.[19]

An important result to notice from the wage equations (Tables C.1–C.3 in Appendix C) is that the average return to schooling in the manufacturing sector is lower than that estimated for other formal sectors. This result suggests that the manufacturing sector in Mexico demands relatively less skilled female laborers (measured in years of formal education) compared to the skills demanded in other formal sectors. Another important result comes from the dummy variable capturing wage differentials between the northern states and the rest of the country. Controlling for selectivity, education, and experience, during the recovery years 1996–2000, female laborers in manufacturing industries located in the north of Mexico earned, on average, 20 percent more than their northern counterparts working in other formal sectors and 25 percent more than manufacturing laborers in other regions. This result supports the hypothesis of an increase in female labor demand in the manufacturing industry explained, in turn, by the rapid growth in exports in this sector during those years.[20]

Table 1 shows the estimation results of the participation and occupation Eq. (11) taking "not active" as the base category; therefore, all the parameters (except for the wage-participation elasticity) are interpreted as changes in the probability of choosing a particular occupation relative to not being active.[21] The first two rows contain the estimates of two occupation attributes, that is, expected wages ($\hat{W}$) and the standard deviation of working hours ($\tilde{h}$). Regarding the latter, the results show that female workers (or possible ones) perceive working hours stability as a positive attribute; therefore, a ceteris paribus increase in the variance of working hours in a particular occupation reduces its probability of being chosen. As we would have expected a priori, an increase in expected wages in a particular sector increases the likelihood of observing workers in that sector. Following our theoretical model, a value of δ of, say, 1 implies a value of λ (the marginal utility valuation of money income) greater than 1. The probability of observing a worker participating increases as a result of an exogenous increase in $\hat{W}$ (i.e., $\delta > 0$).

Based on the estimates of δ, we compute the wage-participation elasticity. The estimated wage-participation elasticity is quite stable over time, ranging from 0.33 in 1998 to 0.39 in 2000 (see dashed line in Fig. 3).[22] This result supports hypothesis (b) postulated in third section, that is, participation can be partly explained by positive changes in real wages occurring in the export-oriented manufacturing sector. The continuous line in Fig. 3 shows the average fitted values of the log of hourly wages ($\hat{w}$) notice the large positive reaction of fitted values of wages between 1996 and 1998 – although still below the pre-crisis level. In the next section, we will quantify the labor participation effects of these changes in expected wages.

From the third row of Table 1 onward, we show the participation and occupation effects of household characteristics $\boldsymbol{Z}$. Remember that all variables included in $\boldsymbol{Z}$ (instruments) affect reservation wages without changing market wages. Hence $\boldsymbol{Z}$'s estimated parameters should be seen as the determinants of females' reservation wage function and orthogonal to $\hat{W}_{ij}$.

Despite an expected a priori negative sign on the parameter relating participation to the number of children in the household, we find that, for many years, this relationship is not significantly different from zero. A

Table 1. Structural Model Results.

	1994	1996	1998	2000
$\hat{W}$	1.3 (0.077)***	1.45 (0.08)***	1.11 (0.087)***	1.5 (0.101)***
$\tilde{h}$	−0.15 (0.008)***	−0.11 (0.007)***	−0.11 (0.007)***	−0.1 (0.008)***
Manufacturing earner (Tradable)				
Intercept	−1.88 (0.161)***	−2.58 (0.165)***	−2.54 (0.201)***	−3.4 (0.216)***
Children	−0.37 (0.085)***	−0.18 (0.078)**	−0.14 (0.066)	−0.02 (0.094)
H_s^a	−1.13 (0.191)***	−1.14 (0.133)***	−1.01 (0.148)***	−0.77 (0.222)***
H_d^a	0.61 (0.181)***	0.78 (0.165)***	1.05 (0.164)***	1.46 (0.232)***
Y_m^0	−5.62 (1.24)***	−9.68 (1.559)***	−10.95 (1.53)***	−10.48 (1.713)***
$(Y_m^0)^2$	1.02 (0.22)	1.31 (0.672)	6.81 (1.377)*	5.88 (1.232)
$Var(Y_m^0)$	0.002 (0.001)	0.002 (0.004)	0.001 (0.001)	−0.033 (0.023)
Other earner (nontradable)				
Intercept	−0.8 (0.122)***	−1.15 (0.118)***	−0.44 (0.152)***	−2.23 (0.249)***
Children	−0.16 (0.055)**	−0.23 (0.036)***	−0.13 (0.042)*	−0.21 (0.085)**
H_s^a	−1.14 (0.096)***	−1.14 (0.085)***	−0.95 (0.088)***	−0.97 (0.115)***
H_d^a	0.62 (0.119)***	0.17 (0.107)	0.64 (0.108)***	0.71 (0.193)***
Y_m^0	−3.91 (0.602)***	−5.02 (0.764)***	−7.62 (1.085)***	−5.33 (1.113)***
$(Y_m^0)^2$	0.7 (0.122)	0.56 (0.639)	6.0 (1.404)*	2.21 (1.035)
$Var(Y_m^0)$	0.002 (0.001)*	0.002 (0.004)	0.001 (0.001)**	0.001 (0.002)
Informal sector				
Children	−0.12 (0.066)	−0.11 (0.05)	−0.12 (0.059)	−0.04 (0.066)
H_s^a	−0.68 (0.162)***	−0.67 (0.121)***	−0.6 (0.135)***	−0.52 (0.182)***
H_d^a	−0.97 (0.221)***	−0.71 (0.207)***	−0.58 (0.251)**	−0.2 (2.62)
Y_m^0	−9.93 (1.422)***	−13.19 (1.694)***	−11.67 (1.624)***	−11.4 (2.301)***
$(Y_m^0)^2$	1.8 (0.226)	1.93 (0.668)	6.89 (1.372)**	3.96 (4.442)
$Var(Y_m^0)$	0.002 (0.001)	0.002 (0.004)	0.002 (0.001)**	0.002 (0.003)
GF	63.12	61.63	59.06	59.42
R^2	0.325	0.293	0.261	0.275
N	32,284	36,292	27,492	24,240

Notes: *, **, *** significant at the 10 percent, 5 percent, and 1 percent level, respectively (with bootstrapped SE).
Standard errors in parenthesis.
GF refers to the goodness of fit of the model, measured as the percentage of cases predicted correctly, respectively.

plausible explanation for this can lie in the strong family ties observed in Mexico, where the presence of grandparents in the household reduces (or eliminates) child care costs. A very interesting pattern arose in the parameters estimating labor participation dependence of female household

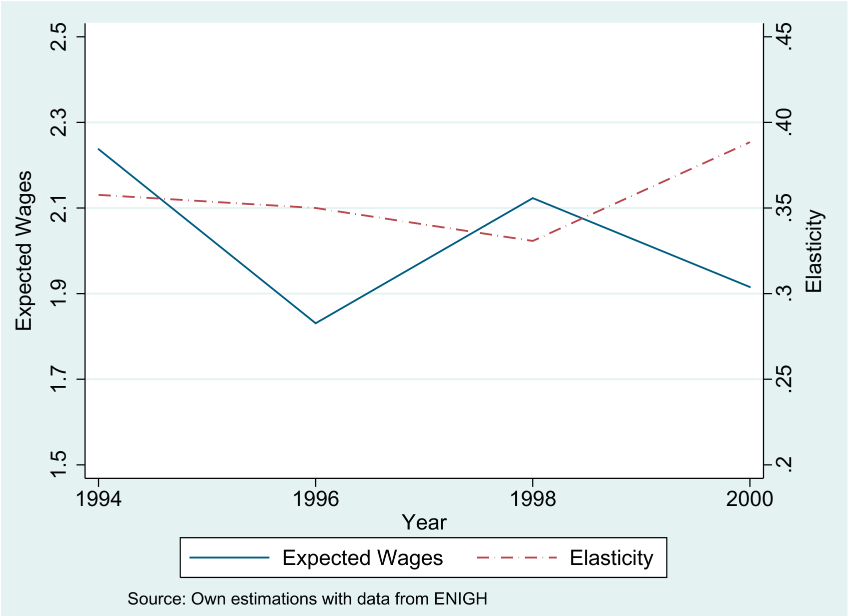

Fig. 3. Wage-Participation Elasticity.

