Effects of Economic Shocks on Children's Employment in Brazil

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Abstract:
Using data from Brazil's Monthly Employment Survey (PME) this paper analyzes employment patterns of Brazilian children and youth from 1982 to 1998. The paper documents substantial declines over this period in the proportion of boys and girls who are working, with most of the decline occurring during the 1990s. Taking advantage of the longitudinal structure of the PME, the paper analyzes transition rates in and out of employment for young workers. The results indicate relatively high volatility in employment, with both higher exit rates and lower entry rates responsible for the decline in youth employment. The paper examines the extent to which these relatively frequent transitions in and out of employment are affected by economic shocks to the household. In particular, the paper presents regressions analyzing the impact on child employment of an adult household member becoming unemployed.

Introduction

One of the concerns about economic volatility in developing countries is that it may induce responses from households that have negative long-term consequences. One response that generates particular concern is potential increases in the labor force activity of young people in response to negative economic shocks to households. If households are not able to buffer short-term economic downturns then children may be sent to work, potentially causing disruptions in their schooling or other possible negative effects of child labor. In addition to direct policy concern over the effects of economic shocks on child labor, researchers may be interested in whether such effects exist because of what they reveal about the ability of households to smooth transitory economic shocks. If an adult becoming unemployed leads to increased work activity by children, this may indicate that households are not able to fully insure against short-term income volatility. The extent to which households can buffer against short-run shocks is an important issue in thinking about the policy implications of economic crises such as those experienced in Latin America during the 1980s or more recently in East Asia.

Brazil is an interesting country in which to analyze the relationship between household economic shocks and child employment. Brazil has had relatively high levels of child employment, especially considering the country's relatively high per capita income. As we will see below, employment rates for 14 year-old boys were around 25% in the 1980s. Concern that high rates of youth employment may be competing with schooling are reinforced by Brazil's poor schooling performance in recent decades (Birdsall and Sabot 1996). Brazil's case is also interesting because of the substantial economic volatility experienced during the 1980s and 1990s. After two decades of rapid economic growth in the 1960s and 1970s, the country experienced an economic crisis in the early 1980s, followed by large fluctuations that left per capita income in 1990 at roughly the 1980 level. A final and important attraction of studying these issues in Brazil is that the country has excellent household survey data. In this paper we exploit an extremely rich source of data on youth employment spanning most of two decades in Brazil. The data include a longitudinal component that allows us to observe month-to-month transitions in and out of employment by all household members age ten and over. We begin by using these data to describe trends in youth employment from 1982 to 1998. We then estimate transitions in and out of employment, demonstrating the extent to which differences between males and females and trends over time are attributable to differences in entry rates versus exit rates.

Brazil's Monthly Employment Survey

The empirical analysis in this paper uses Brazil's Monthly Employment Survey, the Pesquisa Mensal de Emprego (PME). This survey is collected monthly by the Instituto Brasileiro de Geografia e Estatística (IBGE), providing the major source of information on employment and unemployment. The PME survey is organized with a panel structure similar to the United States Current Population Survey. Respondent households are surveyed once a month for four consecutive months, rotate out of the sample for eight months, and then rotate back in for four final months. Beginning in February 1982 the PME includes questions on earnings, hours, education, economic activity during the previous week, occupation, job search, and relationship to household head for everyone in the household age 10 and over. The employment and job search questions are quite detailed, including questions on length of unemployment spells, reason for leaving last job, and receipt of unemployment compensation.

The PME is a random sample of households in six major metropolitan areas of Brazil – Rio de Janeiro, São Paulo, Porto Alegre, Belo Horizonte, Recife, and Salvador. The PME surveys about 35,000 households each month, with 4500 to 7500 households in each of the six metropolitan regions included in the sample. The PME provides data on the employment and earnings of all individuals in the households age 10 and over. Our analysis is based on PME surveys from February 1982 through May 1998. The samples are large enough to allow us to look at single year of age males and females in each city, a valuable feature of the data given potentially large differences by city, age, and gender in youth employment. We observe, for example, an average of about 190 boys and 190 girls age 14 in São Paulo and about 150 boys and 150 girls age 14 in Salvador in any given month between 1982 and 1998. While these numbers are not large enough to eliminate volatility in monthly estimates, they give us a good picture of trends in labor force outcomes and provide a sound basis for the regression analysis presented below.

Trends in Youth Employment in Brazil, 1982-1998

Figure 1 shows the employment rate for 14 year-old boys and girls in two Brazilian cities, São Paulo and Salvador, from 1982 to 1998, using the data from the PME.[1] São Paulo, the largest city in Brazil, is located in the highly industrialized southeastern part of Brazil, while Salvador is located in the much poorer northeastern state of Bahia. Monthly estimates for a single year of age in a single city are highly volatile due to small sample sizes, so the plots show 5-month moving averages of the percentage working in each month. Figure 1 shows that employment rates of 14 year-olds in Brazil have been relatively high, with over 20% of boys and over 10% of girls working in the early 1980s in both cities. Figure 2 shows employment rates for 16 year-olds for the same two cities. It is striking that these rates reach levels over 60% for boys, and 40% for girls, in São Paulo in the 1980s. For both age groups employment rates are higher in São Paulo than in Salvador in all periods, suggesting that demand-side effects of greater employment opportunities may be more important than labor supply effects resulting from Salvador's lower income levels. This is consistent with the argument of Barros et al. (1996) that poverty does not seem to be the driving cause of high child employment rates in Brazil, given the regional pattern in child labor.

Figure 1 and Figure 2 show substantial declines in employment rates for males and females in both age groups from the early 1980s to the late 1990s. In most cases employment rates in 1998 are about half what they were in 1982. Abstracting from seasonal effects and monthly volatility, there is a fairly steady downward trend in employment for all groups in Salvador over this period. The employment rate for sixteen year-old boys in Salvador, for example, falls from around 40% in 1982 to around 20% in 1998. The pattern in São Paulo is considerably different, however, with increases in employment during the 1980s, peaking around 1987, for all groups. The decline in employment in São Paulo doesn't begin until around 1990, followed by fairly

[1] The classification of individuals as employed is based on the answer to a question about their principal activity during the week before the survey. In the case of individuals indicating more than one activity (such as work and school), interviewers were instructed to mark the activity that appears first on the questionnaire, with working being the first activity listed. Although this question will indicate children involved in both work and school as working, it is possible to identify these children from a separate question about schooling.

steady declines during the 1990s. By 1998 the employment rate for 16 year-olds in São Paulo is around 30% for boys and 20% for girls.

Estimating Labor Force Transitions

While the PME's rich detail on employment trends over two decades are extremely valuable, an even more intriguing feature of the data is the ability to follow labor force transitions of all individuals age 10 and over. In analyzing labor force transitions it is useful to think of a simple Markov process as a starting point for interpretation. Consider a Markov process governing transitions into and out of employment across months for a constant population, with constant probabilities of entry and exit that do not depend on past history. The proportion of the population working in month 2 is given by

$$w_2 = w_1 - w_1 p_x + (1 - w_1)\, p_e\,, \qquad (1)$$

where w_t is the proportion working in month t, p_x is the probability of leaving employment, conditional on being employed in month 1, and p_e is the probability of entering employment, conditional on not being employed in month 1. This Markov process will have a steady state in which $w_2 = w_1 = w_t$. Solving for this steady state implies that

$$w_t = \frac{p_e}{p_e + p_x}\,, \qquad (2)$$

a simple relationship linking entry and exit rates to the proportion employed. While we do not expect Brazilian youth employment transitions to behave exactly like a Markov process, Equation (2) provides a useful way for analyzing differences in employment rates between groups or changes over time.

Figure 3 shows estimates of monthly transitions in and out of employment for 14 year-old males and females in São Paulo and Salvador. For each month the PME data are used to calculate the proportion of children who change status from being employed one month to being non-employed in the following month.[2] We define the exit rate for month t as the number of

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[2] Here we classify all individuals as being either working or not. We do not distinguish between being unemployed (looking for work but not working) and being out of the labor force.

children who change from employed in month *t* to non-employed in month *t*+1, divided by the number of children who were employed in month *t*. The entry rate is defined analogously based on those who move from not employed in month *t* to employed in month *t*+1. The figures shown are five-month moving averages. For 14 year-olds in São Paulo, we see that in the early 1980s the probability that a boy who is not working in month *t* is working in month *t*+1 is about 10%, while the entry rate for girls is about 5%. The probability that a working boy leaves employment by the next month is around 25%, with fairly similar estimates for girls.[3]

Thinking of Equation (2), we can consider whether the fact that girls' employment rates are roughly half those for boys, as noted in Figure 1, is attributable more to differences in entry rates or differences in exit rates. We first note that for 14 year-old males around March 1983, p_x is about 0.3 and p_e is about 0.1, implying an employment rate from Equation (2) of 0.25, very similar to the rate actually observed. In fact, a calculation of predicted employment rates using the observed entry and exit rates and the Markovian relationship in Equation (2) turns out to track actual employment rates across all months extremely well. Using this approach, it appears that the lower employment rates for girls are explained almost entirely by the fact that girls have entry rates that are half those for boys. Exit rates are almost identical, which could be interpreted as indicating that girls who do enter employment have similar job attachment as boys.

