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Seasonal Adjustment in a Market for Female Agricultural Workers

1. Introduction

In the last three decades, economists have found that labor markets in developing countries function more efficiently than earlier believed (Binswanger and Rosenzweig, 1981). However, it has also been observed that the adjustment process in the agricultural casual labor markets is often uneven and incomplete resulting in a significant degree of open unemployment because of the seasonality of agricultural demand. This phenomenon has challenged economists to search for additional explanation of the workings of these markets. While several studies claim that agricultural wages are rigid in the face of significant seasonal fluctuation in labor demand and that seasonal adjustment occurs through variations in the rate of unemployment (Bardhan, 1979; Dreze and Mukherjee, 1989), other economists believe that such markets function almost perfectly, with significant seasonal variation in employment and wages occurring in response to changes in demand (Rosenzweig, 1986).

The market for temporary agricultural workers in Chile offers a particularly interesting context to study the adjustment process of agricultural casual labor markets. A notable fact is that land and major economic reforms significantly altered the traditional rural landscape between 1965 and 1985 (Kaufman 1972; Jarvis, 1985, 1992), resulting in an unusually free and competitive agricultural labor market. The continuing expansion of agribusiness in Chile over the past three decades, particularly since 1975, contributed to the radical transformation of the rural sector (Gwynne, 1997; Jarvis, et al., 1993; Jarvis, 2000). The agricultural labor force grew rapidly, as did the proportion of the labor force composed of seasonal workers. A several notable aspects, e.g. unusually large seasonal variations in wages, labor participation and open unemployment, characterize the functioning of this seasonal agricultural labor market. Average daily earnings vary 50%-60% from the peak to the slack season.[1] Despite the large variation in expected daily earnings, male workers tend to remain in the labor force all year. In contrast, female labor force participation responds strongly to (expected) daily earnings, with participation dropping by nearly 30% from peak to slack season. Male unemployment varies somewhat over the season, but is never unusually high. In contrast, female unemployment varies greatly and open unemployment exceeds 50% during the slack season. Female workers appear to absorb the bulk of labor force adjustment, partly because they have higher reservation wages and partly because they have fewer available employment opportunities over the year.

This paper explores the adjustment in the market for temporary agricultural labor to measure the seasonal shifts in wages, labor force participation, and employment, and to consider whether differences in labor force participation between seasons are attributable to the existence of specific 'barriers' to employment within these markets, differences in preferences or differences in observed characteristics. Using a longitudinal Chilean data set collected in 1992, we model labor force participation by estimating a random effects probit that allows for unobserved heterogeneity in preferences. We further model earnings by deriving a two-step estimator for panel data that accounts for the impact of labour force participation on offered daily wage rate while accounting for the endogeneity of participation and unobserved heterogeneity in preferences. To test for the

[1] Expected male wages vary seasonally nearly 50%.Though the use of wages is the predominant incentive system, workers, especially females, are frequently paid on a piece rate basis during the peak season. Piece rate workers earn about 12% more than wage workers during the peak season. Since there are few opportunities to earn more at piece rate pay during the slack season, average daily earnings for females vary nearly 60% over the year.

determinants of labor force participation, we consider certain key variables, such as education, gender, age, household and time related characteristics. Additionally, because we expect seasonal wage variation to explain an important component of the observed changes in labor force participation, we utilize the instrumented expected wage to reestimate the labor force participation equation to directly observe the effect of fluctuating wages on participation. Regressions are simultaneously undertaken for both male and female workers to explore male-female differences in labor market participation and earnings.

This paper adds to the existing literature in a number of ways. First, the data set collected has unique characteristics that allow us to explicitly address the seasonal adjustment of agricultural labor markets using a formal statistical model. Our data contain daily information over one full year regarding participation, earnings, and employment, as well as the personal and family related characteristics of each worker. To the best of our knowledge, similar data do not exist for any other country and no other study has analyzed seasonal changes in wages, participation and unemployment in this manner. Inferences from this study could have relevance for other countries, e.g., anecdotal evidence suggests that the agricultural labor market in California has similarities to Chilean market. The approach used here might also be adopted to obtain appropriate data for similar studies of casual labor markets in other countries. Second, the availability of longitudinal data allows us to control for both unobserved heterogeneity in preferences and sample selection bias. From a methodological point of view, this is a significant improvement over previous studies on seasonal labor market adjustment (Bardhan, 1979; Barrientos, et al., 1999). Lastly, our sample contains male and female workers working for wages and on a piece rate basis. Thus, we can analyze the effect of gender differences in market behavior, under different incentive structures, within a modernizing agricultural sector. Our emphasis is on the behavior of female workers, about which relatively little is known.[2]

In Section 2 we present an overview of the available data and the labor market. Drawing on the neoclassical model of labor force participation, Section 3 develops the econometric specification for panel data. Section 4 discusses model estimation and results, and Section 5 present conclusions and a brief discussion of policy implications.

2. Data Overview

Data description

The study utilizes a primary data set collected during the harvest season (mid-January to mid-March) of 1992. A random sample of 599 individuals was taken from individuals working in 54 table grape packing sheds in Chile[3]. The sample is believed to be fairly representative of the individuals who work as temporary workers in these packing sheds during the harvest season.

Each worker surveyed was asked to sequentially report all periods of employment during 1991 (first and last day of work in each job), the task performed, the location and economic sector of the job, whether remuneration was by wage or piece rate, the daily wage and/or the total amount earned, and when they had been in the labor force during 1991. We also collected detailed information regarding age, education, work experience, household demographics, and household income.

[2] The decline in the number of permanent agricultural workers and the growth in the number of temporary agricultural workers has raised concern in Chile that changes in labor market structure have reduced agricultural worker welfare and the efficiency of labor use (Cox, et al.; Gomez and Echenique, Schurman, Guglielmetti, Leon).
[3] These sheds were located in three regions: Santa Maria, Buin/Paine, and Lontue.

Using this information, we determined, for each worker and each day, the worker's labor force participation,[4] the daily wage or average piece rate earnings when employed and when unemployed.[5] Since some workers were employed on a monthly basis during at least part of 1991, to reduce dependence among the observations for individual workers, we arbitrarily (after some descriptive analysis) used observations only from the second Tuesday of each month to construct the panel. Thus, the sample contained 12 observations for each worker and a total of 7188 observations.