members with respect to the labor status of the head of household. We allow for spouses and daughters to have a different response to the head of the household's participation decision. H_s^a and H_d^a are dummy variables taking a value of one when the woman is a nonhead of household (spouse or daughter, respectively) and the head of the household is actively participating in the labor market. In the case of female spouses, the probability of participation decreases when their husband is working ($H_s^a < 0$). However, notice that this effect is decreasing over time, suggesting that women's participation decisions are becoming less dependent on their husband's labor status. In the case of daughters, the story is completely different, with the probability of being employed in formal sectors increasing when the male head of the household is active, $H_d^a > 0$, and increasing over time. These results suggest that the Mexican labor market is changing in a way such that women's labor participation is less subject to their husband's labor status. Another way of interpreting this result is as a reduction in females' reservation wage or, equivalently, an increase in their *willingness* to work. Therefore, hypothesis (c) suggested in third section also finds support in the data.

The last three controls included in our estimation, Y_m^0, $(Y_m^0)^2$, and $\mathrm{Var}(Y_m^0)$, are capturing, respectively, the income effect, a quadratic form of it and the variance of all other household members' incomes.[23] As we can see from Table 1, the income effect is always *positive*, that is, an increase in exogenous income reduces female labor participation, and with a notsignificant second-order contribution. Only in year 1998 the second-order income effect ($(Y_m^0)^2$) is positive and significant, implying that a positive change in all other household members' income will decrease the probability of female participation and this will be stronger at lower levels of income. Finally, the variable capturing the variance of all other household members' income, $\mathrm{Var}(Y_m^0)$, shows the expected positive sign, although it is only significantly different from zero in 1998. A rise in the variance of household income had as a result an increase in labor participation of female household members during 1998. This could be seen as a rational reaction to try to smooth consumption in a country with strong borrowing constraints like Mexico.

The empirical evidence presented so far shows strong support for the three hypotheses postulated in third section. Given the estimated positive income effect, the negative shock caused by the Peso crisis resulted in more female labor participation. Our wage-participation estimates show that the observed increases in real wages in the manufacturing sector after 1996 also accounts for part of the increase in female participation. Finally, reductions in the dependency between women's labor decisions and the head of household's labor status also played a significant role in explaining the observed increase in female labor participation.

Although this rather simple female labor participation model is able to explain less than a third of the total variation in participation and occupation status of urban women in Mexico, it is enough to predict correctly 60 percent of the cases (see bottom part of Table 1). Appendix D shows that the model has around the same goodness of fit regardless of the age, years of schooling of women, or the size of the household. However, it shows a considerable better fit for women with incomes above \$5,000 pesos per month and those that are not heads of households. Finally, we test the robustness of our results using two other methods of selection-adjustment proposed in Dubin and McFadden (1984) and Bourguignon, Fournier, and Gurgand (2004). Although the value of the parameters changes under these alternative selectivity-correction methods, all the qualitative results hold, making us confident about the robustness of importance played by the three effects described in this section.

The remaining of this chapter quantifies the *relative* importance of the three hypotheses in explaining the increase in labor participation. As we would explain in details in the following section, the microsimulation analysis quantifies the ceteris paribus labor participation effect of changes in the estimated parameters and independent variables. Given the lack of robustness in the *value* (point estimator) of the estimated parameters, the results of the microsimulation analysis should be seen as a first approximation of the quantitative impact on female labor participation of the three competing hypothesis used in the present study: (i) negative income effect brought about by the economic crisis, (ii) increase in real wages in the manufacturing as a result of trade liberalization, and (iii) emancipation of female labor participation decisions.

MICROSIMULATION ANALYSIS

How much of the total increase in female labor participation between 1994 and 2000 can we attribute to the negative income effect caused by the Peso crisis of 1994–1995? What proportion of the increase in participation is explained by changes in female expected wages? How many of the net entrants in the different occupations reported in third section are the outcome of changes in females' reservation wage function? Using a microsimulation exercise helps us understand what are the factors behind the increase in female labor participation in post-NAFTA Mexico.[24]

Define Ω_t as a vector containing all the estimated parameters from the participation function at time t:

$$\boldsymbol{\Omega}_t = (\hat{\delta}_t, \hat{\phi}_t, \hat{\gamma}_t)$$

Similarly, define $\boldsymbol{\chi}_t$ as a vector containing all variables explaining female labor participation and occupation at time t:

$$\boldsymbol{\chi}_t = (\hat{w}_t, \tilde{h}_t, \boldsymbol{Z}_t)$$

Finally introduce a time subindex in the random component of the *utility* function, η. Female labor participation and occupation decisions at time t are hence a function of the three components just defined:

$$\Pr(\cdot)_t = \Pr(\boldsymbol{\Omega_t}, \boldsymbol{\chi}_t, \eta_t) \tag{12}$$

Therefore, any change in the probability of female participation between t and t' can be decomposed into changes in parameters (Ω), exogenous variables ($\boldsymbol{\chi}$), and residuals (η).

As we discussed in third and fourth sections, there are three tested hypotheses explaining the increase in female labor participation: (a) a negative income shock caused by the Peso crisis, (b) a trade-induced positive shift in female labor demand, particularly in the manufacturing sector, and (c) a long-run negative trend in women's reservation wage function. Simulating changes in the components of (12) help us quantify the ceteris paribus labor participation and occupation effects of our three hypotheses.

Measuring the Effects of Changes in $\hat{\boldsymbol{\beta}}$

An exogenous macro shock, for example, currency crisis and trade liberalization, will manifest itself as a change in the relative prices of the economy (both for men and women). In the labor market, the most important "price" is the wage that, in turn, is defined by a set of "prices" or returns to personal characteristics, $\hat{\boldsymbol{\beta}}$. Between 1994 and 1996, we would expect to observe a negative impact on "prices" of personal characteristics of men and women in all occupations as a consequence of the Peso crisis. If this is the case, then *expected* wages, $\hat{w}$, would decrease and, given a positive participation-wage elasticity, participation should be lower as a consequence of the crisis. On the other hand, according to the results of our labor participation model, the same negative shock on the "price" of personal characteristics would reduce household incomes and this, in turn, increases the probability of female participation. To quantify these effects, in our labor participation function, exogenous changes in "prices" will affect elements $\hat{w}$ and $\boldsymbol{Z}$ of component $\boldsymbol{\chi}$. Therefore, the *value* of some of the independent variables defining female participation, $\boldsymbol{\chi}$ (husband's labor participation and all other household member's income), will be a function of the returns to personal characteristics, $c = \chi(\hat{\boldsymbol{\beta}}, \ldots)$.[25] To account for the overall $\hat{\boldsymbol{\beta}}$-induced changes in household incomes and husband's labor participation, it is necessary to parameterize wages and participation decisions for men. This allows us to find out the ceteris paribus effect of changes in "prices" on variables: H_s^a, H_d^a, Y_m^0, and $(Y_m^0)^2$. Remember that H_s^a and H_d^a are dummy variables indicating the labor status of the head of the household (usually the husband) and Y_m^0 measures all other household members' income (strongly dependent on husband's income). Thus, variables H_s^a, H_d^a, Y_m^0, and $(Y_m^0)^2$ will be affected by changes in returns to personal characteristics both in the men's and women's labor market.[26] We, therefore, estimate men's wage equations and participation functions following the same empirical strategy as we did for women; the details of the estimation of husband's wage and participation function can be found in De Hoyos (2005b).[27]