The large decline in employment rates over time, shown in Figures 1 and 2, appears to result from both decreasing entry rates and increasing exit rates. Comparing São Paulo with Salvador, we see that entry rates for 14 year-olds are fairly similar in the two cities, but exit rates are considerably higher in Salvador, rising to over 50% by the late 1990s. In other words, only half of the children who are working in a given month in Salvador in the late 1990s are still working the following month. In São Paulo the exit rates for both males and females are around 30% in the late 1990s, still a very high degree of labor force mobility. While all of these estimates may naturally be subject to measurement error, it seems unlikely that measurement error can explain

[3] The large monthly variations in Figure 3 reflect both seasonal movements and monthly volatility due to small sample sizes. The volatility is especially large in exit rates because of the small number of 14 year-olds observed working in any single month in the sample.

either the large increases in exit rates over time or the differences between São Paulo and Salvador.

Econometric Issues in Analyzing Changes in Employment Status

We will analyze changes in binary outcomes (such as moving from working to not working) in estimating the effects of short-run shocks. This creates some methodological problems that have often been ignored in analysis of discrete responses using panel data. Consider the problem of estimating the effect of a change in the household head's income on a child's employment, conditional on the child being out of the labor force in the initial period. Suppose, in particular, that we are interested in looking at how the effect of changes in the head's income varies across different levels of the head's education. Abstracting from labor market imperfections, we will assume that as in the case of adults, children who do not work in the labor market reveal themselves to have a value of time (from either their own or their parents' perspective) that is higher than their potential market wage in that particular period. Suppose that the child's reservation wage in period *t* can be characterized as

$$r_{i,t} = b_0 + b_1 Y^P + b_2 y_{i,t} + b_3 X_{i,t} + m_i + v_{i,t}\ , \qquad (3)$$

where Y^P is the head's permanent income, y_{it} is the head's transitory income in that period, X_{it} is a set of characteristics and time-specific variables for the child and the family, m_i is a persistent random component reflecting family heterogeneity, and v_{it} is a transitory stochastic component for that period. In a model of perfect foresight and perfect credit markets, such as Heckman and Macurdy (1980), transitory income should have no effect on the reservation wage. In the presence of credit constraints, however, transitory income y_{it} may affect the reservation wage, increasing it if children's schooling and/or leisure are normal goods. It is also important to keep in mind that "transitory" changes in wages of the head or other household members may affect the child's reservation wage even in the case of perfect credit markets, since they will imply price effects on intertemporal allocation decisions. The child's market wage is a function of observable and unobservable individual and family characteristics, plus a period-specific random disturbance,

$$w_{i,t} = g_0 + g_1 X_{i,t} + e_i + u_{i,t}\ , \qquad (4)$$

Although Y^P and y_{it} presumably do not belong in the market wage equation, we note that correlated shocks to the head and the child may cause y_{it} to be correlated with u_{it}, an issue worth keeping in mind in analyzing the effects of income and employment shocks to the head on the child's labor supply. Denoting the difference between the reservation wage and the market wage by $d_{it}= r_{it} - w_{it}$, we assume that d_{it}=0 for children working in the labor market and that d_{it}>0 for children who are not working in the labor market.

One issue we are interested in is the extent to which effects of income shocks are different for households at different socioeconomic levels. Suppose, therefore, that we compare the effect on the labor supply of children of shocks to head's income for heads with different levels of education. Assume that the log of the market wage and the log of the reservation wage for the *i*th child can be described as the mean log wage for children whose heads have schooling level *s* plus a normally distributed deviation from the mean, $r_{si} = \overline{r}_{si} + v_{si}$ and $w_{si} = \overline{w}_{si} + u_{si}$, where $\overline{r}_{si}$ and $\overline{w}_{si}$ are the mean log reservation wage and mean log market wage at schooling level *s*, and v_i and u_i are draws from zero mean normally distributed random variables (we suppress the *t* subscript for simplicity). The gap between the market wage and the reservation wage is

$$d_{si} = \overline{w}_s - \overline{r}_s + u_{si} - v_{si} \qquad (5)$$

with mean $\overline{d}_s = \overline{w}_s - \overline{r}_s$ and variance $s_{ds}^2 = s_{vs}^2 + s_{us}^2 + s_{us,vs}$. An instructive special case is to assume that the variance of d_s is some constant s_d^2 at all levels of schooling.[4] Then the proportion of children working at head's schooling level *s*, P_s, is the proportion for whom d_{si} >0,

$$P_s = \Phi\left[\frac{\overline{w}_s - \overline{r}_s}{s_d}\right] \qquad (6)$$

where Φ is the cumulative standard normal distribution.

Suppose all heads with schooling level *s* experience an identical increase in transitory income, which in turn causes some change in each child's reservation wage. The effect of this

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[4] This would be the case, for example, if *u* and *v* have some constant and equal variance s_u^2 and some constant correlation r at each level of schooling, implying that $s_d^2 = 2(1-r)s_u^2$.

increase in head's income on the proportion of children who are working, indexed by the head's schooling, is given by

$$\frac{\partial P_s}{\partial y_s} = \frac{\partial P_s}{\partial r_s}\frac{\partial r_s}{\partial y_s} \tag{7}$$

Assuming no change in any child's market wage, the effect on the difference between the market wage and the reservation wage for each child is $\partial d_i / \partial y_i = -\partial r_i / \partial y_i$. Referring to the distribution of *d*, $\partial P / \partial d = f(\bar{d} / s_d)$, the normal density evaluated at the threshold separating working from non-working children. An important point of Equation (7) is the role of the density $f(\bar{d} / s_d)$. This captures the fact that the responsiveness of *P* to shocks at the household level depends on the proportion of children who are at the margin of entering (or leaving) the labor force.

Consider two families from different socioeconomic levels, one in which the head has low schooling and one in which the head has high schooling. Suppose the probability of a child working in the less educated household is *P*=0.5, while in the better educated household *P*=0.2. Even if all children experience an identical change in their reservation wage in response to some external shock, the observed change in employment rates depends on the proportion of children who are close to the margin of entering or leaving the labor force. If the variance in *(w-r)* is the same for both groups, then the group with *P*=0.5 will have a higher fraction of children at the margin, and will therefore exhibit a larger increase in the proportion of children working. This may erroneously be interpreted as a greater sensitivity of reservation wages to the shock.

In the case of labor force transitions, we will often want to condition children's behavior on their initial labor force status. For example, we will want to look at labor force entry, using only the sample of children who are out of the labor force in some initial period. In this case we are looking not at the change in the proportion of children in the labor force, but at the proportion of children currently out of the labor force who enter in response to some shock. It is important to take account of the initial conditions, especially when comparisons are made across population sub-groups. For an *e* increase in the head's income, the proportion of children who enter employment, conditional on initially being non-employed, will be

$$\frac{\partial P_s / \partial y_s}{(1 - P_s)} = \left[\frac{\partial r_s}{\partial y_s}\right]\left[\frac{f(\bar{d}_s / s_{ds})}{1 - \Phi(\bar{d}_s / s_{ds})}\right] \tag{8}$$

It is clear from Equation (8) that the sensitivity depends on the fraction of non-working children who are on the margin of entering. This fraction is given by the second term in brackets on the right-hand side of Equation (8), which is the hazard rate or inverse Mill's ratio evaluated at the threshold dividing working from non-working children. It is a property of the normal distribution that the hazard rate $f(x)/[1-\Phi(x)]$ is monotonically increasing in x. In this example this means that the fraction of non-working children who are on the margin of entering the labor force increases as the fraction of children who are working increases. This implies that an equivalent reduction in the reservation wage would cause a larger proportion of non-working children to enter the labor force, the larger the initial fraction working. If two groups of children have the same variance in reservation wages, the group with the larger fraction working will show a larger proportion of non-working children enter the labor force in response to a given change in the reservation wage. If the variance in the reservation wage is different across the two groups, then in general it will be difficult to make predictions about this component of labor supply response.

