Volatility, higher education and inequality in Latin America. Micro and macro evidence from Argentina and Brazil*

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Abstract

The aim of this paper is to analyze the existing relationships between real volatility and demand for higher education in Latin America. We use micro and macro panel data from Argentina and Brazil in order to identify the aggregate and idiosyncratic risk-channels affecting human capital accumulation. Confirming the mail hypothesis of our OLG stochastic model we find out that both, aggregate real volatility and family real income volatility (mainly head's partner real income volatility) reduce demand for higher education. Moreover, this result is not homogeneous across different income levels. Only middle income families (and states) are negativelly affected by real volatility variables entailing a positive correlation between macroeconomic uncertainty and higher education enrollment polarization.

Keywords: Volatility, higher education, inequality and Latin America.
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1 Introduction

Latin America is characterized by a high degree of output volatility (see Caballero, 2000), income inequality (de Ferranti et al., 2004) and foreign indebtness (Dornbusch, 1989), as well as by low levels of tax revenues (Tanzi, 1992) and GDP growth (Solimano and Soto, 2003). As far as regional inequality is concerned, the "human capital channel" has always been mentioned as one of the main determinants of the dynamics of income distribution (see Reimers, 2000 and Reimers, 2004).

Despite the fact that Latin American income inequality is deeply rooted in both institutional factors (de Ferranti et al., 2004) and land ownership concentration (Gavin and Hausmann, 1998 and Morley, 2001), heteroge-

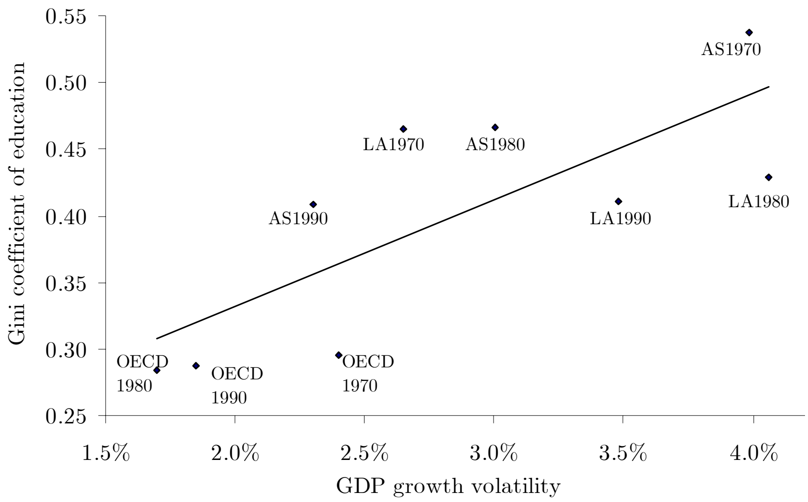

Figure 1: Observed relationship between GDP growth volatility and education inequality for OECD, Latin America (LA) and Asia (AS). Note: Non weighted average regional values from Asia, Latin America and OECD countries (1970-1980-1990). Sources: Groningen Growth and Development Centre and Vinod, Wang and Fan (2000).

higher volatility amongst educated people. The main outcome of this literature is that an increase in uncertainty reduces enrollment rates[3].

A preliminary empirical test of this literature is carried out by Flug et al (1998), using a World Bank database for most countries. This paper argues that different factors could imply either a positive or a negative impact of macroeconomic volatility on school enrollment.

As far as negative impacts are concerned, they argue that, when considering risk averse 'students', a rise in volatility increases the uncertainty of returns to education. Hence, it might lower school enrollment.

On the other hand higher volatility could entail a positive effect on educational choices. It may be possible to claim that high-educated workers have more probability to adapt to systemic shocks because of their higher abilities. For instance, Behrman and Birdsall (1983) find that more educated

[3]The empirical link between education demand and greater volatility for Latin American countries has not been widely investigated yet. Most of the papers concern returns to education and general trends in college enrollments rather than analysing its micro and macro determinants. Nevertheless there are some contributions filling this gap. Buera et al. (2001), Gonzales Rozada and Menendez (2002) and Rucci (2003) analyse aggregate and individual level characteristics affecting high school and college attendance in Argentina. Similar analysis are carried out by Dureya (1998) and Neri et al (2000) for high school enrollments in Brazil.

people face more stable incomes during downturns than low educated people do. In this framework the choice for higher education may be thought of as a sort of insurance. Further, Flug et al (1998) discussed the possibility of a stronger impact of real volatility on the poorest than on the richest even if they did not further explore the subject.

In this paper we wish to rank the effects of volatility on enrollment decisions in a slightly different way, extending the contributions of Fernández and Shioji (2000) and Checchi and García-Peñalosa (2003, C&GP hereafter).

Formally, we want to distinguish two effects:

- the investment effect, which concerns the standard cost-benefit analysis in education decisions. Each student decides to continue to invest in education if and only if her expected returns are greater than both her current and her opportunity costs. Using this framework with risk averse agents, and assuming that the impact of volatility on earnings is stronger for the educated, C&GP claim that an increase in volatility induces a reduction in enrollment and an increase in inequality.

- the wealth effect, which concerns the fact that when volatility increases it might be more likely for poor households to face strong negative shocks, entailing higher difficulties in collecting the liquidity necessary for human capital investments, also because returns to education take place only in the medium-long run. In other words, when facing higher macro instability, some children must join the labour market because of a drop in household income.

C&GP fail to consider this second effect in their model. Our claim is that, in developing countries, this effect could play a very important role because of credit market imperfections, poverty and inequality issues.

Let us explain our framework more precisely. For rich people, liquidity constraints are never binding. Their schooling decisions can be affected by macroeconomic uncertainty, but only through the "investment channel", as in C&GP. On the other hand, the weight of liquidity constraints is always determinant for poor families, implying that neither education premium nor income volatility are really relevant in their schooling decisions[4]. As far as

[4] In this framework, college attendance is always pro-cyclical for low-income students and counter-cyclical for the richest ones (whatever the size of macroeconomic fluctuations). These assumptions are based on empirical evidence suggesting that schooling attendance is counter-cyclical in high income countries (such as US; see Rees and Mocan, 1997)

middle income individuals are concerned, we state that both effects play a significant role. This entails that high volatile environments increase human capital concentration because they especially reduce middle class schooling enrollment (while poor individual's educational choices remain unaffected and rich people's decisions do not suffer from the wealth effect of volatility). Under certain assumptions[5] human capital concentration increases income and wealth inequality involving a high level of social polarization.

The remainder of this paper is structured as follows. In the next section, we develop our theoretical framework. In section 3, we investigate the macroeconomic determinants of Brazilian higher education system (using a panel database at the state level from 1992 to 2002), paying special attention to the role of volatility for both gross state product and employment. The microeconomic approach is presented in section 4. Using a database from Argentina (for individuals and households from 2001 to 2003) we identify the main factors affecting children's transition from high school to college. Finally, we present our main conclusions.

2 Theoretical framework

Following the theoretical framework developed by Fernández and Shioji (2000), we build a stochastic two-period overlapping-generation (OLG) model in order to analyze existing relationships between volatility and enrollment decisions. Our main theoretical contribution lies in a formal analysis of human capital accumulation in which income uncertainty, entailing both wealth and investment effects, has an asymmetric impact across initial wealth levels.

Most papers analyzing microeconomic determinants of the negative relationship between risk and high-school or college enrollment emphasize the role of the investment effect derived from two particular assumptions: a) decreasing absolute risk aversion (DARA) utility functions and b) mean preserving spreads (MPS) increasing with education[6]. These assumptions are also used by C&GP -in a model à la Galor and Zeira, 1993- to explain why aggregate human capital as well as equality in human capital distri-

while it is pro-cyclical for poorer regions where liquidity constraints appear to dominate opportunity costs (see Development Report in World Bank, 1990).

[5]Notably that human capital concentration involves a redistribution process from the middle class to the (highly educated) richest families (because the reduction in labor supply with higher education increase the returns to college degree).

[6]See Levhari and Weiss (1974) or Kodde (1986).

bution are negatively affected by output volatility. Their approach appears to be particularly useful for our objectives. However, the following unlikely implicit characteristics force us to develop an alternative explanation :

1. In the C&GP model there is no "volatility wealth effect" on enrollment decisions because initial distribution of bequest is not affected by aggregate uncertainty (macroeconomic volatility will not change expected transfers from parents to children in the first period).

