Poverty, Income Fluctuations and Work: Argentina 1991-2002

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ABSTRACT

This thesis presents results on the economics of poverty and labour markets, using data from Argentina in the 1991-2002 period for empirical applications. The thesis is divided into two Parts.

The first Part concentrates on poverty and the effects of income fluctuations on well-being. The 1995-2002 period in Argentina was characterised by recurring economic crises that produced large fluctuations in household income. The empirical applications of this Part rely on a rotating panel dataset from the Greater Buenos Aires region to study the effects of this variability.

The first Chapter introduces the data and its characteristics, and describes the economic context of the period. The second Chapter defines a family of indicators of well-being, based on the theory of choice under uncertainty, that account for the negative impact of income fluctuations on household welfare. Chapters 3 and 4 present risk adjusted measures of income and the transient-chronic poverty decomposition, respectively, two methodologies for the study of poverty with panel data which are related to the indicators defined in Chapter 2. In Chapters 3 and 4, the household characteristics associated with income fluctuations and their impact on well-being are identified through regression analysis.

Part II deals with fertility and women's labour supply from an empirical perspective, and uses data from the 1991 Argentine Census for its applications. Chapter 5 presents the theoretical and econometric framework employed to deal with the endogeneity of the fertility decision. This identification strategy exploits parental sex preferences as instrumental variables for further child-bearing. Chapter 6 discusses its validity in developing countries, and provides empirical evidence for Argentina. Chapter 7 presents the main results of the estimation, which state that additional children cause a reduction in their mother's labour supply. Finally, Chapter 8 proposes a new test for the generality of instrumental variables results, which is illustrated with the same dataset.

TO LAURA AND CLARITA

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INTRODUCTION

This thesis presents methodological developments and empirical findings on the economics of poverty and labour markets, using data from Argentina in the 1991-2002 period for empirical applications. It is divided into two Parts, which deal with related issues.

The Chapters in Part I focus on poverty as a dynamic phenomenon, motivated by the recurring economic crises that affect developing countries and the incidence of income fluctuations on household welfare. In the Introduction to a pioneering volume on panel data on incomes, Atkinson and Cowell (1982) noted that these datasets "provide a unique opportunity" for modelling the instability of family well-being and the incidence of poverty, among other economic phenomena. While the increasing availability of household panel data has been exploited in theoretical analysis and empirical applications, the methodological and applied literatures still lack a unified framework. Echoing Atkinson (1987), Part I addresses the question of how poverty should be measured *over time* – or, in more general terms, how to measure well-being based on repeated observations of household income. The aim is to develop and illustrate a set of tools for empirical work based on theoretically sound extensions of the existing methodology for static distributional analysis. Since the proposed family of measures does not rely on a specific functional form, the framework developed in the following pages encompasses some of the existing approaches as special cases.

These tools are illustrated with longitudinal data for Argentina in the 1995-2002 period, which is well suited for this type of analysis given the large fluctuations in household income. As described in Chapter 1, during the 1990s the country's economy underwent a process of market-oriented structural reforms. The resulting openness of the economy and the hard peg of the local currency to the US dollar contributed to a high degree of vulnerability to the succession of international financial crises of the second half of the decade, which was characterised as a period of "boom and bust." This series of external macroeconomic shocks and the weaknesses of the Argentine economy led to a severe economic and social crisis that started at the end of 2001 and continued well into 2002. Chapter 1 describes the trends in poverty and its dynamics during this period, and sets up the basis for the analysis of the following three Chapters: it discusses the methodological issues of poverty measurement in Argentina, introduces the main dataset employed in Part I (a rotating panel from the Greater Buenos Aires region), and covers the existing literature on poverty in Argentina.

Chapter 2 presents a general framework for the evaluation of well-being based on panel data on incomes. The methodology relies on a formal analogy with the theory of choice under uncertainty, and on the existing literature on distributional analysis. It defines a family of indicators that account for the negative impact of income fluctuations on household welfare. The methodology is illustrated with the Greater Buenos Aires panel. The following Chapters present two examples of more detailed empirical analysis, which can be interpreted as special cases of the evaluation framework. Chapter 3 accounts for risk and the effect of fluctuations on household welfare by defining risk adjusted measures of income. The evolution of these indicators is complemented by a regression analysis, which sheds light into the household characteristics associated with the impact of risk on well-being. Finally, Chapter 4 provides a decomposition of poverty into its transient and chronic components, and studies their correlates by means of regression analysis.

The research presented in Part II is motivated by some of the stylised facts in distributional analysis that emerge from regressions of this type. While most poverty profiles find strong links between poverty, childbearing and labour market status, these links cannot be interpreted as causal relationships given the problems of endogeneity and simultaneity that are pervasive in applied economic research.

The Chapters in Part II establish the determinants of the income-generating process of women as primary and secondary earners in the household. Specifically, these Chapters make a series of methodological and empirical contributions by studying the causal effect of fertility on female labour supply from an empirical perspective, based on data from the 1991 Argentine Census.

Chapter 5 presents the theoretical and econometric framework employed to deal with the endogeneity of the fertility decision. The simultaneity problems in the economic analysis of fertility and labour supply arise from the fact that the two are joint decisions: while children provide utility to their parents, they enter the household's budget constraint through the costs in terms of goods and time. Moreover, fertility and labour supply decisions might be driven by unobservable factors, such as preferences and ability, which imply selection problems in the estimation. The identification strategy in Part II exploits parental sex preferences as instrumental variables for childbearing, based on the observation that parents of two children of the same sex exhibit a higher propensity to have another child to obtain a gender-balanced offspring composition.

However, the nature of sex preferences in developing countries poses some challenges to the application of this strategy to the Argentine case: in particular, a stronger preference for boys might have implications in terms of lifetime income and labour supply, invalidating the postulated exogeneity of the instrument. Chapter 6 discusses these problems in the context of developing countries. It provides original evidence in support of the validity of the identification strategy for Argentina, studying the plausibility of the untestable identifying assumptions by means of auxiliary evidence. Based on these results, Chapter 7 presents the instrumental variable estimates of the causal effect of fertility on labour supply. Finally, Chapter 8 proposes a new test for the generality of instrumental variable results, which is illustrated with the same dataset.

The Conclusion reviews the main contributions of both Parts, highlighting their implications for theoretical analysis, empirical application and policy formulation, and outlining possible avenues for further research.

Part I

Poverty and Income Fluctuations, Argentina 1995-2002

CHAPTER 1

ARGENTINA'S CRISES AND THE POOR

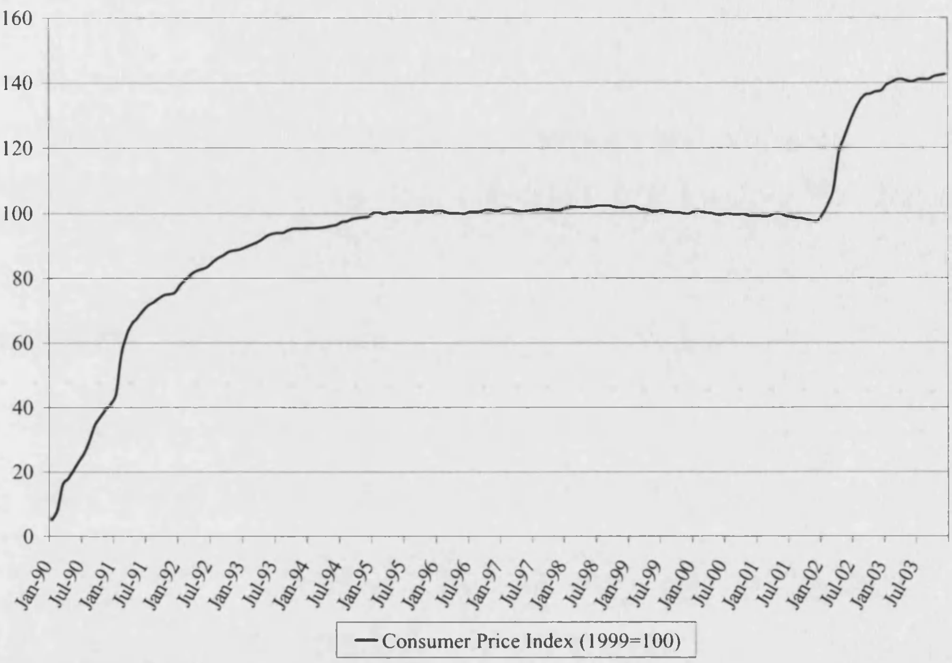
1.1 INTRODUCTION TO PART I: KEY ECONOMIC EVENTS, ARGENTINA 1991-2002

The objective of this introductory Chapter is to set up the context for the rest of Part I, which presents original developments in the measurement of poverty and well-being over time. The main motivation is the effect of the recurring economic crises that affect developing countries and the incidence of income fluctuations on welfare. For this reason, the empirical applications of this Part exploit the longitudinal dimension of household survey data for Argentina in the 1995-2002 period. Since the empirical work of Part II is based on Argentine data from 1991, the following pages present the main economic events of the 1991-2002 period.[1]

The 1980s represented a "lost decade" for most of Latin America. In the case of Argentina, the decade ended in political instability and a series of hyperinflation episodes that extended into 1990 and 1991, as can be appreciated in the evolution of the Consumer Price Index (CPI), presented in Figure 1.1. In March 1991, the country adopted the "Convertibility Plan," a currency board where the Argentine peso was pegged to the US dollar. This plan was accompanied by a series of market oriented structural reforms that included privatisations of public utilities and the opening of the economy to flows of goods and capital. These reforms and the liquidity of international credit markets prompted a steady inflow of capital, which sustained growth between 1991 and 1994. This is depicted in Figure 1.2, which presents the

[1]This summary draws on Lewis (2002), Bonvecchi (2003) and Gerchunoff and Llach (2004a), which are recommended for further reference on the economic history and the political economy of Argentina.

Figure 1.1: Consumer Price Index, Argentina, 1990-2003



Source: INDEC (2003).

evolution of Gross Domestic Product (GDP) annotated with the main economic events of the 1990-2003 period for Argentina.

The Convertibility's currency board, however, made the economy highly vulnerable to external shocks. At the end of 1994, Mexico devalued its currency and triggered an international financial crisis (the "Tequila crisis") that affected most emerging markets. Argentina rapidly suffered from contagion, with runs against the peso and significant capital flights, but the currency board resisted this large external shock. As shown in Figure 1.2, a brief recovery followed during 1996 and 1997, but the economy was hit again by the economic crisis in South-East Asia, which started in Thailand in early 1997, and its aftermath. Russia, in turn, entered a severe financial crisis in August 1998, and its sovereign debt default prompted yet another contagion to Argentina, which was – like most emerging markets – badly hit by capital outflows and interest rate rises. In January 1999, Brazil, Argentina's main trading partner, was forced to devalue its currency, worsening a recession that started around 1998.

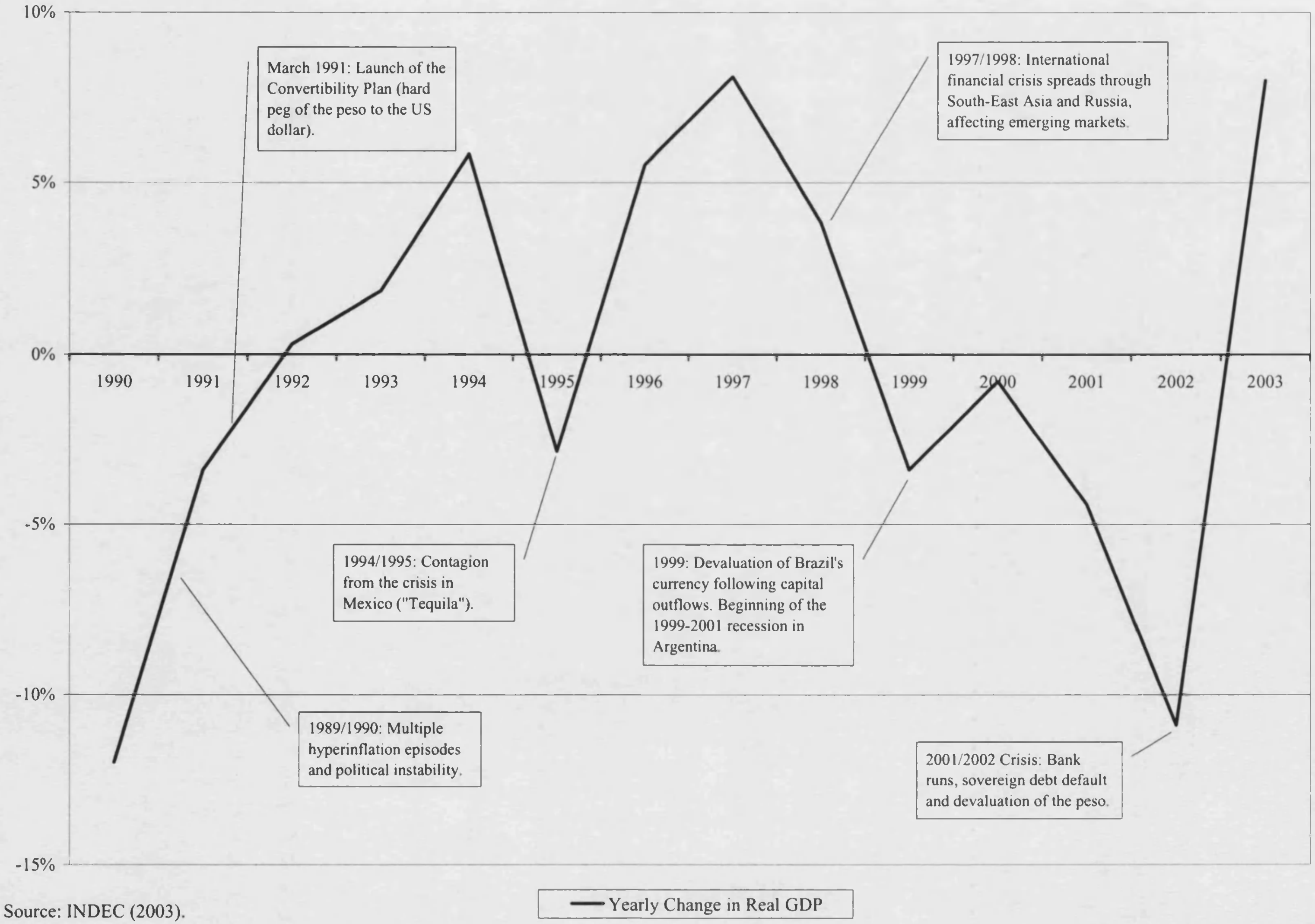
After three years of negative growth, the Argentine government was forced to impose restrictions on bank accounts in late 2001. This precipitated events, which converted the recession into an economic meltdown. The decision to freeze bank deposits was followed by social unrest and political instability, and lead to the resignation of President De La Rua. The currency board could not be sustained in this context, and in early 2002 the new government put an end to the parity between the peso and the US dollar and announced a default on the country's sovereign debt. The subsequent fall in confidence and the disruption of productive activity resulted in a fall in GDP of 10.9 per cent during 2002.

The sources of the crisis can be traced back to, among other factors, the exchange rate parity with the US dollar and the resulting over-valuation of the local currency, the vulnerability of the country to external shocks, and the economy's own structural weaknesses (Galiani et al., 2003).

As discussed in detail in this Chapter, the crisis was reflected in the poverty rates, which reached 53 percent of the population in May 2002, 15 percentage points higher than in October 2001. This increase in poverty mirrored a large fall in household income, caused by two factors (World Bank, 2003). On the one hand, labour market conditions deteriorated sharply: in May 2002, the unemployment rate exceeded 21 percent, more than 3 percentage points higher than in October 2001 (see the discussion of Figure 1.3 below). On the other hand, real incomes fell because of the large increase in consumer prices induced by the devaluation (Figure 1.1).

The rest of this Chapter is organized as follows. Section 1.2 introduces the survey data and the income aggregate. It also discusses methodological issues on poverty measurement in Argentina, and proposes an extension to the official methodology that allows the construction of consistent national poverty figures for the 1995-2002 period. The Section also describes a rotating panel dataset from the Greater Buenos Aires region, which is used extensively in the following Chapters. Section 1.3 builds on the data and income aggregate to present the main trends of poverty during the period at the national and regional levels. It also provides a presentation of the short term poverty dynamics. Finally, Section 1.4 briefly covers the existing literature on poverty in Argentina for this period. Conclusions follow.

Figure 1.2: Yearly Change in Real GDP and Key Economic Events, Argentina, 1990-2003



Source: INDEC (2003).

1.2 Household Data and Measurement of Poverty in Argentina

1.2.1 National cross sections and the Greater Buenos Aires rotating panel

The empirical analysis conducted in Chapters 1 to 4 (Part I) is based on data from the Argentine Permanent Household Survey ("Encuesta Permanente de Hogares," EPH). This is a labour market and living conditions survey that has been collected since 1975 in the Greater Buenos Aires region, which covers the country's capital and adjacent municipalities, and constitutes the country's largest urban centre. The EPH is one of the longest running household surveys in Latin America, and is considered to be of relatively high quality (World Bank, 2000a). The data is collected by the national statistical agency, the Instituto Nacional de Estadísticas y Censos (INDEC), which is responsible for household, expenditure and manufacturing surveys, the national Census, price indices and the national accounts.

During the 1980s and 1990s, other cities were added to the EPH's sampling frame, reaching a maximum of 28 urban centres in 1995 (INDEC, 1996). This made the EPH representative of the urban population of the country – about 80 percent of the total. While some of the estimates in this Part will be referred to as "national," it should be stressed that the results correspond to the urban areas covered by the EPH and are representative at the urban level only.[2] Relatively little is known about the small but not negligible fraction of the population residing in rural areas. Fiszbein et al. (2002), discussed in Section 1.4, provide some limited evidence on living conditions in these areas. The main urban centres covered by the EPH are divided by INDEC into six statistical regions, and it is thus assumed that the cities and provinces within each region share some structural characteristics. The regions are Greater Buenos Aires, Pampeana, Noreste, Noroeste, Cuyo and Patagonia. Appendix B lists the main urban centres covered by the EPH, and places the regions in a map of the country.

During the 1995-2002 period, the survey was collected every year in two waves, in May and October (denoted waves 1 and 2 for each year), and all estimates in this Part are based on the fifteen waves available between May

[2]The empirical application of Part II is based on the 1991 Census and thus covers urban and rural areas.

Table 1.1: Unweighted Sample Sizes for National Cross Sections, EPH

Wave	Households	Individuals
May 1995	22,023	82,721
October 1995	29,509	112,439
May 1996	29,861	113,209
October 1996	27,200	103,847
May 1997	29,506	110,487
October 1997	29,362	109,307
May 1998	28,511	105,399
October 1998	26,810	99,035
May 1999	24,918	92,371
October 1999	24,715	91,512
May 2000	22,834	83,571
October 2000	22,763	83,583
May 2001	22,833	83,264
October 2001	22,998	83,988
May 2002	22,814	83,349

Source: EPH household survey data (INDEC).

1995 and May 2002. The EPH is structured as a rotating sample, where 25 percent of households surveyed are replaced in each wave, and the data is treated as a series of repeated cross sections (INDEC, 2002). The INDEC provides household weights, which are used in all the estimates presented in this Chapter. Table 1.1 presents the unweighted sample sizes for the fifteen waves, both in terms of the number of individuals and the number of households surveyed.

The rotating structure of the EPH's sample implies that households stay in the sample for four consecutive waves, a period of about a year and a half. A consistent series of panels, however, can only be constructed for the Greater Buenos Aires region (GBA), since for other urban centres INDEC did not release all the matching codes, and changes were made to the sample rotations. The Greater Buenos Aires region represents around 60 percent of the total population and 70 percent of the urban population of the country.

The fifteen waves between May 1995 and May 2002 contain data for twelve "cohorts" of households observed in the same four consecutive waves. Table 1.2 illustrates the structure of the panels and clarifies the distinction between waves and cohorts. Only households observed four times and with complete information on income for every member of the household in the four waves are kept in the sample, which results in an average of 453

Table 1.2: Rotating Sample: Cohorts and Waves in the GBA Panel

	Wave:	95-1	95-2	96-1	96-2	97-1	97-2	98-1	98-2	99-1	99-2	00-1	00-2	01-1	01-2	02-1
	Cohort:															
1	95-1 to 96-2	1	1	1	1											
2	95-2 to 97-1		2	2	2	2										
3	96-1 to 97-2			3	3	3	3									
4	96-2 to 98-1				4	4	4	4								
5	97-1 to 98-2					5	5	5	5							
6	97-2 to 99-1						6	6	6	6						
7	98-1 to 99-2							7	7	7	7					
8	98-2 to 00-1						Wave		8	8	8	8	Cohort			
9	99-1 to 00-2									9	9	9	9			
10	99-2 to 01-1										10	10	10	10		
11	00-1 to 01-2											11	11	11	11	
12	00-2 to 02-1												12	12	12	12

retained households per cohort – about 60 percent of the theoretical total for the GBA region. Cruces and Wodon (2003c) argue that the attrition from the panel is compensated by the INDEC's weighting structure, and does not bias income and poverty measures in a significant way. Moreover, given the relatively short span of the panels, the problems identified by Cowell (1982) with respect to changes in family structure do not affect the results. Cruces et al. (2004) discuss alternatives for dealing with these issues in a long panel.

1.2.2 *Income aggregate and equivalence scale*

The EPH collects information on the income and labour market status of every member of a household, as well as some dwelling and individual characteristics. To obtain results which are comparable to official figures and to the literature on poverty and labour economics in Argentina, this Chapter employs INDEC's methodology for the computation of household income aggregates, which is critically assessed below.

The aggregation of income at the household level is not a trivial task, as witnessed by the long discussion in the poverty literature (Ravallion, 1994; Deaton, 1997, cover these debates and most of the issues raised in this Section). While some authors base their estimates on per capita income, this is problematic as an indicator of well-being because it does not allow for economies of scale in the household, nor for differences in needs between members of different age and gender. Ignoring these aspects may result in an over-estimation of the negative impact of household size on poverty

(Coulter et al., 1992; Lanjouw and Ravallion, 1995) and inequality (Cowell and Mercader Prats, 1999).

Following Cowell (2000, Section 2), total family income ψ_i must be adjusted by the characteristics of the household and its members by means of an equivalence scale. This process results in equivalised income y_i^e, which represents a suitable money metric of utility. The procedure of equivalisation is defined by a function χ such that:

$$y_i^e = \chi(\mathbf{a}_i, \psi_i)$$

where $\mathbf{a}_i$ represents a list of demographic and other attributes of the household and its members. Equivalised income is often obtained as

$$y_i^e = \frac{\psi_i}{\nu(\mathbf{a}_i)} \tag{1.1}$$

where $\nu(\mathbf{a}_i)$ is a function that defines the number of equivalent adults in the household. INDEC follows this methodology in the construction of its income aggregate, and accounts for differences in needs between household members by adopting an equivalence scale based on calory intake by age and gender (INDEC, 2002). Specifically, the number of equivalent adults for each household i with k_i members is defined as $\nu(\mathbf{a}_i) = \sum_{j=1}^{k_i} q_j$, where each q_j is determined by member j's age and gender. These adult equivalent coefficients q_j are given in Table 1.3 (reproduced from Morales, 1988) for different categories. The coefficients are defined as the ratio of each category's caloric intake requirements to those of men aged 30 to 59 (2,700 kcal per day), which are defined as an equivalent adult. For instance, a three year old girl requires 1,500 kcal per day, and thus represents 0.56 of an equivalent adult. INDEC's adjustments for differential needs are within the range of those employed in the distributional literature, and they are robust to adjustments for economies of scale in the household.[3]

[3]While INDEC choses not to adjust household income for economies of scale, this is relatively straightforward to implement by means of a parameter s, $0 \leq s \leq 1$, with each extreme representing full and no economies of scale respectively. The number of adult equivalents is then computed as $[\sum_{j=1}^{k_i} q_j]^s$, where q_j is the coefficient in Table 1.3 and k is the size of the household. This is not implemented in this Chapter to maintain compatibility with official statistics and existing academic work. Gasparini (2003a) conducts a sensitivity analysis with EPH data and finds that most income and poverty measures are robust to

Table 1.3: INDEC Equivalence Scale: Caloric Needs by Age and Gender and Equivalent Adults

Age	Gender	Calories needed (kcal)	Units per equivalent adult
Up to 1 year old		1,170	0.43
2	Girls	1,360	0.50
3	and	1,500	0.56
4 to 6	Boys	1,710	0.63
7 to 9		1,950	0.72
10 to 12		2,230	0.83
13 to 15	Men	2,580	0.96
16 to 17		2,840	1.05
10 to 12		1,980	0.73
13 to 15	Women	2,140	0.79
16 to 17		2,140	0.79
18-29		2,860	1.06
30-59	**Men**	**2,700**	**1.00**
60 and +		2,210	0.82
18-29		2,000	0.74
30-59	Women	2,000	0.74
60 and +		1,730	0.64

Source: Morales (1988). The adult equivalent units are defined as the ratio of the age-gender category caloric needs with respect to those of an adult male aged 30 to 59.

To complete the definition of y_i^e in Equation 1.1, total household income is computed by INDEC for each household i with k_i members as $\psi_i = \sum_{j=1}^{k_i} y_i^j$, where y_i^j represents each individual member's total monetary income. Most individuals have only one source of income which consists of salaries for the active population and pensions for those who are retired. Combining this figure and the number of equivalent adults in the household given by the function ν, total household equivalent income is defined by the following expression:

$$y_i^e = \frac{\sum_{j=1}^{k_i} y_i^j}{\sum_{j=1}^{k_i} q_j} \tag{1.2}$$

This aggregate is attributed to every member of the household, which is why the text refers interchangeably to households and individuals. By adjusting for differences in household composition, y_i^e represents a better measure of well-being than per capita income (Deaton, 1997).

reasonable deviations from INDEC's implicit choice of $s = 1$.

As an index of income, INDEC's y_i^e satisfies the basic criteria of measurability and comparability among different individuals (Cowell, 1995, Chapter 1). However, the Chapters in this Part deal with observations spanning the period 1995 to 2002, and y_i^e as defined in Equation 1.2 is not comparable across regions or in different periods if prices differ geographically or over time. While it is possible to deflate y_i^e with respect to prices at a given period to express it in constant units (i.e., in terms of real income), this Chapter and the rest of Part I adapt INDEC's (2002) methodology to time and geographical variations by normalising the adult equivalent income normalised by the contemporaneous poverty line z_t. This income aggregate is defined as:

$$y_{it} = \frac{y_{it}^e}{z_t} = \left[\frac{\sum_{j=1}^{k_i} y_{it}^j}{\sum_{j=1}^{k_i} q_j} \right] / z_t \tag{1.3}$$

This formulation is known as the "welfare ratio" in the literature and has a number of advantages (Blackorby and Donaldson, 1987; Ravallion, 1998). In addition to making equivalised incomes comparable over time and space,[4] Equation 1.3 can be given an interpretation in terms of poverty measurement: $y_{it} < 1$ indicates that a household's income is below the poverty line, and thus its members can be classified as poor.[5] For these reasons, the choice of the poverty line as the unit of measurement is preferable to deflating incomes with respect to the CPI.

Finally, the quality of the income aggregate y_{it} is given by INDEC's validation process, which checks each of the components of individual income for consistency and discards households for which a complete total income cannot be computed, adjusting the sample weights accordingly. The small fraction of households reporting zero total income are kept in the final sample since they are considered valid by INDEC.

[4] As discussed in the following pages, poverty lines vary between regions, and Equation 1.3 should refer to the income of a household living in region r and the regional poverty lines z_{rt}. The notation in the text is preferred for being more compact.

[5] The denominator of the right hand side of Equation 1.3, $\tilde{z}_{it} = z_t \sum_{j=1}^{k_i} q_j$, can be interpreted as a household specific poverty line.

1.2.3 Poverty lines and regional heterogeneity

The rest of this Section covers the construction of poverty lines in Argentina, which establish the fundamental partition of the population between the poor and the non-poor (Cowell, 2003). For each wave of the EPH, INDEC reports the cost of an extreme (or "indigent") poverty line, z_t^I, which is based on a basic food basket (INDEC, 2002). The components of this basket are constructed from a household expenditure survey,[6] and its cost is updated with changes in prices between each wave of the EPH.

The poverty line z_t is derived from the basic food basket z_t^I using the inverse of the Engel coefficient to incorporate the cost of basic non-food goods.[7] The idea behind this approach is that the extreme poor cannot afford a minimum food basket, whereas the moderately poor, while able to cover their basic nutritional needs, cannot afford other essential goods and services. While other alternatives for the definition of poverty lines exist, this Chapter follows the literature on distributional analysis in Argentina and adopts INDEC's methodology to ensure comparability with previous results.

As argued in the discussion of Equation 1.3, normalising incomes by the poverty lines facilitates comparisons over time. Poverty lines are also used in distributional analysis to reflect geographic heterogeneity in prices and in the purchasing power of income, by means of region and time specific lines z_{rt}.

INDEC's geographic coverage, however, is incomplete for most of the 1995-2002 period. While the EPH is collected in the major urban areas of the country, INDEC only constructed poverty lines for the Greater Buenos Aires region. From that wave onwards, INDEC provides official poverty lines for the six statistical regions based on the purchasing power parity of income. The lack of regional poverty lines implies that INDEC only computed official poverty statistics for the GBA region before 2001, even though the regional survey data is available for the 1995-2000 period. These statistics are presented in Appendix C (Table C.1, page 226).

This Chapter proposes a simple method to fill in the gaps in regional esti-

[6]This survey, the "Encuesta Nacional de Gasto de los Hogares," is carried out only every ten years by INDEC. Part II presents some results based on it.

[7]Ravallion (1998) and INDEC (2002) discuss this procedure in detail.

mates. The aim is to complement INDEC's methodology to provide regional and nationwide poverty measures for the period 1995-2000 accounting for the geographic heterogeneity in costs of living. The proposed method relies on an updating rule. The rate of change of the GBA poverty line over the period May 1995-May 2001 represents an implicit GBA poverty line deflator. This deflator can be applied retrospectively to the five remaining official poverty lines of May 2001, applying the GBA rate of change to obtain regional values for the previous waves. The official poverty and extreme poverty lines, and those obtained with the updating procedure, are presented in Appendix C (Table C.1).