To analyze exit rates out of employment we simply use the fraction working as the reference group, that is, use Φ rather than $(1-\Phi)$ in the denominator of Equation (8). This changes the sign of the result, implying that exit rates will be higher for those with the *lower* initial employment rate. The intuition of these results is straightforward. Assuming a normal distribution for the difference between market wages and reservation wages, in a group with a high employment rate those who are not working will on average be relatively close to the margin of entering employment. A given increase in the market wage will therefore cause a relatively high fraction of the non-working to start working. For the same group, those who are working will on average be relatively far from the margin of leaving employment. A given decrease in market wages will therefore induce relatively low numbers of exits.

While the sensitivity of labor force entry and exit to the initial fraction employed appears straightforward, it does not seem to have been taken into account in much of the "added worker" literature. It is especially important when effects are estimated using employment transitions, such as in Lundberg's (1985) analysis of the labor supply of wives. The implication for our analysis is that comparisons of labor force entry or exit rates across children (or other household members) with different socioeconomic characteristics does not necessarily provide a clear signal about the responsiveness of reservation wages to some given shock. The problem is essentially one of unobserved heterogeneity. Non-working children (or women) with different characteristics can be expected to differ systematically in the gap between reservation wages and market wages.

The qualitative predictions derived above can be made more precise by exploiting another important property of the normal distribution. This property implies that if we evaluate the hazard rate at two points on the cumulative distribution, F_1 and F_2, the ratio of the two hazard rates is invariant to the variance of the distribution. Formally, if $l(F_1)$ is the inverse Mill's ratio $f((x-m)/s)/[1-\Phi((x-m)/s)]$ evaluated at some point $F_1(x)$ on the cumulative distribution, then the ratio $l(F_2)/l(F_1)$ is a constant that is invariant to the mean and variance of the underlying distribution[5]. This is a powerful result, because it means that we can make predictions about the relative hazard rates at different points on the distribution without having to make assumptions about the mean and variance of the distribution. Table 1 summarizes the implications of this result by showing the hazard rate for entering employment for one group relative to the hazard rate for a second group, given the initial fractions employed in the two groups. For example, Table 1 implies that if the employment rate for 14 year-old boys is 20% and the employment rate for 14 year-old girls is 10%, then if all other factors affecting entry and exit are identical, we would expect an identical reduction in reservation wages to cause a 1.8 times larger entry rate for boys than for girls. This difference results entirely from the differences in the fraction of each group that is close to the margin of entering, given the fraction initially working. If there are differences in the magnitude of changes in the reservation wage, then this will be an additional source of differences in entry rates. As noted in Figure 1, we see employment rates of roughly 20% for boys and 10% for girls in Salvador in the early 1980s. The results in Figure 2 show entry rates for boys that are roughly double those for girls, results that are broadly consistent with the predicted differences in hazard rates.

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[5] Since the denominators are held constant at some 1- F_1 and 1- F_2, the result comes from the fact that the densities in the numerator simply scale up and down with changes in the variance. It is straightforward to show that when the variance is multiplied by *k*, the density at any given point on the cumulative distribution is multiplied by 1/*k*. Since this is true for all values of the cumulative distribution, the ratio of any two hazard rates is unchanged by the change in the variance.

Given the relatively low initial levels of employment for 14 year-olds, it turns out that there is a smaller difference in exit rates than there is in entry rates. We can read Table 1 in the opposite direction to infer entry rates, comparing girls who are 90% non-employed to boys who are 80% non-employed. This implies that the exit rate for girls will be 1.25 times higher than the exit rates for boys, a smaller difference than predicted for entry rates. Looking at Figure 2, we see that exit rates are generally higher for girls in São Paulo, though they are often higher for boys in Salvador.

These predictions about relative entry and exit rates focus entirely on the second term on the right-hand side of Equation (8), which is the term describing the fraction of a group that is near the margin of entering employment. The first term on the right-hand side of Equation (8) is the piece that relates more closely to conventional arguments about the sensitivity of different groups to transitory shocks. These issues will be analyzed in more detail below, when we estimate regressions analyzing the determinants of entry and exit rates.

Labor Force Transitions by Mother's Education

A simple way of classifying children by socioeconomic status is to use mother's education. Mother's education is non-missing for a high proportion of children, since mothers are much less likely to be absent than fathers, and since we do not require that a measure of income be available. Given the high correlation in mother's and father's schooling and the high explanatory power of schooling in explaining both men's and women's earnings in Brazil (Lam and Schoeni, 1993), mother's education is an attractive variable to use for descriptive analysis of socioeconomic differentials in child employment. Figure 4 shows employment rates for 14 year-old boys and girls in São Paulo divided into two groups – those whose mothers have 4 years of schooling or less, and those who have more than 4 years of schooling. This roughly divides the sample in half at the end of the period. Not surprisingly, children whose mother's are in the lower half of the schooling distribution are more likely to work, though the differences are considerably larger for boys than for girls.

Table 5 shows entry and exit rates for 14 year-old boys in São Paulo for the same two groups. Entry rates are considerably higher for boys whose mothers have less education. While this might be interpreted as evidence that these families are more sensitive to shocks, the results above show that this result could also be explained simply by the fact that this group has higher fractions employed in every period, implying that the non-employed group is closer to the margin of entering employment. Turning to exit rates in the lower panel, a dominant feature of the graph is the high volatility in estimated exit rates for the higher education group. This is the result primarily of the low numbers observed working in the sample in any given month, and probably does not represent actual higher volatility. Abstracting from this monthly volatility, the exit rates appear to be relatively similar for the two groups.

Preliminary Regression Results

We follow children over the first four month period of interviews to examine the effect of changes in the transitory income of the household head on the children's labor supply. Both the entry of children into the labor force and exit from the labor force are examined. Our regression sample includes 14-16 year olds who are coded as either the children of the male household head, or coded as another relative of the male head. For simplicity we will occasionally refer to the male household heads as "fathers" since this is the case for over 90% of the sample.[6] Specifically we focus on the effect of the father becoming unemployed, provided he was employed in the first interview. Since we have data for 4 months we examine the effect of not only the contemporaneous shock, but also lagged shocks. The dependent variable varies according to the child's labor force status in the third month and refers to the child's transition from the third to the fourth month. For example, we examine the probability the child enters the labor force in the fourth month, for all children who are out of the labor force in the third month. While the dependent variable examines only one transition period of the child, the transitions of the head of the household are based on the patterns of the head's employment status over the 4 month period. Table 2 shows the mapping of the 27 possible transitions over the 4 interviews, with E denoting employment, U denoting unemployment and N denoting non-participation in the labor force. The effect of the contemporaneous shock (designated as lag 0) compares the probability of children's entry for "fathers" who have the pattern "EEEU" to "fathers" who remain employed "EEEE"(the omitted category). In other words, does the child enter the labor force in month 4, when the “father” becomes unemployed in month 4. The variable indicating that the head became unemployed with a 1 period lag, signifies that the head became unemployed in period three while the 2 period lag signifies that the head became unemployed in period 2. The cases for which non-participation in the labor force (N) follows the unemployment shock are classified into the unemployment shocks since these fathers may be discouraged workers. However if inactivity preceeds unemployment, the head’s transition may be anticipated and these transitions are thus classified as leaving the labor force. For the purpose of keeping the unemployment “shock” variables clean for comparison with the omitted category, at this time the difficult to classify transitions have also been included in the leaving the labor force category. For example if the “father’s” pattern is EUEE this is different from the two period lag of EUUU (or EUNN etc.) so we prefer to dummy out these transitions. In the future we will separate out these transitions from the leaving the labor force category.

Table 3 shows the variable means for the samples of 14-16 year olds used in the regressions. Recall that the samples are conditional on the household head being employed in the first month and the children being related to the male household head. The labor force participation rate of the children in the third month is 24%, meaning that three quarters will be in the entry sample and only one quarter will be in the exit sample. Since we have combined children from the 6 metropolitan areas our samples are large. There are 75,724 children in the entry sample and 22,024 in the exit sample. The distribution of the type of transitions by the household head is similar for the entry and exit samples. Table 3 shows that approximately 92% of the “fathers” remain employed for the next three months, while 7% are classified into the mixed dummy of leaving the labor force. The large samples are necessary to identify the effect of these rare shocks. Only 1 percent of “fathers” experience a contemporaneous (lag 0) unemployment shock and a smaller percentage experience the lag 1 or lag 2 unemployment shock. For the exit sample, only 38 observations are classified as a lag 2 shock.