2. Moreover, an MPS will always reduce the ratio between skilled and unskilled expected utilities (whatever the agent's initial wealth).

3. Furthermore, C&GP results can be totally reversed if the MPS is rather decreasing in education -a reasonable assumption for Latin American countries, as noted for by Bastourre et al.(2003) and Flug et al.(1998)[7].

In the following sub-sections we present a theoretical model in which aggregate volatility affects human capital accumulation through both investment and wealth effects. The first reflects the impact of macroeconomic uncertainty on the traditional trade-off between opportunity costs and returns to education, while the second stands for the influence of income volatility on the optimal transfer from parents to children.

These effects will not be homogeneous amongst different wealth levels.

An MPS does not change poor children's enrollment decisions because both investment and wealth effects become irrelevant (optimal transfer will always be 0, even without macroeconomic uncertainty).

On the other hand, richest households will only be affected by the investment channel because wealth constraints are never binding (even with a large volatility). The impact of an MPS on human capital accumulation will depend on the form of the utility function and the ratio between skilled and unskilled variance of earnings. Using a DARA/CRRA utility function and different assumptions about the relative variance of earnings, we will show that an MPS could have either a negative or a positive effect on rich children's enrollment decisions (and then it must be empirically determined).

[7]Flug et al. (1998) highlight that the variance of earnings could be decreasing with education because skilled workers are more able to overcome negative shocks. This hypothesis is supported by Bastourre et al. (2003) who find that poor people's relative income (household income / average income) is procyclical while the richest's is countercyclical. This entails that income volatilty is decreasing in wealth, which in turn is positively correlated with education.

Finally, middle wealth families will be affected by both effects. An MPS increase the probability of transition towards poverty, reducing expected transfers from parents to children. This negative wealth effect can be either reinforced or compensated by the investment effect, but it always dominates when the MPS is significant[8].

2.1 Model general structure

Our stochastic two period OLG model assumes a continuum of households that consist of a parent (the first generation) and a child. Household are indexed by a parameter $j \in \Re^{+}$ which represents the initial level of wealth (W_j). In addition each second generation individual is also indexed by a second parameter $i \in (0, 1)$ which identifies the child's ability to transform human capital into earnings.

In the first period, parents work and choose their optimal consumption path (C^p_{j1} and C^p_{j2}, as well as the optimal transfer to their children: T_{ji}) after their stochastic labor income is observed. In period 2, they leave the labor market to consume their savings (as they retire), without any new transfer to the second generation.

Children's optimization problem lies in the enrollment decision. In period 1 (before stochastic revenues were realized) they must decide whether to study or not, assuming that education and labor market participation are mutually exclusive activities. If they join the labor market, their period 1 total income will be equal to the sum of two stochastic components: the expected transfer from their parents and the expected unskilled wage $(E(w_u))$. In the second period they will not receive any transfer and therefore expected total income equals expected unskilled wage (by simplicity, assumed to be time-invariant). On the other hand, expected parental transfer will be the only source of revenues in period 1 if children decide to be enrolled in further education. However, they will have a higher expected wage (the expected skilled wage: $E(w_s)$) in period 2.

2.2 First generation utility maximization

Let $U^p_j(C^p_{j1}, C^p_{j2}, C^c_{ji1})$ be the first generation implicit utility function, where the child's consumption in period 1 (C^c_{ji1}) is an argument of his/her parent's

[8]In such a case, a "zero transfer" scenario becomes more likely and middle wealth children are forced to joint the labor market (even if the investment effect is strongly positive).

welfare. Assuming a DARA/CRRA log utility specification we have that

$$U_j^p = \ln\left(C_{j1}^p\right) + \frac{1}{1+\rho}\ln\left(C_{j2}^p\right) + I(W_j, \underline{Y}, x)\ln(C_{ji1}^c) \tag{1}$$

where $I(W_j, \overline{c}, x)$ is the following indicator function

$$I(W_j, \underline{Y}, x) = \begin{cases} 1 & if \quad W_j + Y_j^p(x) > \underline{Y} \\ 0 & if \quad W_j + Y_j^p(x) \leq \underline{Y} \end{cases} \tag{2}$$

ρ is the rate of time preference, $\underline{Y} = Max[Y_{ij1}^c(z, se)\frac{1-\phi}{\phi}, \underline{c}]$, $Y_{ij1}^c(z, se)\frac{1-\phi}{\phi}$ is minimum level of $W_j + Y_j^p(x)$ derived from the non-negative transfer condition (where $\phi = \frac{(1+\rho)}{2(1+\rho)+1}$ and se stands for "school enrollment", a dummy variable representing the second generation educational choice)[9], $Y_{ij1}^c(z, se)$ is the period 1 children's labor income, z is a random variable, $\underline{c}$ is the two-period absolute poverty line, $Y_j^p(x)$ is the first period parent's labor income and x is another random variable. Because earnings cannot be negative, we assume that x follows a gamma probability distribution[10]:

$$Y_j^p(x) \sim \Gamma(\alpha_j\beta_j, \alpha_j\beta_j^2) = \int_0^x \frac{\left(x/\beta_j\right)^{\alpha_j-1}\exp\left(-x/\beta_j\right)}{\beta_j\Gamma(\alpha_j)}dx \tag{3}$$

where

$$\Gamma(\alpha_j) = \int_0^\infty x^{(\alpha_j-1)}\exp(-x)\,dx \tag{4}$$

By assumption, the mean and the variance of this distribution ($\alpha_j\beta_j$ and $\alpha_j\beta_j^2$) will be equal to θW_j and $\theta W_j\beta_j$ (with $0 < \theta < 1$), respectively, entailing that initial wealth is positively correlated with expected parental earnings.

After $Y_j^p(x)$ and $Y_{ij1}^c(z, se)$ are observed, first generation individuals choose C_{j1}^p, C_{j2}^p and T_{ji} so as to maximize their utility function subject to the following constraints:

[9] See equations 10 and 11.

[10] We use a similar assumption for z in the following sub-section.

$$C_{j1}^p + \frac{1}{1+r} C_{j2}^p + T_{ji} = W_j + Y_j^p(x) \tag{5}$$

and

$$Y_{ji1}^c(z, se) + T_{ji} = C_{ji1}^c \tag{6}$$

From F.O.C. we get the following cases:

Case 1 $x < x^*$, where $W_j + Y_j^p(x^*) = \underline{Y}$

With a probability $\Gamma(x^*) = f(W_j, \underline{Y}, \sigma_x) \in [0,1]$, $W_j + Y_j^p(x)$ will be lower than the minimum required for a positive transfer and then:

$$\left(\frac{C_{j2}^p}{C_{j1}^p} \right)_{x<x^*} = \frac{1+r}{1+\rho} \tag{7}$$

and

$$(T_{ji})_{x<x^*} = 0 \tag{8}$$

Case 2 $x > x^*$ and then $W_j + Y_j^p(x) > \underline{Y}$

With a probability $1 - \Gamma(x^*) = 1 - f(W_j, \underline{Y}, \sigma_x) \in [0,1]$, $W_j + Y_j^p(x)$ will be higher than the minimum required for a positive transfer and then:

$$\left(\frac{C_{j2}^p}{C_{j1}^p} \right)_{x>x^*} = \frac{1+r}{1+\rho} \tag{9}$$

and

$$(T_{ji})_{x>x^*} = \phi \left(W_j + Y_j^p(x) \right) - (1-\phi)\, Y_{ij1}^c(z, se) \tag{10}$$

where

$$\phi = \frac{(1+\rho)}{2(1+\rho)+1} \tag{11}$$

For all $x > x^*$, $W_j + Y_j^p(x) > \underline{Y}$ ensuring a positive $(T_{ji})_{x>x^*}$.

2.3 Second generation enrollment decision

While the explicit form of the first generation lifetime utility function does not (qualitatively) change the optimal transfer from parents to children, it is crucial to determine how much volatility affects enrollment decisions through the "investment effect".

Assuming risk neutral children (linear utility functions) eliminates the investment effect of volatility. Only the wealth channel will be taken into account in order to analyze the impact of macroeconomic uncertainty on enrollment decisions. The same result is derived with DARA/CRRA utility functions (e.g. log utility functions) if the MPS in earnings is the same across different levels of education and ex-ante coefficients of variation are also identical[11].