A hypothetical or simulated set of expected wages and household characteristics, $\hat{w}^i$ and $\boldsymbol{Z}^i$, are created by substituting the estimated returns to personal characteristics for year t', $(\hat{\boldsymbol{\beta}}_{t'})$, into the database for year t. The new vector of returns to personal characteristics will have a direct household income effect via the change in labor income. Furthermore, while simulating household incomes, we allow the men in our sample to re-optimize their labor participation and occupation decisions given the new set of expected wages. The procedures we undertake are the following: (1) Estimate the model for men and women using the cross-sectional data for year t and t'. (2) "Import" the wage parameters of year t' into the parameterized model for t. (3) Compute the new set of hypothetical expected wages and household incomes. (4) Allow male household members to change their occupational status given the new value of expected wages and household income. (5) Simulate household incomes using the hypothetical set of wages and men's occupational status. (6) Finally, we simulate the ceteris paribus female participation effects of changes in $\hat{\boldsymbol{\beta}}$ via the expected wages channel $(\hat{w})$ and the exogenous household income channel $(\boldsymbol{Z})$. This allows us to measure the impact – through its different channels – that an exogenous change in the market returns to personal characteristics $(\hat{\boldsymbol{\beta}})$ between t and t' has on female labor participation:

$$\Pr(\cdot)_t^i = \Pr[\boldsymbol{\Omega}_t, \boldsymbol{\chi}_t^i, \eta_t] \tag{13}$$

where $c_t^i = \chi_t^i[\hat{w}^i(\hat{b}_{t'}), Z^i(\hat{b}_{t'})...]$; $\Pr(\cdot)_t^i$ is a *simulated* probability (since it is not observed) at the *micro* level (since we compute one for each individual in the sample). Using the estimation results of our model plus the estimated parameters for men, the three components of (13), Ω_t, $\boldsymbol{\chi}_t^i$, and η_t, are observed. To summarize our procedure, we are "importing" the estimated wage equation parameters $(\hat{\boldsymbol{\beta}})$ for year t' into the data set for year t. Once the parameters are in the database for year t, we simulate a hypothetical expected wage and household income ($\hat{w}^i$ and $\boldsymbol{Z}^i$) that we then use to construct $\boldsymbol{\chi}_t^i$. Finally we multiply $\boldsymbol{\chi}_t^i$ by Ω_t and add the residual terms η_t. This will create a new *utility*-maximizing decision, and therefore a new set of participation/occupation probabilities for each woman within working age (actual and potential worker). We undertake three separate simulations, taking 1994 as the base year and "importing" the estimated wage parameters for the years 1996, 1998, and 2000, respectively. The simulation results are summarized in Fig. 4.

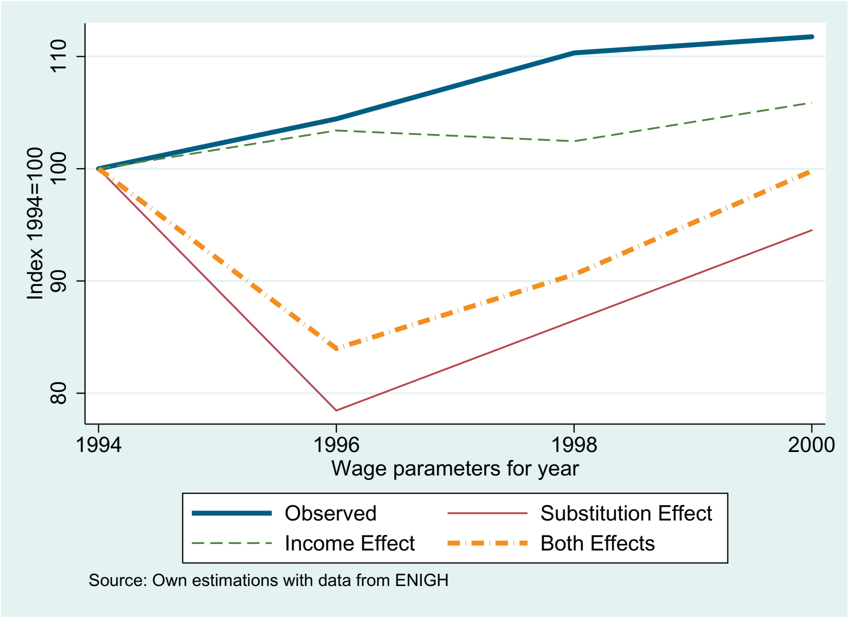

Fig. 4. Simulated Participation Effect of $\Delta\hat{\boldsymbol{\beta}}$.

In Fig. 4, we graph the time trend of the observed and simulated change in participation (with respect to 1994) due to a change in the wage equation parameters. To decompose the effect of $\Delta\hat{\boldsymbol{\beta}}$ even further, we perform three different simulations for each "imported" $\hat{\boldsymbol{\beta}}$ we compute: (1) a simulation where only expected wages, $\hat{w}$, are allowed to change (continuous thin line); (2) a second one where only the household income elements of $\boldsymbol{Z}$ change (dashed thin line), and (3) a third one where both $\hat{w}$ and $\boldsymbol{Z}$ are changing as a consequence of $\Delta\hat{\boldsymbol{\beta}}$ (dashed thick line).[28] We perform these separate simulations because we can interpret the first and second simulations as the *substitution* and *income effects*, respectively, of changes in returns or prices of personal characteristics.

For the moment, let us concentrate on the changes taking place between 1994 and 1996. The observed change in participation (the continuous thick line in Fig. 4) is positive. According to our model, if expected wages were the only element changing during those years of deep economic crisis, female participation would have been reduced by 22 percent (continuous thin line).

Given the positive wage-participation elasticity found in fourth section, this result is explained by the reduction in average expected wages ($\hat{w}$) between 1994 and 1996 (see Fig. 3), which is, in turn, caused by a reduction in returns to personal characteristics ($\hat{\boldsymbol{\beta}}$). Concerning the income effects of the crisis, the estimated reduction in payments to personal characteristics had a negative effect on household's income (Y^0) and also on men's participation decisions.[29] The ceteris paribus simulated participation effect of $\boldsymbol{Z}^i$ is shown in Fig. 4 (dashed thin line). We can see that had the change in household incomes and head of the household participation decisions – as a consequence of a negative shock in $\hat{\boldsymbol{\beta}}$ – been the only change taking place between 1994 and 1996, then female labor participation would have increased as much as the observed increase during those years. This is explained by the crisis' negative income effect that "pushed" more women into the labor market. The final simulation presented in Fig. 4 includes both changes, $\hat{w}^i$ and $\boldsymbol{Z}^i$, together in the same simulation. The simulated net participation effect is negative, in other words, had remunerations to personal characteristics decreased in the way they did between 1994 and 1996, female participation would have decreased 13 percent, ceteris paribus.