A drawback is that this simple rule implicitly assumes that the change in poverty lines over time in all regions is the same as that of the GBA region. While this appears to be a strong assumption, the changes in official poverty lines from May 2001 to May 2002 are strongly correlated across regions, as shown in Table C.1 and depicted in Figure 1.4. The main advantage of this simplifying assumption is that it provides consistency and continuity with INDEC's estimates for 2001 and onwards.[8]

The income aggregate and poverty lines described in this Section are used in the following pages to estimate poverty figures for each region and the country as a whole over the period 1995-2002, complementing the official statistics for 2001-2002.

1.3 Poverty Trends and Short Term Dynamics

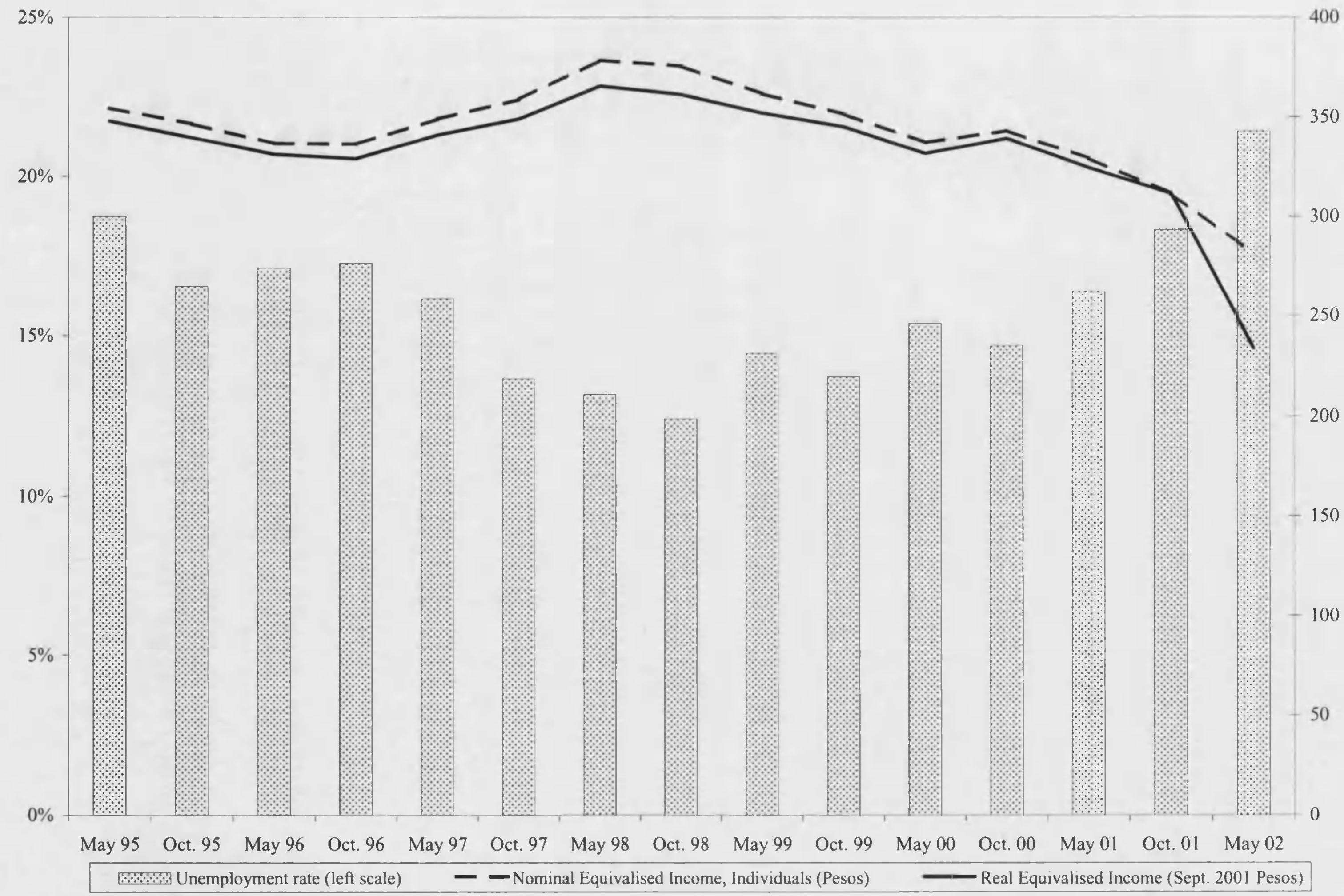
1.3.1 *Income, prices and poverty lines*

This Section presents the main trends in poverty for the period 1995-2002. It first discusses the evolution of the income aggregate and the poverty lines, and then describes the evolution of regional and national poverty figures. The final subsection deals with the short term dynamics of poverty over this period.

The impact of the series of crises and recoveries described in the Introduction to this Chapter can be appreciated in the evolution of the unem-

[8]Cruces and Wodon (2003a) discuss this procedure in more detail, and compare it to the approach developed by Lee (2000). While the latter is more sophisticated, it does not ensure a continuity between the pre- and post-May 2001 measures.

Figure 1.3: Unemployment Rate, Real and Nominal Equivalised Household Income, Urban Argentina, 1995-2002



Source: Author's estimations based on EPH household survey data (INDEC).

ployment rate, which mirrors the changes in household income and GDP, as depicted in Figure 1.3. In the aftermath of the Mexican crisis, the unemployment rate reached 18.8 percent in May 1995, and remained high until October 1996. It fell to 12.4 percent in October 1998 during the recovery, but from that wave onwards it increased again, reaching the highest recorded rate of 21.5 percent in May 2002, with the largest rise between waves of over 3 percentage points between October 2001 and May 2002.

Figure 1.3 also depicts the evolution of the sample average of y^e_{it}, the adult equivalent income defined in Equation 1.2, in nominal (current pesos) and real terms, for all the large urban areas covered by the EPH. Real values are adjusted by the CPI (Figure 1.1) and correspond to September 2001 prices.[9]

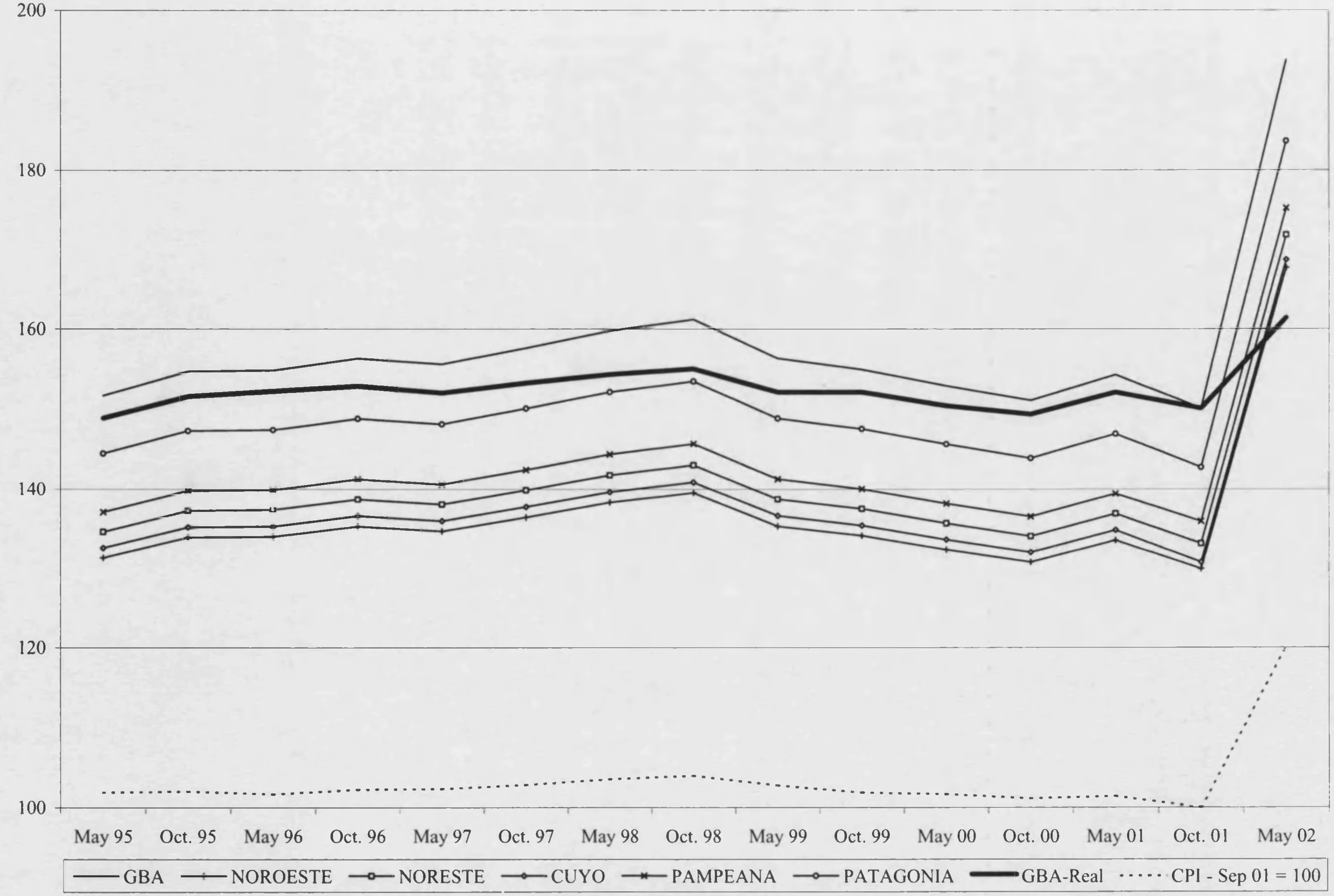
The y^e_{it} aggregate decreased almost 4 percent from May 1995 until October 1996, as a consequence of the contraction that followed the contagion from the Mexican crisis (Figure 1.2). Household income recovered briefly until May 1998, but from then on it fell almost continuously in both nominal and real terms, with the exception of a brief recovery between May and October 2000. The sharpest decrease corresponds to the crisis of 2001-2002, as captured by the May 2002 wave of the EPH (the last in the Figure).

Between October 2001 and May 2002 nominal income fell 10 percent, but it is interesting to note in Figure 1.3 that the sudden surge in consumer prices caused by the crisis of 2001-2002 and depicted in Figure 1.1 was reflected in a much larger fall in real income of 25 percent. This increase in prices is also reflected in Figure 1.4, which shows the evolution of the official and constructed regional poverty lines along with the Consumer Price Index.

The poverty lines followed the trend in the CPI for most of the period: for instance, from October 1998 to October 2001 the poverty lines and the CPI fell in a similar manner, reflecting the deflationary pressures of the period's recession, which also explains why nominal income is above real income in Figure 1.3. Between the last two waves, corresponding to the 2001-2002 crisis, both the CPI and the nominal poverty lines grew sharply. The two effects do not cancel out completely: the Figure also portrays the evo-

[9]The CPI, poverty lines, equivalent income and poverty estimates are available in Tables C.1 and C.2 in Appendix C.

Figure 1.4: Regional Poverty Lines, Urban Argentina, 1995-2002



Source: Author's estimations and official figures by INDEC (2002).

lution of the GBA poverty line in real terms (bold line), which increased by 7.5 percent in real terms from October 2001 to May 2002. This reflects the fact that the rise in the cost of goods consumed by the poor was larger than the overall increase in the CPI, hitting them more than the rest of the society. The Figure also illustrates the regional differences in living costs: the GBA and Patagonia regions have higher poverty lines than the rest of the country for the whole period, while the Noroeste region always has the lowest value.[10]

While Figure 1.4 indicates some geographical heterogeneity in living costs, Figure 1.5 depicts the trend of real adult equivalent income y^e_{it} in September 2001 pesos by region, showing the substantial regional differences in living standards. The urban centres in the GBA and Patagonia regions have the highest levels of income, staying above the national average over the whole period. Those below the average are, in descending order, the Pampeana, Cuyo, Noroeste, and Noreste regions. While there are large regional differences in levels of income – for instance, the average over time for the Noreste region is just above half of that of the Patagonia region – the time trends are nevertheless similar for all the regions. The regions with higher and lower incomes are also those with higher and lower poverty lines, and it is not clear a priori which of the two effects prevails in the resulting poverty measures. This is covered in the following pages.

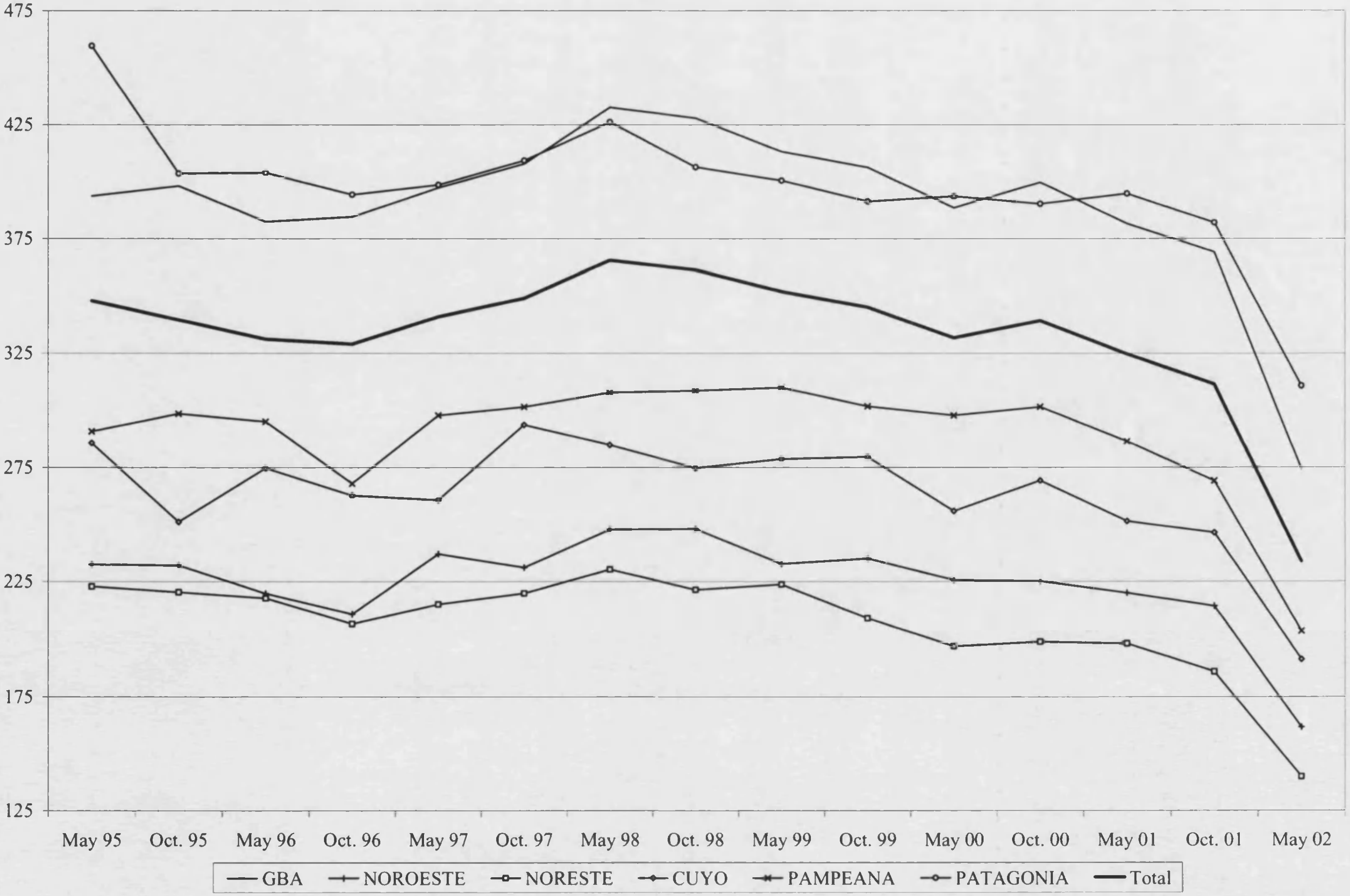
1.3.2 *Poverty trends*

Before discussing the poverty figures for 1995-2002, this Section presents the methodology followed by INDEC to compute its official statistics, which is adopted in this Chapter to provide comparable results.

According to Cowell (2003), the measurement of poverty requires three components: an income estimate, a poverty line, and a measure or index, which represents a device for aggregating the poverty evaluations obtained at the household level into a population figure. The first two components were covered from the methodological and empirical points of view in the preceding pages. Regarding the third element, a household i's poverty evaluation is given by a function defined over its equivalised income y^e_i and a

[10]Appendix B presents a set of regional socio-economic indicators and provides some background on the heterogeneity of Argentina's regions (Table B.1, page 223).

Figure 1.5: Equivalised Household Income in Real Terms (Sept. 2001 pesos) for Individuals, Regions, Urban Argentina, 1995-2002



Source: Author's estimations based on EPH household survey data (INDEC).

poverty line z as (Cowell, 2003):

$$\begin{cases} p\left(y_i^e, z\right) & \text{if } y_i^e < z \\ 0 & \text{otherwise} \end{cases} \tag{1.4}$$

The Chapters in this Part rely on the decomposable poverty measures proposed by Foster et al. (1984), which belong to the general class defined by Atkinson (1987). These FGT measures imply the following functional form for the poverty evaluation:

$$p\left(y_i^e, z\right) = \left[\frac{\max(z - y_i^e, 0)}{z}\right]^{\alpha} \tag{1.5}$$

where α is a sensitivity parameter ($\alpha \geq 0$).[11] The resulting poverty measure is given by the sample average of p, which can be represented as:

$$FGT\left(y^e, z, \alpha\right) = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\max(z - y_i^e, 0)}{z}\right]^{\alpha} \tag{1.6}$$

where N denotes the total number of households or individuals in the population.[12] With the parameter set to $\alpha = 0$, Equation 1.6 represents the poverty headcount. With $\alpha = 1$ and $\alpha = 2$, the resulting measures are the poverty gap and the squared poverty gap, which take into account not only the proportion of the poor in the population (as the headcount does) but also the intensity of poverty.

The following Figures were constructed using the equivalent income y_i^e in the FGT measures in Equation 1.6. Both the poverty lines z_t and extreme poverty lines z_t^I were allowed to vary by region.

Figure 1.6 presents the headcounts of poverty and extreme poverty (indigence) for the urban areas covered by the EPH, corresponding to FGT with $\alpha = 0$ (Equation 1.6).[13] As in the official statistics provided by INDEC, both

[11] If the income aggregate y_i^e is normalised by the poverty line as in Equation 1.3, p simplifies to $p\left(y_{it}, z\right) = [\max(1 - y_{it}, 0)]^{\alpha}$.

[12] The resulting FGT measure can refer to the number of households or the number of individuals in poverty. The latter is derived from computing Equation 1.6 with weights reflecting household size. This procedure is equivalent to defining FGT in terms of N_I, the number of individuals in the population, since the poverty status and the income aggregate are defined at the household level and then assigned to every member.

[13] This Section discusses only the evolution of the poverty headcounts. The poverty gap and squared poverty gap measures for each region are reported in Appendix C (Table C.2).

headcounts are calculated as fractions of the total number of households (share of households in poverty or extreme poverty) and the total number of individuals (share of individuals in poverty or extreme poverty).

As is usually the case, the proportion of individuals under the poverty and extreme poverty lines is always higher than the proportion of households, reflecting the fact that poor households tend to be larger than non-poor households.[14]

Since the income aggregate and the poverty lines were affected by the repeated crises and recoveries of the 1995-2002 period, the measures of poverty based on those numbers were also sensitive to the evolution of the economy. During the contagion from the Mexican crisis, the poverty and extreme poverty headcounts increased significantly from May 1995 to October 1996, then fell slightly from October 1996 until May 1998.

The May 1998 wave of the EPH represents a turning point in the data: the individual-based poverty headcount grew steadily from 28.6 percent to 38.3 percent in October 2001, with a similar trend for extreme poverty and for household-based measures. This rise in poverty of almost 10 percentage points in a little over three years reflects the worsening of the labour market conditions and economic activity during the recession, depicted in Figures 1.2 and 1.3. Over the same period, the proportion of the population in extreme poverty doubled from 6.8 percent to 13.6 percent.

These increases, however, are relatively minor when compared with the changes occurring between the October 2001 and May 2002 waves of the EPH. At the national level, the individual-based poverty headcount jumped from 38.3 percent to 53 percent (13.6 to 24.8 percent for extreme poverty), with household measures following the same upward trend. This jump in poverty rates is the result of the sharp increase in prices and hence poverty lines (Figure 1.4), coupled with the fall in real and nominal income of the households (Figure 1.3).

Finally, with respect to the geographical heterogeneity previously ob-

Their trends are very similar to those observed for the headcounts.

[14]A full poverty profile is beyond the scope of this Chapter, which focuses on the construction of consistent poverty figures at the national level. Tables C.3, C.4, C.5 and C.6 in Appendix C present some characteristics of the samples in general and for the non-poor, the poor and the extremely poor for four of the fifteen waves under study. These descriptive statistics are for illustration only – for more detailed poverty profiles, see World Bank (2000a), World Bank (2003) and Cruces and Wodon (2003a).

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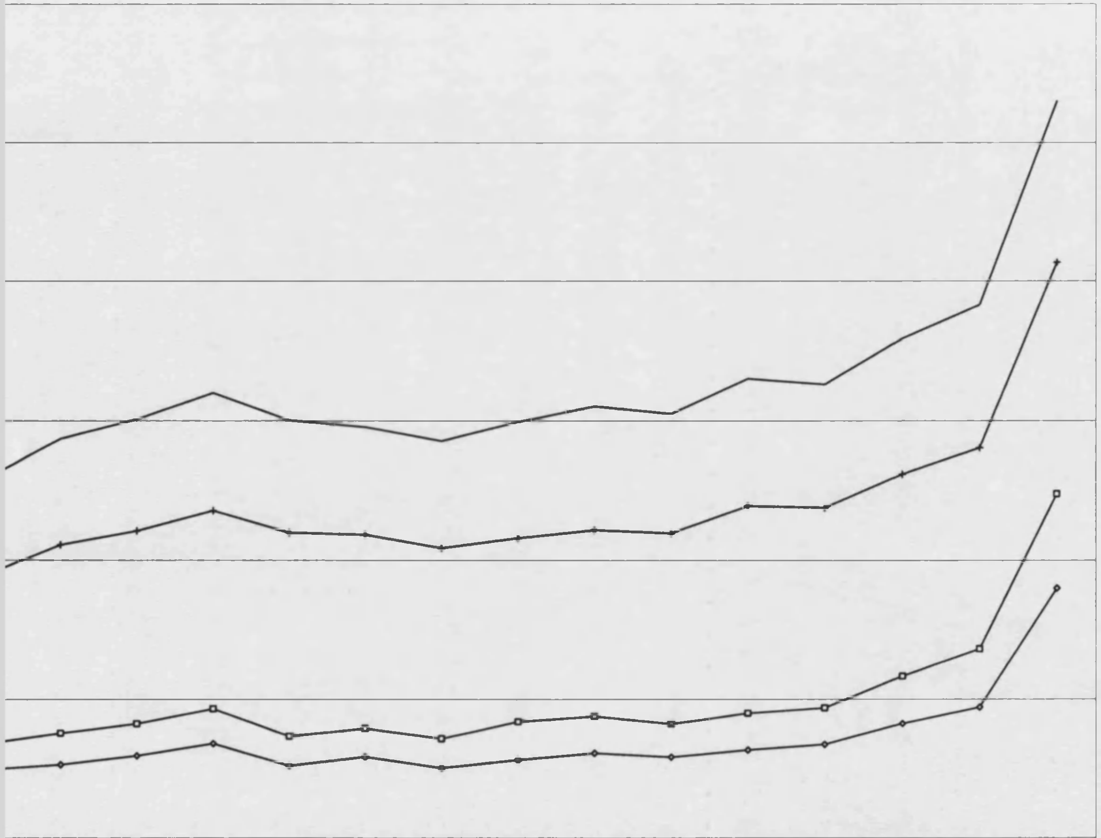


5	Oct. 95	May 96	Oct. 96	May 97	Oct. 97	May 98	Oct. 98	May 99	Oct. 99	May 00	Oct. 00	May 01	Oct. 01	May 02
%	28.7%	30.1%	32.0%	30.0%	29.5%	28.6%	29.9%	31.0%	30.5%	33.0%	32.6%	35.9%	38.3%	53.0%
%	21.1%	22.1%	23.6%	22.0%	21.9%	20.9%	21.6%	22.2%	22.0%	23.9%	23.8%	26.2%	28.1%	41.4%
	7.6%	8.2%	9.3%	7.3%	7.9%	7.2%	8.4%	8.8%	8.2%	9.0%	9.4%	11.6%	13.6%	24.8%
	5.3%	5.9%	6.8%	5.2%	5.9%	5.1%	5.6%	6.1%	5.8%	6.3%	6.7%	8.3%	9.4%	18.0%

sehold survey data (INDEC).

served, Figure 1.7 presents a consistent series of individual-based regional headcounts.[15] While the areas with lower incomes were also those with lower poverty lines, the former prevails: the regional ranking of adult equivalent income of Figure 1.5 is reversed for poverty measures. There are significant differences in poverty rates within the country, with the GBA and Patagonia regions faring systematically better, and the North (Noreste and Noroeste regions) being consistently poorer than the rest of the country. Through most of the period under review, the ranking of the regions in terms of poverty estimates did not change, with fairly similar regional trends. However, the increase in poverty in the GBA area from October 2001 to May 2002 was larger than the rise observed in any of the other regions.

1.3.3 Poverty transitions and short term dynamics

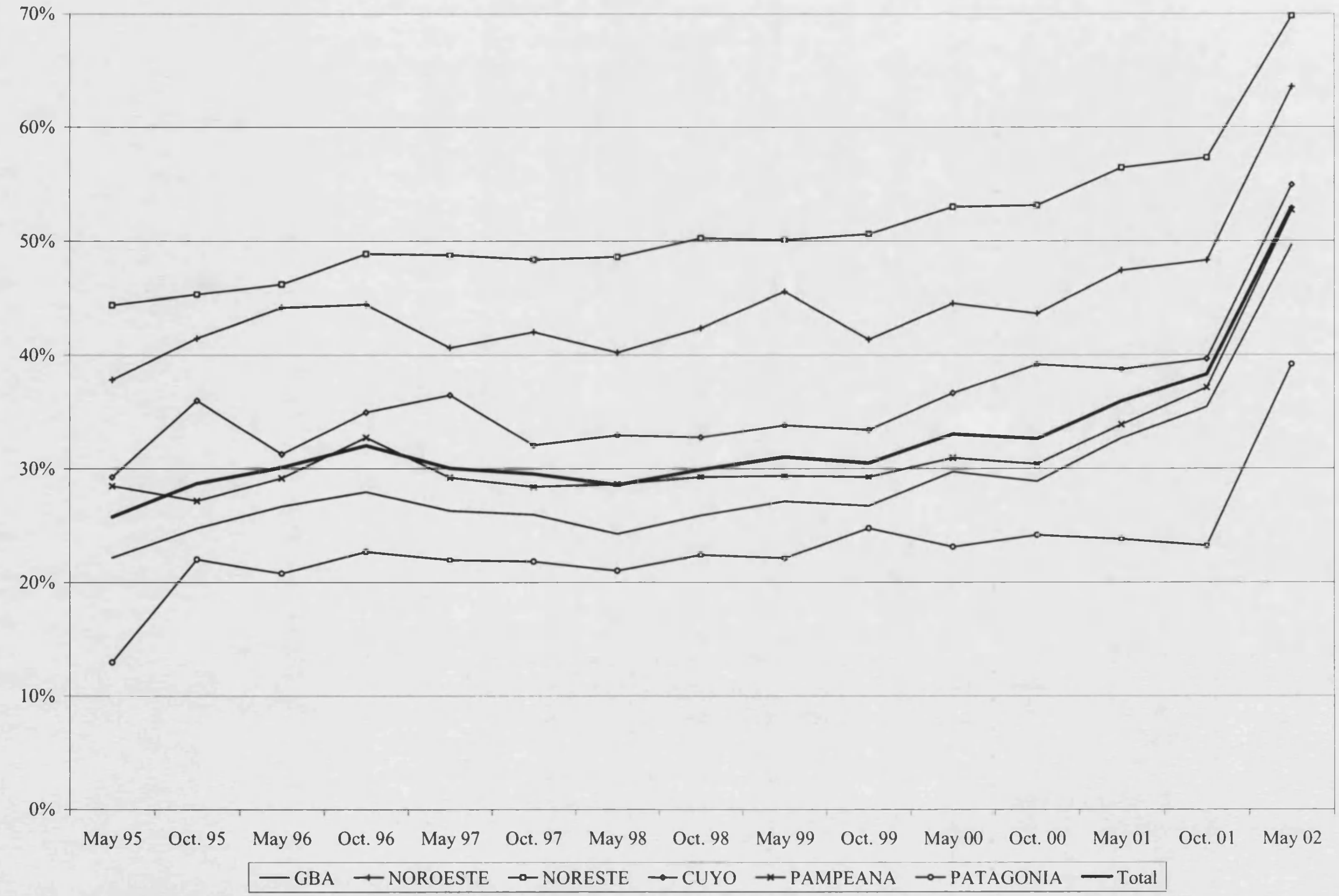
The analysis of cross section data usually results in discussions of changes in poverty rates between two periods, as in Figure 1.6. The rotating sample structure of the EPH, however, allows for a deeper analysis in terms of the poverty transitions of households between two periods. The evidence for Argentina is depicted in Figure 1.8, which is based on a special version of the EPH dataset where households were paired in two consecutive waves, resulting in a series of two-period panels. This dataset is representative at the national level, and because of the sample rotation it contains about 70 percent of the observations listed in Table 1.1.[16]

Figure 1.8 presents the basic poverty transition between two waves (a six-month period). Starting from the October 1995, it decomposes the population into four transition categories, according to their current and past poverty status: the non-poor who stayed non-poor, the poor who stayed poor, the poor who escaped poverty, and the non-poor who became poor in the following period. The Figure represents a decomposition of the change

[15] These regional measures match the official INDEC statistics from 2001 onwards. For 1995-2000, the regional and national poverty rates were constructed using the methodology described in Section 1.2.