Under this these hypotheses, a MPS reduces enrollment for middle wealth and low-ability children, while the more able, the richer and the poorer ones will not substantially modify their choices.

However, risk neutrality and identical MPS are either unlikely or too strong assumptions[12] to be accepted as the representative framework.

For this reason we will analyze in depth only those cases involving risk averse children and MPS either increasing or decreasing with education.

Let $U^c_{ji}(C^c_{ji1}, C^c_{ji2})$ be the children's implicit utility function, where (C^c_{ji2}) is the child ji's consumption in the second period. Using a log utility specification and assuming that both own earnings and first generation income transferts are stochastic (as children's schooling decisions are made before these variables are observed), the second generation problem can be written as:

$$\underset{se}{Max}\; E \left[U_{is} \right.$$

and

$$E\left(\frac{Y^c_{ij2}(z,i,se)}{1+r}\right) = E\left(\frac{C^c_{ji2}}{1+r}\right) \tag{14}$$

where

$$E\left(Y^c_{ij1}(z,se)\right) = \begin{cases} 0 \quad if \quad se = 1\text{[13]} \\ E\left(w_u(z)\right) = E\left(\Gamma_u(z)\right) = \alpha_u\beta_u \quad if \quad se = 0 \end{cases} \tag{15}$$

$$E\left(Y^c_{ij2}(z,i,se)\right) = \begin{cases} E\left(w_s(z,i)\right) = E\left(\Gamma_s(z)\right) = \alpha_s\beta_s \quad if \quad se = 1 \\ E\left(w_u(z)\right) = E\left(\Gamma_u(z)\right) = \alpha_u\beta_u \quad if \quad se = 0 \end{cases} \tag{16}$$

while $E\left(w_s(z,i)\right)$ is the skilled expected wage, $E\left(w_u(z)\right)$ is the unskilled expected wage, $\Gamma_s(z)$ and $\Gamma_u(z)$ are, respectively, the skilled and unskilled gamma wage distribution functions, $\alpha_u\beta_u = \overline{w_u}$ is a constant (the mean of $\Gamma_u(z)$, with variance $\overline{w_u}\beta_u$) and $\alpha_s\beta_s = \overline{w_s}\,(i)$ (the mean of $\Gamma_s(z)$, with variance $\overline{w_s}\beta_s$) is increasing in child's ability (i).

Under these assumptions, we derive the expected utility functions of both skilled and unskilled children.

$$\begin{aligned} E\left(U^c_{sji}\right) &= \Gamma(x^*)\log(0) + (1-\Gamma(x^*))\log(T_{ji}) + \ldots \\ &\quad + \frac{1}{1+\rho}E\left(\log(w_s)\right) \end{aligned} \tag{17}$$

$$\begin{aligned} E\left(U^c_{uji}\right) &= \Gamma(x^*)E\left(\log(w_u)\right) + (1-\Gamma(x^*))\,E\left(\log(w_u+T_{ji})\right) + \ldots \\ &\quad + \frac{1}{1+\rho}E\left(\log(w_u)\right) \end{aligned} \tag{18}$$

Further assuming that $\Pr(w_u = 0) = \Pr(w_s = 0) \simeq 0$, the optimal enrollment condition satisfies $E\left(U^c_{sji}\right) > E\left(U^c_{uji}\right)$, or

$$\begin{aligned} \frac{1}{1+\rho}\left[E\left(\log(w_s)\right) - E\left(\log(w_u)\right)\right] &> \Gamma(x^*)E\left(\log(w_u)\right) + \ldots \\ &\quad + (1-\Gamma(x^*))\,E\left(\log(w_u+T_{ji})\right) - \ldots \\ &\quad - \Gamma(x^*)\log(0) - (1-\Gamma(x^*))\log(T_{ji}) \end{aligned} \tag{19}$$

From previous equations we must differentiate two polar cases.

Case 1 $\Gamma(x^{*}) = f(W_j, \underline{Y}, \boldsymbol{\sigma}_x) > 0$

The representative assumption for poor households. We can see from equation 19 that $E\left(U^c_{sji}\right)$ will always be lower than $E\left(U^c_{uji}\right)$ because $\Gamma(x^*)\log(0) \simeq -\infty$.

Therefore, when $\Gamma(x^*) > 0$ because either $W_j/\underline{Y}$ is not high enough or $1/\sigma_x$ is too low the wealth effect becomes binding and children must forcefully join the labor market in the first period (whatever the level of expected returns to education).

Case 2 $\Gamma(x^{*}) = f(W_j, \underline{Y}, \boldsymbol{\sigma}_x) \simeq 0$

The representative assumption for rich households (e.g. $W_j \geq \underline{Y}$). In this case, $E(T_{ji})$ is strictly positive and equation 19 can be written as:

$$\frac{1}{1+\rho}\left[E\left(\log(w_s)\right) - E\left(\log(w_u)\right)\right] > E\left(\log(w_u + T_{ji})\right) - E\left(\log(T_{ji})\right) \quad (20)$$

From equations 10 ($\frac{\partial T_{ji}}{\partial W_j} > 0$), 16 ($\frac{\partial w_s}{\partial i} > 0$) and 20 we know that the higher the first generation wealth (or the higher the child's ability) the higher the probability for the child to enroll in further education[14].

Because liquidity constraints are not binding, the investment effect becomes now significant to determine the educational choice.

2.4 The role of volatility

In order to understand how aggregate uncertainty affects educational choices it could be useful to recall the difference between investment and wealth channels. While the former involves the impact of volatility on the comparison between returns to education and opportunity costs, the wealth channel stands for the effect of real uncertainty on the expected income transfer from parents to their children. As we have already noted, the latter is always negative (when significant, the wealth channel entails that the higher the volatility the lower the school enrollment) while the investment effect can be either positive or negative.

An MPS increases both, first and second generation earning volatility. The first one affects expected income transfers (from parents to children) because it modifies $\Gamma(x^*)$. From equation 3 we know that

[14]Because $\underset{T_{ji}\to\infty}{Lim}\left[E\left(\log(w_u + T_{ji})\right) - E\left(\log(T_{ji})\right)\right] \simeq 0$ (entailing that forgone period 1 wages are irrelevant for the richest) and $\partial\left[E\left(\log(w_s)\right) - E\left(\log(w_u)\right)\right]/\partial i > 0$.

$$\frac{\partial\Gamma(x^*)}{\partial\sigma_x} = \frac{\partial\Gamma(x^*)}{\partial\left(\alpha_j\beta_j^2\right)} \gtrless 0 \tag{21}$$

depending on W_j and $\underline{Y}$.

For poor families $W_j + E\left(Y_j^p(x)\right) = W_j + \alpha_j\beta_j = W_j + \theta W_j < \underline{Y}$ entailing that

$$\frac{\partial\Gamma(x^*)}{\partial\sigma_x} < 0 \tag{22}$$

However, $\Gamma(x^*)$ is always higher than 0 and then the wealth effect of volatility is not modified.

On the contrary, for rich households $W_j < \underline{Y}$ and then

$$\frac{\partial\Gamma(x^*)}{\partial\sigma_x} = 0 \tag{23}$$

because x follows a gamma distribution determining strictly non-negative values for $E\left(Y_j^p(x)\right)$ -even if σ tends to infinity-. Therefore, there is no wealth effect of volatility for rich people.

Finally, middle income first generation is defined as having a level of wealth $W_j < \underline{Y} < W_j + \theta W_j$. For these families

$$\frac{\partial\Gamma(x^*)}{\partial\sigma_x} > 0 \tag{24}$$

When $\sigma_x \to 0$, $\Gamma(x^*) = 0$ (because $\underline{Y} < W_j + \theta W_j$) but a high enough MPS increases the weigth of both tails of the probability distribution function, entailing a strictly positive $\Gamma(x^*)$.

We can see that the wealth effect of volatility is significant only for middle income families, strongly reducing their children's school enrollment.

On the other hand, the investment effect of volatility is be determined by additional assumptions about relative wage uncertainty.

If MPS are decreasing in education, entailing that

$$\left|\frac{\partial E\left(\log(w_s)\right)}{\partial\sigma_{w_s}}\right| \leq \left|\frac{\partial E\left(\log(w_u)\right)}{\partial\sigma_{w_u}}\right| \tag{25}$$

then the investment effect of volatility (on school enrollment) will be positive (although it concerns only those households without liquidity constraints).