Table 4 shows the results from the estimation of a probit model for labor force entry. The dependent variable is a dichotomous variable indicating whether or not the child enters the labor

[6] The male household head includes the few cases in which a woman was listed as the head of the

force in the fourth month, conditional on being out of the labor force in month three. Along with the variables indicating the transition patterns of the household head, independent variables in the regressions include dummies for the child's age, four categories of age for the household head, 7 categories of completed schooling for the household head, and 6 categories of completed schooling for the child. To control for differences across region and time, we included 5 region dummies (Salvador is omitted) as well as year and month dummies. The first column pools both sexes while the second and third columns are for boys and girls respectively.

The effect of the contemporaneous shock is positive and significant for all three samples. Both girls and boys are more likely to enter the labor force in month 4 if their "father" becomes unemployed in month 4. The effects of the lagged shocks are perplexing, particularly in the case of girls. While there is no effect of the "father" becoming unemployed in the previous month, the effect of the two lag shock is large and significant for girls. Table 5 presents the marginal effects for changes in specific variables included in the regressions. Given the non-linear estimator we have evaluated the marginal effects for a baseline case of a 14 year old in a household in Salvador for which the household head is age 30-39 in the year 1982. The baseline probability of entering the labor market is 10% overall with the girls' probability nearly half of the boys'. The contemporaneous shock reduces the probability of entering by 2 to 4 percentage points, which is approximately the same magnitude as moving the head's education from 0 to 4 years of completed schooling. The results of the probit model confirm the trends described earlier in the paper. Entry rates are higher with older ages and lower over time.

Table 6 shows the results of the estimation of probit models of the child's exit from the labor force. The dependent variable is a dichotomous variable indicating whether or not the child exits the labor force from the third to fourth month, conditional on being in the labor force in month three. The explanatory variables are the same as in the entry probits, with the addition of a set of variables to measure the effect of the child's being in the same industry as the "father". While the effects of the contemporaneous shocks suggest that children are less likely to leave the labor force in month 4 when the "father" becomes unemployed in month 4, the lagged effects are again peculiar and defy any easy interpretation. Controlling for the child's industry is important

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household but her male spouse was present.

since the child is more likely to exit if he or she is in the same industry as the head experiencing the contemporaneous shock. Table 7 presents the marginal effects calculated for a baseline individual. The probability of leaving the labor force falls by approximately 10 percentage points if the head becomes unemployed in month 4 although the probability of exiting is 10 percentage points higher than the baseline if the child is employed in the same industry as the head experiencing the shock.

These results are very preliminary and we hope to have more stable results to present at LACEA.

References

Barros, Ricardo and David Lam (1996) "Income and Education Inequality and Children's Schooling Attainment in Brazil," in Nancy Birdsall and Richard Sabot (eds.), *Opportunity Foregone: Education in Brazil,* Washington: Inter-American Development Bank.

Barros, Ricardo Paes de, Rosane Mendonca, and Tatiana Velazco (1996) "A Pobreza é a Principal Causa do Trabalho Infantil no Brasil Urbano?" in *Economia Brasileira em Perspectiva*, IPEA: Rio de Janeiro, pp. 537-563.

Birdsall, Nancy, and Richard Sabot (eds.) (1996) *Opportunity Foregone: Education in Brazil*, Washington: Inter-American Development Bank.

Deninger, Klaus, and Lyn Squire (1996) "A New Data Set Measuring Income Inequality," *The World Bank Economic Review*, 10(3): 565-91.

Duryea, Suzanne (1997) "Children's Advancement Through School in Brazil: The Role of Transitory Shocks to Household Income," Presented at the 1997 annual meetings of the Population Association of America (PAA) and the Latin American and Caribbean Economic Association (LACEA). Working Paper Series #376, IDB.

Duryea, Suzanne (1995)"Short Run Labor Force Transitions by Married Brazilian Women, 1982-1991: Added Worker Effects," Paper presented at the 1995 annual meeting of the Population Association of America in San Francisco, April 1995

Hanushek, Eric, Joao Batista Gomes-Neto, and Ralph Harbison (1996) "Efficiency-Enhancing Investments in School Quality," in Nancy Birdsall and Richard Sabot (eds.), *Opportunity Foregone: Education in Brazil,* Washington: Inter-American Development Bank.

Heckman, James J. and Macurdy, Thomas E. (1980) "A Life Cycle Model of Female Labour Supply," *Review of Economic Studies*, XLVII: 47-74.

Jacoby, Hanan (1994) "Borrowing Constraints and Progress Through School: Evidence from Peru," *Review of Economics and Statistics* 76(1): 151-160.

Lundberg, Shelly (1985) "The Added Worker Effect," *Journal of Labor Economics* 3(1):11-35.

Lam, David, and Suzanne Duryea (1999) "Effects of Schooling on Fertility, Labor Supply, and Investments in Children, With Evidence From Brazil," *Journal of Human Resources*, 34(1): 160-192.

Lam, David, and Deborah Levison (1992) "Declining Inequality in Schooling in Brazil and its Effects on Inequality in Earnings," Journal of Development Economics, 37: 199-225.

Lam, David, and Robert Schoeni (1993) "Effects of Family Background on Earnings and Returns to Schooling: Evidence from Brazil," *Journal of Political Economy*, 101(4): 710-740.

Levison, Deborah (1991) “Children’s Labor Force Activity and Schooling in Brazil,” Ph.D. dissertation, Univeristy of MIchigan, 1991.

Maloney, Tim (1991) “Unobserved Variables and the Elusive Added Worker Effect,” *Economica*, Vol. 58.

Strauss, John and Duncan Thomas (1995) “Human Resources: Empirical Modeling of Household and Family Decisions," in Jere Behrman and T.N. Srinivasan (eds.) *Handbook of Development Economics*, Volume III, Amsterdam: North Holland Press.

World Bank. (1999) World Development Report 1998/99. New York: Oxford University Press.

Table 1. Ratio of hazard rate for entry into employment for group 1 to hazard rate for group 2, given proportions initially working

Group 2 proportion working	Group 1 proportion working								
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.1	1.00	1.79	2.55	3.30	4.09	4.95	5.94	7.18	9.00
0.2	0.56	1.00	1.42	1.84	2.28	2.76	3.31	4.00	5.01
0.3	0.39	0.70	1.00	1.30	1.61	1.94	2.33	2.82	3.53
0.4	0.30	0.54	0.77	1.00	1.24	1.50	1.80	2.17	2.73
0.5	0.24	0.44	0.62	0.81	1.00	1.21	1.45	1.75	2.20
0.6	0.20	0.36	0.51	0.67	0.83	1.00	1.20	1.45	1.82
0.7	0.17	0.30	0.43	0.56	0.69	0.83	1.00	1.21	1.51
0.8	0.14	0.25	0.35	0.46	0.57	0.69	0.83	1.00	1.25
0.9	0.11	0.20	0.28	0.37	0.45	0.55	0.66	0.80	1.00

Note: Assumes normally distributed log wage and reservation wage with equal variances for two groups. Example: if 30% are working in group 1, and 10% are working in group 2, Group 1's hazard rate for entry into employment is 2.55 times the hazard rate for group 2.

Table 2. Mapping of the 27 Possible Transitions for the Household Head Over the First 4 Months into the 5 transition variables
(conditional on the head being employed in the first month)

variable definitions	month 1	month 2	month 3	month 4	
head employed all 4 months	E	E	E	E	
head unemployed lag 0	E	E	E	U	
head unemployed lag 1	E	E	U	U	
	E	E	U	N	
head unemployed lag 2	E	U	U	U	
	E	U	N	N	
	E	U	U	N	
	E	U	N	U	
head leaves labor force	E	N	N	N	
	E	N	U	N	
	E	N	U	E	
	E	N	E	U	
	E	N	U	U	
	E	N	E	E	
	E	N	E	N	
	E	N	N	U	
	E	N	N	E	(*)
	E	E	N	N	
	E	E	N	U	
	E	E	N	E	
	E	E	E	N	
	E	E	U	E	(*)
	E	U	E	U	(*)
	E	U	E	E	(*)
	E	U	U	E	(*)
	E	U	E	N	(*)
	E	U	N	E	(*)

Note: If leaving the labor force preceeds unemployment the transition is categorized as leaving the labor force.
(*) This category also includes transitions difficult to classify but important to dummy out from the ones we are interested in. In the future these will be separated out in a category for unstable cases.