[16] This paired dataset was prepared and kindly provided by Juan Martín Moreno, from the Argentine Ministry of Labour. It should be noted that the resulting poverty rates are slightly different from the ones presented in Figure 1.6. This is due to the nature of the rotating sample: since the dataset consists of observations paired accross two waves, only a maximum of 75% of the total observations for each wave is available, as illustrated in Table 1.2.

Figure 1.7: Poverty Headcount by Region, Individuals, Urban Argentina, 1995-2002



Source: Author's estimations based on EPH household survey data (INDEC).

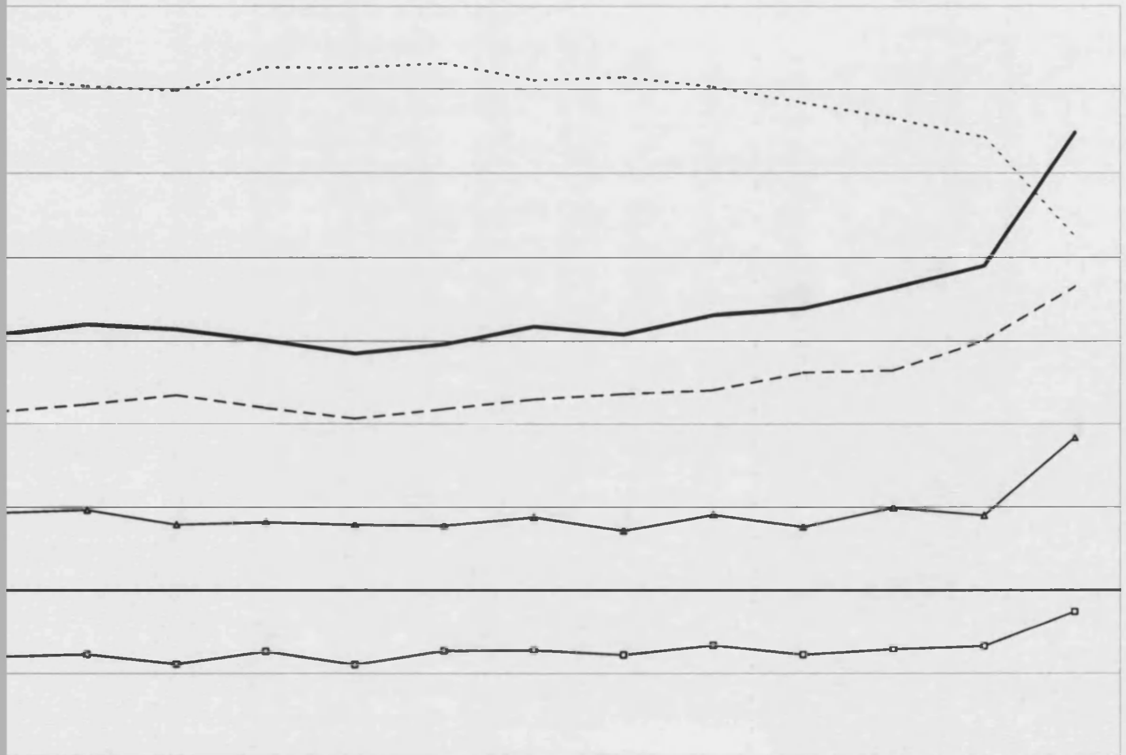
in poverty between two waves of the EPH, which is equal to those who entered poverty minus those who escaped poverty – for this reason, the latter appears as negative in the Figure.

This evidence complements the description of the main poverty trends in Figure 1.6. Excluding the change between the last two waves, which cover the unusual circumstances of the 2001-2002 crisis, the proportion of individuals switching poverty status is fairly stable throughout the 1995-2001 period. In each wave (representing a period of about six months), an average of 7 to 8 percent of the population manages to escape poverty, while an average of 8 to 9 percent of the population enters poverty. These fluctuations are relatively large when compared to the changes in the cross-sectional headcounts, which were never higher than 2.4 percentage points for the same period (Figure 1.6). These large movements in and out of poverty compensate each other and result in relatively low net changes in the static cross-sectional poverty rates. Moreover, it should be noted that these large fluctuations occur even when aggregate rates were falling, as shown in Figure 1.8 for the years 1996-1998.

These relatively high and stable levels of switching in poverty status were affected by the worsening of the economic conditions over the 1995-2001 period. This is manifested in the almost continuous increase in the fraction of the population in poverty that stayed in poverty in the following wave of the survey.

Figure 1.8 also presents interesting results on the effects of the 2001-2002 crisis, which are captured by the changes in poverty status between October 2001 and May 2002. The Figure indicates that the recession and the subsequent crisis affected the persistence of poverty and not only its level. The proportion of individuals who were poor and remained poor increased from 26.4 percent between the waves of October 2000 and May 2001 to 36.6 percent between October 2001 and May 2002. Moreover, 18.3 percent of the population was non-poor in October 2001 but was recorded as poor in May 2002, a major increase when compared to the average of about 8 to 9 percent for the 1995-2001 period. This is also reflected in the proportion of the population that was above the poverty line and remained at that level, which fell from a fairly stable 60 to 65 percent to a low 42.6 percent between the last two waves.

Individuals as a Function of Previous Poverty Status, Urban Argentina, 1995-2002



96	Oct. 96	May 97	Oct. 97	May 98	Oct. 98	May 99	Oct. 99	May 00	Oct. 00	May 01	Oct. 01	May 02
%	60.3%	59.8%	62.6%	62.6%	63.1%	61.0%	61.4%	60.3%	58.4%	56.5%	54.3%	42.6%
%	9.7%	7.9%	8.2%	7.9%	7.8%	8.8%	7.2%	9.1%	7.6%	9.9%	9.0%	18.3%
%	-7.7%	-8.9%	-7.4%	-9.0%	-7.3%	-7.2%	-7.8%	-6.6%	-7.8%	-7.1%	-6.7%	-2.6%
%	22.3%	23.5%	21.9%	20.6%	21.8%	22.9%	23.6%	24.1%	26.2%	26.4%	30.1%	36.6%
%	32.0%	31.4%	30.1%	28.5%	29.6%	31.7%	30.8%	33.1%	33.9%	36.4%	39.0%	54.9%

poor." The legend refers to the transition from the state in t-1 to the state in t. Note also that (5)=(2)+(4)=100-(1)+(3)

l household survey data (INDEC).

Finally, Cruces and Wodon (2003a) provide evidence on movements within the poor using the same paired dataset. An average of around 3 percent of the population was found to switch between extreme poverty and poverty, and vice versa, in every wave of the EPH in the 1995-2001 period. From May 1998 onward however, there was a continuous increase in the share of individuals who were moderately poor and became indigent.

1.4 GUIDE TO THE LITERATURE ON POVERTY IN ARGENTINA

1.4.1 Income distribution and poverty in Argentina

This Section provides a background for the analysis presented in the following Chapters by covering a selection of the literature on poverty in Argentina during the 1995-2002 period. The aim is threefold. Firstly, this Section introduces some of the key contributions on distributional analysis in Argentina for further reference. It also covers some of the related issues that are not explored in the following Chapters, notably the social assistance programmes and active strategies adopted by households to face the repeated economic crises of the period. Finally, it focuses on the few existing studies based on panel data for Argentina, to complement and provide a benchmark for the empirical findings of the following Chapters. Rather than providing a full summary of each article, the Section reviews only the results that are connected to the analysis of Part I.

The availability of household survey data since the mid 1970s has resulted in a substantial literature on income distribution and poverty in Argentina. Nonetheless, most of it focuses on the Greater Buenos Aires region since the EPH was not systematically extended to the rest of the country until the 1980s. Among these studies, Gasparini et al. (2001) cover the whole extension of data available from the EPH, from the mid 1970s until the end of the 1990s. The book details trends in poverty, inequality and social welfare measures. It describes the available data and the methodology for the construction of these measures, and studies the robustness of the identified movements with respect to changes in poverty lines, economies of scale and equivalence scales at the household level. Gerchunoff and Llach (2004b) goes further back in time, providing a long term perspective on equality and growth, from 1880 until the present, in the context of the economic history of Argentina. Given its historical coverage, the book builds on national accounts, tax and a multitude of other data sources.

With respect to the recent past, the articles presented in FIEL (1999) cover different aspects of distributional issues during the 1990s. The volume focuses on the impact of the structural changes in the Argentine economy in this period, and presents an in-depth analysis of poverty, social expenditure and the incidence of the tax system on the income distribution.

Another good source of data and analysis on household welfare can be found in the labour economics literature. Galiani and Hopenhayn (2003) provide a thorough analysis of unemployment risk and duration in the 1990s based on the EPH, while Galiani and Gerchunoff (2003) present a historical account of the evolution of labour market institutions and their role in the economy during the twentieth century in Argentina. Finally, Mackenzie (2004) presents an account of the aggregate economic shocks and labour market responses during the 1995-2002 period.

These volumes and articles provide exhaustive accounts of distributional and household welfare issues in Argentina. For a comparative perspective, Thorp (1998) and World Bank (2004) constitute comprehensive studies of the evolution of poverty, inequality, and their causes and consequences in the context of Latin America, the former in a historical perspective and the latter concentrating on the more recent experience. Finally, Heckman and Pages (2003) and IADB (2004) focus on labour market and employment issues in the countries of the region.

1.4.2 *Economic crises, household welfare and coping strategies*

The studies cited above are mainly descriptive, identifying trends and correlates of poverty. The analysis in World Bank (2000b) assesses the management of social risks in Argentina, studying private and public interventions to derive policy recommendations. This article highlights the fact that although Argentina had the highest GDP per capita in Latin America and some of the region's highest levels of social expenditure during the 1990s, poverty was still widespread as a consequence of the gaps in the provision of basic infrastructure and in the social insurance system. Based mainly on data from the EPH, the article identifies the main risks faced by different age groups, and analyses the social protection programmes designed to prevent and mitigate them.

The study finds that infants (0 to 5 years old) have higher rates of poverty and extreme poverty than any other group in the population, and points to the relative lack of early child development programmes in comparison with other Latin American countries. For the groups ranging from 6 to 14 years and 15 to 24 years, World Bank (2000b) focuses on educational outcomes and how these might lead to low levels of human capital accumulation. While the coverage of primary education is almost universal (98.9 percent), the study questions its quality and efficiency in the poorer regions of the country. The figures for secondary level enrolment and completion are much lower, with the lowest corresponding to the poorest areas.

Moreover, the article identifies employment issues as the main risk for the population aged 25 to 64 years old. While unemployment is one of the most important determinants of poverty in Argentina, World Bank (2000b) reports that a large proportion of the poor and extreme poor are employed, so besides joblessness, this group also faces low levels of wages and underemployment. While some social insurance programmes exist (for instance, unemployment insurance and family income supplements), access is granted mainly through formal work, which limits their impact given the high rate of informality among the population in general and the poor in particular. For the group of those aged 65 years old and more, the main risk is the low level of state pensions.

Finally, for the population in general, social programmes concentrate mainly on housing, with very low coverage, and on the provision of public health. While access to the latter is generally good, the article argues that its quality is relatively low. World Bank (2000b) recommends a social protection strategy based on early child development, retention in the education system and the promotion of formality in the labour force, concentrating the assistance in fewer programmes with better coverage.

While this study concentrates on the years before the economic crisis of 2001-2002, Fiszbein et al. (2002) present the results of a special survey carried out in June and July of 2002, which focuses on the impact of the crisis on household welfare and the strategies adopted to cope with its consequences.

The changes in employment patterns are striking: Fiszbein et al. (2002) find that more than half of those who entered employment during the crisis were secondary workers within the household, implying a change in family roles. They also find evidence of deterioration in the quality of jobs, manifested in an increase in the number of temporary and informal workers, and a reduction of work-related benefits for those in permanent jobs.

An original feature of the survey is that it collects information about subjective welfare and social unrest. Fiszbein et al. (2002) find rising levels of discouragement and pessimism, an increase in participation in various forms of social protest, and high levels of violent crime, which are all attributed to the economic crisis. Another original characteristic of the survey is the collection of data on coping strategies. Most of the households in the sample changed their consumption patterns to cope with the effects of the crisis, resorting to less expensive products. Other active strategies included the addition of a new worker to the family group, although this was not very effective given the fall in labour demand and the high rate of unemployment at the time. The poorest households were those who resorted the most to social networks, relying on assistance from friends, family, non-governmental organizations and the government.

An innovative feature of the data is that, unlike the EPH and most other surveys for Argentina, the study carried out by Fiszbein et al. (2002) covers smaller towns in rural areas. A notable result is the high inequality between rural and urban areas, with the average income in the former only 60 percent of urban average. However, this appears to have only a marginal effect on national poverty and income figures, given the relatively small proportion of the population living in the countryside.

Finally, two articles evaluate the two major public intervention programmes carried out in Argentina during this period. Ravallion and Jalan (2003) review the *Plan Trabajar*, a public works programme introduced in the wake of high unemployment levels after the Mexican financial crisis of 1995. *Trabajar* provided short-term jobs at low wage in infrastructure projects. The central government allocated the programme's budget across provinces based on the unemployment levels among the poor. For practical purposes, *Trabajar* operated as a poverty alleviation programme targeted through unemployment (de Ferranti et al., 2000b).

Ravallion and Jalan (2003) present an evaluation, based on propensity score matching methods, of the programme's efficacy in reducing poverty.

Their results indicate that the *Plan Trabajar* generated income gains among the poor, and that its targeting was relatively good, with 80 percent of beneficiaries in the poorest quintile of the population. Ravallion and Jalan (2003) find that the average gain is one half of the average wage, allowing for the foregone income in the form of jobs displaced by the programme. In terms of the distribution of gains from the programme, the gains are similar for men and women, but they are higher for younger workers.

Galasso and Ravallion (2003) review the *Plan Jefes y Jefas de Hogar Desempleados*, implemented in January 2002 as a safety net for those most affected by the crisis of 2001-2002. The programme consisted of direct income support for unemployed heads of households with dependent children. It was designed as a universal programme, and it eventually reached more than 2 million beneficiaries (INDEC, 2003b).

Galasso and Ravallion (2003) evaluate this programme with counterfactual samples created with matching techniques. The *Plan Jefes y Jefas de Hogar Desempleados* was successful in reducing unemployment, although half of its beneficiaries – mostly women – would have been inactive (and not unemployed) without the programme. The authors found a substantial number of beneficiaries who were ineligible in principle, but its targeting performance, while not as good as that of the *Plan Trabajar*, was still better than the average for social spending in Argentina. Galasso and Ravallion (2003) find that half of the participants in the *Plan Jefes y Jefas* belonged to the lowest quintile of the income distribution. While its design was not completely respected in practice, and it covered more than those unemployed, the programme was successful in providing income support to most of those affected by the crisis, reducing the aggregate levels of extreme poverty.

1.4.3 Longitudinal studies of poverty and well-being in Argentina

The longitudinal dimension given by the rotating structure of the EPH sample, described in Section 1.2, has only recently started to be exploited in the literature on poverty analysis in Argentina.[17] This Section focuses on stud-

[17]Studies based on the EPH panels concentrate mostly on labour markets and employment (Galiani and Hopenhayn, 2003; Mackenzie, 2004). Some exceptions are Lavergne et al. (1999), who discuss the variability of income at the individual level along a cohort of the

ies of EPH panels and deals mainly with poverty spells and dynamics: they can be considered complementary to the results presented in this thesis.

Paz (2002) covers the dynamics of poverty within one cohort of the EPH, using the four waves of the period October 1998 to May of 2000 at the national level. The article provides an analysis of simple transitions similar to the one provided in the previous Section, reaching comparable conclusions about the magnitude of movements into and out of poverty.

The most interesting aspect of the article is a regression analysis of the determinants of poverty duration and entry and exit rates. Paz (2002) finds that persistently poor households tend to be headed by younger individuals with low education and higher unemployment levels, and tend to have fewer income earners. The Noreste and Noroeste regions are significantly correlated with higher levels of persistency. In terms of serial correlation, the poverty status at one point in time is highly correlated with that of previous periods, and that the effect is stronger for periods closer in time. Besides its effect on the duration of poverty, the unemployment of the household head is also found to substantially increase the probability that a household falls into poverty. Finally, older heads with higher education levels significantly increase the probability of leaving poverty (for the poor) and not entering poverty (for the non-poor).

Gasparini (2003b) also uses data from one cohort of the EPH at the national level, although the article concentrates on the yearly change between the October 2000 and October 2001 waves of the survey. Its aim is to identify and describe the characteristics of the households that entered poverty between these two waves, and to study the effects of the deepening of the recession during that period.

An interesting finding of the analysis is that the structure of the household does not have a major impact on the switch in poverty status between the two periods after controlling for other characteristics, with the exception of single-parent households headed by women with low education levels, for which the probability of becoming poor is significantly greater than for others. As in Paz (2002), Gasparini (2003b) finds that households headed by better-educated individuals have a lower probability of falling into poverty,

EPH, and Albornoz and Menéndez (2004), who analyse income mobility and its relationship with inequality.

and also finds that the probability of being poor is highly correlated with the previous poverty status.

Finally, Corbacho et al. (2003) use a series of two-period panels from May 1999 to May 2002, covering the recession of 1999-2001 and the economic crisis of 2001-2002 to study which groups bore the burden of the crisis. They also consider the transmission channels from macro shocks to individuals and the smoothing mechanisms adopted by the households to cope with the crisis.

Their measure of the effect of shocks on household welfare is the change in household income between two waves of the EPH. This proxy for vulnerability is regressed on household characteristics and geographic and time controls. The results show again that households headed by better-educated individuals are less vulnerable, as are those with heads employed in the public sector. Geographically, the inhabitants of the Noreste and Pampeana regions experienced the largest declines in income.

Corbacho et al. (2003) also identify employment status as the main transmission channel between macroeconomic shocks and individual welfare, and provide some evidence on labour market outcomes. They find that unemployment was higher among individuals with lower levels of education, and that younger workers were more likely to lose their jobs over the period. Public employees were those with higher job stability, whereas within the private sector unemployment was higher in the construction sector. Finally, the authors also study whether other income sources allow households to smooth the shocks to the labour income of the household head, finding that almost a third were not able to do any smoothing, with the extremely poor faring worse in this respect than the rest of the population.

1.5 Conclusion

This Chapter has discussed the methodology of poverty measurement in Argentina, presented the main datasets to be employed in this Part and documented the evolution of poverty measures and its components over the 1995-2002 period. Its aim was to provide a framework for the analysis of Chapters 2 to 4, in terms of the characteristics of the data and the economic context.

The Chapter has described the large fluctuations of household income over this turbulent period, and reported evidence of high volatility in movements in and out of poverty. The 2001-2002 crisis was found to have a large impact on the persistence of poverty. An important finding was that relatively modest changes in poverty rates between two periods were the result of large but offsetting movements into and out of poverty. Moreover, these large fluctuations were not restricted to periods of crisis: a substantial fraction of the population was found to enter poverty even when aggregate rates were falling. The use of panels revealed some features of the data that could not have been captured with the cross-sectional datasets usually employed in poverty analysis.

These large fluctuations in household income and poverty status are the main motivation for the following three Chapters, which explore the theoretical basis for the incorporation of income variability in poverty measurement and the definition of well-being, and illustrate different methodologies with empirical implementations based on the Argentine case.

CHAPTER 2

INCOME FLUCTUATIONS, POVERTY AND WELL-BEING OVER TIME

2.1 INTRODUCTION

The previous Chapter covered the movements into and out of poverty in two consecutive periods in urban Argentina (Section 1.3, page 29). This Chapter, and the following two, address a related but different question: echoing Atkinson (1987), they deal with the problem of how poverty should be measured *over time* – or, in more general terms, how to measure well-being based on repeated observations of household income. The framework developed in the following pages accounts explicitly for the negative effects of income variability. This welfare criterion is based on the intuition, derived from the risk aversion literature, that households will prefer a steady stream of income to a variable one with the same mean, at least in a second-best world with incomplete insurance and capital markets (Cowell, 1989).

The evaluation of well-being with panel data can be thought of as an extension of the standard model of distributional analysis. Cowell (2000) describes the welfare theory of income distribution in terms of $\mathcal{F}$, "the space of all univariate probability distributions" F of income y_i, and defines a "welfare ordering" $W : \mathcal{F} \to \mathbb{R}$ as a function that maps income distributions into the real line. The analysis of repeated observations is based on the distribution of N vectors of T observations y_{it} over the period $t = 1$ to T, defined as $\mathbf{y}_i = [y_{i1}, ..., y_{iT}]$, in a population with N households. Accordingly, let $\mathcal{F}^T$ be the space of distributions F^T of vectors $\mathbf{y}$. The methodology focuses on a mapping from $\mathcal{F}^T$ into the real line, with a transformation of the form $W^T : \mathcal{F}^T \to \mathbb{R}$.

The contribution of this Chapter is to define a transformation W^T in two steps, exploiting analogies with well-established results in economics and distributional analysis theory in each stage. The first step is the definition of an aggregate of the observations of income over time for household i that maps each vector $\mathbf{y}_i$ into the real line. As discussed below, the average $\bar{y}_i$ does not account for the welfare effects of income variability: the insight is to exploit the formal analogy between states of the world in the expected utility model and past incomes in a multi-period setting, in a procedure that echoes the social welfare function approach in distributional analysis (Atkinson, 1970). Building on the concept of the certainty equivalent of income, the first step reduces a distribution F^T of N vectors $\mathbf{y}_i$ to F, a distribution of N scalars $\tilde{y}_i$. The second stage of the proposed W^T transformation involves an additional analogy: by showing that these scalars are appropriate money metrics of well-being, all the available tools of distributional analysis can be directly applied to the distribution F. The W^T transformation is done first from each vector $\mathbf{y}_i$ to a scalar $\tilde{y}_i$, and then from $F(\tilde{y}_i)$ into some distributional index.

This methodology owes a great deal to the standard model of risk (Pratt, 1964; Arrow, 1970) and to its reinterpretation in the social welfare context (Atkinson, 1970), as well as to the literature on lifetime income (Cowell, 1979). In terms of recent work in the poverty literature, the methodology is related to (and draws from) the concept of expected poverty (Ravallion, 1988), the transient-chronic decomposition (Jalan and Ravallion, 1998) and the recent body of work on economic vulnerability (Ligon and Schechter, 2003; Calvo and Dercon, 2003). The approach proposed below is discussed in the light of this literature, and it attempts to unify some of the existing methodologies under a general framework.

The discussion starts in Section 2.1 with a simple expected utility model to establish the main intuitions behind the methodology. Section 2.3 then presents the proposed framework for the evaluation of past incomes. Section 2.4 compares this method with existing approaches, which are interpreted as special cases of the evaluation framework. Finally, Section 2.5 specifies functional forms for the general evaluation function of Section 2.3, and illustrates the uses of the methodology with data from the Greater Buenos Aires region in the 1995-2002 period. Conclusions follow.

2.2 Ex-ante and Ex-post Income Variability

2.2.1 *Prospective evaluation of well-being: ex-ante utility and income risk*

The objective of this Chapter is to develop tools for the analysis of well-being based on panel data on household income. To reduce this problem to a tractable form, the proposed methodology aggregates these repeated observations into a single indicator for each household by means of an evaluation function. This Section presents a simple model of choice under uncertainty to introduce the intuition and some formal results for deriving such an indicator, and to clarify the difference between ex-ante and ex-post evaluations of well-being.

The standard expected utility framework, due to von Neumann and Morgenstern (1944), specifies a household's utility function $u(y)$, where y is income, consumption or wealth (henceforth denoted income).[1] In this formulation, utility is defined over a single argument, in the tradition of Friedman and Savage (1948), Pratt (1964) and Arrow (1970).[2] The function u represents a reduced form that encapsulates the utility level resulting from behavioural responses in savings, labour supply and other choice variables (Cowell, 2005, Chapter 9): the focus is placed on the outcome and not on the process through which it is reached.[3]

Following the standard risk literature, the function u is assumed to be differentiable, strictly increasing and strictly concave. Uncertainty enters this model as a countable set Ω of possible future states of the world. The household evaluates its future prospects in time $t = 0$. These uncertain prospects are defined as state-contingent incomes y_ω that materialise in $t = 1$. Each of these possible states of the world $\omega \in \Omega$ has an associated probability τ_ω.

The function u is an ex-post utility function, since it evaluates the utility

[1]The discussion could be based on income or consumption. As money metrics of welfare, the two are used interchangeably in this Chapter. See Ravallion (1994) and Deaton (1997) for discussions of the advantages and disadvantages of using either for evaluating well-being.

[2]A concept lost in this formulation is the function of assets to link consumption in different periods. Kimball (1990), however, demonstrates the formal equivalence of the model of precautionary savings under income risk (Leland, 1968; Sandmo, 1970; Drèze and Modigliani, 1972) and models of choice under uncertainty.

[3]See Besley (1995) and Browning and Lusardi (1996) for reviews on responses to risk. de Ferranti et al. (2000c) covers the empirical evidence for Latin America in recent years.

of a determinate income y (Felli, 2003). The household's ex-ante utility is defined as the expectation over the ex-post outcomes: u is defined on certain incomes, but ex-ante utility is defined on lotteries over incomes. By means of the expected utility theorem (first due to von Neumann and Morgenstern, 1944), ex-ante utility can be expressed as:

$$U = E[u(\hat{y})] = \sum_{\omega \in \Omega} \tau_\omega u(y_\omega) \tag{2.1}$$

where E is the expectations operator, $\hat{y}$ the uncertain income prospect and y_ω the contingent income associated with state of the world ω.[4]

A key result in the theory of choice under uncertainty is that expected utility depends not only on $E[\hat{y}]$, the expectation of future outcomes, but also on their distribution. A simple example clarifies this assertion. The random variable $\hat{y}$ is equal to either $y_H = \bar{y} + h$ or $y_L = \bar{y} - h$ with equal probability, and $h > 0$, so that a change in h represents a mean-preserving spread in future income.[5] Then U can be written as $U = \frac{1}{2}u(y_H) + \frac{1}{2}u(y_L)$, which depends on the value of h in the following way:

$$\frac{\partial U}{\partial h} = \frac{1}{2}u'(y_H) - \frac{1}{2}u'(y_L) \tag{2.2}$$

where u' represents the first derivative of u. Risk aversion follows from the concavity of u, which implies that u' is decreasing, and results in a negative value of $\partial U / \partial h$. The intuition is that greater uncertainty about future income makes a risk averse household worse-off, since by the concavity of u the possibility of a gain is outweighed by the prospect of a loss.

An important implication of risk aversion is that the expected value of income – $E[\hat{y}] = \bar{y}$ in the example above – is not a suitable money metric measure of well-being since it does not reflect the effects of risk on utility (Cowell, 1979). As shown in the example, an increase in h reduces ex-

[4]Alternatively, the set of outcomes can be continuous. In that case, the expectation is defined over the integral of the distribution of $\hat{y}$. It is assumed throughout that this distribution is well-behaved, that $\sum_{\omega \in \Omega} p_\omega = 1$, and that all functions have the regularity conditions of the standard model of choice under uncertainty (Newbery and Stiglitz, 1981b). See Mas-Colell et al. (1995, Chapter 6) for a detailed presentation of the expected utility model and its underlying axioms.

[5]These results hold under the much more general conditions of second order stochastic dominance (Rothschild and Stiglitz, 1969), of which this example is a special case.

pected utility, yet leaves $E[\hat{y}]$ unchanged. However, the concept of certainty equivalence – a fundamental notion in the theory of choice under uncertainty – provides an intuitively appealing indicator of well-being. The (non-random) certainty equivalent income $\tilde{y}_{ce}$ is implicitly defined by:

$$U = E[u(\hat{y})] = u(\tilde{y}_{ce}) \tag{2.3}$$

An expected utility maximising household with preferences defined by u would be indifferent between receiving $\tilde{y}_{ce}$ with certainty in the future or facing the uncertain prospect $\hat{y}$. For a risk-averse household, Equation 2.3 implies, by the concavity of u and Jensen's inequality, that $\tilde{y}_{ce} < E[\hat{y}]$. Moreover, since $E[u(\hat{y})]$ is decreasing in the level of risk, it follows from Equation 2.3 that $\tilde{y}_{ce}$ is also negatively affected by greater uncertainty. The certainty equivalent is thus better suited than $E[\hat{y}]$ as a money metric indicator of well-being, since it captures the disutility arising from uncertainty.

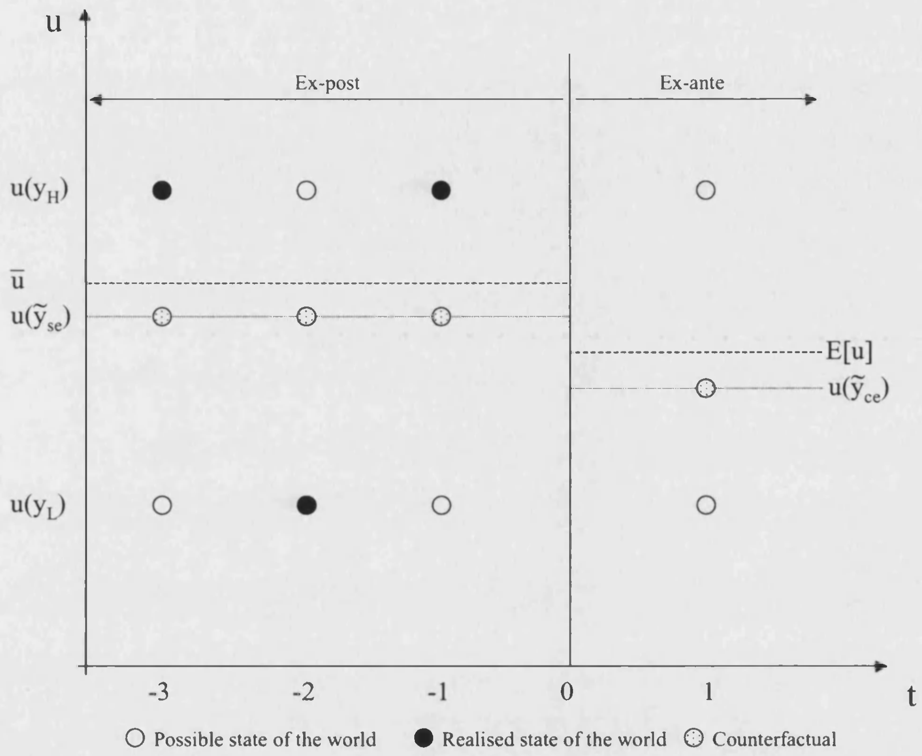
Risk aversion and the certainty equivalent, however, are ex-ante concepts, and this Chapter's aim is to measure well-being based on (ex-post) panel data: the following pages deal with the distinction between ex-ante prospects and ex-post outcomes.