Conversely, if MPS are increasing in education, ensuring that

$$\left| \frac{\partial E\left(\log(w_s)\right)}{\partial \sigma_{w_s}} \right| > \left| \frac{\partial E\left(\log(w_u)\right)}{\partial \sigma_{w_u}} \right| + (1+p) \left| \frac{\partial E\left(\log(w_u + T_{ji})\right)}{\partial \sigma_{w_u}} \right| \tag{26}$$

we have the traditional (and negative) investment effect of volatility, restricted again to those families without liquidity constraints[15].

The overall impact of volatility on school enrollment can be summarized as follows:

1. Poor children will always join the labor market in the first period because of liquidity constraints. There is neither a wealth nor an investment effect of volatility.

2. For rich people there is only an investment effect of volatility. If the relative uncertainty of wages (skilled to unskilled) increases with education, this effect is negative (particularly for low ability children). On the contrary, when the relative uncertainty of wages decreases with education, the investment effect becomes positive (entailing higher school enrollment, specially for low ability children). Educational choices of high ability rich children are not affected by the investment effect of volatility because of their higher *ex-ante* returns to education.

3. When the MPS is moderate, there is no wealth effect of volatility for middle income children. Therefore, the overall impact of volatility on enrollment decisions is derived from the investment effect (with the same features we presented for rich households). However, when volatility is high enough the investment effect becomes irrelevant because the negative wealth effect is now binding. Therefore, a sufficiently large MPS will always reduce school enrollment of middle income families (even for high ability children).

[15] For richest children, $\left| \frac{\partial E\left(\log(w_u + T_{ji})\right)}{\partial \sigma_{w_u}} \right| \simeq 0$ (because $T_{ji} \to \infty$). Therefore, equation 26 can be posed as $\left| \frac{\partial E(\log(w_s))}{\partial \sigma_{w_s}} \right| > \left| \frac{\partial E(\log(w_u))}{\partial \sigma_{w_u}} \right|$

A sufficient condition for a negative impact of volatility on aggregate enrollment rates is the existence of a high volatile environment with a log normal distribution of wealth, ensuring a negative wealth effect for middle income children which cannot be compensated by a (possible) positive investment effect for rich families (because of the non-significant weight of these households in total population). Under this assumption, not only school drop-out but also enrollment inequality increases with volatility, even with an MPS decreasing in education.

3 Macro evidence from Brazil

The educational system in Brazil is divided into 3 stages: primary school concerns children aged 7 to 14; then comes the secondary school composed by three series and eventually university and post-graduate education. Furthermore, the Brazilian university system is split up between private and public institutions. In public universities students do not have to pay fees but they are selected through a difficult and competitive entry examination ("vestibular"), whereas the access to private universities is usually easier, even though enrollment costs are higher and the quality of education is usually lower.

The "Pesquisa Nacional por Amostra de Domicílios" (PNAD) survey published by the Instituto Brasileiro de Geografia e Estatística (IBGE) shows that in 2002 only 41% of the population completed the first degree and 24.6% finished the second one. As far as the university participation rate is concerned, about 8% of the population began university after secondary school, even if only 2% graduate. These rates increase over the 1990's. Nevertheless, this does not mean that higher education is more available to the poorest since university participation rates are highly heterogeneous, depending on socioeconomic characteristics. As reported by INEP (2004) -Instituto Nacional de Estudos e Pesquisas Educacionais (Ministry of Education)- only 4% of poor students attend university, while for the richest this percentage increases up to 23,4%.

Furthermore, it is well-known that Brazil is characterized by one of the highest inequality in the world. Inequality in education distribution and in returns to education are amongst the main factors explaining this great income inequality. As claimed by Narita and Fernandes (2001), the wage of a person that completed university can be more than 100% higher than that of a high-school graduate. Moreover, this gap has been increasing since the eighties. As showed in Barros & Mendonca (1995), educational inequality accounts for a very significant share, from 35% to 50% depending on the macroeconomic regions, of wage inequality.

3.1 Data description and econometric framework

We consider the Brazilian case to investigate the macroeconomic side of our topic, i.e. the impact of volatility on education, which in turn affects inequality. For this reason we use aggregate information for all 27 Brazilian states[16].

Since we are interested in university enrollment we need data concerning the census of graduate education, produced by INEP. Each Brazilian university (private or public) has to answer questions of the INEP census. Our dependent variable is the number of total enrollments in universities from 1992 to 2002 divided by state population, which is also the standard dependent variable in this literature:

$$enr\_rate_{i,t} = \frac{total\_enrollments_{i,t}}{total\_population_{i,t}}$$

where i stands for the state and t for the year.

For macroeconomic volatility we construct two indexes at the state level, using information for both Gross State Product (GSP) and employment. Previous papers on this subject showed that, the effects of GSP and employment volatility can be quite different, as they can be caused by different microeconomic and structural features.

As far as GSP volatility is concerned we use the standard deviation of the real gross product annual growth rate of each state, derived from IBGE. It was defined by taking the GSP standard deviation of the post 4 years, not including the contemporaneous observation. We do not consider the contemporaneous GSP for two reasons. First; each student makes his own education decisions looking at the available information, i.e. the economic

[16] In Brazil states can be aggregated into 5 regions: 1) the North (Amazonas, Amapá, Rondônia, Roraima, Pará, Acre); 2) The Northeast (Bahia, Ceará, Maranhão, Paraíba, Pernambuco, Piauí, Rio Grande do Norte, Sergipe); 3) the Southeast region (São Paulo, Rio de Janeiro, Minas Gerais and Espírito Santo); 4) Center West (Mato Grosso do Sul, Mato Grosso, Goiás and Distrito Federal); 5) the South (Paraná, Santa Catarina and Rio Grande do Sul).

situation of previous years. Second, contemporaneous GSP might be endogenous to enrollment decisions, as argued by Flug et al (1998).

We decided to chose four years in the volatility definitions because we think it represents a reasonable compromise between short period volatility (e.g. monthly) that varies too much with respect to enrollment decisions and long term volatility (e.g. the 30 years considered in Flug et al, 1998 and in C&GP) that displays very little change over time. Moreover, recent studies -for instance Carrera et al (1998)- show that Brazilian business cycle duration is less that five years in average, meaning that the period chosen is representative of the volatility of the business cycle observed by students who have to decide whether to enroll in university.

We also tried to add the contemporaneous year to the previous definition. Results did not vary much, implying that endogeneity problems do not seem to play an important role. In the following, we will check the robustness of these hypotheses through a sensibility analysis.

In addition, in order to capture some non-linear effects of income and volatility on enrollment decisions we construct two additional volatility measures. The first is defined as an interaction variable given by the multiplication between income and GSP volatility. The second captures a quadratic income effect and is made up by multiplying squared income and GSP volatility. In the following we will explore this issue more in depth.

Employment volatility is defined in the same way, using the employment rate standard deviation at the state level. Employment data is obtained from the PNAD survey, in the period 1992-2002[17], which is representative at the household level for all Brazilian States. Furthermore; we construct similar additional measures for employment volatility to capture non linear interaction effects of income and volatility on enrollment decisions. The first one is given by the multiplication between income and employment volatility, while the second one captures a quadratic effect and is defined as the multiplication between squared income and employment volatility.

As suggested by the related literature we computed the following control variables (in brackets: name of the variables):

- average years of education completed for all people aged 45 to 65, a

[17]We do not have information for 1994, because the survey was not implemented, nor for 1991 and 2000, because the survey was replaced by census. In order to calculate employment volatility time series without missing information, we have substituted the 2000 value with the census one. For 1991 and 1994 we used a linear interpolation.

proxy for parents' education[18] (Ed_parents).

- average household per capita income (Income_pc).

- average household per capita income in 1992 (Inc_pc_92).

- unemployment rate (Unempl)

- ratio between the wage of people with a university degree and the wage of people only possessing a high school degree. This represents a proxy for returns to higher education ($\overline{W}$_ed/$\overline{W}$_n-ed).

- proportion of white people (we controlled for this variable because Brazil is characterized by an important difference between black and white's access to university (Race).

- the gini index as an inequality measure (gini).

Finally, we add a second order polynomial trend to capture the exogenous evolution of enrollment decisions, due to cultural and institutional factors.