Table 1 presents key characteristics of workers and of their employment, many of which reflect the fruit industry's rapid growth. The labor force is relatively young, with most between 15–34 years old. Men tend to be slightly younger than women. The labor force is also relatively well educated; 72% of women and 92% percent of men have completed secondary school. About half of female workers and about a third of male workers are married. Female workers have a significantly higher number of children, on average, than their male counterparts. A small proportion of workers are students, 12% of women and 15% of men, who generally worked only during the summer. Most workers are "secondary" workers; we defined an individual as a secondary income earner if his/her annual income provided less than 50% of annual household income. By this somewhat arbitrary criteria, 84% of women and 57% of men were secondary income earners.

[4] On average, workers in this sample participated in the labor market 72% of the days during the year.
[5] Workers were asked to indicate whether there were any periods during which they had not been in the labor force. Next, they were asked whether, for those periods when they claimed to have been in the labor force, they had actively looked for work. Finally, they were asked whether they had looked for work locally, regionally and/or nationally. The latter questions were intended to cause them to reflect on whether and how hard they had looked for work. Workers were categorized as being unemployed on a given period only if they had declared themselves to be in the labor market and actively looking for work on that period.

Although a significant proportion of the individuals surveyed lived in or close to towns, roughly 85% of the jobs reported by this sample of workers were in agriculture. The proportion of agricultural jobs was essentially the same for men and women. Female workers were employed at piece rate tasks significantly more than male workers were during the year; 36% of female jobs compared to 14% of male jobs were paid on a piece rate basis. It is noteworthy that women had significantly higher average daily earnings than did men, particularly as we later present evidence that women suffer wage discrimination in the labor market. Women have higher average daily earnings because they work more frequently on a piece rate basis, which allows them to earn more per day than do workers paid on a wage basis, and because women are employed mainly during the peak season, when earnings are highest.

Labor Force Participation. The labor force participation rates for males and females (including both those employed and those actively seeking employment) are shown in Figure 1 (see also Table 2). Male participation varies considerably less than female participation. In both cases, participation peaks in February when the harvest is at its maximum. Female participation declines sharply from February to May, remains low through September, and then rises steadily to February. Males enjoy two months in which more than 90% of the sample was participating and 10 months of somewhat lower participation rates (never below 80%). Females have three months of high labor force participation (January-March), four months of intermediate participation (April and October-December), and five months of significant low participation (May-September).

Unemployment. Figure 2 shows the open unemployment rates for men and for women. Both are surprisingly high throughout the year. The female open unemployment rate exceeds 50% during the slack season, despite the very large fluctuation in the female labor force participation rate shown in Figure 1. The male open unemployment rate for these temporary workers is also high; however its average (18%) is only half the average unemployment rate for females (37%).

Average daily earnings. Average daily earnings are shown in Figure 3. Daily earnings in agricultural jobs fall significantly from the peak to the slack season, especially for women. Women tend to earn more than men do in agricultural jobs during the peak season, but less than men do during the slack season.[6] Note also that the average earnings reported tend to be higher in agricultural jobs than in non-agricultural jobs throughout the year for both men and women, though the dispersion of earnings on any day is fairly large.[7] As agricultural wages decline, a rising proportion of workers are employed in non-agricultural jobs (ranging from roughly 5% in the peak season to about 30% in the slack one), but apparently because agricultural jobs are so difficult to obtain.

3. The Model and Econometric Specifications

Labor force participation is hypothesized to be dependent upon the individual gaining greater utility from working than from not working. The time spent outside the labor market, the reservation wage, is hypothesized to depend on household responsibilities such as the need to care for children, and the availability of other sources of household income (e.g., the spouse's income). In contrast, the time spent in the labor market is hypothesized to depend upon the anticipated financial return (expected earnings), which in turn depends upon individual characteristics such as education as well

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[6] Average Daily Income for those workers not employed on a fixed daily wage is calculated by dividing the total income earned in each job (per month, if the job spans more than one month-workers were able to report their monthly earnings for piece rate jobs) by the number of days the worker was employed. Some of the seasonal decline in average daily income is probably due to a shorter number of hours being worked during the winter as compared to the summer.

[7]The term "earnings" is used to refer to the total remuneration resulting from work effort, whether from a wage or from a piece rate system. Earnings can thus refer to wage income; at times we specifically differentiate between wages (wage earnings) and piece rate earnings.

as on market conditions. When the expected wage exceeds the reservation wage, an individual will enter the labor market. Because in our sample earnings fluctuate considerably over the year, we hypothesize that seasonal earnings variation is an important aspect of labor market adjustment, especially as it contributes to changes in labor force participation. Consequently, our objective is to estimate an earning function and utilize instrumented expected earnings to reestimate the labor force participation equation that has previously been estimated without them. This approach allows us to determine how alternative earnings prospects, as distinct from individual preferences and characteristics influence the decision to participate in this seasonal labor market.

Labor Market Participation Equation

As previously stated, the current labor force participation decision depends on whether the individual's offered wage (w_{it}) is above the reservation wage (w^*_{iot}) (Huffman, 1991). We assume that both offered and reservation wages are linear functions of each individual's characteristics,

$$w_{it} = X_{it}\beta^k + \varepsilon_{it} \qquad [1]$$

$$w^*_{iot} = X^*_{it}\gamma^k + \varepsilon^*_{it} \qquad [2]$$

where k= w, m indexes whether the individual is a woman or a men, the matrix X_{it} contains the human capital and other variables affecting the offered wage, and the matrix X^*_{it} contains the variables influencing each individual's opportunity costs of working plus other observable variables reflecting work preferences thought to affect the reservation wage. The error terms capture unobserved heterogeneity across individuals; ε_{it} captures unobserved differences in demand and ability, while ε^*_{it} captures unobserved differences in preferences not captured by the variables reflecting work preferences contained in X^*_{it}. Both errors can be decomposed into an individual specific component

(μ_i, μ_i^*) and a time/individual specific component (η_{it}, η_{it}^*) and each error is assumed to be independent and normally distributed.

Combining the specifications for the offered and reservation wages (equations [1] and [2]) yields the following reduced form latent regression model for labor market participation decisions in each period,

$$\begin{aligned} y_{it}^* &= Z_{it}\gamma^k - u_{it} \\ k &= w,\ m \\ t &= 1\text{-}12 \\ i &= 1, N \end{aligned} \qquad [3]$$

with the selection criteria being,

$$y_{it} = 1 \quad if \quad y_{it}^* > 0 \qquad [4]$$

where Z_{it} contains the regressors from the offered wage and the reservation wage so that γ^k captures the (net) effects of the variables in the reservation wage and in the offered earnings functions by gender. Specifically, in the model estimated below, Z_{it} includes the individual's education level, age, marital status, number and age of children in the household, gender and other exogenous household-related characteristics. The equation errors comprise random individual effects, α_i, and random individual specific time effects, υ_{it}, which are assumed to be independent across individuals. Denote u_i as the T vector of u_{it} for individual i. We assume

$$u_i \sim N.I.D.(0, \sigma_\alpha^2 ii' + \sigma_\upsilon^2 I) \qquad [5]$$

Hence, for any individual, the inter-temporal correlation ρ between error terms in successive periods is constant, i.e. $\rho = \dfrac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_u^2}$.