2.2.2 *Retrospective evaluation of well-being: ex-post utility and income fluctuations*

The expected utility U in Equation 2.1 is defined over events that have not occurred, while the underlying utility function u is defined over certain ex-post outcomes. This is an aspect of the theory that is often overlooked (Hammond, 1981; Milne and Shefrin, 1988; Ravallion, 1988, constitute some exceptions). It is necessary to distinguish between "income risk," an ex-ante concept based on variability in future prospects, and "income fluctuations," defined as experienced variability in the past. Panel data on incomes is inherently linked with both concepts: it reflects income fluctuations and thus it is ex-post by definition, but these fluctuations result from the presence of ex-ante income risk, as discussed below.

The setting described by Equation 2.1 corresponds to the case of income risk: once the state of the world ω materialises in $t = 1$, the random variable $\hat{y}$ takes a value and ex-post utility becomes $u(y_\omega)$, either $u(y_H)$ or $u(y_L)$

Figure 2.1: Ex-Ante Risk and Ex-Post Variability: States of the World and Realised Incomes



in the example above. To introduce the idea of income fluctuations, it is necessary to consider multiple past periods. It is assumed that a household at $T+1$ has faced a series of consecutive independent realisations of states of the world drawn from the set Ω, which results in a past stream of income $\mathbf{y} = [y_1, ..., y_T]$. While every $\hat{y}_t$ is a random variable before its realisation, from the retrospective point of view of $t+1$, every y_t is just a determinate quantity given by the materialised state of the world ω_t.

Well-being over time is determined by the experienced income stream $\mathbf{y}$. The average of experienced utilities, while not accounting for time preferences, provides a simple aggregate of utility over the T periods:

$$\bar{u} = \frac{1}{T} \sum_{t=1}^{T} u(y_t) \tag{2.4}$$

Equations 2.1 and 2.4 are formally similar. However, the two represent the distinct but related concepts of income risk and income fluctuations.

The example in Figure 2.1 illustrates this point. The Figure depicts the past outcomes and the future prospects for a household from the point of view of the present ($t = 0$) according to the formulations of Equations 2.1 and 2.4. The income variable $\hat{y}_t$ is assumed to have the same distribution in each period $t = \{-3, -2, -1, 1\}$, being either $y_H = \bar{y} + h$ or $y_L = \bar{y} - h$ with equal probability.

While both U and $\bar{u}$ are determinate quantities, Equation 2.1 reflects the expected utility of the household in $t = 1$ from the point of view of $t = 0$, while Equation 2.4 is the evaluation of a series of past outcomes at $t = \{-3, -2, -1\}$ from the same point of view. To stress this difference, $\bar{u}$ in Figure 2.1 is the result of two y_H and one y_L realisations, which differs from the expected utility $U = E[u]$, represented by the average of $u(y_H)$ and $u(y_L)$.

While income risk as summarised in Equation 2.1 and income fluctuations in Equation 2.4 are different in their nature, the connection between the two is that (ex-ante) risk is the source of (ex-post) fluctuations: with no risk, the distribution of $\hat{y}_t$ would be a fixed value at every point in time, and the resulting stream of past income would be flat.

Moreover, while a risk averse household would prefer lower variability for a given value of expected future prospects (Equation 2.2), a similar intuition applies to the simple aggregate of past utilities given by Equation 2.4: a risk averse household would trade off a reduction in the average for lower variability in past incomes, at least in a second-best world with incomplete insurance and capital markets (Cowell, 1989).

The following Section develops a framework for the evaluation of past incomes based on this analogue of risk aversion in an ex-post setting and on the formal similarity between the formulations of expected and average experienced utilities.

2.3 A Framework for the Evaluation of Income Fluctuations

2.3.1 *The structure of the evaluation function*

A general formulation for an aggregate of household income over time, $\mathbf{y} = [y_1, ..., y_T]$, is given by an evaluation function V that maps a vector of T

observations into the real line:

$$V(\mathbf{y}) = V(y_1, ..., y_T) \tag{2.5}$$

In terms of the terminology used in the Introduction, V defines a transformation $W : \mathcal{F} \to \mathbb{R}$, from the distribution of past incomes for a household into the real line.

The problem remains in defining a functional form for V, which determines the normative criteria associated with the evaluation of $\mathbf{y}$. The presence of the time dimension introduces a higher degree of complexity with respect to the analysis of an income distribution at one point in time.

The framework proposed here concentrates on a series of intuitive criteria. As a starting point, it is reasonable to assume that V should be non-decreasing in its arguments. Moreover, the aggregate level of welfare over the T periods should depend not only on the level of $\mathbf{y}$, but also on its variability. The idea, pervasive in economic theory, is that risk averse agents are willing to trade off a reduction in expected income for certainty. In an ex-post setting, the concept of risk aversion translates into a "dislike" of fluctuations, or variability aversion (to be formally defined below).

These two basic normative principles can be incorporated into the evaluation function V based on the results and intuitions of the previous Section. The evaluation framework, however, does not rely on utility functions u: the function V is interpreted within a social welfare context as a judgement on the welfare value of the experienced income stream. This approach, followed by Cruces and Wodon (2003b) and Ligon and Schechter (2003) among others, implies that it is not necessary to impute a utility function and assume homogeneous preferences in the population.

In the evaluation framework, the stream of past income $\mathbf{y} = [y_1, ..., y_T]$ is assessed retrospectively from the point of view of period $T + 1$. The parallelism of V with the expected utility formulation in Equation 2.1 means that each past income y_t is evaluated by an instantaneous evaluation $v(y_t)$, assumed to be continuous, strictly increasing and twice-differentiable.[6] The result is the following characterisation of V:

[6]While the emphasis is on panel data and thus on the evaluation of *past* incomes, the methodology can be applied to a certain but fluctuating future income stream.

Definition 2.1 Additive, time-separable evaluation function. *The evaluation of the observed stream of past income* $\mathbf{y} = [y_1, ..., y_T]$, $V(\mathbf{y})$, *is the discounted average of the instantaneous evaluation function* v *for each period from* $t = 1$ *to* T*:*

$$V(\mathbf{y}) = \sum_{t=1}^{T} \Delta(t) v(y_t) \tag{2.6}$$

The weights are given by a discounting function $\Delta(t)$, *with* $0 < \Delta(t) \leq 1$, *and normalised (without loss of generality) so that* $\sum_{t=1}^{T} \Delta(t) = 1$.

The structure imposed by Equation 2.6 implies the following analogy: the model of choice under uncertainty in a single period (Equation 2.1) and the evaluation of past incomes based on an additive, time-separable evaluation function as in Equation 2.6 are formally equivalent. The results from the former can be applied to the latter by: a) replacing the function u by its analogue v, b) replacing state-contingent incomes y_ω by observed incomes y_t, and c) replacing probabilities τ_ω by $\Delta(t)$.

This analogy is established by inspection of Equations 2.1 and 2.6: ranking vectors of past incomes $\mathbf{y}$ according to V is formally identical to ranking probability distributions according to the expected utility criterion. From a formal point of view, Equation 2.6 can be treated as a special case of Equation 2.1 with $u = v$, $\omega = t$, $y_\omega = y_t$ and $\tau_\omega = \Delta(t)$, i.e. "as if" past incomes were drawn from T events with outcomes y_t. The formulation for V in Equation 2.6 implies that the formal results from risk theory can be applied directly to the evaluation framework, although the interpretation of these results differs. The connection between the theory of risk and the evaluation framework stems from the discussion of income risk and income fluctuations in the previous Section.[7]

The main difference between risk and the formulation of Equation 2.6 is the presence of the discounting function $\Delta(t)$, which accounts explicitly for the time dimension of the problem of evaluating past incomes. The motivation for the incorporation of $\Delta(t)$ into V is the presence of pure time preferences: in the example of Figure 2.1, a household would not be indif-

[7]The idea of borrowing results from risk theory is at the basis of Atkinson's (1970) re-interpretation of choice under uncertainty in a social welfare context. However, a social welfare function aggregates the distribution of income at a point in time for a population, while V is a social evaluation of *household* welfare as defined by Equation 2.5.

ferent to the ordering of past incomes, giving more weight to more recent events.[8] The function $\Delta(t)$ is thus required to increase as t approaches T. Since the discount factors are normalised to sum 1, they can be interpreted as "discounting weights." In the simplest form of aggregation, every period of time is given an equal weight so that $\Delta(t) = 1/T$. Section 2.5 below discusses specific functional forms for $v(y)$ and $\Delta(t)$.

The parallel with the theory of risk is completed by the following Proposition, which is the evaluation framework's analogue of risk aversion, and specifies a key condition for v:

Proposition 2.1 Variability aversion. *The function v is assumed to be strictly concave, which implies that $V(\mathbf{y})$ is strictly decreasing in the dispersion of $\mathbf{y} = [y_1, ..., y_T]$ weighted by the discounting function $\Delta(t)$. The dispersion is defined in the sense of Rothschild and Stiglitz's (1969) second order stochastic dominance.*

This result derives from the concavity of v, and it is equivalent to the risk aversion result $(\partial U/\partial h < 0)$ in Equation 2.2. The curvature of v determines the degree of variability aversion, and its magnitude can be quantified by defining measures of absolute and relative aversion by analogy with the canonical model of risk (Pratt, 1964; Arrow, 1970).

Proposition 2.1 implies that for a given average discounted income over time, $\bar{y}_\Delta = \sum_{t=1}^{T} \Delta(t) y_t$, a higher variability in the underlying stream reduces welfare as captured by V. The properties of V and v given by Definition 2.1 and Proposition 2.1 adapt the concept of risk aversion to the intertemporal setting, incorporating in the evaluation framework the principle that past fluctuations reduce welfare, and should be penalised by an evaluation function. While not all fluctuations might be considered bad, for instance when income grows over time (Cowell, 1989), the variability aversion is based on the discussion of the effects of riskiness on household utility in Section 2.2. Moreover, the presence of the discounting function $\Delta(t)$ in V ensures that the evaluation of past incomes is not invariant with respect to the ordering of the components of $\mathbf{y}$, except for the special case in which $\Delta(t) = 1/T$. For instance, in a setting with $T = 2$, if $y_2 > y_1$

[8]Alternatively, $\Delta(t)$ can also be motivated by the presence of imperfect storage technologies, in which only a limited amount of income can be kept for future use.

then $V(y_1, y_2) \geq V(y_2, y_1)$: an increasing income stream results in a higher evaluation of well-being than a decreasing stream.

The following pages build on the additive structure of the evaluation function to specify measures of well-being and its variability over time.

2.3.2 *Evaluation of well-being and variability over time*

The concept of variability aversion and the structure of V given by Definition 2.1 imply that another important notion from the theory of choice under uncertainty can be adapted to the evaluation of past incomes. The analogue of the certainty equivalent income (Equation 2.3) is given by:

Definition 2.2 *The* stability equivalent income $\tilde{y}_{se}$ *is a real number such that*

$$V(\mathbf{y}) = v(\tilde{y}_{se}) \tag{2.7}$$

$\tilde{y}_{se}$ is the level of income that, if received in every past period $t = 1$ to T, as $\tilde{\mathbf{y}} = [\tilde{y}_{se}, ..., \tilde{y}_{se}]$, would result in the same level $V(\mathbf{y})$ of the evaluation function as the observed stream $\mathbf{y} = [y_1, ..., y_T]$.

The continuity of v guarantees that $\tilde{y}_{se}$ exists, and its concavity implies that it is decreasing in the dispersion of $\mathbf{y}$. Both results are formally analogous to those for the certainty-equivalent in risk theory (Pratt, 1964).[9]

The counterfactual stability equivalent $\tilde{y}_{se}$ is a function of the shape of v and the level and distribution of y_t in $\mathbf{y}$. Under the assumption that the variability of past income reduces well-being, the $\tilde{y}_{se}$ can be interpreted as a "variability adjusted" income. It constitutes a welfare-based counterpart to the statistical measure $\bar{y}_\Delta$, and it is thus superior to the discounted average income as an indicator of well-being, just as the certainty equivalent $\tilde{y}_{ce}$ was deemed superior to $E[\tilde{y}]$ in the expected utility model of Section 2.2.[10]

Finally, another concept that can be adapted from the theory of choice under uncertainty is the risk premium. Since $\tilde{y}_{se}$ is lower than the average income $\bar{y}_\Delta$ because of the concavity of v, the difference between the two

[9] This stability equivalent income is formally equivalent to Atkinson's (1970) "equally distributed equivalent level of income," and it is closely related to Ravallion's (1988) notion of "stabilised income."

[10] This argument is derived from Cowell's (1979) discussion of a "lifetime welfare-equivalent current income" for an income stream (Definition 2, page 12).

provides a money metric of the loss in household welfare attributable to income fluctuations, as described in the following Definition:

Definition 2.3 *The* variability premium π_v *and the* relative variability premium Π *are real numbers such that*

$$\pi_v(\mathbf{y}) = \bar{y}_\Delta - \tilde{y}_{se} \tag{2.8}$$

$$\Pi(\mathbf{y}) = \frac{\pi_v}{\bar{y}_\Delta} \tag{2.9}$$

where $\bar{y}_\Delta$ is the weighted average income over time given by $\bar{y}_\Delta = \sum_{t=1}^{T} \Delta(t) y_t$, and $\tilde{y}_{se}$ is the stability equivalent income *defined above.*

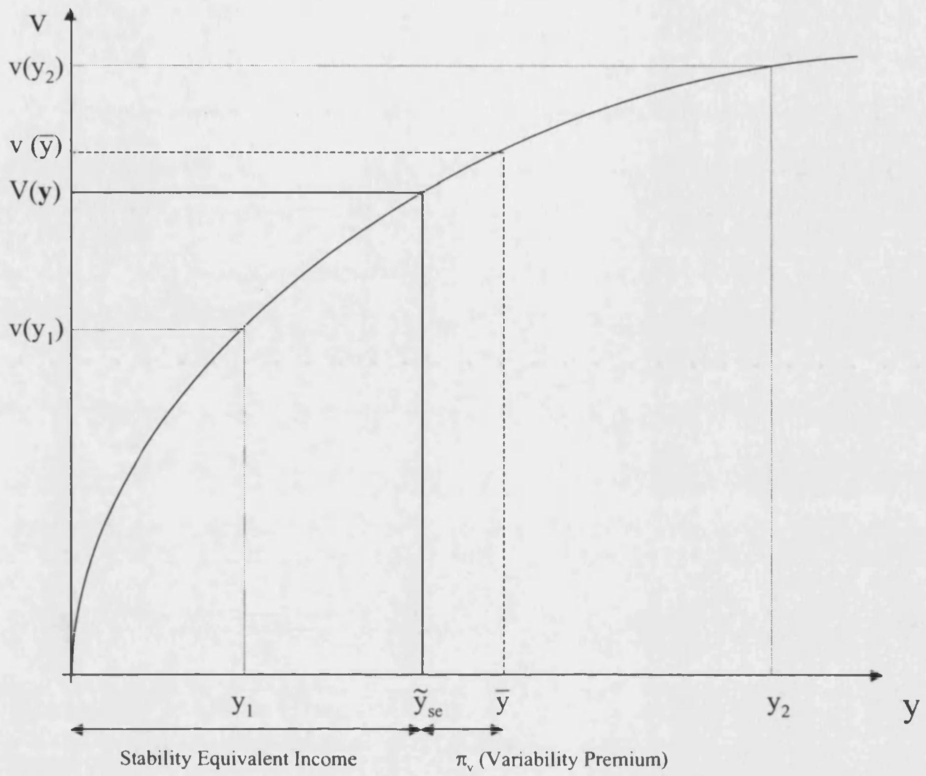
Since $\tilde{y}_{se}$ is decreasing in the dispersion of $\mathbf{y}$, π_v and Π are increasing in the same parameter. Moreover, the curvature of v also affects these quantities through its effect on $\tilde{y}_{se}$: for a given $\mathbf{y}$, the stability equivalent income falls and the premium increases with v's degree of variability aversion. The premium π_v can be considered to be a welfare-based measure of the variability of past incomes, while the relative premium Π shares the same property and has the advantage of being unit-free.[11]

Figure 2.2 depicts $\tilde{y}_{se}$ and π_v for $T = 2$ in the evaluation-income space.[12] As in risk theory, the stability equivalent falls and the variability premium increases with a higher dispersion in past incomes due to the concavity of v. For a fixed level of dispersion, the effect of an increase in the curvature of v is the same. While the Figure is identical to any textbook example of risk aversion, Figure 2.1 presents the setting in the utility-time (or evaluation-time, setting $u = v$) space, stressing the difference between future states of the world (Equation 2.1) and materialised outcomes (Equations 2.4 and 2.6). From this example, it can be seen that the certainty equivalent $\tilde{y}_{ce}$ depends solely on the distribution of one future outcome, whereas only actual realised incomes matter for the stability equivalent $\tilde{y}_{se}$, even if these realised incomes originate in repeated draws from the same distribution as $\tilde{y}_{ce}$.

[11]Some manipulation shows that $\Pi(\mathbf{y}) = 1 - \tilde{y}_{se}/\bar{y}_\Delta$, which is formally equivalent to Atkinson's (1970) simple inequality index.

[12]For expositional convenience, all the diagrams in this Chapter are based on the no discounting case, in which $\Delta(t) = 1/T$. This implies that $V(\mathbf{y})$ represents the simple average of $v(y_t)$ and that $\bar{y}_\Delta = \bar{y} = (1/T)\sum_{t=1}^{T} y_t$.

Figure 2.2: Stability Equivalent Income and Variability Premium



The following pages complete the discussion of the evaluation framework by studying the properties of the stability equivalent $\tilde{y}_{se}$ as a variability adjusted income.

2.3.3 *"Fluctuation adjusted" population measures of well-being*

In terms of the Introduction's terminology, both V and $\tilde{y}_{se}$ define transformations $W : \mathcal{F} \rightarrow \mathbb{R}$ that result in scalar measures of well-being based on a household's past incomes. While $V(\mathbf{y})$ and $\tilde{y}_{se}$ provide equivalent mea-

Proposition 2.2 *The* stability equivalent income $\tilde{y}_{se}$, *given by Definition 2.2, is a sufficient money metric statistic of household welfare defined by the evaluation functions v and V.*

The proof of this Proposition relies on the uniqueness of the certainty equivalent in risk theory (Pratt, 1964). With a well-behaved, standard function v, Equation 2.7 implicitly defines V and $\tilde{y}_{se}$ as monotonic transformations of each other, because v is strictly increasing and continuous. Since v takes income as its argument, the scalar measure of well-being, $\tilde{y}_{se}$, is money metric.

This implies that the stability equivalents $\tilde{y}_{se}$ and $\tilde{y}'_{se}$, corresponding to two functions $V(\mathbf{y})$ and $V'(\mathbf{y})$, are directly comparable because they are both measured in money terms. Besides this property, Proposition 2.2 and the nature of the stability equivalent imply that $\tilde{y}_{se}$ satisfies Cowell's (1995, Chapter 1) requirements for a measure of income, which must be "measurable [...] and comparable among different persons."[13] For this reason, Proposition 2.2 ensures that all the tools of univariate distributional analysis can be applied to the distribution of $\tilde{y}_{se}$.

This procedure constitutes a second $W : \mathcal{F} \longrightarrow \mathbb{R}$ transformation. The problem of studying the distribution of vectors $\mathbf{y}$ in the population is reduced, by means of the evaluation function V, to the study of $F(\tilde{y}_{se})$, the univariate distribution of the stability equivalent income. This means that any poverty measure P, inequality measure I, and social welfare function W defined over the distribution of incomes y at one point in time can also be applied to the distribution of $\tilde{y}_{se}$ (Atkinson and Bourguignon, 2000). Moreover, since $\tilde{y}_{se}$ is money metric, its distribution can be compared to that of the average over time for each household, $\bar{y}$. This exercise is akin to the comparison of distributions before and after tax or transfers, for which there exists an extensive literature and a standard set of tools (Cowell, 1995).

The two-step methodology described in this Section is similar in spirit to the process of equivalisation in distributional analysis. Survey data usually contains information about a number of income-earners in a household. The equivalisation process converts a vector of incomes from different members

[13] Incomes y_t are adjusted for differences in household size and composition by an equivalence scale, and normalised so that they can be compared over time. See Section 1.2 (page 22) for details of these adjustments.

of a household into a single measure, according to some welfare criteria – usually taking into account the gender and age composition of the household (see Section 1.2, page 22, for details on the Argentine case). The analysis is then carried out on the distribution of the scalar equivalised aggregate.

The following Section compares the evaluation framework with the related methodologies in the poverty and distributional literature.

2.4 Comparison with Alternative Approaches

2.4.1 *Ex-post measures: transient and chronic poverty*

The evaluation framework has a series of advantages over the existing approaches for the analysis of panel data on incomes. This Section reviews the results from the two main alternatives in the literature.

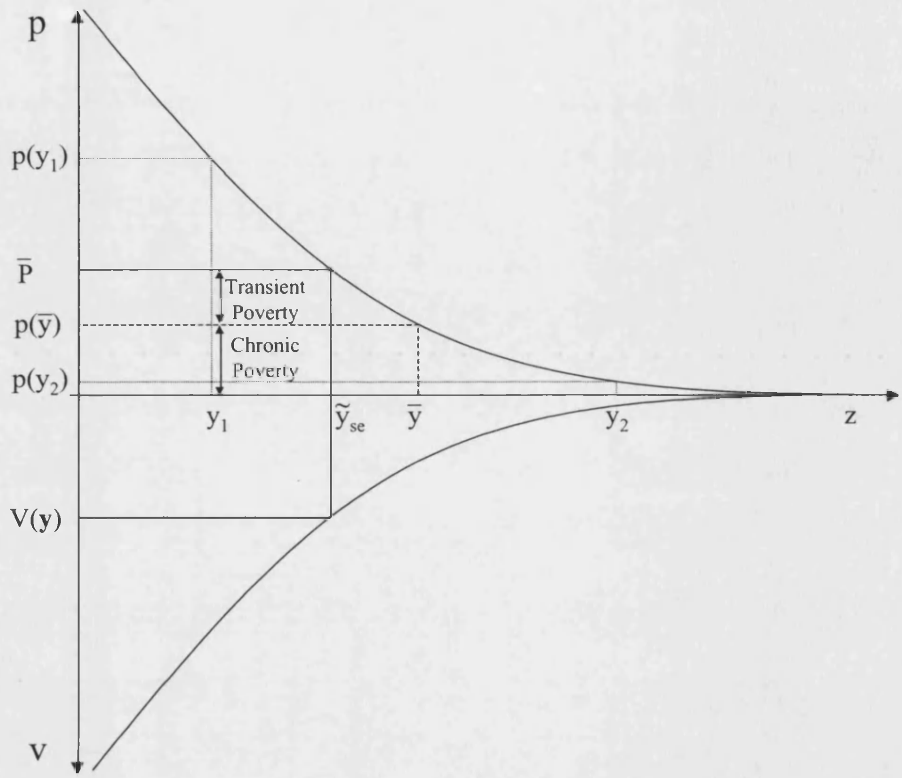
The first approach, widely used in empirical applications, is the transient-chronic poverty decomposition. This methodology originates in Ravallion's (1988) contribution on poverty and welfare variability, on which Jalan and Ravallion (1998; 2000) base their definitions of transient and chronic poverty. Chapter 4 builds on these categories to study the Argentine case.

The approach applies Atkinson's (1987) family of additive poverty measures to a multi-period setting. A household's poverty in time t is given by the evaluation function $p(y_t)$, where p is required to be additive, strictly convex and decreasing up to the poverty line, and taking a value of zero thereafter. Intertemporal poverty P_i, chronic poverty C_i and transient poverty T_i are defined as:

$$\begin{aligned} P_i &= \tfrac{1}{T}\sum_{t=1}^{T} p(y_{it}), \\ C_i &= p(\bar{y}_i) \text{ and} \\ T_i &= P_i - C_i \end{aligned} \tag{2.10}$$

Intertemporal poverty is the undiscounted average of the poverty evaluations over time for a household, while chronic poverty reflects the poverty evaluation at the average income over time for i, $\bar{y}_i$. Finally, transient poverty is calculated as the difference between the two. Jalan and Ravallion (1998) compute these measures for every household and then aggregate

Figure 2.3: Transient, Chronic and Variability Adjusted Measures of Poverty



them into population averages, using the squared poverty gap function for p (Equation 1.5).

In terms of empirical applications, the main difference with the evaluation framework is that Jalan and Ravallion (1998) work with poverty evaluations, whereas the methodology presented in Section 2.3 first derives variability adjusted measures of income with an evaluation function, and then computes poverty indices based on them (Section 2.5 below presents an example of this procedure).

Despite this difference, the transient-chronic decomposition represents a special case of the evaluation framework. The poverty evaluation function p can be interpreted as an evaluation function by setting $v = -p$, which reflects an assessment of i's well-being that gives zero weight to income above the poverty line. This is illustrated in Figure 2.3, which presents an example for $T = 2$, with no discounting ($\Delta(t) = 1/T$) and with y_1 and y_2 below the poverty line. In the Figure, the poverty evaluation p is mirrored by the evaluation function $v = -p$. This representation highlights the connection between the two methodologies: the money metric indicator $\tilde{y}_{se}$ based on $v = -p$ represents the fixed level of income that would result in the same intertemporal poverty P as the observed stream $\mathbf{y}$.

A disadvantage of the Jalan and Ravallion (1998) approach is that the aversion to variability is implicitly built into the poverty evaluation function p, which amalgamates the poverty and time dimensions. This function, however, may not be appropriate for evaluating income over time. For instance, most of the transient-chronic applications are based on the squared poverty gap, which is akin to a quadratic utility function and thus implies the possibly undesirable property of increasing relative risk aversion (Kurosaki, 2003).[14] On the other hand, the two-step procedure proposed here ensures that these two facets are accounted for by a separate set of principles. The stability equivalent is derived from a set of principles specific to the time dimension, summarised by v, and the measure of poverty is then obtained by applying a function p, specific to the income dimension, to this household aggregate.

Finally, the evaluation framework has two additional advantages. On the one hand, it allows the computation of variability adjusted measures of income for the whole population, while the transient-chronic decomposition by definition applies only to the poor. On the other hand, the incorporation of a discount factor in Equation 2.6 accounts for the trajectory of income, whereas the measures in Equation 2.10 are invariant to changes in the ordering of incomes y_t in $\mathbf{y}$.

Some of the advantages of the evaluation framework over the transient-chronic decomposition are also present when compared with the vulnerability approach, analysed in the following pages.

2.4.2 *Ex-ante measures: risk and vulnerability*

The vulnerability approach, as defined by Ligon and Schechter (2003), attempts to capture the ex-ante risk faced by households.[15] They rely on a

[14]The properties of the quadratic utility function in terms of risk aversion are analysed by Deaton and Muellbauer (1980, page 400).

[15]Thorbecke (2003) and Ligon and Schechter (2004) provide extensive overviews of the literature, including its relationship with Ravallion's (1988) concept of "expected poverty."

"welfare function" U_i^{LS} defined over household income y_i. The vulnerability of a household i, V_i^{LS}, is given by the difference between U_i^{LS} evaluated at the poverty line z and the expectation of $U_i^{LS}(y_i)$:

$$V_i^{LS} = U_i^{LS}(z) - E[U_i^{LS}(y_i)] \tag{2.11}$$

which is decomposed into "poverty" and "risk" components:

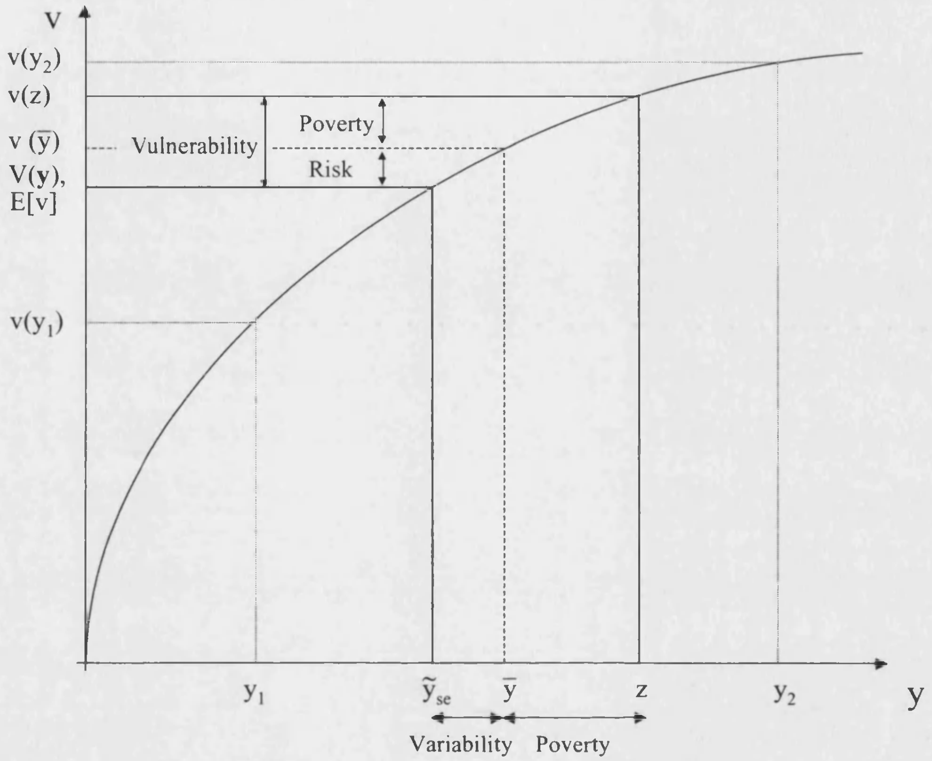
$$V_i^{LS} = \underbrace{\{U_i^{LS}(z) - U_i^{LS}(E[y_i])\}}_{Poverty} + \underbrace{\{U_i^{LS}(E[y_i]) - E[U_i^{LS}(y_i)]\}}_{Risk} \tag{2.12}$$

The expectation operator in Equations 2.11 and 2.12 refers to the distribution of future income: V_i^{LS} is meant to capture ex-ante risk and is thus "inherently forward-looking" (Ligon and Schechter, 2004). This is the main difference between the vulnerability approach and the evaluation framework: the former attempts to capture ex-ante income risk, while the latter evaluates ex-post fluctuations, as illustrated in Figure 2.1 and discussed in Section 2.2.