Let us now analyze the changes that occurred during the recovery period 1996–2000. As $\hat{\boldsymbol{\beta}}$ experienced a positive change, household incomes increased and, given the positive income effect estimated, the participation rate attributable to the income effect decreased, although it remained above the 1994 value (thin dashed line). Regarding wage effects, the increase in returns to personal characteristics taking place between 1996 and 1998 (see Fig. 3) explains the simulated increase in female labor participation between 1996 and 1998 (continuous thin line), although still below the 1994 participation rate. These results show that, controlling for all other changes taking place in the economy between 1994 and 2000, shifts in the returns to personal characteristics would have *decreased* the participation rate by 0.2 percent out of a total *increase* of 12 percent observed during that period.[30]

So far, we have simulated the participation rate that we would have observed if returns to personal characteristics were the only elements changing in the economy, but what about the simulated occupation effects? In Appendix F we present the simulated percentage change in the female participation rate in the manufacturing, other formal and informal sectors. As we can see, the simulated change in participation attributable to shifts in $\hat{w}$ in the manufacturing sector between 1994 and 1996 is positive. Quite the opposite can be said for other formal sectors. These results suggest that, in the absence of labor rationing, the isolated participation effects of changes in $\hat{\boldsymbol{\beta}}$ would have triggered female labor participation in the manufacturing sector and reduced participation in other formal sectors during the crisis years 1994–1996. The effect is explained by the increase in $\hat{\boldsymbol{\beta}}$ taking place in the manufacturing sector even during a time of general contraction of the economy (1994–1996).[31] The positive simulated participation trend in the manufacturing sector remains between the years 1996 and 1998 and then slows down in the period 1998–2000. The figures in Appendix F illustrate the simulated wedge in labor participation that opened between the manufacturing and other formal sectors during the crisis. The negative participation effect brought about by the Peso crisis was cushioned by a trade agreement such as NAFTA, triggering manufacturing exports, increasing relative expected wages, and labor participation. Regarding the occupational changes brought about by the 1994–1996 negative income shock, notice how it has a much larger effect on participation in the informal sector (a 20 percent increase). This result suggests that in the presence of borrowing constraints, the informal sector absorbed part of the female laborers, particularly young ones, that were ''pushed'' into the labor market by the negative income shock.

To summarize, we have shown that the positive post-1994 trend in overall urban labor participation described in Fig. 1 is explained partly by increases in manufacturing sector participation and, to a lesser extent, by an increase in participation in the informal sector. The explanations behind these shifts are completely different. On the one hand, the positive trends in manufacturing participation are explained by positive shifts in $\hat{\boldsymbol{\beta}}$ for manufacturing female laborers. On the other hand, the increase in the informal sector participation is explained by a negative income shock. Therefore, the data supports the hypothesis of a trade-induced increase in female labor demand taking place in the manufacturing sector between 1994 and 2000 and an increase in participation as a consequence of the 1994–1995 Peso crisis, primarily in the informal sector.

Measuring the Effects of Changes in Ω

The previous simulations uncovered the participation and occupation effects of exogenous changes in wage functions parameters that in turn affected the vector of explanatory variables, $\boldsymbol{\chi}$. All the counterfactuals constructed so far had evaluated the labor participation effects of changes in ''prices'' of personal characteristics. Assuming that in the short run labor supply is close to being constant, these changes are basically capturing trade and devaluation-induced shifts in labor demand. In this section, we simulate the participation and occupation effects that are attributable to changes in the parameters defining the "reservation wage function," γ in Eq. (11).

We are interested in quantifying the participation and occupation effects of changes in reservation wage function parameters *free* of labor market effects. To do so, let us separate the variables in $\boldsymbol{Z}$ into two different matrices: $Z = (Z_{w*}, Z_y)$. Z_{w*} contains variables that are strictly affecting female's reservation wage function without being affected by the prevailing market conditions, hence $Z_{w*} = (H_s^a, H_s^a, \text{Children})$. $\boldsymbol{Z}_y$, on the other hand, contains all the income variables: Y_m^0, $(Y_m^0)^2$ and $\text{Var}(Y_m^0)$, which are, as a matter of fact, capturing the Peso devaluation shock. The only parameters that are allowed to vary in the simulations are those in Z_{w*}. The parameters in the income variables (Y_m^0, $(Y_m^0)^2$, and $\text{Var}(Y_m^0)$) are kept constant since they are highly unstable across cross-sections, capturing part of the instability brought about by the Peso crisis. Furthermore, we also keep constant the parameters on δ and φ. Changes in the price-wage elasticity (δ) and the parameter for the standard deviation of hours worked (φ) are not allowed to vary since, as we saw in second section, these parameters are determined by the interaction between expected wages and a female's reservation wage function (see Eqs. (5 and 6)). The varying parameters in the simulation (i.e., those of variables H_s^a, H_s^a, and Children), on the other hand, are parameters that affect female's reservation wage function without affecting market wages; moreover, the parameters of these variables are much more stable in time and are not affected by market conditions. Changes in parameters γ_{w*} would capture the ceteris paribus participation effects of changes in female reservation wage function parameters. A hypothetical value of Ω will be defined as follows:

$$\boldsymbol{\Omega}_t^i = (\hat{\delta}_t, \hat{\varphi}_t, \hat{\gamma}_t^i)$$

where $\hat{\boldsymbol{\gamma}}_t^i$ is a hypothetical vector containing the estimated parameters $\hat{\boldsymbol{\gamma}}_{y,t}$ and the "imported" ones $\hat{\gamma}_{w*,t'}$. Following last section's counterfactual analysis, to capture the dynamics of changes in $\hat{\gamma}_{w*}$, we take the year 1994 as the base and "import," in separate simulations, the "reservation wage function" parameters for the years 1996, 1998, and 2000, respectively. The way we interpret these results is similar to the interpretation given in section "Measuring the Effects of Changes in $\hat{\boldsymbol{\beta}}$"; that is, the simulated participation and occupation decisions yield the ceteris paribus effect of changes in $\hat{\gamma}_{w*}$ observed between t and t'. Based on our structural model, we can think of changes in $\hat{\gamma}_{w*}$ as changes in women's reservation wage function parameters, or their subjective *willingness* to work. As we mentioned before, parameters $\hat{\gamma}_{w*}$ of the participation function (Eq. (11)) should not be affected by changes in market conditions; therefore, the simulations can be interpreted as capturing *exogenous* changes in women's willingness to work. The results of the simulations are shown in Fig. 5.

From Fig. 5 we can see that if the only changes observed between 1994 and 1996 had been the changes in participation function parameters $\hat{\gamma}_{w*}$, then we would have seen a decrease in participation of almost 3 percent. Given that the net participation effect of changes in χ during the crisis years 1994–1996 was negative (see Fig. 4), we can infer that the observed increase in female participation after the Peso crisis was, at least partly, the result of a negative income shock affecting household incomes over and above the reduction in returns to personal characteristics. The rather small participation effects of changes in $\hat{\gamma}_{w*}$ are not surprising given the small pace at which preferences tend to change. In the case of Mexico, we can see that there is a relatively large change in preferences favoring female participation between 1996 and 1998. Although the parametric changes captured by our

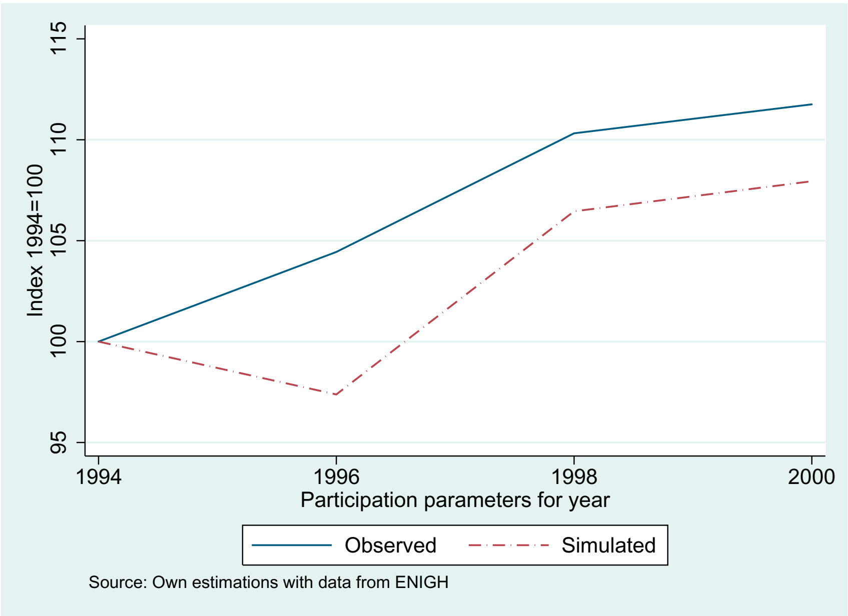

Fig. 5. Simulated Participation Effect of $\hat{\gamma}_{w*}$.

simulations are *free* of market shocks, they might still be capturing, in an indirect fashion, the effects of macroeconomic turmoil. It is difficult to measure the extent to which this result is actually triggered – although indirectly – by the macro shocks of 1995 (NAFTA/devaluation), but certainly these changes help explain the increase in participation in the recovery years 1996–2000.[32] Shifts in $\hat{\gamma}_{w*}$ are enough to explain almost 8 percent of a total increase of 12 percent occurring between 1994 and 2000.