Earnings Equation

The labor force participation decision rule (equation [4]) selects individuals into observed classes (either in or out of the labor force) according to whether the expected value of his/her offered wage or reservation wage is highest. As a result, the earnings actually observed are not random samples of the population, but are instead truncated nonrandom samples. Therefore, the earning equation must be estimated conditional on the outcome of the response process. We follow the procedure adopted by Ridder, and Nijman and Verbeek and generalized by Vella and Verbeek for panel data.

Consider the general form of censoring (the conditional expectations of the error terms in [1], given employment). The resulting bias in the observed means may be calculated as

$$E[\ln w_{it} / y^{w}{}_{it} = 1] = X'_{it}\beta^{k} + E[\mu_i / y^{w}{}_{it} = 1] + E[\eta_{it} / y^{w}{}_{it} = 1] \qquad [6]$$

where we define a new equation:

$$y^{w}{}_{it} = Z^{w}{}_{it}\gamma^{k} + u^{w}{}_{it} \qquad [7]$$

with $y_{it}^{w} > 0$ when the individual is employed (reporting positive earnings). We assume that the regressors from the probability of employment equation [7] are strictly exogenous (not correlated with the error components). Having estimated the probability of having information on wages, and assuming further that the error component can be separated into two components, $u^{w}{}_{it} = \alpha^{w}{}_{i} + \upsilon^{w}{}_{it}$, we can calculate the sample selection correction terms that can be included in our earning models (equation [1]),

$$E[\mu_i / u_i^{w}] = \sigma_{\mu\alpha}\left[\frac{T}{\sigma_{\upsilon}^{2} + T\sigma_{\alpha}^{2}}\bar{u}_i^{\,w}\right] \qquad [8]$$

$$E[e_{it} / u_i^{w}] = \sigma_{e\upsilon}\left[\frac{1}{\sigma_{\upsilon}^{2}}u^{w}{}_{it} - \frac{T\sigma_{\alpha}^{2}}{\sigma_{\upsilon}^{2}(\sigma_{\upsilon}^{2} + T\sigma_{\alpha}^{2})}\bar{u}^{w}{}_{i}\right] \qquad [9]$$

where $\bar{u}_i^{\,w} = 1/T\sum_{t=1}^{T} u^{w}{}_{it}$, $\sigma_{\alpha\mu}$ captures the correlation between the individual effects and $\alpha_{e\upsilon}$ captures the covariance between idiosyncratic shocks (see Appendix I for further details on the estimation of correction terms). The resulting estimated correction terms can be added to [1]. We then estimate equation [1], including these correction terms using OLS. The test for the significance of these terms is a test for nonresponse bias. This approach provides more economic insight into the processes driving the selection bias and helps identify the source of the heterogeneity. Although two-step procedures are generally inefficient (see, for example, Newey) the attraction of our approach, in contrast to maximum likelihood, is its relative computational ease. Further Vella and Verbeek's method provides initial consistent estimators for a LIML approach so that asymptotically efficient estimators can be obtained in one iteration.

Labor Market Participation Equation and Expected Earnings

The sensitivity of individual labor market participation decisions to changes in the expected earnings is studied using the same probit equation [4], except that expected earnings is now included as a regressor. The econometric implications of this procedure are discussed subsequently.

Testing for Gender Differences

If all gender differences in participation and earnings simply arise from differences in the observed characteristics of women and men, then female and male coefficients should be identical. Hence, the general test for the hypothesis that there is no gender difference in labor market behavior is $H_0 : \beta^{w} = \beta^{m}, \gamma^{w} = \gamma^{m}$.

4. Estimation Results

The estimation results of the initial random effects probit for labor force participation for 1991 are presented in Table 3[8]. We report the absolute value of the t-statistic under each coefficient. The equality of the female and male coefficients has also been tested, when appropriate, both individually and jointly using Wald tests. If the individual female coefficient is significantly different from the reported male value (at 5%), the coefficient is starred.

The value of $\rho = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_u^2}$ is also reported. This statistic represents the proportion of the variance that is unexplained by the regressors and accounted for by the variation between individuals. The p-value reported below ρ tests the significance of this coefficient and hence indicates whether taking account of unobserved heterogeneity is important. The coefficient is significant indicating the importance of using the random effects model.

The estimated coefficients on the explanatory variables are generally highly statistically significant for women and in line with prior expectations. In contrast, few of the estimated coefficients are statistically significant for men. In part, the results for males are consistent with the relatively constant labor force participation rate observed for males throughout the year. However, we suspect that the smaller number of male observations, as compared with females, and the relative homogeneity of male respondents contributed to the lack of significant coefficients.

Women tend to participate in the labor force less than men do. For women, labor force participation increases with age, but at a decreasing rate, and decreases with education. Since rising education is associated with higher daily earnings, as will be shown, this result suggests that education may alter the preference for work vs. leisure by the individuals in this sample. School attendance sharply reduces participation for men and women while schools are in session in April-December; no significant difference is found between the male and female behavior.

Marriage reduces labor force participation for females, but does not affect male participation. This result could suggest that women face a social-cultural bias against work and/or that married women have a higher reservation wage because of household responsibilities. Female labor participation (but again not that of male) declines as the number of the worker's children aged 0-5 years increases. The negative effect of the presence of small children on female labor force participation is considerably reduced if there is another adult female living in the household, which suggests that childcare is gender specific and points to the importance of the availability of (household) childcare to female labor force participation. Both men and women are more likely to participate during the peak season and less during the slack season as compared to the transition months of April and October through December.

Determinants of a Worker's Daily Earnings

The dependent variable of the earnings equation is the log of average daily earnings. The group of regressors includes both supply and demand side factors. Human capital variables such as education and experience are hypothesized to influence worker productivity and earnings, while monthly dummies reflect the net influence of seasonal fluctuations in agricultural labor supply and demand. Wages also are hypothesized to vary in response to the worker's decision to seek either piece rate or wage employment,

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[8] All results are estimated by Maximum Likelihood using 8-point Gaussian Quadrature procedures.

and either non-agricultural or agricultural employment. Such choices are assumed to depend on a worker's willingness to supply effort and preference for factors such as work environment and a shorter commute time to work. Since dummy variables are used to measure the effect of working at a piece rate as opposed to a wage, the other coefficients measure the effect of the respective independent variables on the daily wage.