Since observed data is ex-post by definition, this approach requires an identifying assumption to use past realisations "to estimate the probability of possible future outcomes" (Ligon and Schechter, 2003). The assumption made by these authors is stationarity, which imposes the restriction that "the probability distribution of income in one period is identical to the probability distribution of income in any other period" (Ligon and Schechter, 2004). This implies that the last term in Equation 2.11, $E[U_i^{LS}(y_i)]$, becomes $(1/T)\sum_{t=1}^{T} U_i^{LS}(y_{it})$.

However, whether trying to capture past variability or future risk, from an applied point of view only realisations of income $\mathbf{y}$ are available to the researcher. The vulnerability approach and the evaluation framework methodologies differ conceptually, but the identifying assumption made by the former implies that the two result in similar empirical applications. This means that, as the transient-chronic decomposition, Ligon and Schechter's (2003) vulnerability measures can be interpreted as a special case of the evaluation framework. This is illustrated in Figure 2.4 (based on Thorbecke, 2003), which presents an example with $T = 2$ and no discounting ($\Delta(t) = 1/T$). In this setting, the evaluation function defined in Equation 2.6 be-

Figure 2.4: Poverty, Vulnerability and Income Fluctuations – Cardinal and Money Metric Measures



comes $V(\mathbf{y}) = (1/T)\sum_{t=1}^{T} v(y_{it})$. The connection between the two methodologies emerges from setting the evaluation and welfare functions to coincide: assuming $U_i^{LS} = v$ results in $V(\mathbf{y}) = E[v(y_t)] = E[U_i^{LS}(y_i)]$, the last term in Equation 2.11. As can be appreciated in Figure 2.4, Ligon and Schechter's (2003) measure of vulnerability is equivalent, in the evaluation framework, to the difference between the evaluation of the poverty line, $v(z)$, and that of the observed income stream, $V(\mathbf{y})$.

The Figure also illustrates, in its vertical axis, the decomposition of vulnerability given by Equation 2.12. This example shows that the same exercise can be carried out within the evaluation framework: along its horizontal axis, the Figure presents a monotone transformation of the "poverty" and "risk" components of Equation 2.12 in money metric terms, $z - \bar{y}$ and $\bar{y} - \tilde{y}_{se}$ respectively. The latter corresponds to the variability premium defined in Equation 2.8.[16]

A disadvantage of Ligon and Schechter's (2003) vulnerability measure, similar to that of the transient-chronic decomposition, is that the function U_i^{LS} determines not only the value of $U_i^{LS}(E[y_i]) - E[U_i^{LS}(y_i)]$, the "risk" component in Equation 2.12, but also the functional form of the "poverty" component, $U_i^{LS}(z) - U_i^{LS}(E[y_i])$. In the evaluation framework, however, the stability equivalent $\tilde{y}_{se}$ is derived from a function v, and the poverty measures are then based on $\tilde{y}_{se}$, which ensures that fluctuations and poverty are disentangled.

Moreover, V_i^{LS} in Equation 2.11 is derived in units of the cardinal welfare function U_i^{LS} ("utils" in Ligon and Schechter, 2003), which implies that measures of vulnerability based on two functions U_i^{LS} and $U_i^{LS'}$ are not directly comparable. As discussed in Section 2.3, a money metric indicator like $\tilde{y}_{se}$ ensures the comparability of results for different evaluation functions.

Finally, by attempting to capture the ex-ante risk faced by the households, the stationarity assumption means that the measure of vulnerability in Equation 2.11 does not take into account the dynamic dimension of the observed stream $\mathbf{y}$: V_i^{LS} is the same for the vectors $\mathbf{y} = [y_1, y_2]$ and $\mathbf{y}' = [y_2, y_1]$ with $y_1 \neq y_2$. While assuming stationarity is plausible in some contexts, the evaluation framework can account for the dynamic nature of $\mathbf{y}$ through the discounting function $\Delta(t)$. This is illustrated in the empirical applications presented in the following Section.

2.5 Empirical Implementation and Application to Argentina

2.5.1 *Empirical implementation: alternative evaluation functions*

This Section deals with the implementation of the evaluation framework. It adds structure to the formulation in Section 2.3 by stipulating a series of functional forms for v and studying the characteristics of the resulting stability equivalent incomes $\tilde{y}_{se}$.

The definition of V in Equation 2.6 relies on the functions v and Δ. The empirical applications presented below are based on an exponential dis-

[16] Moreover, the representation of V_i^{LS} in terms of income on the horizontal axis of Figure 2.4 reveals that this measure of vulnerability is a monotone transformation of the poverty gap ($\alpha = 1$ in Equation 1.5, page 35) evaluated at $\tilde{y}_{se}$.

counting function, although $\Delta(t)$ can in principle accommodate hyperbolic discounting or other suitable principles (O'Donoghue and Rabin, 1999). In what follows, $\Delta(t)$ is given by:

$$\Delta(t, T, \delta) = \frac{\delta^{T-t}}{\sum_{t=1}^{T} \delta^{T-t}} \tag{2.13}$$

with a bounded discount factor, $0 < \delta \leq 1$. The weighted or discounted average of income is then defined as:

$$\bar{y}_{\Delta} = \sum_{t=1}^{T} \left[\frac{\delta^{T-t}}{\sum_{t=1}^{T} \delta^{T-t}} y_t \right] \tag{2.14}$$

The formulation in Equation 2.13 and the bounds in the parameter δ ensure that $\sum_{t=1}^{T} \Delta(t) = 1$ and that the function is increasing in t.[17] The parameter δ is the discount factor, which defines the relative weight given to the recent past with respect to events further away in time. As δ approaches 0, more weight is placed in the last period, T, and in the limit $\Delta_{\delta \to 0}(T) = 1$ and $\Delta_{\delta \to 0}(t \neq T) = 0$. The opposite case is that of no discounting, which corresponds to $\delta = 1$: this implies that the "discount weights" simplify to $\Delta(t) = 1/T$. In this case, the evaluation function V becomes the average of $v(y_t)$, and Equation 2.14 represents $\bar{y}$.

Regarding the functional form of v, the prominence of choice under uncertainty in the evaluation framework implies that intuitive functional forms for v are derived from the instantaneous utility functions used in the theory of risk.

A first alternative is the analogue of the isoelastic utility function,[18] the Constant Relative Variability Aversion (CRVA). The following Equations describe this function and the implied stability equivalent income:

$$v(y) = \begin{cases} \frac{y^{1-\rho}}{1-\rho} & \text{if } \rho \neq 1 \\ \ln y & \text{if } \rho = 1 \end{cases} \tag{2.15}$$

[17]The motivation for an increasing $\Delta(t)$ derives from pure time preferences, which give more weight to more recent events. However, the formulation in Equation 2.13 allows for a decreasing $\Delta(t)$ if $\delta \geqslant 1$. In that case, larger values of δ imply more weight for events further in the past. In the limit, $\Delta_{\delta \to +\infty}(1) = 1$ and $\Delta_{\delta \to +\infty}(t \neq 1) = 0$.

[18]This formulation is also known as the the Constant Relative Risk Aversion (CRRA) utility function.

which results in

$$\tilde{y}_{se} = \begin{cases} \left[\sum_{t=1}^{T} \Delta(t) y_t^{1-\rho}\right]^{\frac{1}{1-\rho}} & \text{if } \rho \neq 1 \\ \prod_{t=1}^{T} y_t^{\Delta(t)} & \text{if } \rho = 1 \end{cases} \tag{2.16}$$

This functional form allows for a sensitivity parameter ρ, the analogue of the relative risk aversion parameter in the Constant Relative Risk Aversion (CRRA) utility function. Since $\tilde{y}_{se}$ is decreasing in ρ, it quantifies the effect of past variability on well-being: for a fixed dispersion of past incomes, higher values of ρ result in lower stability equivalent incomes.

The CRVA form implies that the degree of aversion to fluctuations is constant relative to the household's income, since the curvature of v is constant. This is consistent with the intuition that "the rich are more tolerant of risks than the poor" (Deaton and Muellbauer, 1980, Chapter 14), and it is reflected in the fact that the relative stability premium Π (Equation 2.9) based on Equation 2.16 remains constant when all incomes in $\mathbf{y}$ are multiplied by the same positive factor (in the case of no discounting).

An alternative to the CRVA functional form is given by the analogue of the Constant Absolute Risk Aversion (CARA) utility function, which is also widely used in the risk literature. The Constant Absolute Variability Aversion (CAVA) is given by:

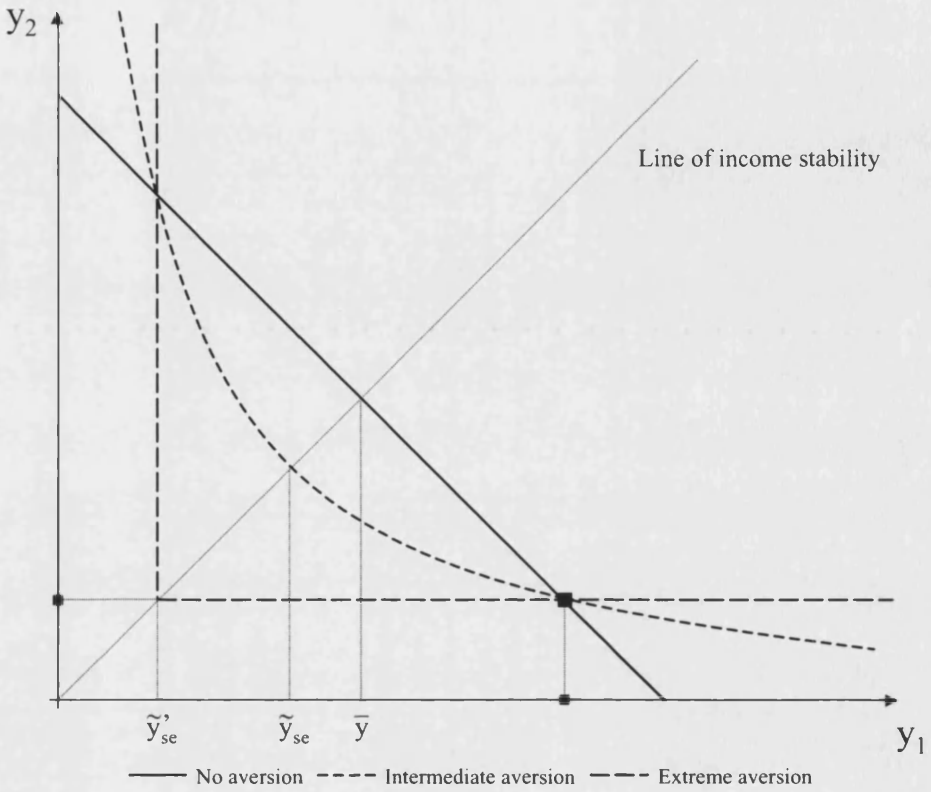
$$v(y) = -\frac{1}{\eta} e^{-\eta y} \tag{2.17}$$

resulting in the stability equivalent:

$$\tilde{y}_{se} = -\frac{1}{\eta} \ln \left[\sum_{t=1}^{T} \Delta(t) e^{-\eta y_t}\right] \tag{2.18}$$

Equation 2.17 also allows for a sensitivity parameter, $\eta \neq 0$, which captures the degree of variability aversion, since larger values of η imply lower stability equivalents $\tilde{y}_{se}$. Moreover, this formulation is also consistent with the intuition mentioned above, namely that as income grows, households are willing to accept larger fluctuations. Compared to the CRVA, the CAVA functional form implies that the relative stability premium Π (Equation 2.9) falls when all incomes in $\mathbf{y}$ are multiplied by the same positive factor (again,

Figure 2.5: Evaluation Function Contours for Different Degrees of Variability Aversion



in the case of $\delta = 1$).

Finally, two extreme cases are presented for illustration. The first case, in which v is not strictly concave, is given by a linear evaluation function:

$$v(y) = y \tag{2.19}$$

resulting in

$$\tilde{y}_{se} = \bar{y}_{\Delta} = \sum_{t=1}^{T} \Delta(t) y_t \tag{2.20}$$

This formulation can be interpreted as the limit case of the CRRA function with $\rho = 0$, in other words, with no variability aversion, the fluctuation adjusted income reduces to the discounted average over time.

The opposite case to Equation 2.19 is given by extreme variability aversion, corresponding to the limit case of the CRRA function with $\rho \to +\infty$.

In the case of no discounting, this formulation results in:

$$\tilde{y}_{se} = \min(y_t) \tag{2.21}$$

The implied evaluation function only takes into account the lowest of past incomes, and it is the analogue, in the evaluation context, of a "Rawlsian" social welfare function (Hammond, 1975).

Figure 2.5 highlights the difference between these different degrees of variability aversion, which are not readily apparent in the evaluation-income space of previous figures. With $T = 2$, the Figure represents the stability equivalent income in the y_1, y_2 space for evaluation function contours with different degrees of variability aversion and no discounting. The CRVA and CAVA cases are represented by the "intermediate aversion" curve in the Figure, while the contour implied by Equation 2.19 is the "no aversion" solid straight line, which results in $\tilde{y}_{se} = \bar{y}$. Finally, the extreme aversion case is depicted by the kinked contour in Figure 2.5.

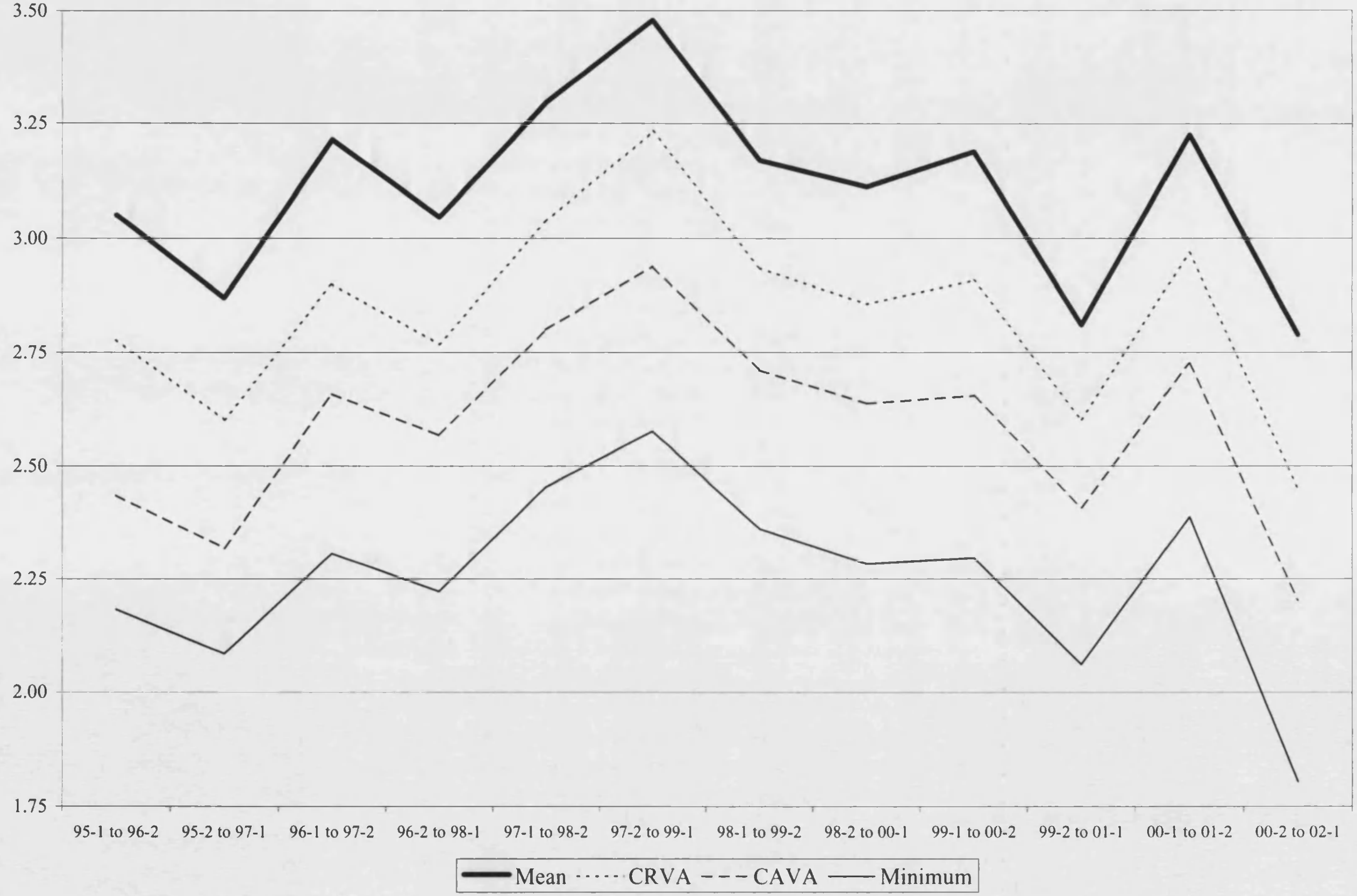
2.5.2 *Application to Argentina*

The following pages present alternatives for empirical analysis using the evaluation framework and the functional forms discussed above. The results in Chapters 3 and 4, which can be interpreted in the evaluation context (as discussed in Section 2.4), provide further examples of empirical work.

The data corresponds to the Greater Buenos Aires dataset described in Section 1.2 (page 22) – a series of rotating panels over the 1995-2002 period with twelve cohorts of households with four observations each (i.e. $T = 4$). The evaluation functions and stability equivalents defined above are applied to the equivalised and normalised income of these households, given by y_{it} in Equation 1.3 (page 27).

The simplest analysis can be carried out over the population average of $\tilde{y}_{se}$, depicted in Figure 2.6 for each of the twelve cohorts. The evaluation functions in this Figure are the CRVA (Equation 2.15), CAVA (Equation 2.17) and the extreme aversion (Equation 2.21) functions, while the average of income over time (Equation 2.19) is used as the benchmark case. For the CRVA and CAVA formulations, the parameters ρ and η are set to 2, a value adopted for empirical analysis in Chapter 3 and by Ligon and Schechter

Figure 2.6: Variability Adjusted Measures of Income for Different Evaluation Functions, Greater Buenos Aires, 1995-2002



Source: Author's estimations based on EPH household survey data (INDEC).

(2003), among others.[19] This example concentrates on different functional forms, and thus the parameter δ in Equation 2.13 is set to 1, resulting in $\Delta(t) = 1/T$.

As described in Chapter 1, incomes are normalised by their contemporaneous poverty lines so their unit is the poverty line. The four variability adjusted measures and the average income in Figure 2.6 follow the basic trends described in Section 1.3 (page 29), confirming the highly pro-cyclical nature of household income. Notably, the difference between the average of income over the four periods in which households are observed (bold solid line) and its minimum (solid line) is quite sizeable at about three quarters of the poverty line. This indicates the presence of strong within-panel fluctuations in household income. Moreover, the difference between the two is large even in periods of income growth, for instance during the years 1996-1998.

This "minimum" stability equivalent can be interpreted as the result of an extreme aversion evaluation function, while the average income represents no aversion and the CRVA and CAVA constitute intermediate cases (see the diagram in Figure 2.5). This implies that in Figure 2.6 the stability equivalents based on these two formulations fluctuate between the average and the minimum. On average, the difference between the stability equivalent given by the CRVA function with $\rho = 2$ and the average income is around a quarter of the poverty line, while the difference between the latter and $\tilde{y}_{se}$ based on the CAVA with $\eta = 2$ is about half of this unit. These differences represent the population averages of the absolute variability premium defined in Equation 2.8, and they are relatively large with respect to the average income, which fluctuates between around 3 and 3.25 times the poverty line. Finally, while the four measures tend to move similarly, the CRVA is more sensitive to increases and decreases in the average income over time, magnifying its fluctuations.

Another type of empirical analysis based on the evaluation framework is presented in Table 2.1, which depicts the evolution of the relative variability premium Π (defined in Equation 2.9) by quintile of average income, based on a CRVA with $\rho = 2$ and no discounting. The advantage of this for-

[19] Section 3.3 (page 89) discusses the range of plausible values and the sensitivity of measures of this type with respect to ρ.

Table 2.1: Relative Variability Premium by Quintile of Mean Income, Isoelastic Evaluation Function with Aversion Parameter=2, Greater Buenos Aires, 1995-2002

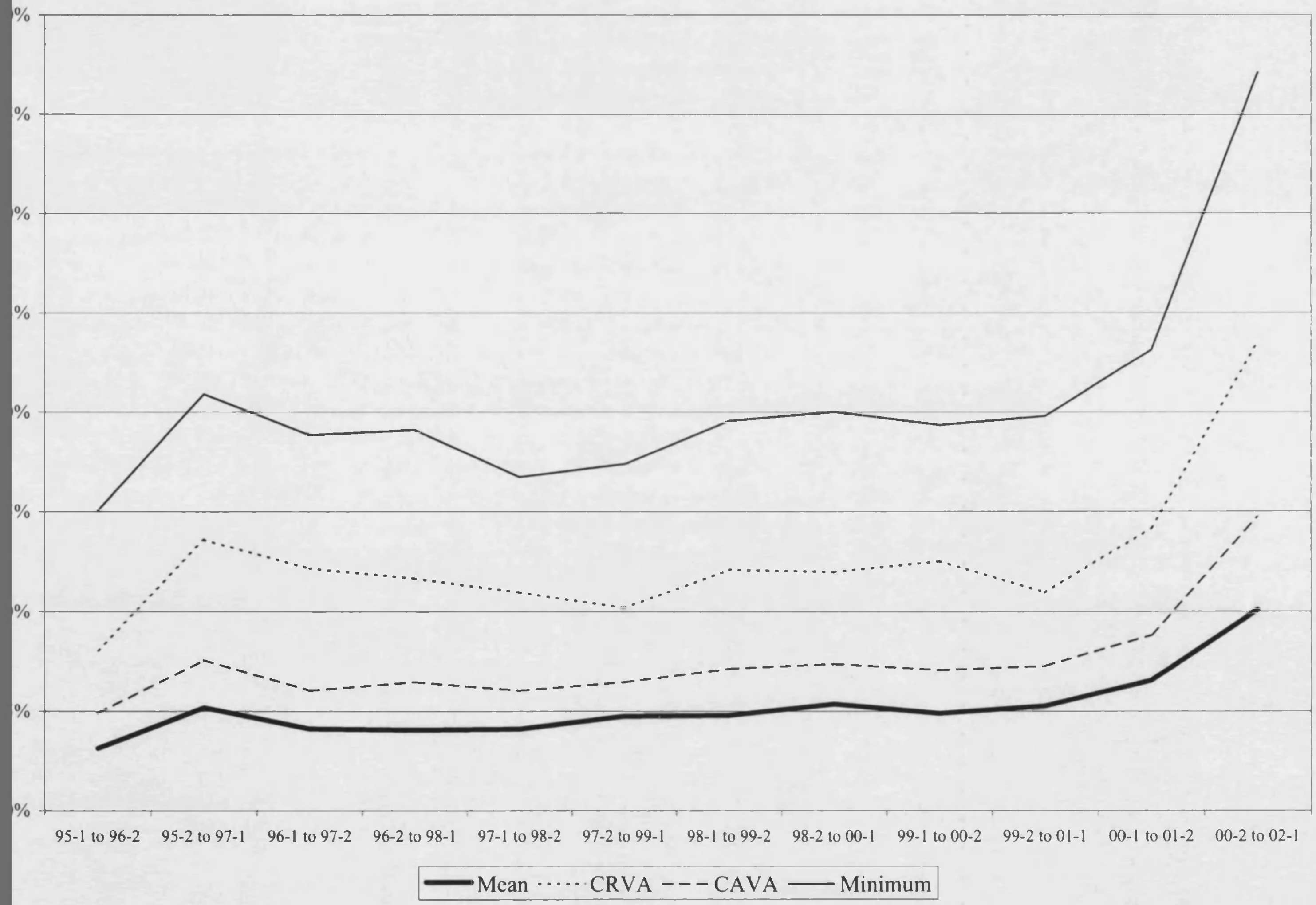
Cohort	Bottom Quintile	Second Quintile	Third Quintile	Fourth Quintile	Top Quintile	Overall
95-1 to 96-2	16.7%	11.3%	9.0%	10.4%	7.8%	11.0%
95-2 to 97-1	25.5%	9.4%	8.2%	11.2%	8.2%	12.4%
96-1 to 97-2	22.9%	14.3%	9.5%	10.0%	7.5%	12.7%
96-2 to 98-1	19.2%	11.9%	9.8%	9.4%	8.8%	11.8%
97-1 to 98-2	24.6%	8.6%	7.6%	6.9%	6.9%	11.0%
97-2 to 99-1	22.1%	10.4%	7.2%	7.4%	5.3%	10.4%
98-1 to 99-2	24.4%	11.0%	8.1%	7.9%	5.2%	11.2%
98-2 to 00-1	21.9%	12.8%	7.2%	5.6%	7.1%	10.9%
99-1 to 00-2	24.3%	10.1%	7.3%	5.2%	7.4%	10.8%
99-2 to 01-1	22.2%	10.0%	10.1%	7.5%	5.1%	10.9%
00-1 to 01-2	20.7%	15.2%	7.6%	5.8%	7.0%	11.2%
00-2 to 02-1	34.9%	19.7%	13.2%	12.2%	9.8%	17.9%
Overall	23.3%	12.1%	8.7%	8.3%	7.2%	11.8%

Source: Author's estimations based on EPH household survey data (INDEC).

mulation is that the relative variability premium is constant with respect to proportional changes in the income vector **y** when $\delta = 1$, so that differences in its value at different points of the income distribution reflect the differential impact of income fluctuations as a proportion of total income. As can be appreciated from the Table, the poorest quintile bears the highest level of fluctuations in relative terms, with values of around 20 and 25 percent of the average income, and with a peak of almost 35 percent in the period corresponding to the 2001-2002 crisis (see Section 1.3, page 29, for details). The second quintile also has a relatively high level of the variability premium at around 12 percent, but for the three richest groups a pattern is not clearly discernible, remaining between 7 and 9 percent on average.

Figure 2.7 presents the population squared poverty gap for the different evaluation functions considered above, with $\rho = 2$, $\eta = 2$ and $\delta = 1$. These poverty measures are based on the stability equivalent incomes presented in Figure 2.6: as expected, the order of the series is reversed with respect to

.7: Variability Adjusted Squared Poverty Gap with Different Evaluation Functions, Greater Buenos Aires, 1995-2002



e: Author's estimations based on EPH household survey data (INDEC).

Table 2.2: Variability Adjusted Income for Different Values of the Discount Factor, Isoelastic Evaluation Function with Aversion Parameter=2

	Observed Income					Stability Equivalent, CRVA α=2			
Income Profile	t=1	t=2	t=3	t=4	σ	δ=1	δ=0.9	δ=0.5	δ=0.1
Flat	1	1	1	1	0	1.00	1.00	1.00	1.00
"Early" MPS	1.5	0.5	1	1	0.35	0.86	0.85	0.90	0.99
"Late" MPS	1	1	1.5	0.5	0.35	0.86	0.83	0.69	0.53
Increasing	0.5	0.75	1.25	1.5	0.40	0.83	0.88	1.14	1.46
Decreasing	1.5	1.25	0.75	0.5	0.40	0.83	0.79	0.64	0.52

Note: MPS refers to a mean preserving spread of income over time. The constant relative variability aversion (CRVA) function and the stability equivalent are defined in the text.

that Figure, with the highest poverty when using the minimum income over the period and the lowest when using the average over time. The difference between these two series is again sizeable, but the most notable fact from the Figure is the evolution of the CRVA series. While the averaging of incomes over time smooths income and poverty measures – a fact discussed at length in Chapter 3 – the CRVA formulation is more sensitive than the CAVA to the variability of the underlying incomes. This can be appreciated in its higher curvature at the points where the poverty measure (based on average income) changes its trend.

Finally, while the previous examples concentrated on functional forms for v and thus considered cases with no discounting, Table 2.2 illustrates the effect of different values of δ in Equation 2.13 on the evaluation of past incomes.[20] The left hand side panel of the Table presents five benchmark cases of income trajectories with $T = 4$ ($\mathbf{y} = [y_1, y_2, y_3, y_4]$) and $\bar{y} = 1$ and their standard deviations σ, while the right hand side panel reports the resulting stability equivalent based on a CRVA function with $\rho = 2$ and four values of the discount factor: $\delta \in \{1, 0.9, 0.5, 0.1\}$.