3.2 Empirical results

Our estimation period is from 1992-2002 for all 26 Brazilian states (actually, 25 states and the capital Brasília-Distrito Federal). Due to data limitations, the state of Tocantins had to be removed from the database and the years 1994 and 2000 were not considered since PNAD survey was not carried out. We therefore end up with 234 observations.

As far as the econometric specification is concerned, we try to exploit all the database information implementing both OLS and panel estimates. Since fixed effects and independent variables are clearly correlated we cannot use the random effect estimates since they are biased (the Hausman test is rejected). In order to derive unbiased estimates we had to explicitly consider this correlation using the "Within estimator" Of course, when using this estimator it is impossible to take into account the control variables that do not vary overtime.

Let us begin with the OLS estimates. We carry out four different specifications. In column (1) we add GSP volatility to the control variables, in column (2) we add employment volatility, in column (3) we are interested in the joint effect of these two volatility measures while in column (4), we consider non linear effects.

Firstly, we investigate the impact of control variables. As shown in table 1, trend coefficients are always significant. These coefficients are used to

[18] We do not consider the average education at the state level because it is strongly correlated with parents' education (approximatly 0.93).

capture the exogenous evolution of enrollment rates in all Brazilian states, which is increasing overtime, especially at the end of the period. Further, as was already stressed in the literature, parents' education is one of the main determinants of educational choices: its effect is positive and significant in all specifications. Another important finding is the positive impact of the proportion of white people in each state (race). Using OLS estimates we are interested in the cross section side of this impact, and we point out, not surprisingly, that all states showing a higher proportion of white population also display higher enrollment rates.

The inequality coefficient is positive when significant. At first sight, this seems to be the opposite of what is expected. However, a deeper analysis might allow us to derive a better interpretation. It is plausible to argue that in developing countries a higher Gini index entails that at least the richest attend university. On the contrary, a more egalitarian income distribution in poor countries might entail a lower enrollment rate because the majority of the population cannot afford a higher education. This could explain a positive relationship between the two variables.

A more standard result is that higher income has a positive impact on enrollment in a cross countries estimate. Finally, the higher the unemployment rate the lower the number of enrollments, meaning that the wealth effect (or liquidity constraint) is more important than the opportunity cost effect.

Dependent Variable Enrollment rate	(1)		(2)		(3)		(4)	
	Coeff.	t	Coeff.	t	Coeff.	t	Coeff.	t
trend	-0.227	-7.23	-0.261	-7.69	-0.261	-7.69	-0.219	-6.46
trend2	0.032	10.26	0.037	10.24	0.037	10.24	0.032	8.98
edpais	0.057	2.04	0.074	2.36	0.074	2.36	0.081	2.75
race	0.009	7.85	0.008	6.30	0.008	6.30	0.010	6.95
Unempl	NS		-0.015	-1.98	-0.015	-1.98	-0.013	-1.75
Gini	2.303	4.64	NS		NS		1.331	2.69
W_ed/W_n-ed	NS		NS		NS		NS	
Income_92	NS		NS		NS		NS	
income_pc	0.003	9.75	0.003	9.58	0.003	9.58	0.002	5.21
income_pc^2	NS		NS		NS		NS	
gsp_vol	NS		-		NS		19.243	3.3
income*gsp_vol	-		-		-		0.0184	2.26
income^2*gsp_vol	-		-		-		-0.000	-2.42
emp_vol	-		-4.239	-2.77	-4.239	-2.77	NS	
income*emp_vol	-		-		-		-0.184	-4.93
income^2*emp_vol	-		-		-		0.000	5.32
ADJ-R^2	0.83		0.84		0.84		0.86	

*NS stands for not significant coefficients at 20%, "-" stands for 'variable not present in the estimate'

Table 1. Volatility impact on enrollment decisions usign different OLS estimates

Let us move to the analysis of the volatility impact. From column (1) it is possible to note that GSP volatility is not significant when added to the control variables. On the contrary, column (2) shows that employment volatility is negative and significant, meaning that enrollment decisions decrease when employment is more volatile. These results are consistent with Flug et al (1998). Moreover, column (3) shows that when considering together the two volatility variables only employment volatility is negative and significant.

Interesting results come out when considering non linear interaction effects of income and volatility on enrollment decisions. As far as the employment coefficients are concerned we derive a U-shape curve of income meaning that the negative impact of employment volatility on enrollment rates is stronger for middle income levels and weaker for higher and lower ones. This result is consistent with our theoretical predictions[19].

Moving to the Within estimator we are able to control for state fixed effects, which are clearly correlated to the control variables. Generally speaking it is possible to argue that using OLS estimates we are interested in cross section analysis and that using within estimates we are looking more at the

[19]For the coefficients regarding GSP volatility we do not have a clear-cut explanation. However, this effect is not significant when considering the "Within estimator".

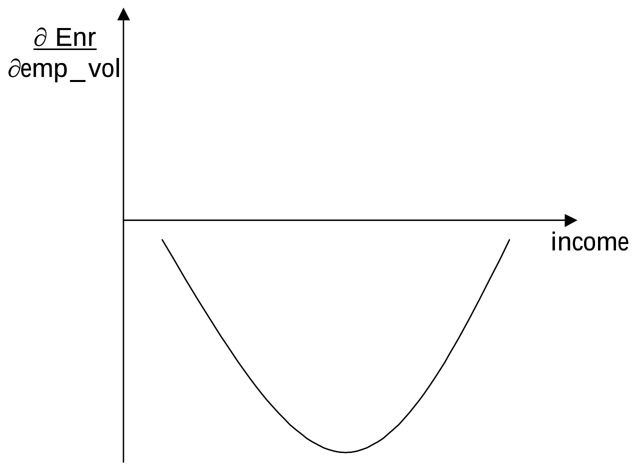

Figure 2: Impact of employment volatility on enrollment decisions according to different income levels

time series process. The control variables display similar coefficients with respect to the OLS ones, even if the unemployment rate and Gini coefficients become not significant.

Dependent Variable Enrollment rate	(1)		(2)		(3)		(4)	
	Coeff.	t	Coeff.	t	Coeff.	t	Coeff.	t
trend	-0.172	-6.32	-0.200	-6.96	-0.188	-6.48	-0.156	-5.58
trend2	0.025	9.99	0.029	10.29	0.028	9.52	0.025	9.15
ed_parents	0.102	2.64	0.097	2.49	0.097	2.5	0.080	2.24
race	-0.013	-2.98	-0.011	-2.72	-0.012	-2.93	-0.012	-2.92
unempl	NS		NS		NS		NS	
Gini	NS		NS		NS		NS	
W_ed/W_n-ed	NS		NS		NS		NS	
income_pc	0.002	4.73	0.002	4.58	0.002	4.63	0.003	2.39
income_pc^2	NS		NS		NS		0.000	-2.22
gsp_vol	-1.757	-2.26	-		-1.639	-2.11	NS	
income*gsp_vol	-		-		-		NS	
income^2*gsp_vol	-		-		-		NS	
emp_vol	-		-2.005	-1.76	-1.771	-1.56	15.423	1.87
income*emp_vol	-		-		-		-0.171	-3.06
income^2*emp_vol	-		-		-		0.000	4.02
R^2-within	0.80		0.80		0.81		0.84	
R^2-overall	0.35		0.43		0.36		0.34	

*NS stands for not significant coefficients at 20%, "-" stands for 'variable not present in the estimate'

Table 2. Volatility impact on enrollment decisions usign different within estimates

As far as the volatility coefficients are concerned, we find some relevant differences due to the fact that it is now possible to control for state fixed effects. Column (1) shows that GSP volatility is negative and significant, while using OLS it was not. Column (2) confirms OLS estimates showing that employment volatility has a negative impact on enrollment decisions. In addition, using Within estimates we find out in column (3) that when considering at the same time GSP and employment volatility both entail negative effects. Finally, from column (4) it is possible to derive a non-linear interaction effect regarding income and employment volatility, implying a stronger impact of volatility for medium income levels (see figure 2). On the contrary, GSP interaction effects are non-significant.

In order to check the robustness of our empirical analysis we tested the two main and stronger hypotheses.

The first one concerns the definition of the volatility measure as the standard deviation of the past four years of both GSP and employment rate. In this sensibility analysis we changed the period considered, using standard deviation of the 3, 7 and 10 previous years of the employment rate[20]. From Table 3 we can check that our previous results are consistent with these changes in volatility definitions, using both OLS and within estimator. More precisely, when we consider only the employment volatility the coefficient is always negative when significant. Further, considering the non-linear interaction effects we always derive similar results to the ones previously showed. Only when using the past 10 years in the volatility definition and the within estimator this effect becomes not significant. In all other cases the sensibility analysis confirms the result that volatility affects negatively enrollment decisions and that this effect is stronger for the middle class.