Consistent estimates of the earnings function are obtained using the two-step estimator proposed by Vella and Verbeek. The results for both men and women are reported in Table 4. The absolute value of the t-statistic is reported under each coefficient. Further if the individual female coefficient is significantly different from the reported male value (5%), the coefficient is starred.

The earnings function equation performs well if judged by the statistical significance and sign of the estimated coefficients and the relatively good fit of the equation. It also provides a number of insights into the functioning of the labor market. For example, for both men and women daily earnings increase as expected with schooling. These results suggest that education significantly increases labor productivity in agricultural work although some of the higher return shown is probably due to the innate ability that allows individuals to successfully complete additional schooling.

Experience also has a significant positive impact on female daily earnings in jobs throughout the year; the analogous coefficient is not significant for males. The square of experience has a significant negative coefficient, indicating that rising experience has a non-linear effect. Note that experience and education have somewhat similar effects on earnings, e.g., over the expected range of sample variation.

Dummy variables are used for each month to measure the effect of seasonal changes in labor supply and demand on daily earnings. The omitted period is the month of January, which constitutes a peak season month. The seasonal dummies show that daily earnings in December, February, March and April closely approximate those in January. Daily earnings decline about 25 percent during May-September relative to those earned during January and daily earnings rise to an intermediate level in October-November, remaining 10 percent-15 percent lower than earnings during the peak period.

A dummy variable is also used to measure the earnings effect of working on a piece rate basis. The effect of the piece rate incentive system is of interest for two reasons. First, a piece rate system is frequently used to motivate and remunerate temporary agricultural workers in the fruit sector. Workers in this sample report that about 35 percent of their jobs are paid on a piece rate basis. A substantial theoretical literature indicates that the piece rate system increases worker's productivity and that piece rate workers earn more per time period than wage workers (Gibbons; Lazear, 1986; Pencavel; Stiglitz).

Second, as shown in Table 1, women are paid on a piece rate basis much more frequently than men, especially when working in fruit packing sheds during the peak season, receiving higher daily earnings than men do. However, since many more women work on a piece rate basis during the peak season, but few during the slack season, women's daily earnings show a higher seasonal variation than do men's daily earnings.

The estimated coefficient on the piece rate dummy indicates that piece rate jobs earn a daily premium of about 12 percent relative to wage jobs.[9] Since nearly all individuals in the sample worked in packing sheds during the peak season and since nearly all of these individuals worked similar hours, the estimated coefficient is probably

[9] The choices of whether to work at piece rate or wage, and in the agricultural and non-agricultural sector, are endogenous to the determination of daily earnings, but lacking instruments that would allow us to treat this endogeneity, we chose to include the piece rate dummy.

a good approximation to the true premium.[10] The premium estimated here is similar to those estimated in piece rate studies in other contexts (Lazear, 1996; Seiler), but smaller than the premium usually said by packing shed management to exist in Chile.[11] That most women and relatively few men work at piece rate suggests that women's elasticity of effort with respect to piece rate pay is higher than that of men in this context.

A dummy variable is also used to measure the effect of working in the agricultural as opposed to the non-agricultural sector. Agricultural work pays substantially more than non-agricultural work, particularly for women (Figure 2). This result could indicate that workers in this sample tend to have a higher productivity when employed in tasks for which they have developed a specialization and/or that pay for temporary agricultural work is higher because such jobs have short duration and workers have high search costs. The results show that men's wages in this sample are about 18 percent higher when working in agriculture while women's wages are about 37 percent higher (the attractiveness for women of agricultural jobs is still greater when the premium for piece rate work is considered, as piece rate jobs are found almost exclusively in agriculture).

As earlier noted, women's average daily earnings are higher than men's average daily earnings (see Table 1). Women working as temporary agricultural laborers are thought to earn relatively high wages in the Chilean fruit sector and these data support that view (Rodriguez and Venegas). Nonetheless, according to the estimated gender

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[10]We do not have a measure of the number of hours worked per day, but the workday is known to be significantly longer during the peak season than the workday during the slack season. If we measured the effect of working at a piece rate throughout the year, the estimated premium could be biased by the hours effect. On the other hand, some packing shed firms switch to a guaranteed wage on days when the supply of grapes is insufficient to allow workers an acceptable income if paid on a piece rate basis (Newman and Jarvis). If some wages are thusly constrained, the estimated premium for piece rate work could be upward biased.

[11] In a study in a US autoglass installer plant, Lazear found that after a switch from wage to piece rate pay workers' earnings rose by 9.6%. This was about half the 20% increase in average productivity per individual worker. Thus, workers in the US plant captured about half of the total increase in productivity.

dummy, men earn substantially more than men do in wage employment, once earnings are adjusted for observed and unobserved characteristics. We included additional seasonal dummies interacting with a gender dummy to test whether gender had the same effect throughout the season (regression not shown). The estimated coefficients were all insignificant, indicating that the gender wage differential did not vary seasonally.

Although females have higher average daily earnings than men, women earn less than men when working for a wage, but not when working on piece rate basis. We suspect that these results indicate discrimination in the wage market. The results suggest that there is lesser possibility of discrimination when workers are employed on a piece rate basis (unless workers are denied access to such jobs) since pay is then directly linked to each worker's productivity. The large magnitude of the somewhat surprising wage differential suggests an interesting area for further analysis.[12]

Both correction terms in the earnings equation are statistically significant indicating that the two forms of endogeneity/selectivity are present. Selection operates through the individual specific effects term ($\sigma_{\alpha\mu}$) and the idiosyncratic term ($\sigma_{\eta\upsilon}$). The negative significant coefficient on the individual effects term indicates that the time-invariant unobserved individual effect that increases participation unexpectedly decreases the earning level. This result is different from that usually encountered in such regressions, where the individual effect that increases participation also increases the

[12] Both men and women worked in each of the piece rate tasks from which we drew our sample during the summer of 1991. Workers of both sexes were asked and generally specifically replied that workers of the other sex could do their task equally well. Nonetheless, the workers in each of the tasks were largely of one gender. The tasks could be gender type because productivity in each task is linked to a gender-related attribute. For example, it might be argued that most women excel at the tasks of cleaning and packing grapes because they possess greater finger dexterity, pay greater attention to detail, have better eyesight--particularly as related to color discrimination, and perhaps possess a greater willingness to endure long periods of work in a stationary position, relative to men. Nonetheless, based on anecdotal information received during interviews and observation, we believe that men and women tend to prefer for social

earnings level (Lee). Such results are generally encountered in panel data spanning years where each individual confronts a similar situation each year. In our situation, the data are for a single year. More workers participate during the period when earnings are high, but those who have the highest earnings also have the highest reservation wages and thus tend to drop out of the labor force as earnings decline in the slack season. We note that the average education level of workers participating during the peak season is significantly higher than the average education level of those participating during the slack season. Similarly, the time varying effects generating the simultaneity of wages to labor participation appears to increase participation and decrease wages.