Table 3. Variable Means for Samples of 14-16 Year Olds

A. Pooled Sample	**Mean**	**Std. Dev.**	
child employment rate month 3	0.21	0.41	
child LFP rate month 3	0.24	0.43	
B. Sample for Children's Entry from month 3 to 4	**Mean**	**Std. Dev.**	**No. Observations**
head employed all 4 months	0.92	0.27	69715
head leaves labor force	0.07	0.25	5063
head unemployed lag 0	0.01	0.09	605
head unemployed lag 1	0.00	0.05	227
head unemployed lag 2	0.00	0.04	114
C. Sample for Children's Exit from month 3 to 4	**Mean**	**Std. Dev.**	
head employed all 4 months	0.91	0.28	20066
head leaves labor force	0.07	0.26	1640
head unemployed lag 0	0.01	0.10	217
head unemployed lag 1	0.00	0.05	64
head unemployed lag 2	0.00	0.04	38

Note: Samples are conditional on the household head being employed in the first month and the children being related to the household head.

Table 4. Probits for Children's Entry into the Labor Force from month 3 to 4
Conditional on male household head being employed in the first month
and the child being out of the labor force in the third month
Sample: 14-16 year olds who are related to the male household head in all 6 metropolitan areas

Dependent Variable: Child Enters Labor Force from month 3 to month 4

	Total		**Boys**		**Girls**	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
constant	-1.70 *	0.24	-1.36 *	0.42	-2.20 *	0.32
head unemployed lag 0	0.19 *	0.07	0.17 ***	0.10	0.21 **	0.10
head unemployed lag 1	0.02	0.13	-0.06	0.18	0.10	0.18
head unemployed lag 2	0.25	0.16	-0.12	0.31	0.42 **	0.19
head leaves labor force	0.06 **	0.03	0.01	0.04	0.13 *	0.04
female	-0.33 *	0.01				
child age 15	0.25 *	0.02	0.27 *	0.02	0.23 *	0.03
child age 16	0.46 *	0.02	0.47 *	0.03	0.46 *	0.03
head age 20-29	0.53 **	0.23	0.15	0.41	0.66 **	0.30
head age 30-39	0.39	0.23	0.03	0.41	0.51 ***	0.29
head age 40-49	0.35	0.23	-0.03	0.41	0.47 ***	0.29
head age 50-59	0.31	0.23	-0.05	0.41	0.42	0.29
head 1-3 years school	-0.10 *	0.02	-0.06 ***	0.03	-0.14 *	0.03
head 4 years school	-0.23 *	0.02	-0.23 *	0.03	-0.23 *	0.03
head 5-7 years school	-0.32 *	0.04	-0.29 *	0.05	-0.37 *	0.05
head 8 years school	-0.42 *	0.03	-0.41 *	0.05	-0.44 *	0.05
head 9-10 years school	-0.48 *	0.06	-0.42 *	0.08	-0.56 *	0.09
head 11 years school	-0.58 *	0.04	-0.57 *	0.05	-0.59 *	0.05
head 12-15 years school	-0.88 *	0.09	-0.98 *	0.13	-0.74 *	0.13
head >=15 years school	-0.88 *	0.05	-0.93 *	0.06	-0.81 *	0.07
child 1-3 years school	0.07	0.06	0.02	0.08	0.17	0.11
child 4 years school	0.02	0.06	-0.02	0.08	0.10	0.11
child 5-7 years school	-0.14 *	0.06	-0.16 **	0.08	-0.07	0.10
child 8 years school	-0.19 *	0.06	-0.24 *	0.08	-0.10	0.11
child 9-10 years school	-0.33 *	0.07	-0.48 *	0.09	-0.17	0.11
child 11 years school	-0.01	0.09	-0.01	0.11	0.01	0.15

Belo Horizonte	0.23 *	0.03	0.18 *	0.04	0.28 *	0.04
Recife	0.03	0.03	0.00	0.04	0.06	0.04
Rio de Janeiro	-0.14 *	0.03	-0.22 *	0.04	-0.05	0.04
Porto Alegre	0.23 *	0.03	0.21 *	0.04	0.25 *	0.04
Sao Paulo	0.34 *	0.03	0.27 *	0.04	0.43 *	0.04
year 1983	0.13 **	0.06	0.16 **	0.08	0.12	0.08
year 1984	0.09 *	0.03	0.09 **	0.04	0.08 ***	0.04
year 1985	0.07	0.06	0.20 **	0.08	-0.03	0.08
year 1986	0.05	0.03	0.03	0.04	0.07	0.04
year 1987	0.08	0.06	0.21 **	0.09	-0.02	0.09
year 1988	0.03	0.03	0.05	0.05	0.00	0.05
year 1989	0.07	0.06	0.10	0.09	0.07	0.09
year 1990	0.04	0.03	0.01	0.05	0.08	0.05
year 1991	0.05	0.06	0.12	0.09	-0.14 *	0.05
year 1992	-0.17 *	0.04	-0.19 *	0.05	0.04	0.09
year 1994	-0.14 *	0.03	-0.22 *	0.05	-0.07	0.05
year 1995	-0.03	0.06	0.06	0.09	-0.10	0.09
year 1996	-0.17 *	0.03	-0.15 *	0.05	-0.20 *	0.05
year 1997	-0.13 **	0.06	-0.05	0.09	-0.20 **	0.09
year 1998	-0.18 *	0.06	-0.21 *	0.08	-0.14	0.10
February	0.08 **	0.04	0.11 **	0.05	0.04	0.05
March	-0.03	0.04	0.01	0.05	-0.07	0.05
April	0.12 **	0.06	0.27 *	0.08	0.00	0.09
May	0.01	0.06	0.13	0.08	-0.08	0.08
June	0.03	0.06	0.16 **	0.08	-0.07	0.09
July	0.04	0.06	0.11	0.08	0.00	0.08
August	0.07	0.06	0.15 ***	0.08	0.01	0.08
September	0.02	0.06	0.11	0.08	-0.03	0.08
October	0.04	0.06	0.16 ***	0.08	-0.05	0.08
November	0.05	0.06	0.18 **	0.08	-0.04	0.08
December	0.20 **	0.06	0.32 *	0.08	0.10	0.08
N		75724	33487		42237	
Pseudo R-squared		0.08	0.08		0.07	

Notes:
* .01
** .05
*** .10

Table 5. Marginal Effects of Entry Probits

A. Baseline Probability of Entering is evaluated at the following characteristics:
14 year old in Salvador living in a household in which the male head is age 30-39, has no education, and is employed in all 4 months, in the year 1982.

Baseline Probability	**Pooled**	**Boys**	**Girls**
	0.10	0.09	0.05

B. Change in the Baseline Probability of the Child Entering from months 3 to 4, conditional on the household head being employed in the first month, and the child being out of the labor force in the third month

Change in Percentage Points	**Pooled**	**Boys**	**Girls**
head becomes unemployed month 4 (lag 0)	0.04	0.03	0.02
head becomes unemployed month 3 (lag 1)	0.00	-0.01	0.01
head becomes unemployed month 2 (lag 2)	0.05	-0.02	0.06
head leaves the labor force	0.01	0.00	0.01
head's schooling increases to 4 years	-0.03	-0.03	-0.02
child's age increases from 14 to 16	0.10	0.10	0.06
metro changes from Salvador to Sao Paulo	0.07	0.05	0.06
year changes from 1982 to 1998	-0.03	-0.03	-0.01

Table 6. Probits for Children's Exit from the Labor Force from month 3 to 4
Conditional on male household head being employed in the first month
and the child being in the labor force in the third month
Sample: 14-16 year olds who are related to the male household head in all 6 metropolitan areas