In Appendix G, we present the simulated changes in occupation given the new set of parameters $\hat{\gamma}_{w*}$. The results are revealing. The change in participation function parameters between 1994 and 1996 made participation in the manufacturing sector more likely and quite the opposite for the nonmanufacturing sectors. This could be seen as a sign of a general increase, during the crisis years of 1995–1996, in female preferences for manufacturing sectors as opposed to the nonmanufacturing ones. Nevertheless changes in $\hat{\gamma}_{w*}$ can only explain 6 percent of the total 20 percent increase in female participation in the manufacturing sector. Hence, the observed increase in this sector after NAFTA and the Peso devaluation is explained mainly by the relative increase in returns to personal characteristics in the manufacturing sector $\hat{\boldsymbol{\beta}}_{\text{manu}}$, and to a lesser extent by changes in $\hat{\gamma}_{w*}$.

The simulated changes in $\hat{\gamma}_{w*}$ in the nonmanufacturing formal sectors follows quite closely the observed overall participation performance in those sectors. This is not the case for the informal sector, where the simulated participation is actually moving opposite the trend shown by the observed informal sector participation. This last result suggests that, although participation in the informal sector was increasing during the crisis years, this sector was seen as an unwanted option. Therefore, during the years of economic crisis, the informal sector represented a labor option that was chosen more as a mean for increasing household incomes than as a real preferred alternative.

We showed that although some of the parameters defining female reservation wage function moved in a way that favored labor participation, once we quantify their simultaneous changes, they cannot explain the observed increase in female labor participation between 1994 and 1996. During the recovery period 1996–2000, the positive change in participation is explained by an increase in expected wages (see section "Measuring the Effects of Changes in $\hat{\boldsymbol{\beta}}$"), on the one hand, and changes in women's *willingness to work* on the other. As we discussed in section "Measuring the Effects of Changes in $\hat{\boldsymbol{\beta}}$," the occupational effect of changes occurring during the crisis shows that the trade-driven buoyant manufacturing sector was absorbing most of the new entrants throughout this period.

Our microsimulation exercises undertaken in sections "Measuring the Effects of Changes in $\hat{\beta}$" and "Measuring the Effects of Changes in Ω" showed the usefulness of this type of analysis in terms of quantifying several changes occurring at the same time. Nevertheless, they also exhibit the weakness of the microsimulation analysis in a framework with few time periods and large parameter volatility.

SUMMARY AND CONCLUSIONS

We developed a structural model describing female labor participation and occupation decisions. In our model, women's participation and occupation decisions are taken in a simultaneous way, with participation decisions being embedded in the occupational one. The structural model is used to define and interpret a microeconometric model suitable for estimation. We correct for selectivity in the wage equations by parameterizing the conditional probabilities of labor participation as suggested by Lee (1983). Our model creates an explicit and causal relationship between expected selectivity-adjusted wages and participation/occupation decisions. Other factors such as the labor status of the head of the household, the number of children, and all other household members' incomes are used as controls within a generalized MNL framework.

We apply the model to Mexican urban household data for the years 1994, 1996, 1998, and 2000, respectively. The estimated wage-participation elasticity shows stability fluctuating from a lower value of 0.33 to an upper one of 0.39. Between 1994 and 2000, female participation in Mexico rose by 12 percent. Three hypotheses for the documented increase in female labor participation have been suggested and tested in this chapter: (a) a negative income shock caused by the Peso crisis of 1994–1995, (b) a trade-induced increase in female labor demand in the manufacturing sector, and (c) a change in the female reservation wage function favoring participation. The results from our micro model support all three hypotheses suggesting that the observed increase was the outcome of simultaneous and, sometimes, opposing effects being at work between 1994 and 2000.

Using microsimulation techniques, we were able to quantify the female participation/occupation effects attributable to changes in the parameters defining the participation and wage functions between 1994 and 2000. The results show that the increase in participation observed between 1994 and 1996 is partly explained by the negative income shocks of the Peso crisis. During the recovery period 1996–2000, increasing female participation is the outcome of relatively higher expected wages in the manufacturing sector and changes in women's *willingness* to work, the reservation function parameters.

There is still plenty of scope for future increases in female labor participation in Mexico. We found a significant expansion in female labor market opportunities, primarily in the export-oriented manufacturing sector. Nonmarket-related changes in women's *willingness* to work also help to explain the recent positive trend. As we have shown, women's reaction to market incentives are increasing over time, with higher wage-participation elasticities, and less labor dependency with respect to the (male) head of the household. Most of the positive shifts in female participation are explained by relative increases in real wages in trade-driven manufacturing sector. Therefore, trade policy in manufacturing-intensive less developed countries can be seen as a tool to increase female labor participation (see Bussolo & De Hoyos, 2009). The Mexican government should, therefore, promote export-oriented firms and investment, while creating training programs so that more women presently employed in informal sectors can find a place in the manufacturing industry.

NOTES

1. Elizabeth Monroy and Ricardo Charles provided useful data assistance. The usual caveat applies.

2. In the empirical section, the term utility defined here should be taken with caution since probably it embeds demand-side restrictions in the labor market, hence the observed *choice* might not be entirely the outcome of a personal utility-maximizing process.

3. To clarify the notation, $\boldsymbol{\lambda}$ is a scalar, $\boldsymbol{\gamma}'_j$ and $\boldsymbol{\gamma}_j$ are vectors of size K_1 and K_2 reflecting the effects of personal and household characteristics, respectively, on reservation wages measured in utility units.

4. As stated by Heckman: "Participation (or employment) decisions generally manifest greater responsiveness to wage and income variation than do hours-of-work equations for workers" (Heckman, 1993, p. 117).

5. A sufficient assumption to have a single parameter for expected wages across all outcomes is that $\gamma'_j/mib\hat{\boldsymbol{\beta}}_j = c \; \forall \; j$ where c is a constant (see Eq. (5)). This is equivalent to imposing a constant ratio of marginal market *price* of characteristics $\boldsymbol{X}_i$ relative to its subjective valuation (in terms of reservation wage) across occupations. In other words, every time personal characteristics increase their market remuneration in a particular occupation, individuals will increase, in the same proportion, their subjective valuation of them. This implies, obviously, a constant wage-participation elasticity across all individuals and occupations; this is certainly a restrictive assumption.

6. Notice that Eq. (8) imputes an estimated wage for each of the J possible occupations for each women, regardless of their working status. In the case of ''nonactive,'' the impute wage is zero.

7. This model, as opposed to others such as the multinomial probit or the random effects model, has the drawback that it imposes the independence of irrelevant alternatives (IIA) assumption. Therefore, all our results should be analyzed bearing this restriction in mind.