Probit Equation Including Expected Earnings

The sensitivity of individuals' labor force participation decisions to changes in the estimated earnings is studied from a probit equation that includes the same regressors as in Table 3 plus expected earnings. The results, reported in Table 5, show that the coefficient on expected earnings is positive and highly significant. The other coefficients are closely similar to those obtained from the probit equation (Table 3) that did not include expected earnings as an independent variable. There is some question whether the inclusion of expected earnings leads to inconsistent results (Harris, personal communication), but we see a potential advantage from including directly the variable which is likely to have the greatest effect on seasonal fluctuations in labor force participation.

Labor force participation for men and women responds strongly and positively to the expected wage. However, the women's labor force participation rate varies substantially more than that of men because women tend to have a higher reservation

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reasons to work with others of their same sex. The sharing of jokes and casual conversation, as well as life wage, as shown by the larger magnitude of the coefficient on the expected wage, as well as by the coefficients on variables related to marriage and household responsibilities, including the care of small children.

Unemployment variation.

Although wages vary greatly on a seasonal basis, they do not vary sufficiently to fully equate the supply and demand of labor with zero unemployment. Given the very high observed variation in wages, it is hard to argue that wages are sticky, but one might well ask why wages do not vary still more so as to bring about lower, if not zero unemployment? Even though the labor force varies greatly, the number of workers openly unemployed increases greatly. See Table 2. It is unlikely that an efficiency wage argument (Weiss 1980, Akerlof and Yellen, 1986, Solow 1990) is a plausible explanation for the types of temporary employment held by individuals in our sample.

Three factors seem likely to explain the high unemployment found. First, the relatively large component of frictional unemployment result of individuals entering and/or leaving the labor force, changing jobs, and searching for employment. Frictional unemployment is likely to be especially high in a spatially dispersed market where jobs are relatively short lived and search costs relatively high. There is some evidence to support this assertion. Most of the jobs reported were of relatively short duration, so that most of the workers employed would have needed to seek new employment frequently. The average number of jobs held by each worker during the year was 6.5 (s.d. = 2.86), with the number ranging between 1 (n = 42) and 16 (n = 1). Even during the period November-March, when competition for workers is intense, unemployment, measured on a daily basis, is high-- roughly 11% for men and 20% for women. Most of the workers in

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experiences and daily concerns was particularly important to the women interviewed.

our sample changed jobs at least once in this period as they moved from field tasks to packing shed tasks and new workers, mainly students, entered the labor force. In other months of the year, job duration was shorter and many fewer jobs were reported, suggesting that search costs would have been greater.

Second, the average reported wage in agriculture lies above the average reported wage obtained by our sample of workers in the non-agricultural sector throughout the year. Thus, waiting for an agricultural job could easily have been the better strategy for most workers even when few agricultural jobs were available. Due to lack of data, it was not possible to estimate the separate unemployment rates for workers who were seeking agricultural as opposed to non-agricultural work, since there is no clear distinction among workers. The number of individuals accepting non-agricultural employment rises during the slack season, indicating that some workers can transition to non-agricultural employment, albeit at a lower wage. However, most do not. High search costs and the short duration of agricultural jobs may help explain why the wage for temporary agricultural workers does not fall more during the slack season, even though measured unemployment is high.[13]

The third factor that may explain the high measured unemployment is that some workers, especially females, report incorrectly having been in the labor force and actively seeking work when in fact they were not. Alternatively, they considered themselves in the labor force, but searched only within a small, local area, where there were no jobs.

[13] The workers that accept non-agricultural jobs could be among the lower-earning agricultural workers and may not be accepting a lower wage than they would face in agriculture. The wide distribution of agricultural earnings during the summer indicates that the work force is heterogeneous. The non-agricultural jobs that workers accept could be of longer duration than the agricultural jobs available during the winter, so that, net of continuing search costs, the non-agricultural wage could again be higher. Finally, non-agricultural jobs could be preferred for other reasons, such as lower transportation costs or better working conditions.

A significant proportion of the workers who declared they had been in the labor force during the slack season also reported having been employed for at least a few days during nearly every month of this period. Since these individuals were in the labor force on dates closely proximate to the dates when they did not have work, they were probably truly unemployed. Nonetheless, a large number of other women reported having been in the labor force throughout the five-month slack season even though they did not work a single day during that season. For example, 350 individuals in our sample, roughly 60%, declared themselves to be in the labor force, employed or actively seeking work, throughout the period May-September. Of these 350 workers (297 women and 53 men), 121 (119 women and 2 men) reported no employment during this five month period.

Since other workers with similarly observable characteristics were obtaining at least some work during this period, most workers who reported no employment over such a long period probably were not actively seeking employment and thus were not truly unemployed. Since a much higher proportion of women (22%) than men (3%) are in this category, similar misstatements could explain much of the difference between female and male unemployment rate throughout the year.[14] However, respondents were asked both whether and also where they had actively sought work when not employed in an effort to ensure that they responded accurately regarding efforts to seek work. Women who responded seemed to understand the questions well. Many of the unemployed women said that they had been in the labor force, in the sense that they were willing to work at the prevailing wage during the slack season and that they actively searched for a job, albeit within a very local area. Their failure to search more widely may, if true, could

[14] Note that if an additional number of women reported leaving the labor force during the slack season, the differentiation between male and female labor force behavior would become even starker than estimated in the labor force participation equations.

reflect their relatively high costs of search due to their need, in many cases, to satisfy the time-constrained aspects of family care. Highly seasonal labor demand makes it difficult to provide rural women with full employment.

5. Summary and Conclusions

This paper explored seasonal adjustment in the market for casual agricultural labor. It measured seasonal shifts in wages, labor force participation, and open unemployment. Several results conform closely with economists' expectations of behavior in a competitive market facing large demand shifts. For example, wages varied seasonally by more than 50% in real terms and female labor force participation responded by varying about 30%. The adjustments in wages and in labor force participation suggest that the labor market accommodated drastic demand shifts reasonably efficiently, as argued by Rosenzweig (1986). Earnings varied more for women than for men and female labor force participation varied much more than male labor force participation. Nonetheless, the market did not fully accommodate through changes in the wage and labor force participation since the rate of female open unemployment was high and also fluctuated considerably, in line with the findings of Bardhan, 1978, and Dreze and Mukherjee, 1989.