Dependent Variable: Child Exits Labor Force from month 3 to month 4

	Total		**Boys**		**Girls**	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
constant	-0.13	0.24	0.30	0.31	-0.29	0.38
head unemployed lag 0	-0.27 **	0.11	-0.27 ***	0.15	-0.24	0.17
head unemployed lag 1	0.41 *	0.15	0.35 ***	0.19	0.53 **	0.24
head unemployed lag 2	-0.36	0.25	-0.38	0.37	-0.34	0.34
head leaves labor force	0.11 **	0.04	0.15 *	0.06	0.05	0.07
female	0.18 *	0.02				
child age 15	-0.15 *	0.03	-0.17 *	0.03	-0.12 *	0.04
child age 16	-0.33 *	0.03	-0.33 *	0.03	-0.32 *	0.04
head age 20-29	0.10	0.22	-0.02	0.29	0.25	0.33
head age 30-39	0.08	0.21	-0.04	0.28	0.22	0.32
head age 40-49	0.11	0.21	-0.02	0.28	0.26	0.32
head age 50-59	0.12	0.21	-0.07	0.28	0.36	0.32
head 1-3 years school	0.06 **	0.03	0.07 ***	0.04	0.06	0.05
head 4 years school	0.11 *	0.03	0.11 *	0.04	0.11 **	0.05
head 5-7 years school	0.12 *	0.05	0.15 **	0.06	0.09	0.08
head 8 years school	0.15 *	0.05	0.11 ***	0.06	0.22 *	0.08
head 9-10 years school	0.19 **	0.09	0.22 **	0.11	0.16	0.14
head 11 years school	0.23 *	0.06	0.24 *	0.07	0.22 **	0.09
head 12-15 years school	0.47 *	0.13	0.38 **	0.16	0.72 *	0.21
head >=15 years school	0.32 *	0.08	0.42 *	0.11	0.21	0.14
same industry	-0.15 *	0.03	-0.13 *	0.03	-0.19 *	0.05
same industry*EUMlag0	0.69 **	0.29	0.81 **	0.36	0.43	0.50
same industry*EN	0.51 *	0.13	0.55 *	0.16	0.41 **	0.25
child 1-3 years school	0.14 ***	0.08	0.07	0.09	0.39 *	0.16
child 4 years school	0.11	0.08	0.02	0.09	0.41 *	0.16
child 5-7 years school	0.15 **	0.08	0.04	0.09	0.49 *	0.16
child 8 years school	0.08	0.08	-0.10	0.10	0.49 *	0.16
child 9-10 years school	0.11	0.09	-0.06	0.11	0.48 *	0.17
child 11 years school	-0.08	0.11	-0.27 **	0.13	0.40 ***	0.21

Belo Horizonte	-0.53 *	0.04	-0.51 *	0.05	-0.56 *	0.07
Recife	-0.29 *	0.04	-0.28 *	0.05	-0.30 *	0.08
Rio de Janeiro	-0.60 *	0.04	-0.54 *	0.05	-0.70 *	0.07
Porto Alegre	-0.75 *	0.04	-0.74 *	0.05	-0.77 *	0.07
Sao Paulo	-0.73 *	0.04	-0.75 *	0.05	-0.72 *	0.06
year 1983	-0.28 *	0.08	-0.46 *	0.10	-0.45 *	0.14
year 1984	0.13 *	0.04	0.13 *	0.05	0.14 **	0.06
year 1985	-0.14 ***	0.08	-0.29 *	0.10	-0.35 *	0.14
year 1986	0.07 ***	0.04	0.08	0.05	0.06	0.07
year 1987	-0.31 *	0.08	-0.51 *	0.11	-0.45 *	0.14
year 1988	0.16 *	0.04	0.17 *	0.05	0.15 **	0.07
year 1989	-0.24 *	0.08	-0.38 *	0.11	-0.49 *	0.15
year 1990	0.10 **	0.04	0.09	0.06	0.12	0.07
year 1991	-0.27 *	0.09	-0.43 *	0.11	-0.48 *	0.15
year 1992	0.14 *	0.05	0.17 *	0.06	0.08	0.08
year 1994	0.29 *	0.05	-0.14	0.12	-0.27 ***	0.16
year 1995	-0.11	0.09	0.29 *	0.06	0.29 *	0.08
year 1996	0.36 *	0.05	-0.28 *	0.12	-0.32 **	0.15
year 1997	0.17 ***	0.09	0.27 *	0.06	0.48 *	0.08
year 1998	0.56 *	0.10	0.68 *	0.13	0.40 **	0.17
February	-0.11 **	0.05	-0.12 **	0.06	-0.07	0.08
March	-0.04	0.05	-0.02	0.06	-0.06	0.08
April	-0.55 *	0.08	-0.71 *	0.11	-0.75 *	0.15
May	-0.48 *	0.08	-0.71 *	0.11	-0.57 *	0.14
June	-0.52 *	0.08	-0.79 *	0.11	-0.57 *	0.14
July	-0.49 *	0.08	-0.65 *	0.11	-0.68 *	0.14
August	-0.38 *	0.08	-0.57 *	0.11	-0.53 *	0.14
September	-0.51 *	0.08	-0.71 *	0.11	-0.63 *	0.14
October	-0.48 *	0.08	-0.72 *	0.11	-0.57 *	0.14
November	-0.54 *	0.08	-0.73 *	0.11	-0.67 *	0.14
December	-0.37 *	0.08	-0.56 *	0.11	-0.52 *	0.14
N		22024	14101		7923	
Pseudo R-squared		0.05	0.05		0.04	

Notes:
* .01
** .05
*** .10

Table 7. Marginal Effects Calculated from Exit Probits

A. Baseline Probability of Exiting is evaluated at the following characteristics:
14 year old in Salvador living in a household in which the male head is age 30-39,
has no education, and is employed in all 4 months, in the year 1982.

Baseline Probability	**Pooled**	**Boys**	**Girls**
	0.47	0.60	0.47

B. Change in the Baseline Probability of the Child Exiting from months 3 to 4,
conditional on the household head being employed in the first month,
and being in the labor force in the third month

Change in Percentage Points	**Pooled**	**Boys**	**Girls**
head becomes unemployed month 4 (lag 0)	-0.10	-0.08	-0.11
head becomes unemployed month 3 (lag 1)	0.17	0.14	0.21
head becomes unemployed month 2 (lag 2)	-0.12	-0.14	-0.11
head leaves the labor force	0.05	0.06	0.03
head's schooling increases to 4 years	0.04	0.04	0.04
child's age increases from 14 to 16	-0.13	-0.13	-0.12
metro changes from Salvador to Sao Paulo	-0.26	-0.29	-0.25
year changes from 1982 to 1998	0.22	0.23	0.17
head unemployed (lag 0) * same industry	0.12	0.06	0.21

Figure 1. Percent of 14 year-old males and females working in metropolitan São Paulo and Salvador, 1982-1998, 5-month moving averages, Brazil PME