The second hypothesis tested in this sensibility analysis is the choice of the dependent variable. Until now we used the number of students (stock variable) enrolled in Brazilian universities, in all academic years, as is usually the case in this literature. A plausible alternative would be to consider only the new enrollments, i.e. students enrolled in the first academic year. From the last column of table 3 it is possible to check that using the new enrollments -and keeping the previous volatility definition (past four years)- do not change significantly the results. More precisely, the non-linear interaction effects are similar to the previous ones, while when considering

[20]We cannot carry out the same sensibility analysis for the GSP volatility since we do not have a detailed data information at the state level from the beginning of the '80.

employment volatility only coefficients become not significant.

	OLS estimates							
	Different definitions of the volatility variables						Dep. Variable	
	Previous 3 years		Prev. 7 years		Prev. 10 years		New enrollments*	
	Coeff.	t	Coeff.	t	Coeff.	t	Coeff.	t
emp_vol (only)	-4.2012	-3.17	NS		NS		NS	
emp_vol	12.3216	2.34	21.4819	3.66	16.0756	2.70	9.2295	3.49
income*emp_vol	-0.1303	-3.91	-0.1912	-5.40	-0.1123	-3.63	-0.0549	-3.64
income^2*emp_vol	0.0002	4.52	0.0004	5.86	0.0002	3.94	0.0001	2.79
	Within estimates							
	Different definitions of the volatility variables						Dep. Variable	
	Previous 3 years		Prev. 7 years		Prev. 10 years		New enrollments*	
	Coeff.	t	Coeff.	t	Coeff.	t	Coeff.	t
emp_vol (only)	-1.9567	-2.00	NS		-2.4069	-1.69	NS	
emp_vol	NS		NS		NS		11.7245	3.03
income*emp_vol	-0.0464	-5.34	-0.0836	-6.95	NS		-0.0860	-3.20
income^2*emp_vol	0.0001	5.69	0.0003	8.12	NS		0.0001	3.35

Table 3: Sensibility analysis using both different measures of volatility and a different dependent variable

* In this column we use the same volatility variable of the previous tables (stand.dev. of previous 4 years)

To conclude, we can claim that volatility plays an important role in university enrollment in the Brazilian case. More precisely, the higher the employment and GSP volatility, the lower the university enrollment. Furthermore, it is possible to derive a non linear interaction effect implying that the negative impact of employment volatility on demand for higher education is stronger for middle-income households.

Of course, this represents only a macro analysis and therefore it is not possible to disentangle the microeconomic mechanisms behind this macro evidence. To investigate this issue we carry out a microeconometrics analysis in the following section using Argentinean databases.

4 Micro evidence from Argentina

Since 1993, the "Federal Education Law" (Nba 24195) established a national education system composed of four consecutive levels:

1. The initial level ("Educación inicial") for 3 to 5 years old,

2. Primary school ("Educación General Básica") for children aged 6 to 15 years,

3. High school ("Educación Polimodal"), a three year level after primary school, and

4. Higher education ("Educación Superior, Profesional y Académica de Grado"), including both undergraduate and post-graduate education.

One of the main contributions of this controversial normative is the extension of the compulsory education period from 7 to 10 years (involving mandatory school attendance from the last year of the initial level up to the last year of primary school).

Education at all levels is supplied for free by public institutions. Official statistics from the Educational Ministry of Argentina show that private school enrollment represents 20% of primary schools and 27% for high schools, over 1996-2000 (see Rucci, 2003)[21].

As far as higher education is concerned, we found that 17% of the working age population (15 years and over) had a higher education level in 2001 (entailing an increase of 25% with respect to 1991). These figures are quite different from Brazilian ones because public supply of (free) higher education in Argentina represents a larger share of college enrollment: half of the Brazilian college students attend private institutions[22], while public universities in Argentina account for 87% of total enrollments[23].

Higher human capital accumulation in Argentina (with respect to most Latin American countries) would explain why returns to education were not so important in this country (see Psacharopoulos and Patrinos, 2002 or Psacharopoulos, 1994). Nevertheless, since 1992 the increase in returns to education was one of the main factors explaining the rise in inequality in Argentina (Gasparini et al., 2000). Furthermore, unequal access to higher education by regions and social classes is particularly relevant for this country (as noted by Buera et al., 2001; or Gonzales Rozada and Menendez, 2002) and it appears to be reinforced by general trends in macroeconomic uncertainty.

[21] Higher education supply in Argentina involves 94 different institutions. Amongst them we found 36 national public universities, 42 private universities, 1 state university and 15 non-university colleges.

[22] See INEP (2000), "Sinopse Estatística da Educaçao Superior".

[23] See Ministerio de Educación Ciencia y Tecnología (2001), "Anuario 99-00 de Estadísticas Universitarias".

4.1 Data description and econometric framework

Using micro-data from October 2001 to May 2003 we analyze the impact of real income volatility on the transition from high-school to college.

Since 1995, two-year rotating panels[24] (from Household Permanent Surveys) became available for academic research. In this paper we use the latest four waves of this survey in order to emphasize the role of our variable of interest. Indeed, Argentina's real volatility is quite impressive between 2001 and 2003 real GDP fell by 10.9% from 2001 to 2002, and increased by 8.7% from 2002 to 2003.

Our original unbalanced database includes information about household and individual characteristics for 29 urban agglomerates involving 312,157 observations (representative of 61% of the national population).

Because we are interested in the dynamic nature of children's behavior, we restrict our attention to households with four consecutive observations for individuals aged 15 to 25 in October 2001. We then keep 6,308 observations from 1,577 individuals belonging to 1,012 different households.

However, there is still too much irrelevant information. Filtering-off all cases that do not provide any transition either from high-school to college or from high-school to labor market from these cases (and disregarding information about students making transitions without previously obtaining the high school degree) entails a reduced database with 1304 observations from 326 individuals and 284 households.

Finally, the panel data is transformed into cross-sectional data with retrospective variables as the available information does not allow us to estimate the volatility variables for 2 consecutive observations[25] (the minimum required for fixed-effect panel estimations).

With this database we estimate the micro-economic impact of real income volatility on high-school-to-college transition in Argentina. Our dependent variable is the dummy "college" denoting whether the individual moves from high-school to college or not. Amongst the independent variables we define six different groups:

1. Child variables: including gender (dummy variable "gender", equal

[24]Each household is followed for four consecutive (by-yearly) waves and after that it is replaced with a new household.

[25]As we will show later, real income volatility is calculated using four consecutive observations of real income. Therefore, it is impossible to build a time series for that variable using a two-year short panel.

to 1 for females), age ("Age"), previous wave real income ("lag-real-inc[26]") and occupational status (using the dummy variables "lag-emp" and "lag-unemp"[27])[28],

2. Family and household variables: in this group we use the number of family members less than 14 years old ("Under-14") as a proxy of the number of siblings. Furthermore, we use as a covariate the home-ownership category ("Owner" or "Tenant", while "Free-tenant" is the reference category), the home type (where "Apart" stands for apartment, while "House" is the reference category), the family structure ("One person", "Lone parent" and "Extended" family[29] -using the "Traditional" composition[30] as the reference category) and a dummy variable for "Poor" families.

3. Household head variables, including information about gender ("Hsex"), education (with two dummy variables identifying household heads with higher education -"Hhigher-edu"- and household heads with high school education -"Hhschool-edu"-, where "Hprimary" is the reference category), occupational status ("Hemployed" and "Hunemployed", with "Hinactive" as the reference category), employment characteristics (Entrepreneur -"Hentrepreneur"-, self employed -"Hself-emp."-, public sector employed -"Hpublic-sect-emp"- and big firm worker -"Hbigf-worker", where wage earners, private sector employed and small firm worker are the reference categories), job tenure ("Hjob-tenure", equal to 0 if unemployed), unemployment duration ("Hun-duration", equal to 0 if employed), real income ("Hreal-income") and household head nationality (a dummy variable "Hforeign" for foreign household heads).