Female labor force participation rate varied more than that of men because women tended to have a higher reservation wage that was related to marriage and household responsibilities, including the care of small children. Many women moved in and out of the labor force as the wage exceeded and then fell short of their (higher) reservation wage. Women's daily earnings showed greater seasonal variation than did men's earnings and this greater variation contributed to the larger variation in women's rate of labor force participation. Men tended to remain in the labor force even as the expected wage varied seasonally since their reservation wage lay always below the market wage. Men's labor force participation was not affected by either marriage or by having children.

Nevertheless, although wages varied greatly across seasons, wages did not vary sufficiently to fully equate the supply and demand of labor and achieve zero unemployment. A considerable part of the observed unemployment appears to be frictional, the result of individuals entering and/or leaving the labor force, changing jobs, and searching for employment. This level of frictional unemployment is higher than expected in what is thought to be a fairly tight, competitive market, but it probably reflects the nature of temporary employment in a spatially dispersed market where jobs are of relatively short duration and search costs are relatively high. It also appears that a large number of female workers systematically declared themselves to be in the labor force and actively seeking for work during the slack season, even though many of these workers reported no paid work. It is possible that these females were "actively" seeking work, albeit within a much smaller geographical area than men did.

Since the female unemployment rate was so much higher than the male unemployment rate during the slack season, the results appear consistent with discrimination against women when excess labor supply was present. Women seem to have earned relatively high wages when their labor was needed during the peak season, but they may have had trouble gaining entry to jobs that had traditionally been filled by men during the rest of the year. These issues remain an interesting area for further research. On a related note, we find some evidence to support the view that the welfare effect of a falling wage was less severe, on average, for women, given their higher average reservation wage. Offsetting that view, however, is the dramatic seasonal variation in female unemployment, which suggests that many rural females bear a great burden from the seasonal shift in labor demand. That is, many women suffer a decline in wages while suffer unemployment during the slack season. Since women increasingly seek employment throughout the year and yet lack viable employment opportunities during the slack season, the government might examine whether it can efficiently facilitate the development of complementary agricultural and non-agricultural employment opportunities for rural female workers.

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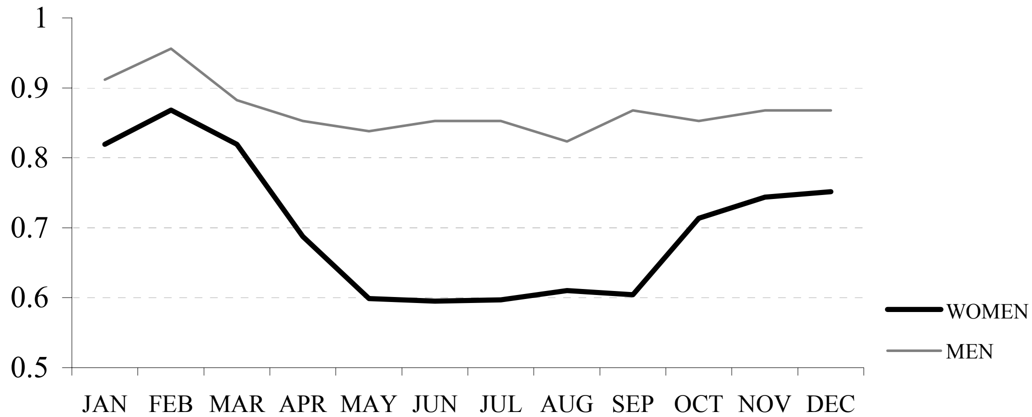

Figure 1: Labor Force Participation Rates of Surveyed Workers on the 2nd Tuesday of each Month, 1991

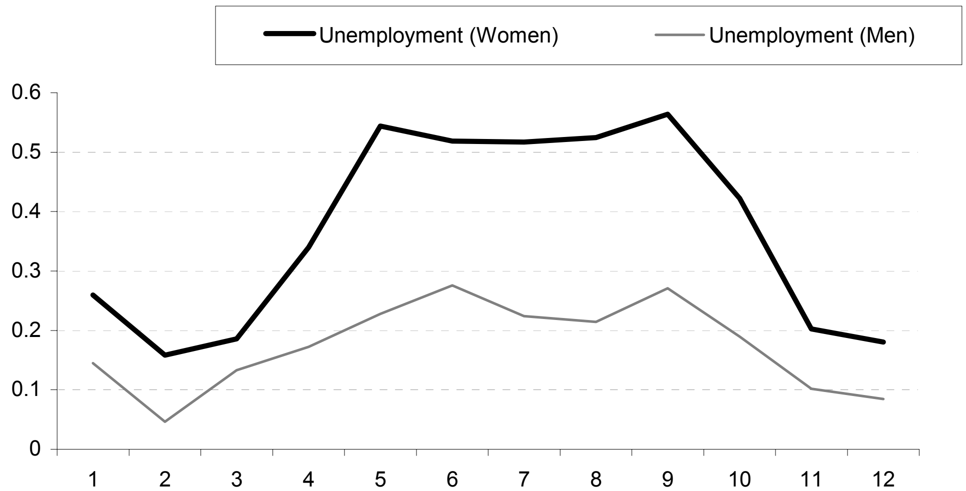

Figure 2: Unemployment rates of surveyed workers on 2nd Tuesday of each Month, 1991

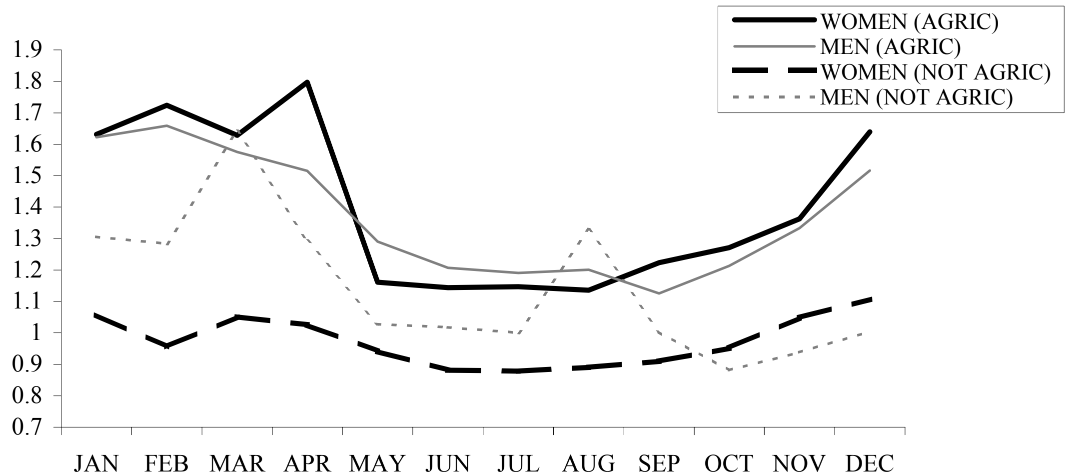

Figure 3: Average Daily Income in Agricultural work of Surveyed Workers, 1991 (Thousand of Pesos)