With $\delta = 1$, the discounting weight is equal to $\Delta(t) = 1/T$ for every period, which is the case for the previous applications. The first line of the Table represents a "flat" income trajectory, which results in a stability

[20]The introduction of $\Delta(t)$ with $\delta \neq 1$ in the GBA examples given by Figures 2.6 and 2.7 shifts the level of the stability equivalents and poverty measures. Table 2.2 is more informative since it illustrates the effect of δ on household income trajectories.

equivalent (given by Equation 2.16) equal to $\tilde{y}_{se} = \bar{y} = 1$. The following rows of the Table illustrate the effect of a mean-preserving spread in $\mathbf{y}$ on $\tilde{y}_{se}$: with a mean of $\bar{y} = 1$, the stability equivalent falls to 0.86 (second and third rows) and 0.83 (fourth and fifth rows) as the standard deviation increases.

The comparison between the second and third (and fourth and fifth) rows of the Table illustrates the invariance of the stability equivalent with respect to the ordering of incomes y_t in $\mathbf{y}$ when no discounting is applied. The second and third rows represent mean-preserving spreads (MPS) of the "flat" income trajectory, the difference being that for the former the spread occurs at $t = 1$ and $t = 2$, while for the latter it occurs closer to the present at $t = 3$ and $t = 4$. The stability equivalent $\tilde{y}_{se}$ with $\delta = 1$ is the same in both cases, since this implies that $\Delta(t) = 1/T$ and thus $V(\mathbf{y}) = V(\mathbf{y}')$ when $\mathbf{y}'$ is a permutation of $\mathbf{y}$.[21] However, the introduction of discounting changes this invariance result: with $\delta = 0.9$, the stability equivalents are 0.85 and 0.83, respectively, and the difference between the two reflects the fact that more weight is given to the low realisation for $t = 4$ in the "late MPS" trajectory. The $\tilde{y}_{se}$ resulting from $\delta = 0.5$ and $\delta = 0.1$, in turn, reflects the trade-off between mean and dispersion: while $\bar{y} = 1$ for all trajectories in the Table, the discount weights imply that $\bar{y}_\Delta$ changes with δ. With $\delta = 0.1$, most of the weight is placed on $t = 4$ and very little on $t = 1$, which explains the large difference in $\tilde{y}_{se}$ between the second and third rows.[22]

Finally, the fourth and fifth rows of Table 2.2 present the same incomes as an increasing and a decreasing trajectory. As discussed above, the dynamic structure of $\mathbf{y}$ does not affect the stability equivalent for $\delta = 1$, but as this parameter increases, $\tilde{y}_{se}$ is higher for the increasing case and lower for the decreasing trajectory. This example shows that the discounting function $\Delta(t)$ incorporates the dynamics of income streams into the evaluation framework.

[21]See Cowell and Cruces (2004) for a study of the effect of mean preserving spreads in individual perceptions of risk and inequality.

[22]For $\delta = 1$ and $T = 4$, $\Delta(t) = 0.25$ for all periods. For $\delta = 0.9$, the discounting weights are 0.21, 0.24, 0.26 and 0.29 (for $t = 1, 2, 3$ and 4 respectively); for $\delta = 0.5$, the weights are 0.07, 0.13, 0.27 and 0.53; and for $\delta = 0.1$, the weights are 0.001, 0.01, 0.09 and 0.90.

2.6 CONCLUSION

This Chapter has presented a framework for the evaluation of well-being based on panel data on household income. The methodology relies on an analogy with choice under uncertainty and the expected utility model to define a family of welfare-based indicators of well-being and variability over time. This is achieved by means of a two-step procedure, which involves aggregating vectors of observations over time for a household into a scalar and then studying the distribution of this aggregate.

The methodology was discussed in the context of alternative approaches, such as the transient-chronic poverty and measures of vulnerability. The evaluation framework differs from the latter in that its measures are money metric, and in that it explicitly recognises the ex-post nature of observed data, allowing the incorporation of the dynamic nature of income processes through time preferences. Moreover, an advantage of the proposed approach is its flexibility: the first step – the derivation of a summary measure of well-being over time – does not depend on an *ad hoc* statistical procedure but on an explicit normative evaluation function of past incomes. Finally, the researcher can choose the appropriate measure (poverty, inequality, etc.) for the analysis in the second step.

The empirical results from this Chapter indicated a relatively large negative effect of income fluctuations on household welfare in Argentina, assuming only moderate levels of variability aversion in line with most estimates of risk aversion in the uncertainty literature. Moreover, the large fluctuations of income over time had a significant negative effect on household welfare even during periods of aggregate growth.

The Conclusion to this Part (page 205) discusses some possible extensions to the evaluation framework by incorporating other principles beyond variability aversion. The following two Chapters shift the focus from the measurement of well-being and income fluctuations to the study of its main correlates: Chapters 3 and 4 use regression analysis to study the determinants of variations of the measures proposed in this Chapter.

CHAPTER 3

RISK ADJUSTED POVERTY IN ARGENTINA

3.1 INTRODUCTION

In the introduction to a pioneering volume on panel data on incomes, Cowell (1982) noted that these datasets "provide a unique opportunity" for the modelling of the instability of family well-being and the incidence of poverty, among other economic phenomena. Since then, ample evidence has been gathered showing that poor households have highly variable living standards, and are prone to suffering from adverse shocks. As suggested by Blundell and Preston (1998), if insurance markets were complete, households would be able to fully offset the impact of any shocks. While these perfect markets do not exist in advanced economies, the situation in developing countries is even worse since credit markets and social safety nets tend to be underdeveloped. Jalan and Ravallion (1999), for instance, find that household consumption is never fully insured against income variability in rural China, and that poorer households are not as well insured as others. Despite the importance of income risk in these processes, much of the literature concentrates on the impact of specific shocks or on movements into and out of poverty – see for instance Glewwe and Hall (1998), Dercon and Krishnan (2000), and Scott (2000), among others.

This Chapter does not rely on the analysis of insurance, shocks or poverty dynamics. Instead, it shares with Chapter 2 the aim of accounting for income variability in general, but it particularly focuses on the effects of risk on well-being. As Morduch (1994) notes, "while the economics of poverty and the economics of uncertainty are well developed, the nexus of issues at their intersection has been left relatively unexplored." This Chapter attempts to fill the void between the theories of poverty and uncertainty by following Morduch's (1994) proposal of measuring poverty in terms of the certainty equivalent of income, and develops a measure of income that reflects the disutility induced by risk. This modus operandi is similar in spirit to the model described by Cowell (1979), who defines the concept of lifetime income under uncertainty in a similar way.

This Chapter describes the empirical implementation of the certainty equivalent as a basis for adjusting incomes for risk, under the assumption that insurance and capital markets are imperfect and that individuals are risk averse. This methodology can be interpreted as a special case of the evaluation framework presented in Chapter 2 (Section 2.4, page 64). The main difference is that the discussion in the following pages relies explicitly on choice under uncertainty in the expected utility model by assuming that past observations of income for a household are representative of its future prospects.

The estimates of risk adjusted income are aggregated into risk adjusted poverty measures for the population. The procedure also allows to assess the determinants of risk adjusted income by means of regression analysis. Variations of this methodology were applied to risk adjusted measures of inequality by Makdissi and Wodon (2003), and extended to comparisons of long term relative deprivation between groups by Cruces et al. (2004).

This framework is illustrated with panel data on household income from the Greater Buenos Aires region for the period 1995-2002. The use of Argentine data is especially appropriate given the repeated shocks that have affected the country during the period, which resulted in large fluctuations in household income as described in Chapter 1. These can be interpreted as increases in the risk faced by households.

The rest of the Chapter is organized as follows. Section 3.2 presents the conceptual framework for the estimation of risk adjusted measures of income and poverty, and for the analysis of their determinants. Section 3.3 presents the empirical results using the Greater Buenos Aires panel. A brief conclusion follows.

3.2 Methodology

3.2.1 *Risk adjusted income*

The starting point of this methodology is the theory of choice under uncertainty in the expected utility model, discussed in Section 2.2 (page 52). A household's utility is represented by the function u, which is assumed to be differentiable, strictly increasing and strictly concave. The household faces uncertainty with respect to its future income, represented by the random variable $\hat{y}$. The distribution of $\hat{y}$ is given by S possible future states of the world, each characterised by a state-contingent income y_s and its probability τ_s. The household's expected utility is defined analogously to Equation 2.1 (page 53) as:

$$U = E[u(\hat{y})] = \sum_{s=1}^{S} \tau_s u(y_s) \tag{3.1}$$

where E is the expectations operator. To avoid the problems implied by the assumption of homogeneity of preferences in a population (see the discussion in Section 2.3, page 56), the functions U and u in this Chapter are defined within a social welfare context as representing the social judgment on the welfare value of the random variable $\hat{y}$ (Makdissi and Wodon, 2003).

As discussed in Section 2.2, the certainty equivalent income, $\tilde{y}_{ce}$, is the amount of income that, if received with certainty, would provide the same level of utility as the expected utility of $\hat{y}$ in Equation 3.1. With S possible states of nature, $\tilde{y}_{ce}$ can be implicitly defined as in Equation 2.3 (page 54):

$$u(\tilde{y}_{ce}) = \sum_{s=1}^{S} \tau_s u(y_s) \tag{3.2}$$

The certainty equivalent $\tilde{y}_{ce}$ depends on the shape of u, and it is a function of the random variable $\hat{y}$. Section 2.2 argued that $\tilde{y}_{ce}$ was better suited than the expectation of $\hat{y}$ as a measure of well-being, since the latter is by definition not affected by mean-preserving spreads in the distribution of $\hat{y}$, while the certainty equivalent is a decreasing function of $\hat{y}$'s dispersion. This desirable property for $\tilde{y}_{ce}$ reflects the principle of risk aversion, given in this framework by the assumed concavity of u.

The certainty equivalent $\tilde{y}_{ce}$ is determined by its underlying utility function u, and its properties as a measure of well-being depend entirely on those of u. The methodology presented in this Chapter relies on the Constant Relative Risk Aversion (CRRA) utility function, which is widely used in the risk literature and was discussed in the evaluation framework context in Section 2.5 (page 69). This function is increasing in its argument (reflecting non-satiation) and concave (reflecting risk aversion):

$$u(y) = \begin{cases} \frac{y^{1-\rho}}{1-\rho} & \text{if } \rho \neq 1 \\ \ln y & \text{if } \rho = 1 \end{cases} \tag{3.3}$$

The sensitivity parameter ρ represents the Arrow-Pratt measure of relative risk aversion for this function, which is constant for all values of y. This property is the main reason for the widespread use of the isoelastic formulation in the economics of risk: as discussed in Section 2.5, its implication in terms of the tolerable degree of risk at different levels of income is intuitively sound and empirically plausible (Browning and Lusardi, 1996). It can be argued that other formulations might better capture risk aversion at certain points in the distribution: a constant absolute risk aversion formulation, for instance, might be better suited for the limited range of income between zero and the poverty line. However, the purpose of this Chapter is to derive risk adjusted measures of income for all levels, and the CRRA formulation results in a parsimonious representation of utility along the income distribution.

3.2.2 *Identifying assumption and risk adjusted poverty measures*

The previous discussion highlighted the relevance of a CRRA utility function for the certainty equivalent income $\tilde{y}_{ce}$ as a measure of income adjusted for the disutility of risk. The elements of Equations 3.1 and 3.2, however, are inherently unobservable, and thus neither cross section nor panel data can be used for their empirical implementation without further assumptions on the nature of the underlying data generating process.

Some studies based on cross section data rely on the assumption that a household's distribution of future states of nature can be inferred from the observed distribution for the whole population (Elbers and Gunning, 2003; Ligon and Schechter, 2004, discuss alternative assumptions employed in the literature). Following Makdissi and Wodon (2003), Cruces et al. (2004)

and Ligon and Schechter (2003), the methodology presented in this Chapter relies on an operational version of Equation 3.1 derived from a stationarity identifying assumption, which is only possible to make when repeated observations are available for every unit. The stationarity assumption exploits the panel dimension of the data, allowing for heterogeneity between households. The identification relies on the assumption that the underlying income process for each household is stable: the probability distribution of income for a household – the distribution of $\hat{y}$ – is identical at every point in time. Every past observation represents a typical outcome for the household, and its past experience can be extrapolated to represent the distribution of prospects at any future period (Ligon and Schechter, 2004).

Under stationarity, the series of observed past incomes for a household i, $\mathbf{y}_i = [y_{i1}, ..., y_{iT}]$, represents a set of equally probable draws from the distribution of possible incomes for i. It is thus an empirical distribution of $\hat{y}_i$, where each y_{it} in $\mathbf{y}_i$ is a possible state of the world y_s in Equations 3.1 and 3.2, with associated probability $\tau_s = 1/T$.

The certainty equivalent income for a household i can then be represented in terms of observed quantities – i's stream of past incomes $\mathbf{y}_i$ – as:

$$u(\tilde{y}_{ce_i}) = \tfrac{1}{T} \sum_{t=1}^{T} u(y_{it}) \tag{3.4}$$

A common practice in the risk literature (see, for instance, Newbery and Stiglitz, 1981a) is to use a Taylor approximation for the certainty equivalent implicitly defined in Equation 3.4, given by:

$$\tilde{y}_{ce_i} \approx \bar{y}_i - \tfrac{1}{2} R_A(\rho) \sigma^2_{y_i} \tag{3.5}$$

where $\bar{y}_i$ is i's mean income over the whole period under consideration, $\sigma^2_{y_i}$ its variance and $R_A(\rho)$ is the Arrow-Pratt measure of absolute risk aversion, equal to $\frac{\rho}{\bar{y}_i}$ for the CRRA formulation. The problem with the Taylor approximation is that it is only valid for small levels of risks (Pratt, 1964), and thus is likely to produce biased results for high values of ρ. Given the analytical convenience of the isoelastic CRRA formulation, this Chapter relies on the exact measure of risk adjusted income implied by Equations 3.3 and 3.4, which is a function of ρ and is equal to:

$$\tilde{y}_{ce_i}(\rho) = \begin{cases} \left[\frac{1}{T}\sum_{t=1}^{T} y_{it}^{1-\rho}\right]^{\frac{1}{1-\rho}} & \text{if } \rho \neq 1 \\ y_i = \prod_{t=1}^{T} y_{it}^{1/T} & \text{if } \rho = 1 \end{cases} \tag{3.6}$$

It is evident that the formulation of the certainty equivalent in Equation 3.6 is identical to the stability equivalent with a constant variability aversion evaluation function given in Equation 2.15 (page 70). This derives from the stationarity assumption, which expresses the general formulation of $\tilde{y}_{ce}$ in Equation 3.2 in terms of observed quantities in Equation 3.4. The latter is observationally equivalent to Equation 2.7 (page 60) with no discounting ($\Delta(t) = 1/T$), despite the conceptual differences between the two discussed in Section 2.2: while one estimates the effects of ex-ante risk, the other captures the negative impact of ex-post fluctuations. As noted in Chapter 2 (Section 2.4), alternative approaches sometimes result in the same type of empirical implementations when they are based on the same observed incomes $\mathbf{y}$.

The definition of the certainty equivalent income in Equation 3.6 provides a straightforward way of implementing risk adjusted poverty measures: $\tilde{y}_{ce}$ is a money metric of well-being, and thus represents a risk adjusted measure of income. The components of $\mathbf{y}_i$ are given by the equivalised and normalised incomes y_{it} of Equation 1.3 (page 27), so that households with $y_{it} < 1$ are considered poor at time t. Instead of focusing on this static condition, the methodology presented in this Chapter relies on the distribution of certainty equivalents $\tilde{y}_{ce}$ to define risk adjusted measures of poverty.

These measures are modified versions of the additive poverty indices of the FGT class defined in Equation 1.6 (page 35), and rely on the FGT evaluated at the risk adjusted incomes $\tilde{y}_{ce}$. The new class of indices is thus implicitly a function of the distribution of the vectors $\mathbf{y}$ and of the risk aversion parameter ρ:

$$FGT_{RA}(\mathbf{y}, \rho, \alpha) = \frac{1}{N}\sum_{i=1}^{N} \left[\max(1 - \tilde{y}_{ce_i}, 0)\right]^{\alpha} \tag{3.7}$$

where N is the total number of households and α can be interpreted as a sensitivity parameter to the depth of poverty: with $\alpha = 0$, Equation 3.7 defines a risk adjusted headcount, and $\alpha = 1$ and $\alpha = 2$ define the risk adjusted poverty gap and squared poverty gap respectively. The special case of $\rho = 0$ corresponds to the FGT measure evaluated at the mean of each household's income over time, $FGT(\bar{y}, \alpha) = \frac{1}{N}\sum_{i=1}^{N}[\max(1-\bar{y}_i, 0)]^{\alpha}$.

The measures defined in Equation 3.7 can be compared to Jalan and Ravallion's (1998) transient-chronic poverty decomposition, covered in Section 2.4 and applied to the Greater Buenos Aires panel in the next Chapter. A virtue of this decomposition is that it presents the contribution of income variability to an overall measure of poverty, while the risk adjusted measure of poverty based on the certainty equivalent of income seems to merge the level and variability of income into one measure. However, a comparison between risk adjusted poverty with $\rho = 0$ (corresponding to $FGT(\bar{y}, \alpha)$) and $\rho > 0$ allows an analysis which is similar in spirit to Jalan and Ravallion's (1998). This comparison captures the degree of poverty that is due to income risk and, as argued in Section 2.4 for the stability adjusted measures, the parameter ρ in the risk adjusted methodology allows for an extra degree of freedom over the transient-chronic approach.

Another characteristic of the risk adjusted poverty measures is their sensitivity to fluctuations around the poverty line. With standard poverty measurement procedures, a household with income just above the poverty line during the T periods in which it is observed would not be considered poor. However, the risk aversion implicit in $\tilde{y}_{ce}$ means that the same household may have a positive value of risk adjusted poverty if there is enough variation in income. Thus, even with an average just above the poverty line, the adjustment for risk might result in $\tilde{y}_{ce} < 1$ for some value of ρ.

Finally, a potential problem arising from the use of panel data is that a trend in income over time may be interpreted as risk, since it leads to fluctuations in y_{it} if incomes are not normalised (for instance, by the contemporaneous population mean) to neutralise the effect of a common trend. Moreover, this could invalidate the stationarity assumption, although it is possible to assume stationarity of normalised incomes. Cruces et al. (2004) discuss these issues in the context of a nine-year panel from the United Kingdom, where the use of relative poverty measures corrects the impact of growth in household income. In the present application to the GBA panel, however, this is not much of an issue since each cohort spans a relatively short period of 1.5 years, and as discussed in Chapter 1 there is no uniform trend in household income over the whole period.

3.2.3 Determinants of risk and risk adjusted income

Besides the estimation of risk adjusted measures of poverty, the derivation of the certainty equivalent from observed data allows to study its main determinants and the correlates of risk. Poverty profiles are usually based on the effect of different individual and household characteristics on the probability of being poor, obtained by linear regression with the adult equivalent income (or its logarithm) as the dependent variable. It is then possible to infer the probability of being poor while avoiding the specification problems that occur with probits and logits (Ravallion and Wodon, 1999).

The approach in this Chapter is similar, using the logarithm of the risk adjusted income as the dependent variable in the regressions. Denoting by X_i the vector of characteristics for a household i, and by $\bar{y}_i$ its mean income over time, a comparison of the effect of the components of X_i on average and risk adjusted incomes can be estimated by means of the following system:

$$\begin{aligned} \log \bar{y}_i &= X_i'\beta + \varepsilon_i \\ \log \tilde{y}_{ce_i} &= X_i'\beta_{RA} + \varepsilon_{RA_i} \end{aligned} \tag{3.8}$$

where ε_i and ε_{RA_i} are regression error terms, and X_i contains a constant. Differences in the parameters in β and β_{RA} can be interpreted as differential impacts of the underlying variables on well-being as captured by $\bar{y}$ and $\tilde{y}_{ce}$.

While these two regressions could be estimated independently by Ordinary Least Squares (OLS), the analysis presented in the following Section exploits the theoretical relation between expected income and the certainty equivalent, and estimates the two equations jointly by means of Seemingly Unrelated Regression (SUR) techniques. The insight arises from the definition of the risk premium in choice under uncertainty, given by $\pi_r = \bar{y} - \tilde{y}$, which represents a measure of the impact of risk on well-being – see the discussion of the variability premium π_v (Equation 2.8, page 61), the counterpart of π_r in the evaluation framework, in Section 2.3. The difference of the logs of average and risk adjusted incomes can be interpreted as a "logarithmic" version of the risk premium.

Since the same set of independent variables X_i are used in the two regressions in Equation 3.8, SUR provides the same coefficients β and β_{RA} as OLS. The advantage of using SUR to estimate the system of Equation 3.8 is that it allows for a formal test for the difference in coefficient estimates between the two regressions, $\beta - \beta_{RA}$. Moreover, since the Equations in 3.8 are linear, the estimation of the system is analogous to a regression with the "logarithmic" risk premium as the dependent variable:

$$\log \bar{y}_i - \log \tilde{y}_{ce_i} = X_i'\beta_{RP} + \varepsilon_{RP_i} \tag{3.9}$$

where $\beta_{RP} = \beta - \beta_{RA}$. Testing for differences in the coefficients estimated by SUR is equivalent to testing for the statistical significance of the β_{RP} parameters in the risk premium regression defined in Equation 3.9. The advantage over computing Equation 3.9 directly is that by definition $0 \leq \tilde{y}/\bar{y} \leq 1$, which implies that the error term in Equation 3.9 might not have a normally distributed error term.

The individual regressions in Equation 3.8 provide an assessment of the effect of each characteristic on average and risk adjusted incomes, while the SUR test of differences in coefficients reveals the impact of these characteristics on the risk faced by the household. A positive and statistically significant value of $\beta - \beta_{RA}$ implies that the related independent variable contributes to an increase in the "logarithmic" risk premium. This provides a straightforward interpretation of the impact of various variables on income and risk: characteristics with a positive value of $\beta - \beta_{RA}$ are associated with higher risk and with a lower level of utility.

3.3 Risk Adjusted Poverty: Aggregates and Determinants

3.3.1 *Descriptive results*

The risk adjusted framework described in the previous Section can be applied to the study of poverty in Argentina using the EPH data. This Section exploits the longitudinal dimension of the survey with the Greater Buenos Aires rotating panel, described at length in Section 1.2 (page 22). The applications are based on the fifteen waves corresponding to the period May

1995-May 2002, which result in twelve cohorts as illustrated in Table 1.2 (page 61). Each cohort represents a group of households that are observed over the same four waves: all observations in a cohort start at the same wave and span the same period, and they are indicated by the waves they follow (99-2 to 01-1, for instance, means that the cohort covers from the second (i.e., October) wave of the EPH in 1999 until the first wave (i.e., May) of 2001).

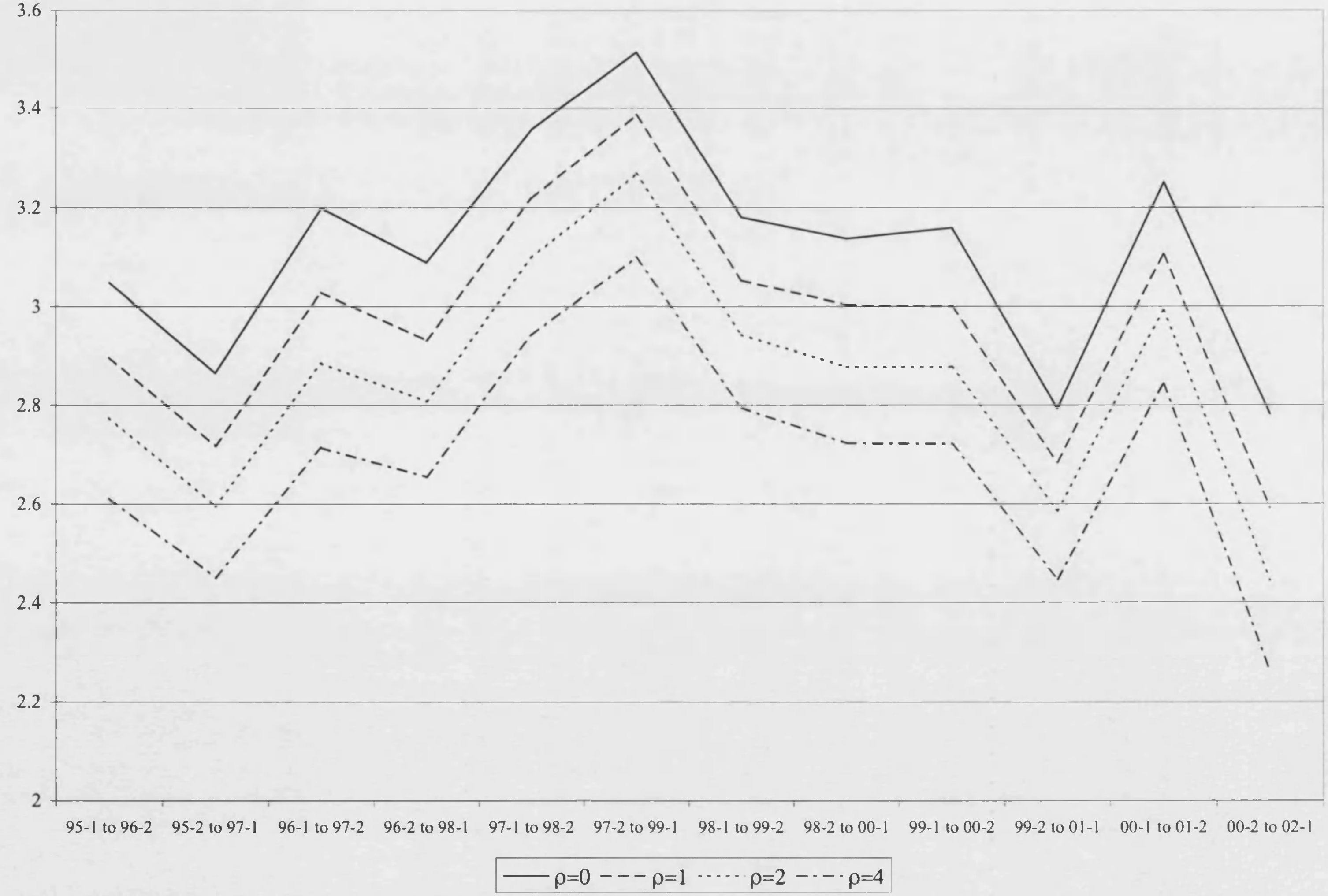
As discussed in Section 1.2, some aggregates of household income are equal to zero but still considered valid by INDEC. Of almost 5,500 households in the final panel sample, only two reported zero incomes in all four waves, and just 1 percent of the 21,788 observations of income were equal to zero. To minimize the loss of potentially important observations, the cases with valid zeroes were assigned a token value of 1 percent of the poverty line in the analysis. This correction is necessary for computational reasons, since $\tilde{y}_{ce}$ is not defined for $y_{it} = 0$ with $\rho > 1$ (Equation 3.6). The poverty measures presented below are virtually unaffected by this procedure since the focus in this Section is on the headcount index.[1]

Figure 3.1 presents the sample average by cohort of the risk adjusted income $\tilde{y}_{ce}$ of Equation 3.6 for $\rho = 0, 1, 2,$ and 4. The value corresponding to $\rho = 0$ represents the average of the normalised adult equivalent income, defined in Equation 1.3 – the unit of the Figure is thus the contemporaneous poverty line.

The evolution of risk adjusted income by cohort is similar to that of equivalent real income by wave (Figure 1.3, page 30) and of variability adjusted measures for different evaluation functions (Figure 2.6, page 74). The downward trend between the first two cohorts reflects the negative effect of the contagion from the Mexican crisis of 1995, while the recovery from this crisis explains the upward tendency for the following four cohorts. From the peak of the 97-2/99-1 cohort, the trend is almost continuously negative due to the prolonged recession of 1999-2001, and devaluation and subsequent crisis of 2002. The increase between the 99-2/01-1 and 00-1/01-2 corresponds to the slight slowdown of the downward trend in GDP and employment between 1999 and 2000 depicted in Figures 1.2 and 1.3 – see Section 1.1 (page 74) for

[1]The results of this Section are robust to alternative token values in the 0.25-1.5 percent range. Since the lowest value of y_{it} for $y_{it} > 0$ is 1.5 percent of the poverty line, the token value of 1 percent ensures the presence of strictly positive incomes without affecting the ranking of households in the income distribution.

Figure 3.1: Risk Adjusted Normalised Income by Cohort, Greater Buenos Aires, 1995-2002



Source: Author's estimations based on EPH household survey data (INDEC).

a summary of the key economic events of the period.

The differences between the risk adjusted incomes with $\rho = 0, 1, 2$, and 4 in Figure 3.1 contain valuable information about the risk faced by households in this period. The ordering of the series is due to the fact that $\tilde{y}_{ce}$ is decreasing in ρ (Equation 3.6). It can be noted that each extra "unit" of ρ implies a reduction in the average of $\tilde{y}_{ce}$ of 10 to 20 percent of the poverty line. These differences are not constant, which indicates the varying level of risk for different cohorts. For instance, the difference between incomes with $\rho = 0$ and $\rho = 4$ are constant at around 40 percent of the poverty line for most cohorts, but in the last one – corresponding to the 2001-2002 crisis and arguably the one with largest fluctuations in income – this difference increases to more than 50 percent of the poverty line.