4. Head's partner variables: including information concerning head's partner education ("Phigher-edu" and "Phschol-edu"), occupational status ("Pemployed" and "Punemployed") and real income ("Preal-income").

[26] All real variables are estimated using self-reported nominal values and time-variant regional poverty lines from the INDEC.

[27] "Lag-inactive" is the reference category.

[28] We do not use contemporaneous values for young-children real income and occupational status because these variables are endogenously determined by schooling decisions. To avoid such a problem we use the six-month lagged values.

[29] An extended family includes parents, children and other family members.

[30] The traditional compositions stands for a family with two parents and one or more children.

5. Other control variables: regional dummies ("NorthWest", "North-East", "Cuyo (Center-West)", "Pampeana (Center)" and "Patagonia (South)", while "GBA" -Great Buenos Aires- is the reference category), and two additional variables concerning investment decisions (returns to education -"Return-edu"- and uncertainty about returns to education -"Return-edu-risk"[31]).

6. Volatility variables: we use the Household head's real income volatility ("Hhead-real-inc-vol." or "Hvol"), the Head's partner's real income volatility ("Partner-real-inc-vol." or "Pvol")[32], computed as the standard deviation of the four available waves. As in the macro analysis concerning the Brazilian case we also computed two non linear interaction effects of income and volatility on enrollment decisions. The first one is defined by an interaction variable given by the multiplication between head's income and head's income volatility ($Hvol * Hreal - income$). The second one captures a quadratic income effect defined by the multiplication of the square of head's income and the head's volatility $\left(Hvol * Hreal - income^2\right)$. Similar variables were constructed using the partner variables ($Pvol * Preal - income$, $Pvol * Preal - income^2$).

4.2 Empirical results

In tables 4 and 5 we present logit coefficients and marginal probabilities for those variables being significant at 10% in at least one model specification for high school to college transitions. In table 6 and figure 2 we present the ROC analysis[33], showing that logit specifications are quite robust as long as 80% of the cases are correctly classified (in average for different cut-off points) and the area under the ROC curve is 0.87.

Using 326 observations for each specification, we estimate 3 different models including control variables only in column 1, control and volatility

[31] From the original database we estimate real income differentials between college and high school degrees for 112 different groups (defined by poor males, poor females, non-poor males and non-poor females for each of the 28 urban agglomerates in October 2002). We use within group means and intertemporal standard deviations of means as proxy variables for returns to education and uncertainty about returns to education, respectively, in the reduced database (matching information through state, poor and gender variables).

[32] We do not use total family and per capita real income volatility because these variables, as well as young-children real income volatility, are endogenously determined by the young's schooling decision.

[33] See Westin, 2001 for an introduction to ROC analysis.

variables ("Hvol" and "Pvol") in column 2, and control variables, volatility variables and non-linear volatility variables in column 3.

To avoid having a collinearity bias in significant coefficients we drop-out non-significant covariates using the traditional "stepwise backward selection procedure". Furthermore, we use White's correction for robust standard errors (see White, 1980) because of potential heteroskedasticity problems in our cross-sectional estimates.

As far as children's variables are concerned, we find that high-school-to-college transitions decrease with age and previous real income. As already stressed by the human capital literature, the older the individual, the shorter the time period to appreciate the life-time returns to education (and also the higher the teenager household responsibilities). The negative coefficient of the past real income is a clear evidence that opportunity costs (reflected by this variable) are particularly binding in our estimations. In accordance with previous literature[34], the gender coefficient shows that female teenagers have a higher probability of high-school-to-college transition than males. This result could be derived from existing gender differences in both employment opportunities and real wages. Male children's expected real income (with high-school degree) would be higher than female's and then it would be more efficient from the family point of view to use male children labor market participation as a consumption smoothing mechanism if need be. However, the teenager gender coefficient becomes non-significant when volatility variables are included (see columns 2 and 3).

Amongst family control variables the number of household members aged less than 14 (a proxy variable for the number of siblings) robustly reduces the high-school-to-college transitions (regardless of the econometric specification). As noted by Heer (1985), multiple siblings increases liquidity constraints, thus reducing the probability of college enrollment (as long as children labor market participation might be necessary to escape from extreme poverty). On the contrary, extended families (with other members than parents and children) have a positive influence on high school to college transitions when volatility variables are included in the econometric specification. As a possible explanation, we can argue that (controlling for household size) extended families have a lower dependency ratio than traditional ones because children are under-represented in this type of families (and "other household members" are usually older than 14).

[34]See Conley (2001).

Home-ownership and home-type covariates also affect high-school-to-college transitions. When including volatility variables, we find that living in an apartment (and not in a house) significantly reduces the likelihood of college enrollment, while house non-ownership ("Tenant" coefficients) increases by 0.62 or 0.71 depending on the econometric model.

As far as the household head variables are concerned we find that many significant coefficients become irrelevant when the volatility variables are taken into account (such as gender, real income and some employment characteristic like self-employment and public sector employment). Amongst the most robust effects, we find a positive correlation between the household head's physical capital and children's human capital accumulation. Household head entrepreneurship increases by 0.83 to 0.87 the teenager's probability of high-school-to-college transition[35]. Furthermore, household head's education is positively correlated with college enrollment. When the household head has a higher education degree, her children's probability of high school to college transition rises by 0.32 to 0.35 with respect to those children with high school degree parents[36] (see table 5, columns 2 and 3).

There is, nonetheless, a peculiar result. Household head unemployment is always positively correlated with children's college enrollment. When controlling for household head's real income (see table 5 column 1), the positive effect of household head unemployment on children's probabilities of high school to college transition entails an increase in that probability by 0.77. This result changes slightly when we take into account the coefficients of household head household unemployment duration. The composite effect involves a positive correlation between household head unemployment and children's college enrollment for short-term unemployed family heads but a (more comprehensible) negative relationship for medium and long term unemployed household heads[37].

When the head's partner variables are considered, we find two main positive effects on children's probabilities of high-school-to-college transition. First, we note that head's partner higher education not only increases teenager transition from high school to college but its effect is twice higher than household head one. Assuming that most partners in Argentina are females (e.g. in our database 72% of the household heads are males), it is in-

[35] For a survey about the relationship between parents' wealth and children's schooling see Axinn, Duncan and Thorton (1997).

[36] See Rumberger (1983) for a deeper analysis of this well documented result.

[37] For an interesting discussion on this subject see Fernández and Shioji (2000).

teresting to notice that mother's education is more important than father's human capital accumulation in order to increase children's transition from high-school to college. This result is often emphasized in the literature as noted by the recent contribution of Chevalier (2004). On the other hand, it is really surprising that head's partner employment is more important than household head's occupational status (in fact, household head's employment is not significant at 10%). It seems that the higher the mother's bargaining power, the higher the weight of children's education in the allocation of family income.

In the group of "other control variables" one regional dummy only is significant at 10% in every econometric specifications. Living in "Patagonia" (the South of the country) increases children's probability of high-school-to-college transition. It is not surprising as southern urban agglomerates are relatively richer than others as. It must be emphasized that investment-related covariates are not significant for children's schooling decisions. We find one econometric specification only where the uncertainty about returns to education is significant at 10%, but its marginal probability coefficient is really low, and disappears when volatility variables are taken into account.

Let us now analyze our variables of interest. According to previous results, there is nothing but mother's real income volatility that matters for children's transition from high-school to college. As expected, this variable presents a negative coefficient entailing that children's probability of high-school-to-college transition decreases by 0.10 when head's partner real income volatility increases by one poverty line. However this effect is not homogeneous for different income levels. Allowing for non-linear interaction effects, we find that mother's real income volatility is particularly important for middle income levels. As a general result, we find the same non-linear feature we described in figure 3 (for the macroeconomic analysis). While poorest families are not affected by real income volatility, middle income households reduce their children's college enrollment as long as volatility increases. Furthermore, the positive second order interaction effects entail that richest families could have an opposite effect increasing human capital polarization.