8. Experience is measured as age minus years of schooling minus 6; the regional dummy variable takes the value of 1 when the state is in the north of Mexico. The mean and standard deviation of all the variables included in our model are shown in Appendix A.

9. We classify workers as being in the informal sector when they are nonprofessional self-employed workers. We exclude family workers who get no monetary remuneration (see Maloney, 1999).

10. Not active agents include women who were actively looking for a job (unemployed), not active housewives, and ''other not active'' (e.g., women such as pensioners and landladies). Housewives and ''other not active'' women account for 95 percent and 3 percent of the total inactive female population, respectively. Less than 2 percent of the female inactive population in 2000 was actively looking for a job; hence, the use of a theoretical framework where one of the utility-maximizing choices is to be inactive is, at least, a plausible first approximation of the participation decision process.

11. As it is shown in Heckman's (1979) influential paper, sample selection bias can be thought as a specification error. Including a transformation of the conditional probability of participation is enough to control for selection bias. For a more recent discussion of the advantages and disadvantages of the different ways to control for sample selection bias using a MNL, see Bourguignon et al. (2004).

12. Given the two-step nature of the procedure, all the standard errors presented in fourth section are corrected via bootstrapping methods.

13. To construct this variable, we segmented the population into different labor cohorts (education, experience, and working position); we used this information to compute the variance of all other household members' income (see Appendix B for details.)

14. In our case, a combination of a conditional and a MNL. Maddala (1983) shows that these two models are mathematically the same; hence, I will simply refer to it as a MNL.

15. Notice that expected wages in (11) are in levels so the expected wage of outcome ''not active'' is equal to zero.

16. Since ENIGH is not a probabilistic survey, we account for sampling design taking expansion factors, stratification, and clustering into account. All the statistical analysis carried out throughout the paper accounts for survey design (see De Hoyos (2005a) for details).

17. The actual increase in female labor participation observed between 1994 and 2000 is 1,779,105 new entrants. The difference between the net entrants (707,993) and the actual one (1,779,105) is explained by an increase in the base population, that is, by demographic and population changes as well as rural–urban migration during those years.

18. Equation (10) is estimated using our own Stata command, *svyselmlog*. *svyselmlog* is the survey version of the original *selmlog*. The command estimates the parameters of the main equation (in this case wages) correcting for selectivity using a MNL and accounting for survey design effects; several forms of selectivity correction are available. *svyselmlog* is available from the SSC (Boston College) archives (De Hoyos, 2005c).

19. Because of space limitations, we do not present the results from the first-stage estimations, $\Pr(\boldsymbol{X}, \boldsymbol{Z})$; however, they are available from the author upon request.

20. Most of the ''maquiladoras'' (export processing zones) created after 1994 were located in the north of Mexico (Nicita, 2009; De Hoyos & Lustig, 2009).

21. In fact, the parameters in Table 1 are the effects on the latent function determining the participation probabilities – the utility function (6); the marginal effect of $\hat{W}$ on the probability of being active is shown in Fig. 3.

22. The wage-participation elasticity figures in 1998 and 2000 are not statistically different from each other.

23. For presentational purposes, all income variables were rescaled to 1:100,000.

24. For a detailed explanation on the microsimulation technique used in this section, see Bourguignon and Ferreira (2005).

25. The income variables used in the participation functions (Y_m^0) include the sum of income of *all other* household members; hence, although they are being parameterized here, they can be seen as being strictly exogenous for each particular individual.

26. If our database was longitudinal, we wouldn't have to compute these hypothetical $\boldsymbol{Z}$ values, we could have used the *observed* change in income for each household. However, we cannot identify the same family in two different points in time; therefore, we have to simulate the *exogenous* change in household income based on the observed changes in ''prices'' of personal characteristics.

27. The variables determining men's wages are the same as the ones used for women ($\boldsymbol{X}$). The identification variables $\boldsymbol{Z}$ for men include the size of the household and all other household members' income and its squared form. All the estimation results for men are available from De Hoyos (2005b).

28. Although the sum of the substitution and income effects are very close to the simulation where both effects are allowed, the decomposition methodology that we use does not show additive properties. Therefore, the sum of the effects brought about by the different elements in Eq. (12) is not necessarily equal to the total effect.

29. See Appendix E with the simulated mean household income brought about by $\Delta\hat{\boldsymbol{\beta}}$.

30. This result depends very much on the nonrationed labor markets assumption; that is, labor participation and occupation decisions are purely the outcome of a utility-maximizing process and do not face labor demand restrictions.

31. At this point, is it worthwhile to remind the reader that, since we are controlling for selectivity, $\hat{\boldsymbol{\beta}}_j$ can be interpreted as a sector *j*-specific *treatment* effect; that is, a relative increase in $\hat{\boldsymbol{\beta}}$ in the manufacturing sector, compared to other sectors, is indicating a manufacturing-specific wage premium.

32. In fact, the microsimulation exercise undertaken here uncovers a weakness of this type of analysis. As we mentioned before, the microsimulation analysis relies on certain degree of parameter stability. When parameters are not stable (or not significant), it is cumbersome to make any inference based on a ceteris paribus

change in parameters between two points in time. A solution for this could be to smooth the estimated parameters with a time trend polynomial term; however, fitting a polynomial term with only four points in time tends to be a rather meaningless exercise.

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APPENDIX A: DESCRIPTIVE STATISTICS OF THE VARIABLES USED IN THE MODEL

	1994	1996	1998	2000
Notactive				
Hourly wages (W)	0	0	0	0
Hours worked	0	0	0	0
Children	0.823	0.852	0.770	0.718
	(0.983)	(0.985)	(0.949)	(0.913)
H_s^a	0.642	0.637	0.655	0.664
	(0.479)	(0.481)	(0.475)	(0.472)
H_d^a	0.157	0.168	0.149	0.133
	(0.364)	(0.374)	(0.356)	(0.340)
Y_m^0	0.119	0.083	0.083	0.098
	(0.158)	(0.14)	(0.094)	(0.121)
$(Y_m^0)^2$	0.039	0.027	0.016	0.024
	(0.457)	(0.595)	(0.079)	(0.120)
$Var(Y_m^0)$	11.271	6.717	9.867	6.629
	(79.472)	(129.104)	(59.598)	(60.599)
Schooling	6.790	7.059	7.160	7.549
	(3.824)	(3.759)	(3.756)	(3.878)
$Schooling * I(Y_s > 11)$	1.842	1.675	1.656	2.257
	(4.624)	(4.561)	(4.556)	(5.187)
Experience	22.753	22.387	23.194	23.533
	(15.171)	(14.978)	(14.93)	(14.826)
Experience	747.855	725.535	760.869	773.648
	(827.305)	(807.355)	(814.037)	(805.865)
North	0.336	0.352	0.368	0.368
	(0.472)	(0.478)	(0.482)	(0.482)
Manufacturing earner (tradable)				
Hourly wages (W)	2.807	2.468	2.536	2.752
	0.845	0.891	0.874	0.839
Hours worked	47.422	47.473	47.414	47.181
	10.736	10.520	9.486	9.526
Children	0.489	0.631	0.590	0.629
	(0.780)	(0.985)	(0.856)	(0.884)
H_s^a	0.341	0.314	0.343	0.331
	(0.474)	(0.481)	(0.475)	(0.471)