Table 1. Key Sample Characteristics

		Whole sample (n = 591)		Persistently in labor force (n = 321)	
		Women	Men	Women	Men
AGE	< 15	1.52	1.53	0.36	0.00
		(0.15)	(0.44)	(0.10)	
	15- 24	32.69	52.30†	23.24	48.97†
		(0.59)	(1.78)	(0.74)	(2.06)
	25 - 34	35.93	33.84	39.11	34.69
		(0.60)	(1.69)	(0.85)	(1.96)
	35 - 44	20.72	9.23†	27.67	12.24†
		(0.51)	(1.03)	(0.78)	(1.35)
	>=45	9.12	3.07†	9.59	4.08†
		(0.36)	(0.61)	(0.51)	(0.81)
CHILDREN	No children	45.24	66.15†	48.04	59.18†
		(0.62)	(1.69)	(0.86)	(02.02)
	1 child	30.22	16.92†	32.47	20.40†
		(0.57)	(1.34)	(0.82)	(1.66)
	2 children	17.87	12.30†	17.71	14.285
		(0.48)	(1.17)	(0.66)	(1.44)
	3+ children	6.65	4.61	7.01	6.12
		(0.31)	(0.75)	(0.44)	(0.98)
SCHOOL	No formal schooling	1.90	1.53	1.47	2.04
		(0.17)	(0.44)	(0.21)	(0.58)
	Had 1-5 years of schooling	15.77	3.07†	21.40	4.08†
		(0.45)	(0.61)	(0.71)	(0.81)
	Completed primary school	10.26	3.07†	10.33	4.08†
		(0.38)	(0.61)	(0.53)	(0.81)
	Completed secondary school	66.34	84.61†	62.36	85.71†
		(0.59)	(1.29)	(0.84)	(1.44)
	Some postsecondary schooling	5.70	7.69†	4.42	4.08
		(0.28)	(0.90)	(0.36)	(0.81)
REGION	Region 1	46.00	40†	53.13	40.81†
		(0.62)	(1.75)	(0.87)	(2.02)
	Region 2	40.87	47.69†	38.37	48.97†
		(0.61)	(1.78)	(0.85)	(2.06)
	Region 3	13.11	12.30	8.48	10.20
		(0.42)	(1.17)	(0.48)	(1.24)
MARRIED	Dummy= 1 if married or living together	50.76	36.92†	51.66	44.89†
		(0.62)	(1.72)	(0.87)	(2.05)
WPAR	Dummy= 1 if small children and additional female adult in hhold	19.39	33.84†	23.61	40.81†
		(0.49)	(1.69)	(0.74)	(2.02)
IN SCHOOL	Dummy=1 if currently in school	12.54	15.38†	4.79	4.08
		(00.41)	(1.29)	(0.37)	(0.81)
PIECE	Dummy, 1 if paid on a piece rate	35.53	13.87†	34.04	13.23†
		(0.89)	(1.46)	(1.09)	(1.55)
DAGRIC	Dummy, 1 if agricultural sector	85.65	83.78	82.94	85.50
		(0.65)	(1.56)	(00.87)	(1.61)
EXPERIEN	Years of experience in Packing sheds	7.05	4.65†	7.1624	4.8273†
		(0.11)	(0.14)	(0.13)	(0.15)
INCOME	Average daily income in 1991Chilean pesos	1426.39	1353.33†	1397.59	1341.40†
		(13.86)	(27.70)	(16.92)	(31.05)

Note: Averages in columns 1 and 2 are based on observations for the whole sample (591 workers); averages in columns 3 and 4 are for the subsample (320 workers) that participated in the labor force every month of 1991 (reporting earnings or being unemployed). Note: Only 64 individuals reported positive earnings for the second Tuesday of each month throughout 1991. Standard errors are in brackets.

† Indicates that the difference between the male and female subsamples is significant at 5% using adjusted Wald Test where the null hypothesis is: $H_0 : \%^W = \%^M$.

Table 2: Seasonal Changes in Labor Force and Its Composition

	Women (N=531)				**Men (N=68)**			
	LFP	*EMP*	*UNEMP*	*OUT*	*LFP*	*EMP*	*UNEMP*	*OUT*
January	435	*322*	*113*	96	62	*53*	*9*	6
February	461	*388*	*73*	70	65	*62*	*3*	3
March	436	*355*	*81*	95	60	*52*	*8*	8
April	365	*241*	*124*	166	58	*48*	*10*	10
May	318	*145*	*173*	213	57	*44*	*13*	11
June	316	*152*	*164*	215	58	*42*	*16*	10
July	317	*153*	*164*	214	58	*45*	*13*	10
August	324	*154*	*170*	207	56	*44*	*12*	12
September	321	*140*	*181*	210	59	*43*	*16*	9
October	379	*219*	*160*	152	58	*47*	*11*	10
November	395	*315*	*80*	136	59	*53*	*6*	9
December	399	*327*	*72*	132	59	*54*	*5*	9

LFP: Labor Force Participants; **EMP**: Employed; **UNEMP**: Unemployed; **OUT**: Out of the Labor Force.

Table 3. Random Effects Probit Estimation of Labor Force Participation: Static Model[@]

	Women	Men
Constant	-4.075	
	(13.02)	
Dummy=1 if Male		7.905
		(0.59)
Age	0.347	-0.570
	(17.20)	(0.45)
Age squared	-0.005	0.018
	(16.26)	(0.59)
No. Children <5	-0.583	-2.952
	(10.72)	(0.48)
Dummy=1 if Married	-0.184	-1.211
	(2.37)	(0.06)
Dummy=1 if young children and additional female	0.883 (9.79)	5.300 (0.24)
Dummy=1 if currently in School	-0.556 (4.69)	-2.232 (4.00)
Peak Season (Jan-Mar)	0.915	1.128*
	(17.31)	(2.32)
Slack Season (May-Sep)	-1.014	-0.319
	(21.17)	(0.52)
Dummy=1 if Post-secondary Education	-0.020 (0.15)	-0.349 (0.20)
Dummy=1 if Primary Education[1]	0.476 (6.72)	
ρ	0.795	
(p-value)	(0.000)	
N=599, T=12		

[@] Where dummies have been utilized, the estimated coefficients shown include the total effect of the regressor on labor force participation for men and for women, respectively.
* Male Coefficient significantly different from Female at 5%
[1] Dummy=1 if primary education does not contain enough number of observations for the male category.
Omitted categories are: Intermediate season (April, October through December) and Secondary school education.