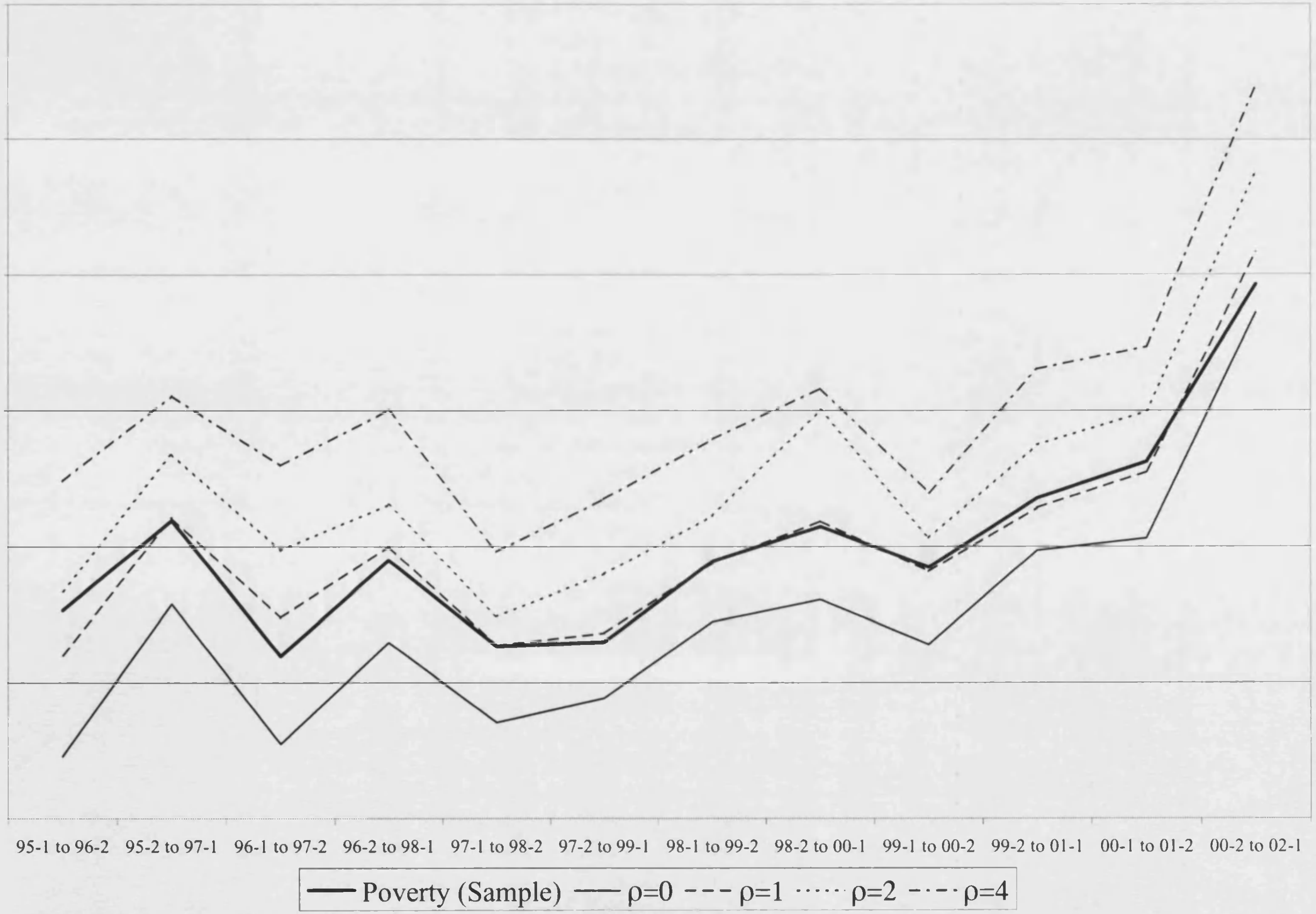
Figure 3.2 presents the share of the population with risk adjusted incomes below the poverty line, corresponding to the FGT_{RA} measure with $\alpha = 0$ (Equation 3.7) based on the incomes presented in Figure 3.1.[2] The risk adjusted headcount is computed for $\rho = 0, 1, 2$, and 4, with $\rho = 0$ representing the measure based on average income over time. Moreover, Figure 3.2 presents the headcount computed for each cohort by pooling – but not averaging – the four observations available for each household, which can be combined since incomes y_{it} are normalised by their contemporaneous poverty lines.[3]

The first fact that stands out from Figure 3.2 is the difference between the cross-sectional measure (bold line) and the risk adjusted panel-based estimates: the use of the mean income ($\rho = 0$) reduces the headcount by about 5 percentage points with respect to the pooled sample estimate. This is due to the "smoothing" effect: poverty measures based on average income over time are lower than the cross-sectional figures because the averaging reduces the effect of transitory income shocks, which is not apparent

[2]The analysis in this Section concentrates on the headcount to emphasize the importance of changes in income around the poverty line. For the sensitivity of the "depth" of poverty based on the certainty equivalent, it should be noted that Figure 2.7 (page 77) can be interpreted as presenting the risk adjusted squared poverty gap ($\alpha = 2$ in Equation 3.7).

[3]A simple example with two households and two periods of time may clarify the setting. The two households have observed streams of y_{it} given by $\mathbf{y}_1 = [y_{11}, y_{12}]$ and $\mathbf{y}_2 = [y_{21}, y_{21}]$. These observations are used to compute the averages $\bar{y}_1$ and $\bar{y}_2$, and the risk adjusted measures $\tilde{y}_{ce_1}(\rho)$ and $\tilde{y}_{ce_2}(\rho)$. Figure 3.2 presents poverty measures based on $\bar{y}$ and $\tilde{y}_{ce}$, but also on the cross-sectional use of the panel, which implies computing the FGT measure of Equation 1.6 over the pooled incomes $[y_{11}, y_{12}, y_{21}, y_{21}]$.

Figure 3.2: Risk Adjusted Measures of Poverty by Cohort, Greater Buenos Aires, 1995-2002



Author's estimations based on EPH household survey data (INDEC).

in Figure 3.1.[4] While this "smoothing" effect is well known in the distributional literature (Shorrocks, 1978), the interesting feature in the Figure is the subsequent increase in the poverty measures from $\rho = 0$ (based on average income) to $\rho > 0$: the introduction of risk aversion increases poverty substantially, with the "smoothing" effect practically neutralised with $\rho = 1$. Risk adjusted poverty headcounts with $\rho = 2$ and $\rho = 4$ are consistently greater than those based on the pooled sample.

In terms of general trends, the evolution of the poverty headcounts in Figure 3.2 mirrors that of the risk adjusted incomes in Figure 3.1, with rates varying between 12-23 percent (for $\rho = 0$ and 4, respectively) for the first cohort up to a high 29-37 percent (for $\rho = 0$ and 4) for the last one. As for income, however, the impact of changes in ρ differs markedly between cohorts. For instance, for the 96-2/98-1 cohort the difference between the headcount with $\rho = 1$ and the headcount with $\rho = 2$ is relatively small, while the difference between measures with $\rho = 2$ and $\rho = 4$ is large. For the 98-2/01-1 cohort, in turn, the latter is much smaller than the period's average. The sensitivity of the headcounts to the values of ρ reflects the concentration of incomes around the poverty line: some values of ρ imply large falls in risk adjusted income, which makes a substantial number of households become poor. Finally, it can be noted that the large fall in income for the last cohort implies that the "smoothing" effect almost disappears, with the difference between the pooled sample and the headcount based on average income reduced to less than one percentage point, compared to 3 to 5 points over the period.

3.3.2 *Regression analysis*

This Section complements the analysis of trends in risk adjusted incomes and poverty by implementing the regressions defined in Equation 3.8. The aim is to establish the determinants of average and risk adjusted income, and to study which household characteristics are associated with larger or smaller effects of risk on well-being.

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[4] By definition, the average of the pooled observations of y_{it} in a cohort and the average of $\bar{y}_i$ (the average of y_{it} for households in the same cohort) are equal, given the linearity of the expectation operator. In the example of the previous footnote, the average of $[y_{11}, y_{12}, y_{21}, y_{21}]$ is equal to the average of $[\bar{y}_1, \bar{y}_2]$. This is not necessarily true for other functions of $\mathbf{y}$, for instance for the *FGT* measures.

As discussed in the previous Section, the system of Equation 3.8 is estimated by SUR, with the logs of $\bar{y}_i$ and $\tilde{y}_{ce_i}$ as the dependent variables of each regression. The twelve cohorts are pooled for the regressions, resulting in a dataset of 5,446 observations (each derived from four values of y_{it} per household).

The independent variables X_i are: (a) household level variables, including the number of infants, children, youths, adults, and elderly household members, and the square of their values; whether the household head has a spouse; (b) characteristics of the household head, including gender; the age of the head and its square; migration status in the last five years; level of education (where the omitted category is incomplete primary or no formal education); whether he/she is unemployed or inactive (with employed as the omitted category); whether he/she is an employer, a self-employed worker, an informal worker,[5] or a wage earner (omitted); the type of qualification (omitting the no qualification category);[6] and whether he/she works in the public sector; and (c) the same set of characteristics for the spouse of the household head, when there is one. All these variables correspond to the initial conditions, that is, the values at the first observation in the cohort for each household. In addition, the regressions include controls for each of the cohorts, excluding the first one: given the degree of macroeconomic volatility over the 1995-2002 period, each cohort has been affected by different aggregate shocks, and these controls aim to capture their effects.

Table 3.1 provides summary statistics of the variables used in the estimation. The sample mean for the logarithm of average income over time is 0.754 (corresponding to 2.13 times the poverty line), while the average logarithm of risk adjusted income with $\rho = 2$ is 0.549 (corresponding to 1.73 times the poverty line). This suggests that assuming $\rho = 2$ as the coefficient for risk aversion results in a fall with respect to average income of almost 20

[5]There are several characterizations of informality in the literature – see Moreno and Roca (2002) for the discussion of alternatives in the Argentine case. The definition employed in this Chapter corresponds broadly to the International Labour Organization's recommendations: a worker is "informal" if he or she is non-professional and either self employed or a wage earner in a small firm (less than five employees), or working without a wage.

[6]Education and qualification measures might appear to be highly collinear. The correlation matrix, however, indicates a relatively low level of 0.46 between professional qualifications and higher education, with all other coefficients being lower. The results are not substantially affected by removing either group of variables from the regression.

Table 3.1: Summary Statistics for the Dependent and Independent Variables, Risk Adjusted Income Regressions

Variable	Mean	Std. Dev.	Min	Max
Log of Average Income (ρ=0)	0.754	0.844	-4.610	3.951
Log of Risk Adjusted Income, ρ=0.5	0.720	0.866	-4.605	3.946
Log of Risk Adjusted Income, ρ=1	0.669	0.921	-4.605	3.942
Log of Risk Adjusted Income, ρ=2	0.549	1.129	-4.605	3.933
Log of Risk Adjusted Income, ρ=4	0.441	1.251	-4.605	3.915
Number of infants (ages 0-5)	0.349	0.693	0	6
Number of children (ages 6-14)	0.543	0.922	0	8
Number of youths (ages 15-24)	0.586	0.907	0	6
Number of adults (ages 25-64)	1.552	0.940	0	6
Number of elderly (ages 65+)	0.395	0.677	0	4
Age of the head	51.002	16.061	15	96
Share of female headed households	0.242	0.428	0	1
Head is recent migrant	0.026	0.159	0	1
Head inactive	0.279	0.449	0	1
Head unemployed	0.069	0.254	0	1
Head: employer	0.032	0.177	0	1
Head: self-employed	0.143	0.351	0	1
Head: informal worker	0.232	0.422	0	1
Head in public sector	0.082	0.274	0	1
Head: operative (qualification)	0.350	0.477	0	1
Head: technical worker (qualification)	0.112	0.315	0	1
Head: professional worker (qualification)	0.068	0.252	0	1
Head with primary education - Complete	0.345	0.475	0	1
Head with secondary education - Incomplete	0.177	0.382	0	1
Head with secondary education - Complete	0.143	0.350	0	1
Head with further education - Incomplete	0.008	0.090	0	1
Head with further education - Complete	0.026	0.158	0	1
Head with university education	0.146	0.353	0	1
No spouse in the household	0.306	0.461	0	1
Spouse inactive	0.418	0.493	0	1
Spouse unemployed	0.048	0.215	0	1
Spouse: employer	0.007	0.081	0	1
Spouse: self-employed	0.056	0.229	0	1
Spouse: informal worker	0.103	0.303	0	1
Spouse: operative (qualification)	0.066	0.249	0	1
Spouse: technical worker (qualification)	0.050	0.218	0	1
Spouse: professional worker (qualification)	0.026	0.159	0	1
Spouse in public sector	0.044	0.206	0	1
Spouse with primary education - Complete	0.252	0.434	0	1
Spouse with secondary education - Incomplete	0.115	0.319	0	1
Spouse with secondary education - Complete	0.119	0.324	0	1
Spouse with superior education - Incomplete	0.010	0.097	0	1
Spouse with superior education - Complete	0.034	0.182	0	1
Spouse with university education	0.071	0.257	0	1

Source: Author's estimations based on EPH household survey data (INDEC).

percent. The interpretation of the other variables presented in Table 3.1 is straightforward: most of them are indicators, and so their means represent the share of the sample with these characteristics.

The dependent variable $\tilde{y}_{ce}$ is a function of the constant risk aversion parameter ρ. Arrow (1970) argues on theoretical grounds that ρ should be around 1, which is consistent with the results of Chetty (2003) based on labour supply. However, Friend and Blume (1975) present empirical evidence based on portfolio holdings that the coefficient may be around 2, Hildreth and Knowles (1982) obtain estimates between 1 and 2, and in a review of the literature Cowell and Gardiner (2000) indicate a range of values from 0.5 to 4 depending on the type of evidence. To allow for a sizeable effect of risk, the regressions presented in Table 3.2 are based on $\tilde{y}_{ce}$ computed with $\rho = 2$, which is within the boundaries in the literature. This value is used in other empirical applications based on the CRRA utility function (Ligon and Schechter, 2003). A robustness check of the regression results for alternative values of ρ is discussed below.

Table 3.2 presents the results of the regression analysis of the system of Equation 3.8 by SUR in the first two columns, and the tests for statistically significant differences in the parameter estimates of the two models in the third column, which corresponds to Equation 3.9.

The first column of the table corresponds to the logarithm of mean income over time ($\rho = 0$). The results are fairly intuitive. Larger households (whether having more infants, children, or adults) tend to have lower values of average income, but the impact is decreasing at the margin. In the case of elderly members, the impact on average income is not statistically significant, although part of its effect may be captured by the inactivity indicators for the household head or spouse, which have negative coefficients. Households with older and/or female heads tend to have higher incomes, although the coefficient on female heads is only significant at the 10 percent level. There seems to be no statistically significant impact from the migrant status of the head.

The fact that the head or its spouse are inactive or unemployed is associated with lower average income. The status of either of them as an employer or a self-employed worker does not have a statistically significant impact on average income, although the signs of the coefficients are posi-

Table 3.2: Determinants of Log Average Income and Log Risk Adjusted Income

	Log average income [1]	Log risk-adjusted income [2]	Difference [1]-[2] and P-value
Household characteristics			
Number of infants (ages 0-5)	-0.272	-0.297	0.024
	[0.02661]***	[0.04225]***	0.378
Number of infants squared	0.028	0.030	-0.002
	[0.01007]***	[0.01600]*	0.819
Number of children (ages 6-14)	-0.374	-0.365	-0.009
	[0.01826]***	[0.02899]***	0.640
Number of children squared	0.040	0.034	0.006
	[0.00539]***	[0.00855]***	0.258
Number of youths (ages 15-24)	-0.209	-0.187	-0.023
	[0.01913]***	[0.03038]***	0.251
Number of youths squared	0.038	0.042	-0.004
	[0.00630]***	[0.01000]***	0.521
Number of adults (ages 25-64)	-0.096	-0.085	-0.011
	[0.02706]***	[0.04295]**	0.695
Number of adults squared	0.023	0.027	-0.004
	[0.00642]***	[0.01019]***	0.559
Number of elderly members (ages 65+)	0.016	0.115	-0.099
	[0.03901]	[0.06194]*	0.014 **
Number of elderly members, squared	-0.021	-0.039	0.018
	[0.01667]	[0.02646]	0.293
No spouse in the household	0.103	0.059	0.044
	[0.05138]**	[0.08157]	0.402
Characteristics of the head			
Age	0.007	0.009	-0.002
	[0.00355]**	[0.00563]*	0.570
Age squared	0.000	0.000	0.000
	[0.00004]	[0.00006]	0.998
Female head	0.051	0.079	-0.028
	[0.02658]*	[0.04219]*	0.312
Recent migrant	-0.010	-0.098	0.089
	[0.04660]	[0.07398]	0.065 *
Inactive	-0.134	-0.157	0.022
	[0.04082]***	[0.05242]***	0.512
Unemployed	-0.440	-0.866	0.426
	[0.05073]***	[0.05790]***	0.000 ***
Employer	0.071	0.020	0.051
	[0.04619]	[0.07333]	0.287
Self-employed	-0.051	0.047	-0.098
	[0.02762]	[0.04386]	0.401
Informal Worker	-0.147	-0.224	0.077
	[0.02540]***	[0.04032]***	0.003 ***
Public Sector Worker	-0.063	-0.035	-0.028
	[0.02927]**	[0.04646]	0.350
Job Qualification: Operative	0.121	0.158	-0.037
	[0.03997]	[0.03914]***	0.143
Job Qualification: Technical	0.336	0.372	-0.036
	[0.05132]	[0.05480]***	0.315
Job Qualification: Professional	0.244	0.698	-0.454
	[0.04329]***	[0.06873]***	0.424
Primary Education – Complete	0.156	0.196	-0.039
	[0.02288]***	[0.03632]***	0.096 *
Secondary Education - Incomplete	0.319	0.345	-0.027
	[0.02705]***	[0.04294]***	0.341
Secondary Education - Complete	0.534	0.604	-0.070
	[0.03460]***	[0.04670]***	0.021 **
Further Education – Incomplete	0.217	0.976	-0.759
	[0.08275]***	[0.13137]***	0.009 ***
Further Education – Complete	0.731	0.833	-0.103
	[0.05243]***	[0.08285]***	0.056 *
University Education	0.423	0.847	-0.423
	[0.04477]***	[0.05398]***	0.049 **

(continued)	Log Income [1]	Log risk-adjusted income [2]	Difference [1]-[2] and P-value
Characteristics of the spouse			
Inactive	-0.244	-0.331	0.087
	[0.03302]***	[0.06480]***	0.040 **
Unemployed	-0.355	-0.543	0.187
	[0.03647]***	[0.08053]***	0.000 ***
Employer	-0.044	-0.126	0.082
	[0.09697]	[0.15395]	0.413
Self-employed	0.024	-0.071	0.095
	[0.04175]	[0.06629]	0.636
Informal Worker	-0.097	-0.122	0.025
	[0.04289]**	[0.06810]*	0.568
Job Qualification: Operative	0.052	0.024	0.028
	[0.02465]***	[0.06347]	0.496
Job Qualification: Technical	0.075	0.090	-0.015
	[0.03452]***	[0.08147]	0.770
Job Qualification: Professional	0.662	0.244	0.418
	[0.06642]***	[0.10545]**	0.996
Public Sector Worker	-0.017	-0.027	0.011
	[0.04416]	[0.07011]	0.816
Primary Education - Complete	0.152	0.207	-0.056
	[0.02857]***	[0.04535]***	0.060 *
Secondary Education - Incomplete	0.229	0.306	-0.076
	[0.03370]***	[0.05351]***	0.028 **
Secondary Education - Complete	0.313	0.425	-0.112
	[0.02942]***	[0.05492]***	0.002 ***
Further Education - Incomplete	0.754	0.177	0.578
	[0.07953]***	[0.12627]	0.625
Further Education - Complete	0.371	0.477	-0.106
	[0.05219]***	[0.08323]***	0.051 *
University Education	0.777	0.517	0.260
	[0.03400]***	[0.07107]***	0.042 **
Cohort controls			
95-2 to 97-1	-0.038	-0.083	0.046
	[0.03653]	[0.05800]	0.226
96-1 to 97-2	-0.013	-0.084	0.071
	[0.03672]	[0.05829]	0.062 *
96-2 to 98-1	-0.003	-0.042	0.039
	[0.03615]	[0.05739]	0.297
97-1 to 98-2	0.034	0.008	0.025
	[0.03606]	[0.05725]	0.494
97-2 to 99-1	0.021	0.026	-0.004
	[0.03559]	[0.05651]	0.904
98-1 to 99-2	-0.043	-0.070	0.027
	[0.03549]	[0.05634]	0.459
98-2 to 00-1	-0.028	-0.037	0.010
	[0.03579]	[0.05682]	0.797
99-1 to 00-2	-0.022	-0.031	0.008
	[0.03575]	[0.05675]	0.819
99-2 to 01-1	-0.107	-0.108	0.001
	[0.03670]***	[0.05826]*	0.975
00-1 to 01-2	-0.115	-0.127	0.012
	[0.03635]***	[0.05770]**	0.748
00-2 to 02-1	-0.164	-0.316	0.152
	[0.03723]***	[0.05911]***	0.000 ***
Constant	0.424	0.080	
	[0.09885]***	[0.15693]	
Observations	5446	5446	

Standard errors in brackets (significant: * at 10%; ** at 5%; *** at 1%)
P-Value of the test below the difference for the fourth column.
Source: Author's estimations based on EPH household survey data (INDEC).

tive as expected since the excluded category is wage earner. However, part of the impact of being self-employed – for those with no professional qualifications – is reflected by the negative and statistically significant coefficient for the informal worker indicator for both the head and the spouse.

A higher job qualification of the head (at the professional level) or the spouse (at each of the three levels considered) have a positive impact on the average income of the household, as do the education levels of the head and the spouse, with higher levels of education implying progressively higher household income. Being in the public sector reduces expected income in the case of the head, although for the spouse the impact is also negative but not statistically significant. Finally, only the three cohorts covering the period October 1999-May 2002 are associated with statistically significant and negative coefficients, reflecting the progressive deepening of the recession and the subsequent crisis.

The data confirms the stylised facts that richer households are smaller, better-educated, and have employed heads or spouses in better jobs. The parameters obtained in the second column of Table 3.2 correspond to the regression with risk adjusted income as the dependent variable, and it is easy to notice that most of the results from the first column still apply. The most interesting results of Table 3.2, however, are related to the impact (or the lack of impact) of the same independent variables on the risk faced by the household, and thus the discussion focuses on the tests of differences obtained by the estimation of the system by SUR.

The third column of Table 3.2 presents the tests of statistical significance for the differences in the coefficients of the two regressions. If the difference is not significantly different from zero, it can be interpreted that the associated independent variable has the same effect (or lack of effect) in both mean and risk adjusted incomes, and thus no discernible correlation with risk. However, a significant difference implies that the independent variable has a differential effect on the two dependent variables, or, in other words, it has an effect on risk. As explained in the previous Section, the SUR test can also be interpreted as a regression with the "logarithmic" risk premium as the dependent variable (Equation 3.9). In that context, a negative value of $\beta - \beta_{RA}$ represents a negative effect of a variable on the risk premium, which is associated with lower risk, while a positive value implies a higher risk premium.

Only a subset of the variables in X_i has a significant effect on risk. Regarding the structure of the household, only the presence of adults aged 65 and over significantly affects the household's level of risk in a negative way. This can be explained by the fact that the elderly often receive a steady stream of income from pensions (Fiszbein et al., 2002), and consequently experience less income variability – and face lower income risk – than other age groups.

While there is no statistically significant impact of the age or gender of the head on risk, other characteristics do have an effect. If the head has migrated to the GBA region (from other provinces in Argentina or from other countries) in the last five years, the household suffers more from risk. Interestingly, the same indicator was found to have no statistically significant impact on average income after controlling for human capital and other characteristics. This result implies that recent migrants are more exposed to income risk than non-migrants.

For both the head and the spouse, being unemployed contributes to risk over and above the negative effect of this characteristic on average income. The same is true for the informality of the head in the current job, or in the previous job if unemployed. Most importantly, a higher level of education has a negative impact on the risk faced by the household: the less-educated suffer not only from a lower average income, but also from higher levels of risk.

Finally, two cohort indicators signal a positive effect on risk. This is the case for the last cohort, which is not surprising given the large fall in real incomes induced by the crisis of 2001-2002 (see Figure 1.3). The cohort covering the period 1996-1997 also indicates a higher level of risk, which may be due to the variability in incomes induced by the aftermath of the 1994-1995 crisis and the subsequent recovery.

The regressions in Table 3.2 are based on risk adjusted income with $\rho = 2$ since, as discussed above, this value was found to be reasonable and within the range employed in the literature. The analysis of income and poverty aggregates, however, was done with different values of the risk aversion parameter, and Table 3.3 presents the correspondent robustness check of the regression analysis for $\rho \in \{0.5, 1, 2, 4\}$. It is not necessary to emulate

Table 3.3: Difference in Coefficients of Determinants of Log Average Income and Log Risk Adjusted Income for Different Values of Risk Aversion

	ρ=0.5	ρ=1	ρ=2	ρ=4
Household characteristics				
Number of infants (ages 0-5)	0.0028	0.0072	0.0242	0.0355
Number of infants squared	-0.0001	-0.0003	-0.0024	-0.0033
Number of children (ages 6-14)	-0.0002	-0.0028	-0.0088	-0.0045
Number of children squared	0.0007	0.0023	0.0063	0.0076
Number of youths (ages 15-24)	0.0002	-0.0048	-0.0227	-0.0187
Number of youths squared	-0.0013 *	-0.0027	-0.0042	-0.0067
Number of adults (ages 25-64)	-0.0012	-0.0046	-0.0110	-0.0100
Number of adults squared	-0.0006	-0.0015	-0.0039	-0.0057
Number of elderly (ages 65+)	-0.0107 **	-0.0361 **	-0.0995 **	-0.1268 **
Number of elderly members, squared	0.0014	0.0057	0.0181	0.0224
Characteristics of the head				
Age	-0.0002	-0.0007	-0.0021	-0.0030
Age Squared	0.0000	0.0000	0.0000	0.0000
Female head	-0.0044	-0.0139	-0.0277	-0.0280
Recent migrant	0.0087	0.0308 *	0.0886 *	0.1091 *
Inactive	-0.1070	0.0090	0.0224	0.0228
Unemployed	0.1434 ***	0.2572 ***	0.4264 ***	0.6395 ***
Employer	0.0087	0.0208	-0.0635	0.0725
Self-employed	-0.0722	-0.0767	-0.0240	-0.0969
Informal Worker	0.0084 ***	0.0267 ***	0.0771 ***	0.1024 ***
Public Sector Worker	0.0424	-0.0107	-0.0282	0.0068
Job Qualification: Operative	-0.0041	-0.0128	-0.0373	-0.0536 *
Job Qualification: Technical	-0.2662	-0.2733	-0.0358	-0.0554
Job Qualification: Professional	-0.4224	-0.4310	-0.0358	-0.4657
Primary Education – Complete	-0.0106 **	-0.0212 *	-0.0393 *	-0.0566 *
Secondary Education - Incomplete	-0.0062 *	-0.0137	-0.1160	-0.1289
Secondary Education - Complete	-0.0127 ***	-0.2535 ***	-0.2911 **	-0.3198 **
Further Education – Incomplete	-0.5699 ***	-0.0907 ***	-0.2221 ***	-0.8319 ***
Further Education – Complete	-0.3736 **	-0.0432 **	-0.4624 *	-0.4859 *
University Education	-0.0151 ***	-0.3901 ***	-0.4232 **	-0.4561 **
No Spouse	0.0079	0.0260	0.0444	0.0358
Characteristics of the spouse				
Inactive	0.1203 **	0.0328 **	0.0867 **	0.1053 **
Unemployed	-0.0632 ***	-0.0181 ***	0.1873 ***	0.1533 ***
Employer	0.0182	0.0415	0.1963	0.1194
Self-employed	0.0781	0.0825	0.0204	0.1078
Informal Worker	0.0037	0.0110	0.0253	0.0279
Job Qualification: Operative	0.0039	0.0110	0.0281	0.0300
Job Qualification: Technical	0.2573	0.2529	-0.0155	-0.0260
Job Qualification: Professional	0.4185	0.4177	0.0004	0.4131
Public Sector Worker	-0.0451	0.0035	0.0106	-0.0395
Primary Education - Complete	-0.0020 *	-0.0141 *	-0.0555 *	-0.0724 **
Secondary Education - Incomplete	-0.0101 **	-0.0267 **	0.0132 **	-0.0211 **
Secondary Education - Complete	-0.0119 ***	0.1853 ***	0.1097 ***	0.0649 ***
Further Education - Incomplete	0.5362	0.0090	0.0401	0.5665
Further Education - Complete	0.3527	-0.0275	0.2539 *	0.2130 **
University Education	-0.0088	0.3290	0.2600 **	0.2231 **
Cohort controls				
95-2 to 97-1	0.0026	0.0117	0.0457	0.0544
96-1 to 97-2	0.0046	0.0191	0.0707 *	0.0913 *
96-2 to 98-1	0.0032	0.0123	0.0389	0.0449
97-1 to 98-2	-0.0001	0.0028	0.0255	0.0306
97-2 to 99-1	-0.0016	-0.0043	-0.0044	-0.0056
98-1 to 99-2	0.0017	0.0068	0.0271	0.0322
98-2 to 00-1	-0.0018	-0.0016	0.0095	0.0134
99-1 to 00-2	-0.0034	-0.0047	0.0084	0.0077
99-2 to 01-1	-0.0006	-0.0031	0.0012	0.0089
00-1 to 01-2	-0.0013	-0.0019	0.0121	0.0179
00-2 to 02-1	0.0240 ***	0.0633 ***	0.1521 ***	0.2154 ***
Observations	5446	5446	5446	5446

Superscripts indicate levels of significance (* 10%; ** 5%; *** 1%).
Source: Author's estimations based on EPH household survey data (INDEC).

the structure of Table 3.2, since the first column (the regression of the log average income) need not be repeated: Table 3.3 only presents the equivalent of the third column of Table 3.2, namely the difference in the parameters for average and risk adjusted incomes, for each value of ρ.

While higher values of ρ accentuate the disutility arising from income risk and lower values attenuate it, Table 3.3 is reassuring in terms of the robustness of Table 3.2's results. With the exception of the education variables of the spouse, all the variables that were found to be significantly correlated with the risk faced by the household, under the assumption that $\rho = 2$, are also relevant for all other values of ρ in the Table. While the magnitude of the effects is sometimes different, their statistical significance is markedly similar.

3.4 CONCLUSION

This Chapter presented a simple methodology for incorporating the disutility arising from income risk in the measurement of poverty. The methodology, based on the economics of choice under uncertainty, was applied to household panel data from the Greater Buenos Aires region for the period 1995-2002.

This application demonstrates that averaging income data over time at the household level reduces poverty measures by mitigating the impact of negative shocks, but this effect is more than offset when the disutility from income fluctuations is taken into account with plausible levels of risk aversion.