	1994	1996	1998	2000
H_d^a	0.319	0.359	0.337	0.391
	(0.466)	(0.374)	(0.473)	(0.488)
Y_m^0	0.091	0.059	0.062	0.065
	(0.102)	(0.14)	(0.077)	(0.052)
$(Y_m^0)^2$	0.019	0.006	0.010	0.007
	(0.082)	(0.595)	(0.051)	(0.013)
$Var(Y_m^0)$	14.770	7.275	17.130	1.931
	(74.576)	(129.104)	(157.016)	(7.756)
Schooling	8.539	8.252	8.428	8.435
	(3.279)	(3.759)	(3.268)	(3.307)
Schooling * $\mathrm{I}(Y_s > 11)$	2.663	1.961	2.158	2.051
	(5.463)	(4.561)	(5.136)	(5.015)
Experience	12.963	14.134	13.830	14.231
	(10.555)	(14.978)	(10.740)	(11.205)
Experience	279.455	328.551	306.611	328.067
	(432.293)	(807.355)	(437.686)	(483.550)
North	0.495	0.434	0.508	0.597
	(0.500)	(0.478)	(0.500)	(0.490)
Other earner (nontradable)				
Hourly wages (W)	2.985	2.623	2.633	2.819
	0.964	0.930	0.984	0.905
Hours worked	45.219	45.551	45.273	45.292
	14.753	14.929	15.042	14.230
Children	0.590	0.574	0.569	0.467
	(0.873)	(0.845)	(0.876)	(0.767)
H_s^a	0.371	0.407	0.404	0.416
	(0.483)	(0.491)	(0.491)	(0.493)
H_d^a	0.296	0.224	0.268	0.245
	(0.456)	(0.417)	(0.443)	(0.430)
Y_m^0	0.110	0.074	0.078	0.089
	(0.124)	(0.093)	(0.110)	(0.097)
$(Y_m^0)^2$	0.028	0.014	0.018	0.017
	(0.101)	(0.126)	(0.241)	(0.070)
$Var(Y_m^0)$	25.756	74.821	37.540	11.889
	(140.278)	(2496.283)	(336.419)	(55.853)
Schooling	9.643	9.911	9.870	10.386
	(4.516)	(4.427)	(4.549)	(4.426)

	1994	1996	1998	2000
Schooling * $I(Y_s > 11)$	5.593	5.430	5.327	5.959
	(7.081)	(7.181)	(7.254)	(7.449)
Experience	16.141	16.989	16.923	17.237
	(11.76)	(11.877)	(12.393)	(12.266)
Experience^2	398.827	429.702	439.974	447.570
	(520.172)	(537.881)	(559.289)	(541.501)
North	0.351	0.332	0.335	0.325
	(0.477)	(0.471)	(0.472)	(0.468)
Informal sector				
Hourly wages (*W*)	2.491	2.068	2.113	1.985
	1.072	1.533	1.833	1.197
Hours worked	42.293	40.973	40.815	41.461
	21.766	21.321	21.387	19.898
Children	0.666	0.674	0.615	0.580
	(0.842)	(0.885)	(0.893)	(0.824)
H_s^a	0.529	0.529	0.549	0.560
	(0.499)	(0.499)	(0.498)	(0.496)
H_d^a	0.073	0.077	0.088	0.069
	(0.261)	(0.267)	(0.284)	(0.254)
Y_m^0	0.068	0.047	0.054	0.056
	(0.075)	(0.045)	(0.058)	(0.048)
$(Y_m^0)^2$	0.010	0.004	0.006	0.005
	(0.035)	(0.011)	(0.025)	(0.011)
$Var(Y_m^0)$	17.697	4.605	27.901	7.383
	(104.926)	(21.75)	(251.354)	(41.474)
Schooling	5.761	5.856	6.195	6.535
	(3.811)	(3.947)	(3.929)	(4.017)
Schooling * $I(Y_s > 11)$	1.319	1.180	1.322	1.561
	(3.919)	(3.945)	(4.161)	(4.404)
Experience	28.577	27.446	27.725	28.412
	(13.885)	(13.671)	(13.611)	(13.332)
Experience	1009.462	940.149	953.938	985.005
	(860.215)	(796.212)	(792.715)	(807.199)
North	0.357	0.325	0.308	0.302
	(0.479)	(0.468)	(0.461)	(0.459)

Note: Standard errors in parenthesis.

APPENDIX B: MEASURING HOUSEHOLD INCOME VARIANCE

To estimate the way in which household income variations affects female labor participation, we have to construct a variable able to capture variations in household incomes as *perceived* by *each* household member. Let us start by defining a measure of household income variance. In a cross-sectional framework, we cannot estimate the time variation in household incomes; therefore, we have to use the observed variation within socioeconomic and demographic groups. These groups were defined according to the following observable characteristics: gender, formal education, experience, and position in their working place. The combination of these characteristics formed a total of 263 groups each of them containing different average income (μ) and variance [Var(Y)]. Household income variance is computed using the within population cohorts variance. The way in which the population cohort and the household variances are linked must be consistent with a measure of household variance showing some desired properties. Following Attanasio, Low, and Sánchez-Marcos (2004), we define Axiom 1:

> **Axiom 1.** In the presence of borrowing constraints, where rational agents' optimal choice is to smooth consumption, women's participation probability increases as a response to a rise in the *expected* variance of household incomes. Therefore, the *observed* income variance of a household whose female member is active should be smaller than the one that we would have observed had participation not occurred.

Our preferred measure of household income should comply with Axiom 1. It turned out that the measure of household income variance that we propose here satisfies Axiom 1.

While forming income variance expectations, agents are aware of all other household members' characteristics; for example, a household wife knows the characteristics of her husband and children. Assume that the mean income and variance attached to each of the 262 population cohorts is constant over time and that this information is known by each of the

Table B.1. Average Income and Variance.

	Men	Women
μ	4,704	3,358
$Var(Y)$	5.24e + 07	1.14e + 07

household members. In the process of deciding whether to participate in the labor market or not, agents form their personal *perception* of what the variance of household income will be. This personal *perception* is the expected value of the variance of all other household members' income. For agents who are not participating in the labor market:

$$\mathrm{Var}(Y_h^i) = \sum_j^m \frac{\mu_j}{\sum_j^m \mu_j} \mathrm{Var}(Y_j) \quad \forall\ j = 1...m : \text{Active Members} \tag{14}$$

Each nonactive household member's expectation will be a weighted average of income variance of all active members. The weight assigned to each active member *j* is formed by the average income within *j*'s population cohort divided by the sum of average incomes of all population cohorts where active household members belong to. In the case of active members, the expected variance will be formed by the variance that they would observe if they decided to abandon the labor market. This is equivalent to create a household income variance with the following counterfactual: what would the variance look like had the agent decided not to participate. This definition of variance for the active members is comparable to the one computed for nonactive members, since it is computing the household variance as if the active member became not active:

$$\mathrm{Var}(Y_h^{i'}) = \sum_j^{m-1} \frac{\mu_j}{\sum_j^{m-1} \mu_j} \mathrm{Var}(Y_j) \quad \forall\ j = 1...m : \text{Active Members} \tag{15}$$

Given our definition of household income variance, a sufficient condition for it to satisfy Axiom 1 is:

Axiom 2. The population cohort variance [Var(*Y*)] of the marginal women entering the labor market is smaller than the observed weighted average values for all other household members.

If Axiom 2 is true, then the counterfactual variance – that is, the variance in the absence of their participation – for participating women will be larger than the observed one. Equivalently, the total household income variance should decrease as an outcome of their participation. If Axiom 1 is true and this information is known by female household members, then participating in the labor market is a consumption-smoothing decision. This is exactly the property stated by Axiom 1. For the Mexican labor market, Axiom 2 turns out to be an empirical regularity; that is, the observed income variance within female population subgroups is less than the observed statistic for male subgroups.

APPENDIX C: SELECTIVITY-ADJUSTED WAGES

Table C.1. Wage Functions for the Manufacturing Sector.