Table 4. Estimation of Earning Equation with Vella & Verbeek Correction[@]

	Women	Men
Constant	-0.098	
	(1.83)	
Dummy =1 if Male		0.253
		(3.32)
Dummy = 1 if Piece Rate	0.115	0.127
	(5.52)	(2.08)
Experience	0.031	0.021
	(7.44)	(1.03)
$Experience^2$	-0.001	-0.0003
	(5.58)	(0.23)
Dummy = 1 if agricultural employment	0.371	0.181*
	(13.93)	(3.18)
Dummy = 1 if February	0.042	
	(1.22)	-
Dummy = 1 if March	-0.024	
	(0.65)	-
Dummy = 1 if April	0.064	
	(1.59)	-
Dummy = 1 if May	-0.176	
	(3.30)	-
Dummy = 1 if June	-0.216	
	(4.11)	-
Dummy = 1 if July	-0.232	
	(4.39)	-
Dummy = 1 if August	-0.238	
	(4.51)	-
Dummy = 1 if September	-0.180	
	(3.35)	-
Dummy = 1 if October	-0.146	
	(3.45)	-
Dummy = 1 if November	-0.056	
	(1.34)	-
Dummy = 1 if December	0.067	
	(1.86)	-
Dummy = 1 if Postsecondary school	0.125	0.145
	(3.26)	(2.01)
Dummy = 1 if Primary school	-0.125	-0.783*
	(6.32)	(9.47)
A1i	-0.050	
	(2.75)	
A2it	-0.110	
	(2.87)	
R^2	0.2317	
N	3498	

[@] Where dummies have been utilized, the estimated coefficients shown include the total effect of the regressor on labor force participation for men and for women, respectively.

Table 5. Random Effects Probit Estimation of Labor Force Participation: Static Model with Expected Earnings

	Women	Men
Constant	1.023	
	(2.51)	
Dummy=1 if Male		14.649
		(1.89)
Age	0.038	-2.538
	(1.42)	(1.78)
Age squared	-0.001	0.059
	(1.64)	(1.87)
No. Children <5	-1.120	-0.489
	(12.12)	(0.17)
Dummy=1 if Married	-0.104	1.531
	(1.05)	(0.27)
Dummy=1 if young children and additional female	0.782	-
	(5.95)	
Dummy=1 if Currently in School	-1.678	-7.418
	(11.45)	(4.81)
Dummy = 1 if Peak Season (Jan-Mar)	0.285	1.290
	(3.35)	(2.51)
Dummy = 1 if Slack Season (May-Sept)	0.683	-0.117
	(8.14)	(0.23)
Dummy=1 if Post-secondary Education	-	-
Dummy=1 if Primary Education*	-	-
Expected Earnings	7.930	6.548*
	(28.21)	(6.33)
ρ	0.860	
(p-value)	(0.000)	
N = 599, T = 12		

[@] Where dummies have been utilized, the estimated coefficients shown include the total effect of the regressor on labor force participation for men and for women, respectively.
Omitted categories: Intermediate season (April, October through December).
* Male Coefficient significantly different from Female at 5%.

APPENDIX I: CALCULATION OF THE SAMPLE SELECTION TERMS

In this appendix we present the estimation method of the appropriate correction terms, following Vella and Verbeek (1998). The respective error terms are represented as:

$$v_{it} = \mu_i + e_{it} \qquad u_{it} = \alpha_i + \upsilon_{it} \tag{A1}$$

We need to compute the conditional expectation of the elements of v_{it}, given the T vector y_i (i.e. given the inequality constraints on all T elements of u_{it}). Employing our assumption of joint normality, the conditional expectation of v_{it}, given the vector u_i, can be derived from the standard formulae for the conditional expectation of normally distributed vectors, resulting in

$$E[\mu_i / u_i] = \sigma_{\mu\alpha}\left[\frac{T}{\sigma_\upsilon^2 + T\sigma_\alpha^2}\bar{u}_i\right] \tag{A2}$$

$$E[e_{it} / u_i] = \sigma_{e\upsilon}\left[\frac{1}{\sigma_\upsilon^2}u_{it} - \frac{T\sigma_\alpha^2}{\sigma_\upsilon^2(\sigma_\upsilon^2 + T\sigma_\alpha^2)}\bar{u}_i\right] \tag{A3}$$

where $\bar{u}_i = 1/T\sum_{t=1}^{T} u_{it}$. To obtain the conditional expectations, given the vector y_i, we replace the u_{it}'s in equations (A2) and (A3) by their conditional expectations, given y_i. This expectation can be written:

$$E[u_{it} / y_i = 1] = \int\left[\alpha_i + E\{\upsilon_{it} / y_i, \alpha_i\}\right]f(\alpha_i / y_i)d\alpha_i \tag{A4}$$

where $f(\alpha_i / y_i)$ represents the conditional density of α_i and $E\{\upsilon_{it} / y_i, \alpha_i\}$ is the generalized residual from the probit model of labour force participation given by

$$E[\upsilon_{it} / y_i, \alpha_i] = (2y_{it} - 1)\sigma_\upsilon \frac{\phi(f_{it})}{\Phi(f_{it})} \tag{A5}$$

Further,

$$f(\alpha_i / y_i) = \frac{f(y_i / \alpha_i) f(\alpha_i / z_i)}{f(y_i / z_i)} \tag{A6}$$

where $f(y_i / z_i) = \int f(y_i / z_i, \alpha_i) f(\alpha_i / z_i) d\alpha_i$ is the likelihood contribution of individual i in equation [4]; $f(\alpha_i / z_i) = f(\alpha_i)$ is a normal density and $f(y_i / \alpha_i) = \prod_{t=1}^{T} f(y_{it} / z_i, \alpha_i)$ where $f(y_{it} / z_i, \alpha_i)$ has the form of the likelihood contribution in the cross-sectional case.

Consequently, given the parameter estimates for the probit model of participation (including the variance components), the correction terms can be computed from equation (A4) using equations (A5) and (A6). This requires numerical integration over one dimension (in both equation (A6) and (A4)).