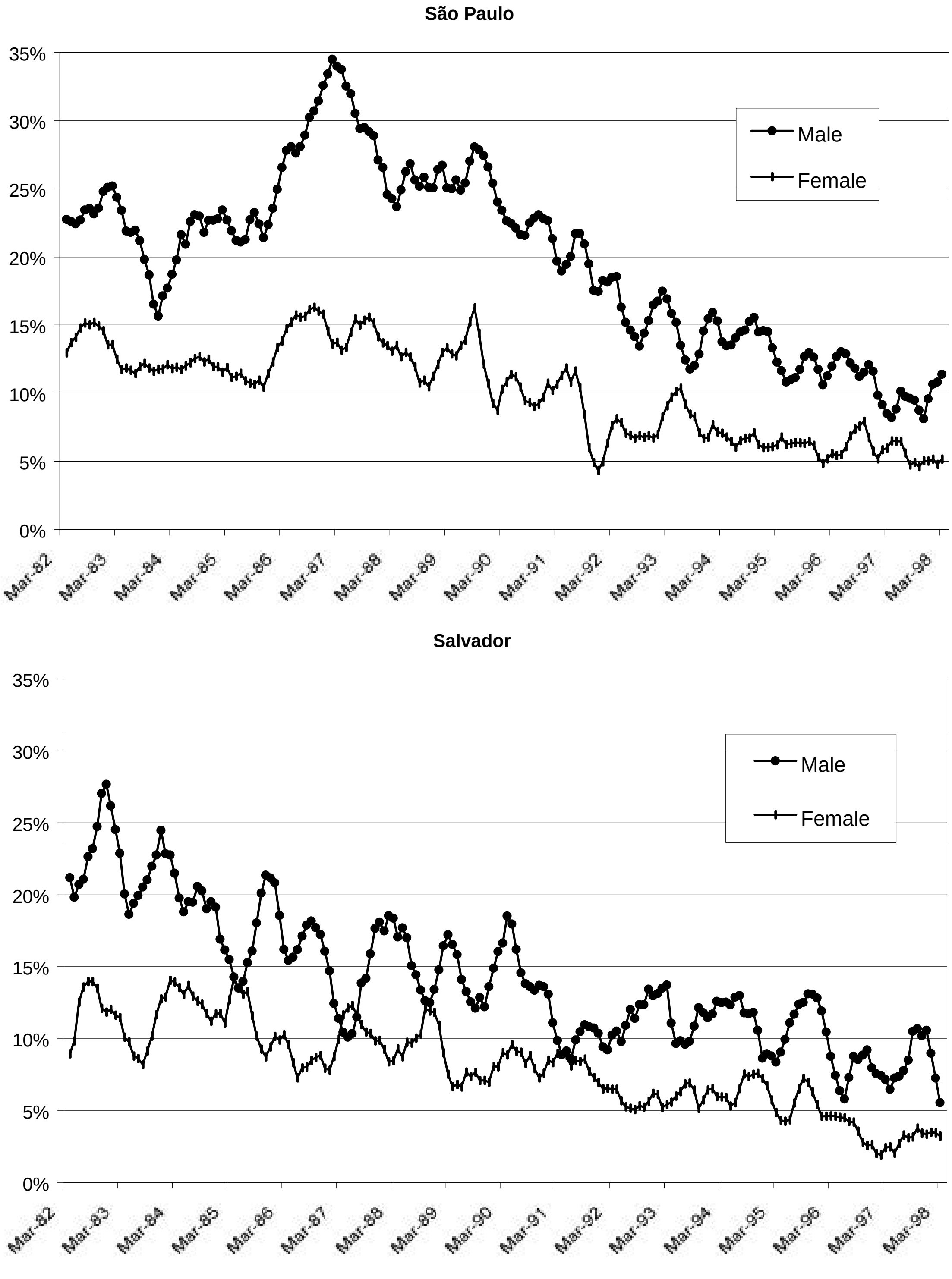
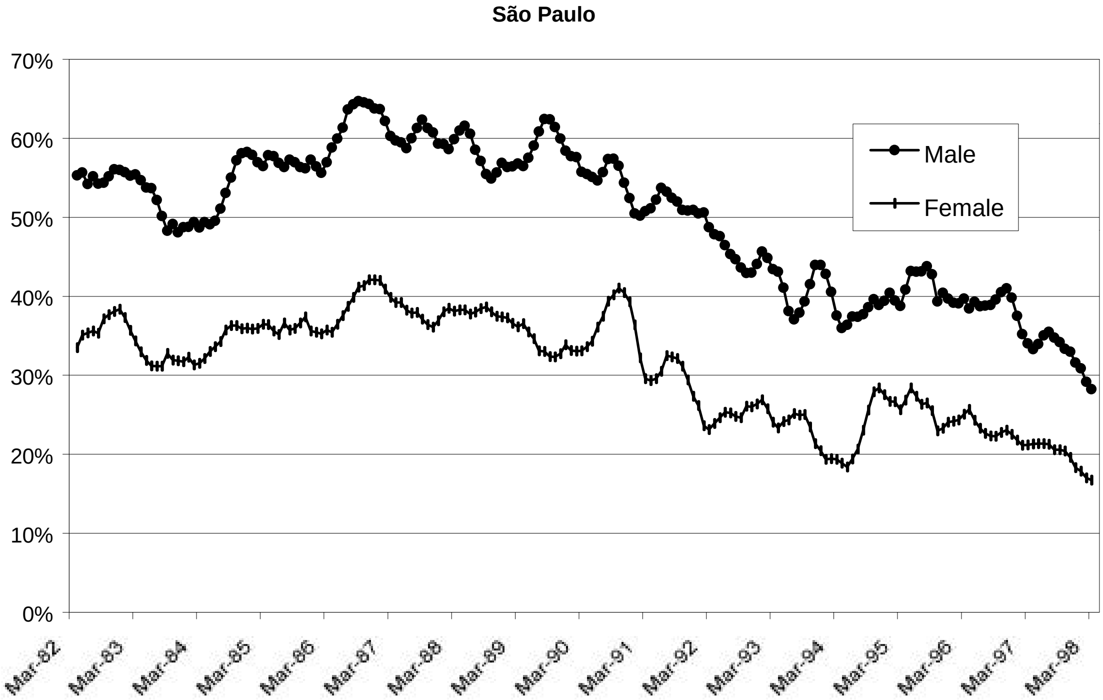


Figure 2. Percent of 16 year-old males and females working in metropolitan São Paulo and Salvador, 1982-1998, 5-month moving averages, Brazil PME



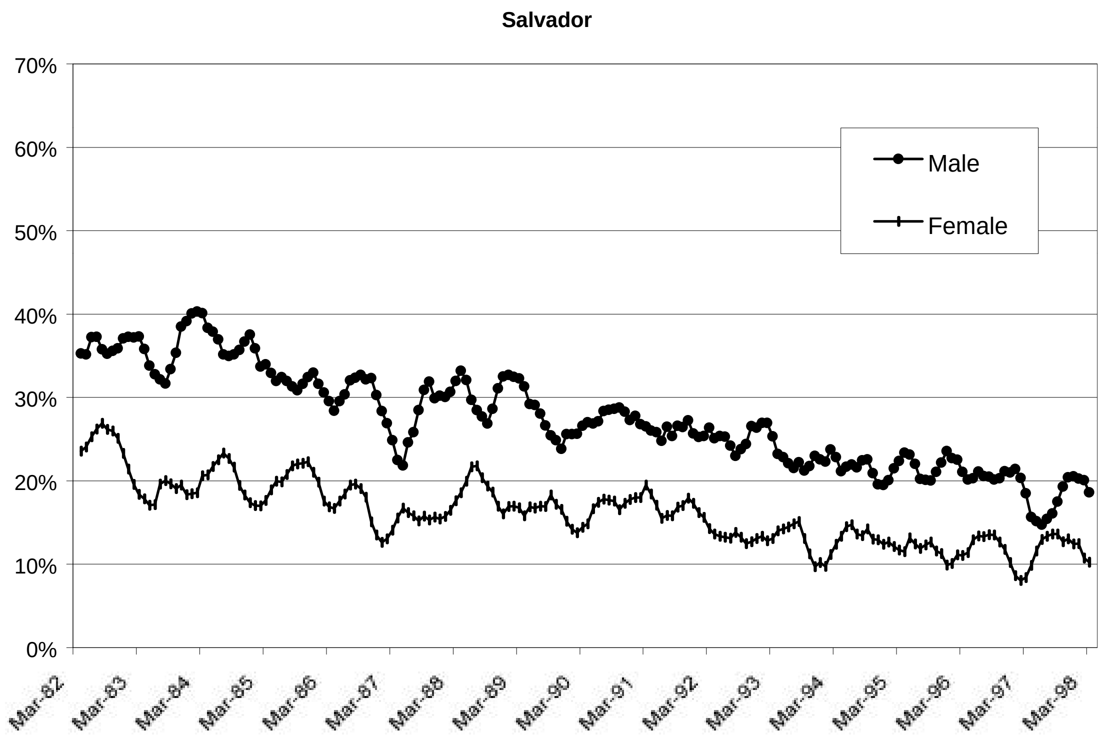
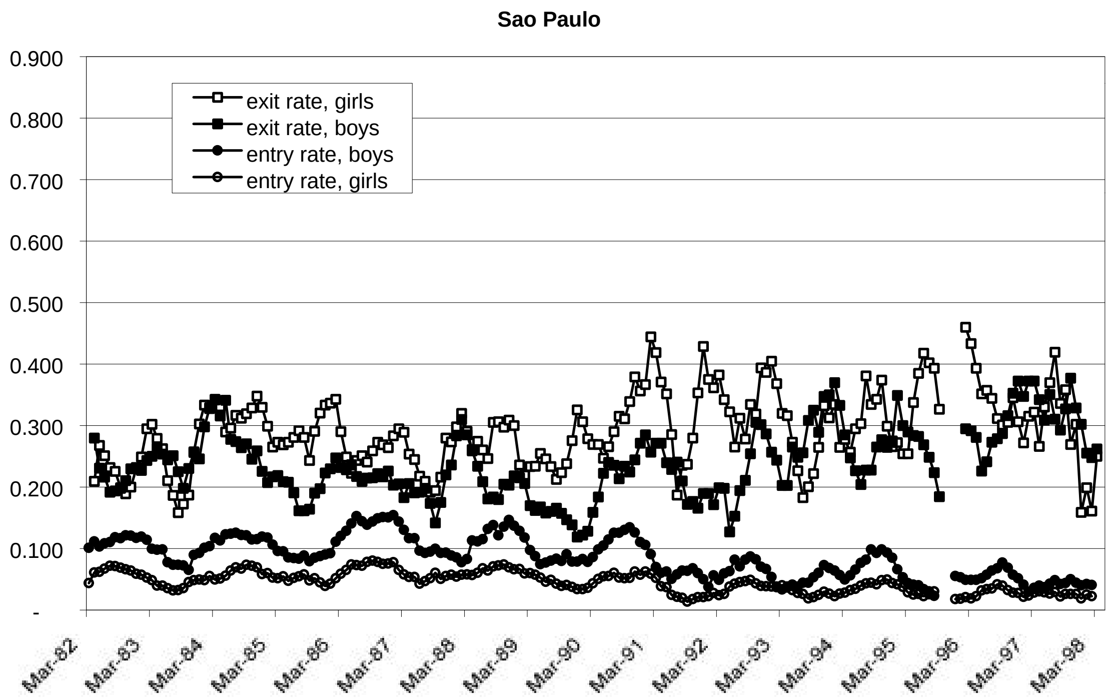