Dependent variable: High school to college transition		(1) Coeff.	(1) z	(2) Coeff.	(2) z	(3) Coeff.	(3) z
Young variables	Age	-0.519	-4.30	-0.485	-4.15	-0.451	-4.06
	Gender	1.036	1.83	N/S		N/S	
	lag-real-inc	-2.259	-2.31	-3.247	-3.07	-3.123	-3.45
Family variables	Under-14	-0.683	-3.08	-0.755	-3.04	-0.730	-3.11
	Extended	N/S		1.676	2.28	1.818	2.66
	Appart	N/S		-1.607	-1.70	-1.898	-2.00
	Tenant	N/S		3.281	2.66	3.668	3.06
Household head variables	Gender	1.876	2.22	N/S		N/S	
	Hhigher-edu	N/S		2.042	2.02	2.081	2.17
	Hhshool-edu	N/S		1.458	2.63	1.649	2.87
	Hreal-income	0.324	2.19	N/S		N/S	
	Hunemployed	4.328	4.32	2.310	2.70	2.033	2.76
	Hun-duration	-0.260	-2.79	-0.175	-2.85	-0.160	-2.86
	Hentrepreneur	4.818	4.56	5.352	3.16	5.123	2.86
	Hself-emp.	1.690	2.18	N/S		N/S	
	Hpublic-sect-emp.	1.158	1.72	N/S		N/S	
Head's Partner variables	Phigher-edu	3.917	3.48	3.096	2.61	3.340	2.29
	Phshool-edu	1.190	2.01	N/S		N/S	
	Preal-income	-0.506	-2.11	N/S		N/S	
	Pemployed	1.325	1.86	1.928	2.99	1.922	3.04
Other control variables	Return-edu-risk	0.018	1.82	N/S		N/S	
	NorthWest	1.589	2.75	1.000	1.67	N/S	
	NorthEast	1.188	1.84	N/S		N/S	
	Cuyo (Center-West)	N/S		-1.538	-1.89	-1.857	-2.16
	Patagonia (South)	1.821	2.15	2.106	2.41	1.937	2.37
Volatility variables	Partner-real-inc-vol (Pvol)	-		-1.142	-2.74	N/S	
	Pvol*Preal-income	-		-		-1.034	-2.33
	Pvol*(Preal-income^2)	-		-		0.180	1.80
Observations:		323		323		323	
Pseudo $R^{2:}$		0.54		0.53		0.56	
Log pseudo-likelihood:		-94.31		-96.16		-90.80	

Note: We only include those variable whose coefficients were (at least once) significantly different from 0 at 10%. NS stands for not significant coefficient at 10%. "-" stands for 'variable not present in the estimate'.

Table 4. Determinants of High School to College Transition. Logit Coefficients from Argentina micro-data (2001-2003)

Dependent variable: High school to college transition		(1) Coeff.	(1) z	(2) Coeff.	(2) z	(3) Coeff.	(3) z
Young variables	Age	-0.052	-2.88	-0.043	-2.48	-0.046	-2.63
	Gender	0.103	1.56	N/S		N/S	
	lag-real-inc	-0.225	-3.22	-0.288	-4.44	-0.317	-4.76
Family variables	Under-14	-0.068	-2.34	-0.067	-2.31	-0.074	-2.53
	Extended	N/S		0.210	1.77	0.260	2.02
	Appart	N/S		-0.100	-1.70	-0.129	-2.04
	Tenant	N/S		0.620	2.76	0.707	4.06
Household head variables	Gender	0.291	1.70	N/S		N/S	
	Hhigher-edu	N/S		0.315	1.25	0.352	1.44
	Hhshool-edu	N/S		0.146	1.73	0.190	1.43
	Hreal-income	0.032	1.83	N/S		N/S	
	Hunemployed	0.769	6.66	0.363	2.05	0.332	2.14
	Hun-duration	-0.026	-2.09	-0.016	-1.92	-0.016	-2.00
	Hentrepreneur	0.832	11.66	0.866	10.59	0.848	9.28
	Hself-emp.	0.252	1.69	N/S		N/S	
	Hpublic-sect-emp.	0.155	1.41	N/S		N/S	
Head's Partner variables	Phigher-edu	0.722	4.12	0.551	2.05	0.626	2.11
	Phshool-edu	0.141	1.52	N/S		N/S	
	Preal-income	-0.050	-1.69	N/S		N/S	
	Pemployed	0.164	1.35	0.240	1.84	0.265	2.02
Other control variables	Return-edu-risk	0.002	1.56	N/S		N/S	
	NorthWest	0.245	2.16	0.121	1.34	N/S	
	NorthEast	0.175	1.55	N/S		N/S	
	Cuyo (Center-West)	N/S		-0.083	-1.99	-0.106	-2.41
	Patagonia (South)	0.320	1.54	0.367	1.74	0.352	1.75
Volatility variables	Partner-real-inc-vol (Pvol)	-		-0.101	-1.81	N/S	
	Pvol*Preal-income	-		-		-0.105	-1.69
	Pvol*(Preal-incomeˆ2)	-		-		0.018	2.06
Observations:		323		323		323	
Pred. prob. of high school to college trans.:		0.13		0.10		0.13	

Note: We only include those variable whose coefficients were (at least once) significantly different from 0 at 10%. NS stands for not significant coefficient at 10%. "-" stands for 'variable not present in the estimate'.

Table 5. Determinants of High School to College Transition. Logit Marginal probabilities from Argentina micro-data (2001-2003)

Cutoff point	Sensitivity	Specificity	C. Classified	LR+	LR-
0.30	75.5%	82.0%	80.1%	4.20	0.30
0.50	55.1%	91.2%	80.4%	6.28	0.49
0.70	48.0%	96.5%	81.9%	13.67	0.54
Max.Cor.Clas.: 0.70	48.0%	96.5%	81.9%	13.67	0.54
Sen.= Spec.: 0.27	79.6%	79.4%	79.5%	3.86	0.26

Table 6: ROC Analysis from Logit Estimates

5 Conclusions

This paper adresses the empirical links between macro and microeconomic real instability and human capital accumulation, especially for higher education demand. We consider two Latin American countries characterized by high levels of real volatility: Argentina and Brazil. The negative relationship between high real volatility and human capital accumulation is a major

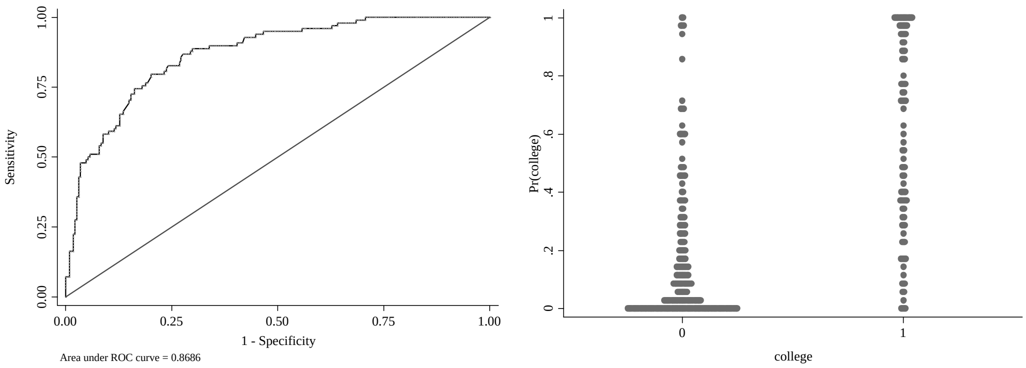

Figure 3: Graphical representation of ROC analysis. Specificity, sensitivity and Probability distribution.

factor to explain income inequality, especially in Latin American countries. Therefore, Argentinean and Brazilian cases are used for testing our main hypothesis: as soon as real volatility increases, human capital investment goes down and inequality in education rises.

Using a macroeconomic database constructed from the Pesquisa Nacional por Amostra de Domicílios (PNAD/IBGE) for 26 Brazilian states in 1992-2002 period, we investigate the "human capital channel" in the relationship between real volatility (GSP and employment volatilities) and education inequality, and show that real uncertainty is a key variable for higher education choices. As employment and GSP volatilities increase, enrollment rates decrease, but this negative impact is stronger for middle income states.

In order to clarify this macroeconomic evidence, we consider the Argentinean case using a short-panel database from October 2001 to May 2003, constructed from the Household Permanent Survey (Encuesta Permanente de Hogares, EPH-INDEC). We point out that mother's real income volatility variables have a negative impact on children's high-school-to-college transition. This effect is not linear, entailing that middle income families are strongly affected by real volatility, whereas the poorest and the richest households seem not to be affected by income uncertainty.

Therefore, macro and micro evidence shows that real volatility heterogeneously decreases the demand for higher education. Furthermore, we show that macroeconomic uncertainty not only reduces human capital accumulation but also increases education inequality.

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