	1994	1996	1998	2000
Schooling	0.138***	0.105***	0.149***	0.111***
Schooling * $I(Y_s > 11)$	−0.004	0.022*	0.003	0
Experience	0.068***	0.042***	0.071***	0.031**
Experience^2	−0.001***	−0.001**	−0.001***	0
North	0.074	0.141**	0.269***	0.333***
Pr(manufacture)†	0.275	0.142	−0.076	0.105
Intercept	0.355	0.579*	0.295	0.801**
R^2	0.267	0.246	0.28	0.236
N	491	609	511	428

Notes:
*, **, *** significant at the 10 percent, 5 percent, and 1 percent level, respectively.
Bootstrapped standard errors with 200 replications.
Data source: ENIGH 1994, 1996, 1998, and 2000.
$\Pr(\cdot)^\dagger$ are computed accordingly to Eq. (10).

Table C.2. Wage Functions for Other Earning Sectors.

	1994	1996	1998	2000
Schooling	0.148***	0.136***	0.143***	0.131***
*Schooling** $I(Y_s > 11)$	0.020***	0.014***	0.021***	0.011*
Experience	0.077***	0.069***	0.060***	0.057***
Experience^2	−0.001***	−0.001***	−0.001***	−0.001***
North	−0.046	0.004	0.083*	0.105**
Pr(other earner)†	0.290***	0.245***	0.243*	0.065
Intercept	0.337**	0.21	0.059	0.637***
R^2	0.468	0.374	0.409	0.402
N	2,213	2,393	1,950	1,850

Notes:
*, **, *** significant at the 10 percent, 5 percent, and 1 percent level, respectively.
Bootstrapped standard errors with 200 replications.
Data source: ENIGH 1994, 1996, 1998, and 2000.
$Pr(\cdot)^\dagger$ are computed accordingly to Eq. (10).

Table C.3. Wage Functions for the Informal Sector.

	1994	1996	1998	2000
Schooling	0.081***	0.064***	0.052**	0.037
Schooling $I(Y_s > 11)$	0.013	0.004	0.034*	0.026
Experience	0.023	0.046***	0.033*	0.063**
Experience^2	0.0	−0.001**	0.0	−0.001*
North	−0.124	0.034	−0.076	−0.096
Pr(informal)†	0.062	0.364	0.143	0.701*
Intercept	1.368**	0.272	0.902	−0.23
R^2	0.053	0.062	0.052	0.084
N	620	857	663	581

Notes:
*, **, *** significant at the 10 percent, 5 percent, and 1 percent level, respectively.
Bootstrapped standard errors with 200 replications.
Data source: ENIGH 1994, 1996, 1998, and 2000.
$\Pr(\cdot)^{\dagger}$ are computed accordingly to Eq. (10).

APPENDIX D: GOODNESS OF FIT OF THE MODEL

Table D.1. Proportion of Correct Predictions by Sociodemographic Group (%).

		1994	1996	1998	2000
Age	1	65.3	63.0	60.1	60.7
	0	60.2	59.7	57.5	57.3
Years of schooling	1	59.8	59.8	58.7	61.7
	0	64.0	62.5	59.4	59.9
Income	1	85.9	89.0	86.6	86.1
	0	24.0	26.6	27.9	27.5
Household size	1	63.5	61.1	58.9	61.5
	0	62.8	62.1	59.2	57.0
Head	1	48.3	47.2	45.2	45.4
	0	64.8	63.5	61.0	61.4

Notes:
All sociodemographic characteristics are captured by dummy variables.
"Age"' gets the value of 1 if woman is 30 years or older.
"Years of schooling"' get the value of 1 if woman has 11 or more years of formal schooling.
"Income"' gets the value of 1 if personal monthly income is higher than $5,000.
"Household size" gets the value of 1 if the household is composed of 4 or more members.

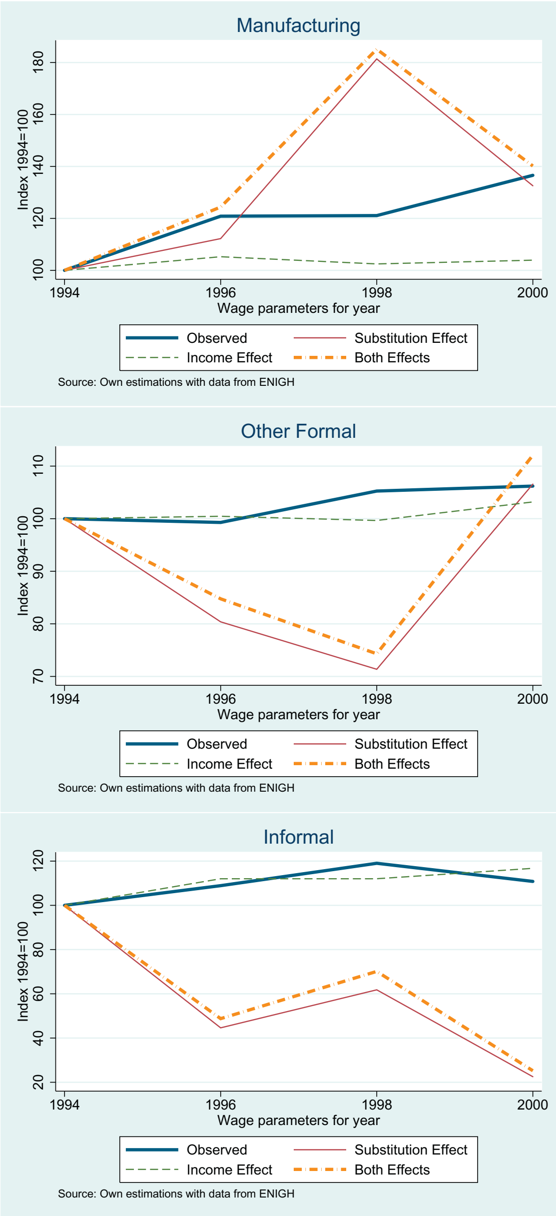
APPENDIX E: SIMULATED HOUSEHOLD INCOME EFFECTS OF $\Delta\hat{\boldsymbol{\beta}}$

In order to capture within-household participation effects of $\Delta\hat{\boldsymbol{\beta}}$ we parameterize household incomes, including female and male members. We assume that men's participation decisions are independent from all other household member's labor status. Female household members, on the other hand, decide whether to enter the labor market or not taking into account all other household member's income (Y_m^0) and the head of the household labor status (H^a). H^a and Y_m^0 are endogenous once full household incomes have been parameterized. Hence, an economy-wide shock on $\hat{\boldsymbol{\beta}}$ will have an effect on these two variables. In the next table, we show the simulated values of H^a and Y_m^0 for the different estimated values of β. The change in remunerations to personal characteristics resulted in an increase in male participation – the result is totally explained by increases in manufacturing expected wages. Therefore, had the change in β been the only change occurring between 1994 and 1996, the proportion of active men would have increased from 88.8 percent to 92.1 percent. The simulated values correspond with the observed increase in the male participation rate between 1994 and 1998. Regarding simulated Y_m^0, the trend is following very closely the observed path, with a huge negative shock between 1994 and 1996 and a gradual recovery thereafter. The advantage of the microsimulation over a simple distributional-neutral change in average incomes is that we can capture the changes in each and every household in our dataset. Hence, we do not need to assume that overall economy shocks have an homogeneous effect on every household.

	1994	1996	1998	2000
H^a				
Observed	0.888	0.889	0.902	0.920
Simulated	–	0.921	0.929	0.843
Y_m^0				
Observed	10,955	7,539	7,825	8,912
Simulated	–	7,091	7,950	8,807

Income figures are in real Pesos of August 2002.

APPENDIX F: SIMULATED OCCUPATION EFFECT OF $\Delta\hat{\beta}$



APPENDIX G: SIMULATED OCCUPATION EFFECT OF ΔΩ