Figure 3. Rates of entry and exit into employment, 14 year old boys and girls, Sao Paulo and Salvador, 1982-1998, 5-month moving averages, Brazil PME



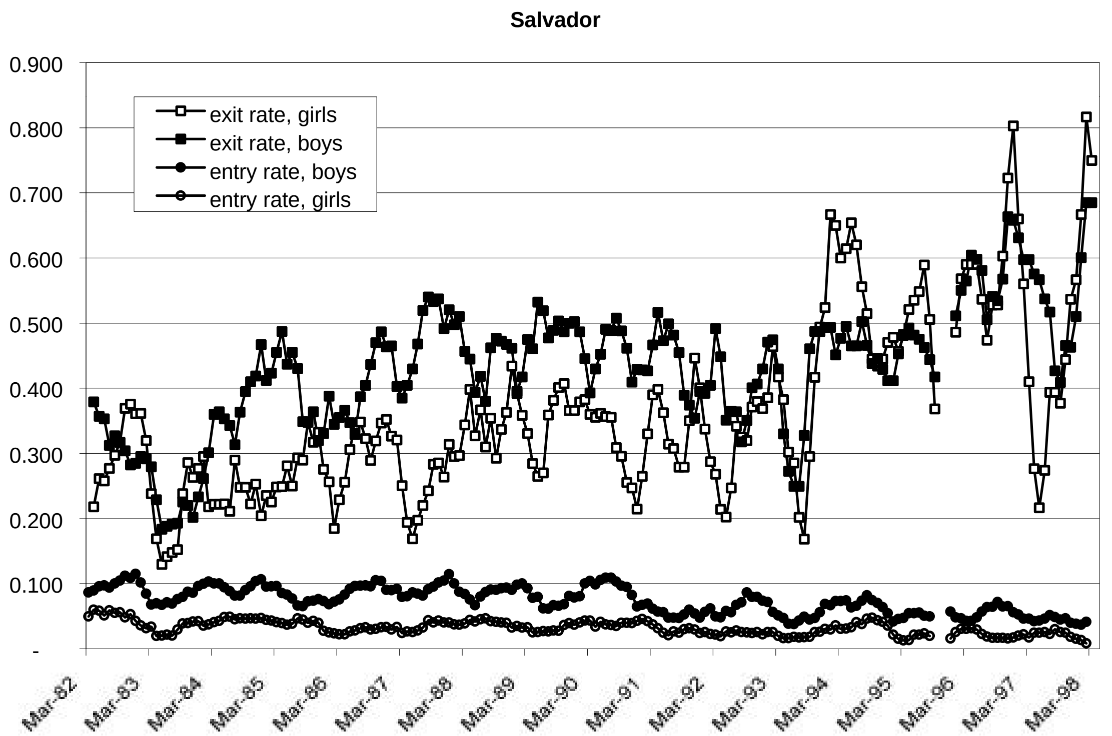
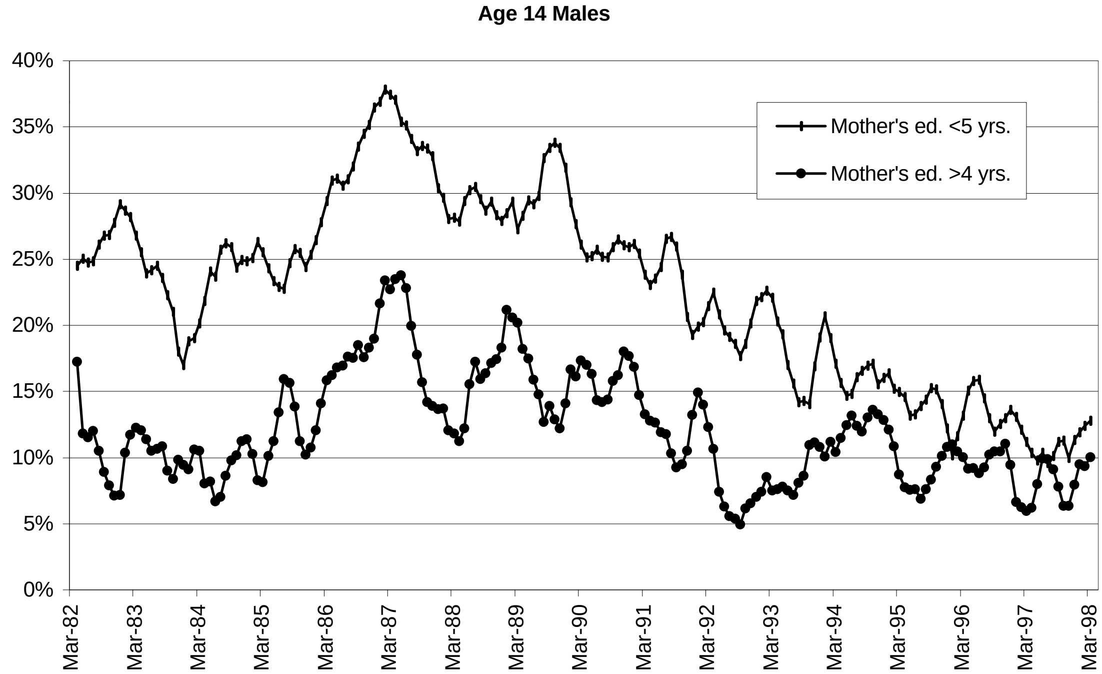


Figure 4. Percent of 14 year-old males and females working in metropolitan São Paulo by mother's education, 1982-1998, 5-month moving averages, Brazil PME



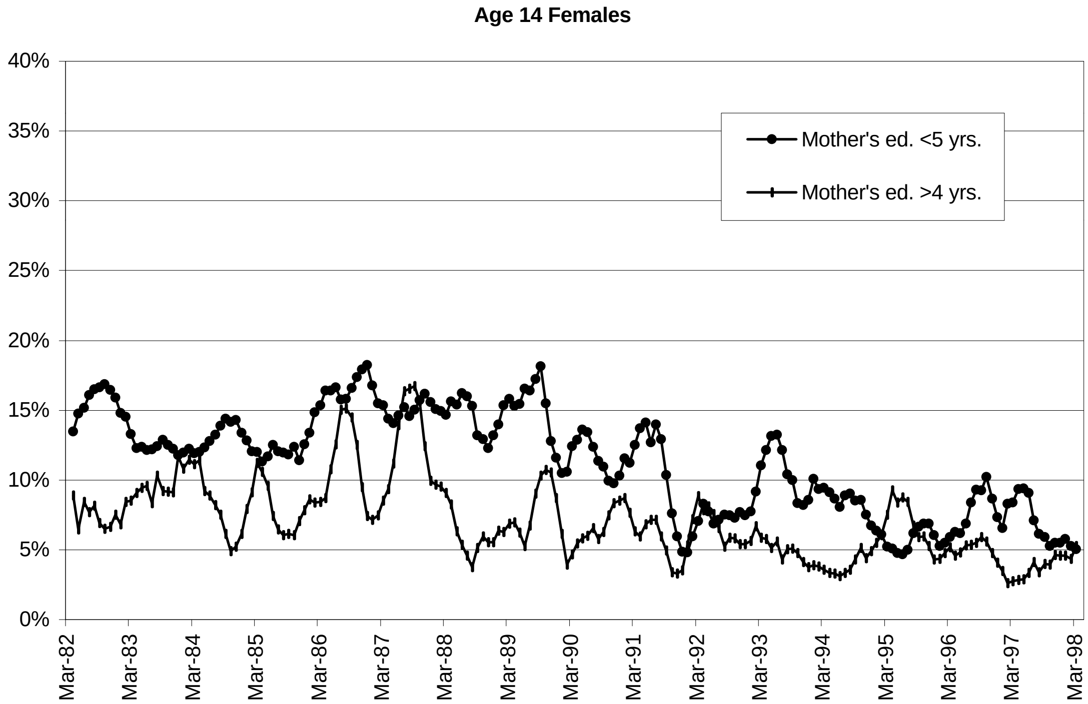


Figure 5. Rates of entry and exit into employment, 14 year old boys, São Paulo by mother's education, 1982-1998, 5-month moving averages, Brazil PME