A regression analysis of the determinants of risk adjusted income reveals that risk is not uniform across households. The effect of a number of household characteristics on risk adjusted measures differs from their impact on average income. This implies that these characteristics are related to the risk faced by the household over and above their correlation with average income. Households with better-educated members not only have higher incomes, but also experience lower levels of income risk. Households with elderly members, as well as households with informal workers and/or unemployed or inactive members tend to suffer more from risk than other types of households. Being a recent migrant also increases risk, even though it does not affect average income. Finally, at the broader macroeconomic level, an economic crisis not only reduces income levels, but also increases risk, which magnifies its overall negative impact on poverty and well-being.

An alternative to the methodology presented in this Chapter consists of studying the mean of poverty evaluations for a household over time, instead of evaluating poverty at average or adjusted levels of income. This alternative approach is pursued in the following Chapter.

CHAPTER 4

CHRONIC AND TRANSIENT POVERTY IN TURBULENT TIMES

4.1 INTRODUCTION

The previous Chapters presented different approaches for the study of well-being based on panel data on incomes. Chapter 1 provided results on poverty transitions and short term dynamics by means of a series of two-period panels, which suggested that there were sizeable movements both within and into and out of poverty in the Argentine data. Chapter 2, in turn, proposed and illustrated a general framework for the welfare-based evaluation of income fluctuations and well-being over time, while Chapter 3 presented a related methodology that derives the impact of income risk from observed data.

The methodologies of the previous two Chapters concentrated on the derivation of measures of income adjusted for fluctuations and risk for the whole population, and used those measures to compute poverty and other distributional parameters for that population. The approach in this Chapter, which was briefly discussed in Section 2.4 in the context of the evaluation framework, focuses on poverty over time, providing a methodology for decomposing it into its chronic and transient components. This methodology was developed by Jalan and Ravallion (1998; 2000) to account for fluctuations of household income and poverty status over time, such as those observed during 1995 to 2002 in Argentina (Section 1.3, page 29). Moreover, given its prominence in the poverty and development literatures (Baulch and Hoddinott, 2000; Hulme and Shepherd, 2003, introduce two special journal editions related to the methodology), the results presented below constitute an important benchmark for the applications of Chapters 2 and 3, and provide a complement to their results.

These two components of poverty constitute important inputs for the design of poverty alleviation and risk mitigation policies. Since the determinants and consequences of chronic and transient poverty are not necessarily the same, interventions to deal with each of them may differ. For instance, the reduction of chronic poverty may involve forms of asset redistribution and human capital investments in education and health, while the alleviation of transient poverty may be related to employment policies and the development of coping mechanisms and insurance devices. Given these crucial implications, this Chapter presents a regression analysis of the correlates of both components of poverty.

The Chapter is organised as follows. Section 4.2 introduces the methodology for decomposing poverty into its chronic and transient components, and presents the estimation strategy for the analysis of their determinants. Section 4.3 presents the empirical results. A brief conclusion follows.

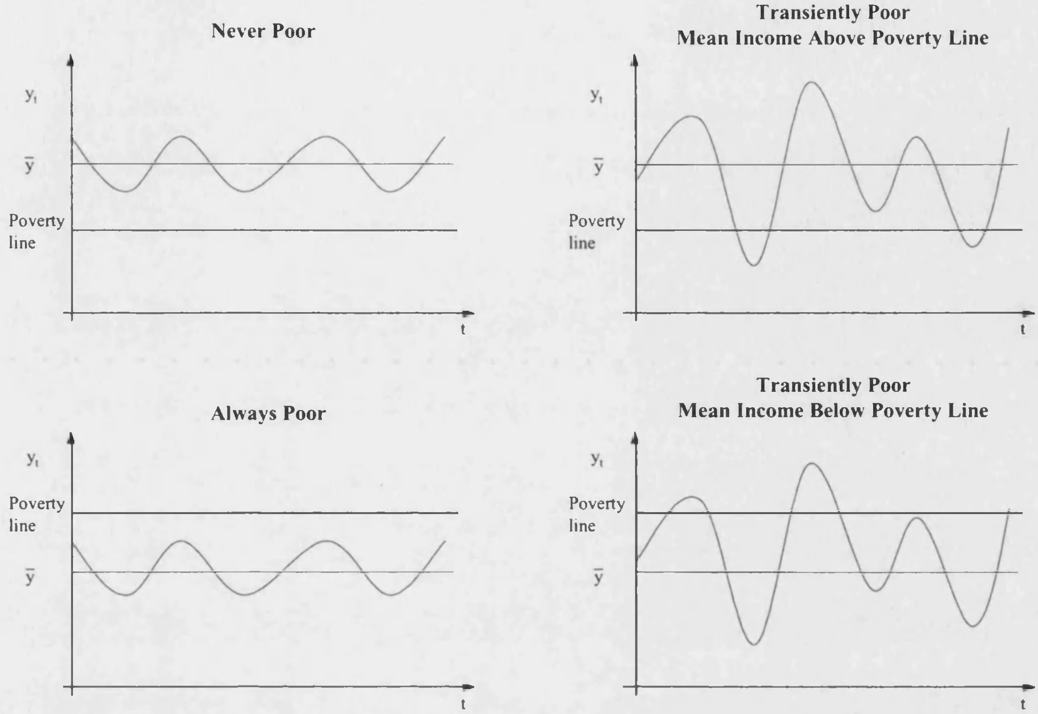
4.2 METHODOLOGY

4.2.1 *Definitions of transient and chronic poverty*

The decomposition of poverty originates in Ravallion's (1988) discussion of expected poverty and welfare variability, on which Jalan and Ravallion (1998; 2000) elaborate to define the notions of transient and chronic poverty. The decomposition can be motivated by the division of the population into four mutually exclusive groups according to the evolution of their income over time and its average, as depicted in Figure 4.1 (adapted from Hulme and Shepherd, 2003). The four groups are the always poor (with income below the poverty line at all periods), the never poor, and types of transiently poor. The transiently poor are only poor for some intervals, and they can be further divided into those with mean income above the poverty line and those with mean income below that threshold.

This partition of the population is extremely informative about the nature of poverty and income processes over time. As found in Section 1.3 for Argentina, those who are poor at one point in time may have different past experiences and future prospects.

Figure 4.1: Population Groups by Mean Income and Persistence of Poverty Status



Jalan and Ravallion (1998; 2000) build their decomposition of poverty into chronic and transient components on the two parameters that define these four categories: average income over time and fluctuations around the poverty line. The basis of the decomposition is the vector of observed incomes over T periods for a household i, $\mathbf{y}_i = [y_{i1}, ..., y_{iT}]$, where y_{it} are equivalised and normalised by the contemporaneous poverty line as shown in Equation 1.3 (page 27). A household's poverty at a point in time is given by the evaluation function $p(y_{it})$, which is required to be additive, strictly convex and decreasing up to the poverty line (and taking a value of zero thereafter).

Jalan and Ravallion (1998) define the intertemporal poverty of a household i, P_i, as the average of the poverty evaluations over time:

$$P_i = \frac{1}{T} \sum_{t=1}^{T} p(y_{it}) \tag{4.1}$$

P_i represents the average of i's poverty evaluation. This intertemporal measure is the total amount that Jalan and Ravallion (1998) decompose into chronic and transient components as $P_i = C_i + T_i$.

As the partition illustrated in Figure 4.1 shows, the decomposition does not depend only on fluctuations in income but also on its average over time, $\bar{y}_i$. Jalan and Ravallion's (1998) concept of chronic poverty is based on the poverty evaluation of this average level:

$$C_i = p(\bar{y}_i) = p(\tfrac{1}{T}\textstyle\sum_{t=1}^{T} y_{it}) \tag{4.2}$$

C_i accounts for the depth of poverty over time.

Finally, transient poverty is obtained as the residual of total poverty and its chronic component:

$$T_i = P_i - C_i = \frac{1}{T}\sum_{t=1}^{T}\left[p(y_{it}) - p(\bar{y}_i)\right] \tag{4.3}$$

As illustrated by the term on the right of Equation 4.3, T_i can be interpreted as the average of the gaps between the poverty evaluation at each point in time and the evaluation of average income. Furthermore, the convexity of p ensures (by Jensen's inequality) that T_i is always greater than or equal to zero.

The intuition behind the definitions of P_i, C_i and T_i can be presented in terms of the differences between the four categories defined above and illustrated in Figure 4.1. The role of average income over time in Equation 4.2 implies that both the never poor and the transiently poor with mean income above the poverty line have a zero measure of chronic poverty, while this is positive for the other two categories. The difference between the never poor and the transiently poor with $\bar{y} > z$ is that the latter group has a positive value of the transient component, since it is poor for part of the period.

The two panels in the bottom of Figure 4.1 depict the difference between chronic and transient poverty: while in the Figure the groups in the two panels have the same chronic measure (since $\bar{y}$ is the same), the always poor are below the poverty line in every period. This results in positive values of $p(y_{it})$ at every point in time, whereas the transiently poor have $p(y_{it}) = 0$ for the period or periods when they are above the poverty line. The always poor, then, have higher values of both intertemporal and transient poverty than those in the bottom right panel.

The description of the methodology is completed by the specification of the aggregation procedure and the functional form for the poverty evaluation p. The aggregate measures of total, chronic and transient poverty are obtained by computing Equations 4.1, 4.2 and 4.3 for each household i, and averaging over the population.

Regarding the poverty evaluation function p, the strict convexity requirement rules out the use of the p functions implied by the headcount and poverty gap measures, defined in Equation 1.5 with $\alpha = 0$ and $\alpha = 1$ respectively. The practice in applied work has followed Jalan and Ravallion (1998; 2000) and used the squared poverty gap for this decomposition (Dercon and Krishnan, 2000; McCulloch and Baulch, 2000). This implies a functional form for p given by:

$$p\left(y_{it}\right) = \left[\max(1 - y_{it}, 0)\right]^2 \tag{4.4}$$

which is a simplified version of Equation 1.5 (page 35), since it is based on income normalised by the poverty line. The chronic and transient decomposition is thus based on the *FGT* measures of Equation 1.6 (page 35).

The squared poverty gap, however, is not the only measure that fulfils the requirements set out for p. Kurosaki (2003) presents an in-depth study of the sensitivity of the transient-chronic approach to alternative underlying poverty evaluation functions, and makes an interesting parallel between the squared poverty gap and quadratic utility functions. He proposes using the Clark-Watts family of measures (Watts, 1968; Clark et al., 1981) given its affinity to the Constant Relative Risk Aversion utility function (see the discussions in Sections 2.4 and 3.2, pages 64 and 83).

4.2.2 *Determinants of poverty*

The study of the correlates of intertemporal, chronic and transient poverty relies on regression analysis with the corresponding measures defined in the Equations above as the dependent variables. This results in the following three models:

$$\begin{aligned} T_i &= X_i'\beta_T + \varepsilon_{Ti} \\ C_i &= X_i'\beta_C + \varepsilon_{Ci} \\ P_i &= X_i'\beta_P + \varepsilon_{Pi} \end{aligned} \tag{4.5}$$

As in Equation 3.8 (page 88), the set of household characteristics used as explanatory variables is given by the vector X_i (which includes a constant term), and ε_{1i}, ε_{2i} and ε_{3i} are regression errors.

The three dependent variables are censored by definition, since they are bounded by 0 and 1 – the three take a value of zero for the non-poor, while $P_i = C_i = 1 - T_i = 1$ when $\bar{y}_i = 0$. The Tobit model is the usual choice of estimator in these situations. However, it may suffer from severe bias from non-normality and heteroskedastic errors, and there is no a priori reason to assume that the error ε in Equation 4.5 will be normally distributed. For this reason, the Chapter follows Jalan and Ravallion (2000) in estimating the three models by Censored Least Absolute Deviations (CLAD), which allows for non-normal, non-homoskedastic and non-symmetric errors by imposing the relatively less stringent condition of zero median error terms (Chay and Powell, 2001). The semiparametric estimation is based on quantile regression methods, and uses an iterative estimation process based on Buchinsky (1994).[1]

However, the magnitude of the poverty figures for Argentina implies that the P_i, C_i, and T_i measures are heavily censored. For most of the 1995-2002 period, the poverty headcount in the GBA region fluctuated between 20 and 30 percent (see Section 1.3, page 29, and Appendix C), implying that between 70 and 80 percent of the population has a value of $p(y_{it}) = 0$ in Equation 4.4. With such a large fraction of the sample with censored values, the regression coefficients in Equation 4.5 must be estimated at very high quantiles – at least above 0.75. To reduce the level of censoring, the poverty line is scaled up by 50 percent of its value when conducting the regressions

[1]The estimation was performed using the *qcenreg* Stata routine developed by Robert Vigfusson of Northwestern University. This is an implementation of Buchinsky's (1994) recensoring-regression algorithm: starting from an unrestricted quantile regression, the observations with a predicted value of the quantile below the censoring point are excluded, a procedure which is repeated until the estimate converges.

in Equation 4.5, since this reduces significantly the number of observations with a zero value of intertemporal, transient and chronic poverty, the dependent variables.[2] This is the procedure adopted by Jalan and Ravallion (2000) for their analysis of chronic and transient poverty in rural China. For consistency with the estimates reported in the previous Chapters, however, the Tables and Figures in the next Section rely on the normal poverty line.

4.3 Empirical Results

4.3.1 *Population groups and poverty decompositions*

The applications presented in this Section are based on the Greater Buenos Aires (GBA) panel described in Section 1.2. Given the structure of the rotating panel, the fifteen waves between May 1995 and May 2002 contain data for twelve cohorts with four consecutive observations over a period of a year and a half, with an average of 453 households and 1812 observations per cohort.

Other studies based on the transient-chronic decomposition use panels that follow households for a longer period of time, but they typically present only one point-estimate of chronic and transient poverty for the whole period (Dercon and Krishnan, 2000; Cruces and Wodon, 2004). The advantage of the GBA dataset is that, as a series of twelve panels of four observations, it allows the construction of time series of transient and chronic poverty measures.

Table 4.1 presents the partition of the population according to the persistence of the poverty status of the household, as discussed in the previous Section and illustrated in Figure 4.1. As expected, the trends in these four categories follow the evolution of the economy in general. The proportion of those always poor is above the average for the period from the May 1999 to May 2001 cohort, reaching its highest point in the last cohort which corresponds to the economic crisis of 2001-2002. The proportion of those who are classified as never poor mirrors that of the previous group, reaching its lowest point of 42.7 percent for the last cohort, which reflects both the in-

[2]The change from 1 to 1.5 poverty lines reduces the level of censoring (observations with P_i, C_i, or $T_i = 0$) from 66 and 82 percent of the observations for the transient and chronic measures, to 48 and 66 percent respectively.

Table 4.1: Population Groups by Mean Income and Persistence of Poverty Status by Cohort, Greater Buenos Aires, 1995-2002

Cohort	Persistently Poor	Sometimes poor, mean income below pov. line	Sometimes poor, mean income above pov. line	Never Poor
95-1 to 96-2	9.4%	23.8%	8.0%	58.8%
95-2 to 97-1	16.0%	17.5%	10.5%	56.0%
96-1 to 97-2	8.1%	18.7%	11.6%	61.6%
96-2 to 98-1	12.0%	17.5%	13.1%	57.3%
97-1 to 98-2	10.8%	15.1%	8.6%	65.5%
97-2 to 99-1	9.9%	16.6%	12.1%	61.4%
98-1 to 99-2	13.8%	15.4%	12.8%	58.1%
98-2 to 00-1	13.9%	18.5%	11.6%	56.0%
99-1 to 00-2	17.4%	15.8%	7.5%	59.4%
99-2 to 01-1	14.5%	18.6%	15.0%	51.9%
00-1 to 01-2	18.8%	14.9%	10.5%	55.9%
00-2 to 02-1	23.3%	17.2%	16.8%	42.7%
Average	14.0%	17.5%	11.5%	57.0%

Source: Author's estimations based on EPH household survey data (INDEC).

crease in cross-sectional poverty and the fall in households who stay out of poverty for two consecutive waves, as described in Section 1.3. These numbers imply that for the last cohort, covering the period October 2000 to May 2002, almost a quarter of individuals in the Greater Buenos Aires region were poor in the four waves of the EPH, while almost 60 percent were poor in at least one of the surveys.

Besides the evolution of these two "chronic" categories (the always poor and the never poor), Table 4.1 also reflects the considerable movements across the poverty line which were identified in Section 1.3 (Figure 1.8, page 41) and in the empirical applications of Chapters 2 and 3. The downward trend in average household income over the period (Figure 1.3, page 30) explains the fall in the proportion of the sometimes poor with mean income above the poverty line and the increase in the proportion of the sometimes poor with $\bar{y} > z$. Taken together, the evidence in Figure 1.3 and Table 4.1 means that those who escaped poverty in at least one of the four waves are more likely to have average incomes below the poverty line the generalised deterioration of household income over the period.

Figure 4.2 quantifies these effects by presenting the sample averages of

Table 4.2: Decomposition of Squared Poverty Gap, Greater Buenos Aires, 1995-2002

Cohort	Squared Poverty Gap	Chronic Poverty	Transient Poverty	% Chronic	% Transient
95-1 to 96-2	4.5%	2.5%	1.9%	56.7%	43.3%
95-2 to 97-1	6.5%	4.2%	2.2%	65.2%	34.8%
96-1 to 97-2	5.1%	3.1%	2.0%	60.6%	39.4%
96-2 to 98-1	5.7%	3.4%	2.4%	58.7%	41.3%
97-1 to 98-2	5.0%	3.0%	1.9%	60.7%	39.3%
97-2 to 99-1	5.4%	3.5%	2.0%	63.7%	36.3%
98-1 to 99-2	6.3%	4.0%	2.3%	63.2%	36.8%
98-2 to 00-1	6.1%	4.0%	2.1%	65.9%	34.1%
99-1 to 00-2	6.0%	4.0%	2.0%	67.1%	32.9%
99-2 to 01-1	6.9%	4.6%	2.3%	67.2%	32.8%
00-1 to 01-2	7.0%	4.9%	2.1%	69.7%	30.3%
00-2 to 02-1	11.6%	8.0%	3.6%	69.2%	30.8%
Average	6.3%	4.1%	2.2%	64.0%	36.0%

Source: Author's estimations based on EPH household survey data (INDEC).

the measures defined in Equations 4.1, 4.2 and 4.3. The Figure presents the squared poverty gap and its decomposition into its chronic and transient components, and it is complemented by Table 4.2, which also computes the proportion of total poverty attributable to each of these two components.

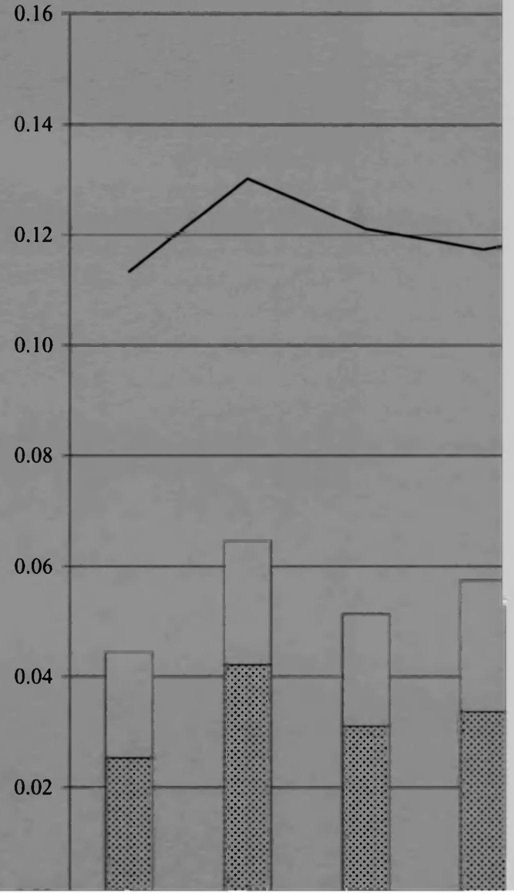
As expected from the discussion of the previous Chapters, there is a clear upward trend in total poverty, with an increase in the average of P_i from 0.045 for the first cohort to 0.116 for the last one. The results from the partition of the population presented in Table 4.1 are also reflected in Table 4.2: the increase in the always poor explains the large increase in chronic poverty from 0.025 to 0.080, which can also be traced to the fall in household income during the period.

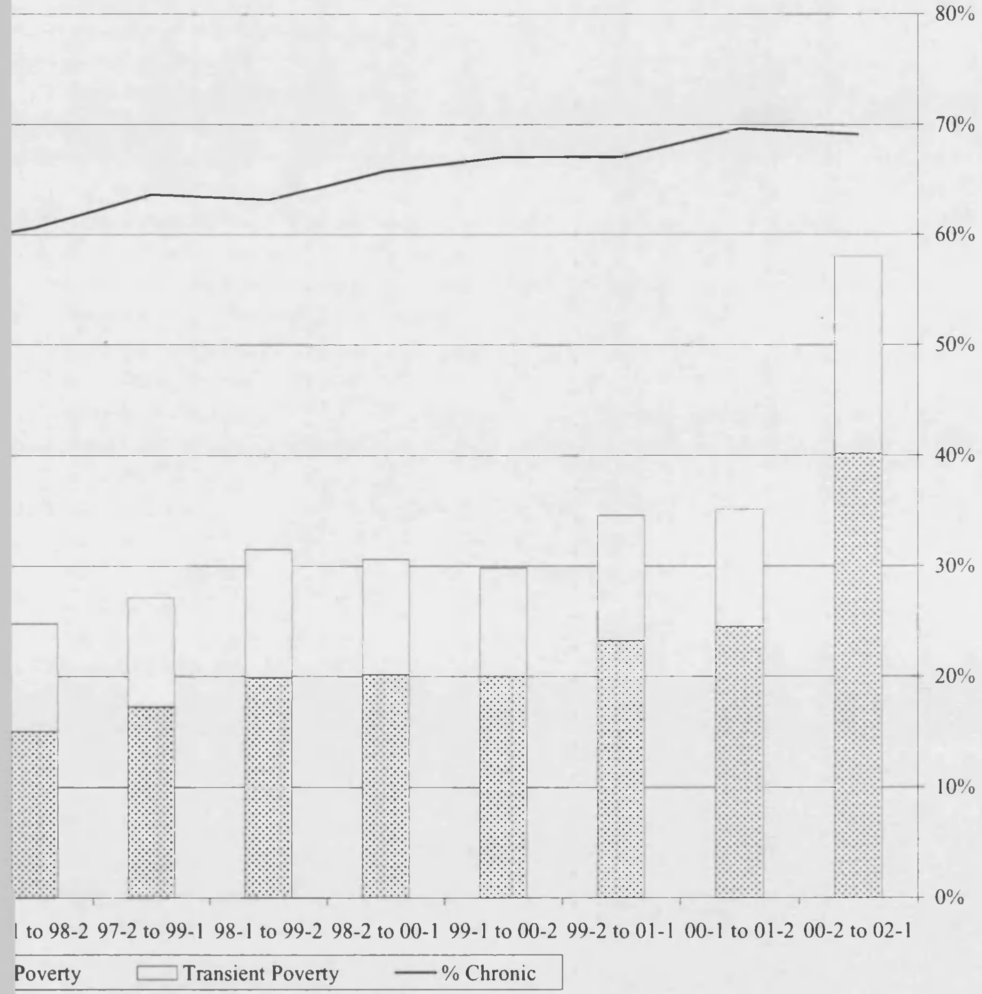
The previous Chapters pointed out that the downward trend in income was accompanied by a marked increase in its variability. The results in Table 4.2 imply that the "level" effect is the most important in terms of this Chapter's decomposition. Despite a large increase in transient poverty from 0.019 to 0.036, its share of total poverty is lower and falls over time at the expense of the chronic measure (last two columns of Table 4.2). The share of chronic poverty increases from 57 percent of the intertemporal measure for the first cohort to almost 70 percent for the last two cohorts.

Note: Left scale for squared poverty gap and its compo

Source: Author's estimations based on EPH household

Figure 4.2: Decomposition of Total Po in Chronic and Transient Components, Greater Buenos Aires, 1995-2002





ht scale for share of squared poverty gap that is chronic.

ata (INDEC).

4.3.2 *Regression analysis*

Table 4.3 presents the result from the estimation of the three regressions in Equation 4.5 by CLAD. Following suggestions in Buchinsky (1994) and given the level of censoring in the data, the regressions are estimated at the 0.8 quantile.

The independent variables are similar to those used for the SUR system of Equation 3.8. They include the initial conditions for (a) household level variables, including the number of infants, children, young adults, adults, and elderly household members, and the square of their values; whether the household head has a spouse; (b) characteristics of the household head, including five age intervals; his/her employment status; his/her level of education; his/her gender; his/her migration status (in the last five years); whether he/she is an employer, a self-employed worker, or a wage earner; the type of his/her qualifications; his/her education level; and whether he/she works in the public sector or is an informal worker; and (c) a subset of these characteristics for the spouse of the household head, when there is one. In addition, the regressions include indicators for each of the cohorts, excluding the first one. The summary statistics of these independent variables are presented in Table 3.1 (page 96).

The results for total poverty (first column of Table 4.3, corresponding to the regression of P_i from Equation 4.1) are similar to those for chronic poverty (second column, with C_i from Equation 4.2 as the dependent variable), and are relatively standard for poverty profiles and regressions of this type (World Bank, 2000a; Cruces and Wodon, 2003a, present more detailed profiles for Argentina).

For P_i and C_i, the number of infants and children is associated with higher levels of poverty despite the adjustments made with the equivalence scale of Table 1.3 (page 1.4) according to Equation 1.3, although the magnitude of this result may be sensitive to the specific choice of scale (Lanjouw and Ravallion, 1995). While the gender of the head does not have a statistically significant effect, heads in the 40-49 age range (the excluded category) are associated with lower levels of poverty. With respect to labour market indicators, unemployment, inactivity and informality of the head or spouse have a very high positive impact on the poverty measures. Self employment of the household head and his/her status (and that of the spouse) as an employer have a positive effect on observed poverty. While surprising, this probably results from the nature of the sample, which consists only of poor people. Among them, the self-employed and those with employees tend to be part of the informal economy with small and precarious businesses (Moreno and Roca, 2002) – this is discussed below in terms of the effect of these indicators on transient poverty. Finally, as expected, higher education levels and professional qualifications of the head and the spouse are unambiguously associated with lower levels of poverty (the excluded categories are no education and no qualifications). These results are broadly consistent with those of Paz (2002) and Gasparini (2003b), discussed in Section 1.4 (page 42).

The most interesting feature of Table 4.3, however, is the presence of disparities in the determinants of chronic and transient poverty, which indicates a differential impact of a household characteristic on the two components.

While the results for the composition of the household are relatively homogeneous among the three columns, households with young heads (19 years or below) have lower levels of chronic poverty but higher levels of transient poverty. The first effect might be due to self-selection: younger individuals might chose to live with relatives if facing chronic poverty on their own. The positive coefficient on transient poverty, on the other hand, implies that younger individuals are subject to more fluctuations in the depth of poverty, probably due to lower job tenure and higher vulnerability to labour market shocks (Mackenzie, 2004). With respect to older heads of household, those aged 65 and more are not associated with higher total poverty (the coefficient is not statistically different from zero), although this characteristic has a negative effect on chronic and transient poverty, which probably reflects the fact that most of these individuals receive steady income streams in the form of pensions.

Another interesting feature of the Table is the public sector indicator, which has a positive and highly significant effect on total poverty for both the head and his/her spouse. This is probably due to the relatively low salaries of civil servants. However, the stability of this income source – and of public employment – is reflected in the lack of effect on transient poverty

Table 4.3: Censored Quantile Regressions for Total, Chronic and Transient Poverty, Greater Buenos Aires, 1995-2002

	Total Poverty	Chronic	Transient
Household characteristics			
Number of infants (age 0-5)	0.02513	0.04728	0.01322
	[0.00495]***	[0.00656]***	[0.00163]***
Number of infants squared	0.01001	0.00589	-0.00214
	[0.00140]***	[0.00230]**	[0.00048]***
Number of children (age 6-14)	0.10942	0.14871	0.02124
	[0.00407]***	[0.00332]***	[0.00111]***
Number of children squared	-0.00882	-0.01415	-0.00321
	[0.00088]***	[0.00062]***	[0.00023]***
Number of Youths (age 15-24)	-0.00633	0.02441	0.01252
	[0.00442]	[0.00395]***	[0.00135]***
Number of Youths squared	0.00465	-0.00683	-0.00333
	[0.00119]***	[0.00104]***	[0.00038]***
Number of adults (age 25-64)	0.02972	0.00383	0.00837
	[0.00744]***	[0.00748]	[0.00219]***
Number of adults squared	-0.01396	-0.00806	-0.00184
	[0.00169]***	[0.00150]***	[0.00046]***
Number of elderly members (age 65+)	-0.10748	-0.15352	-0.01712
	[0.01159]***	[0.01153]***	[0.00413]***
Number of elderly members, squared	0.02211	0.04187	0.00272
	[0.00473]***	[0.00423]***	[0.00218]
No spouse in the household	-0.01436	-0.01835	-0.01101
	[0.01290]	[0.01226]	[0.00411]***
Characteristics of the head			
Age - 19 and younger	0.1144	-0.17914	0.05603
	[0.02546]***	[0.01358]***	[0.00724]***
Age - 20-29	0.06319	0.03264	0.00745
	[0.00864]***	[0.00781]***	[0.00267]***
Age - 30-39	0.02578	0.00103	0.00174
	[0.00596]***	[0.00526]	[0.00183]
Age - 50-59	0.02224	-0.01307	-0.00725
	[0.00665]***	[0.00591]**	[0.00193]***
Age - 60 and older	0.00291	-0.01523	-0.00956
	[0.00909]	[0.00835]*	[0.00266]***
Female	-0.00593	0.00734	-0.00018
	[0.00725]	[0.00764]	[0.00228]
Recent migrant	-0.12515	-0.02718	-0.01861
	[0.01651]***	[0.01188]**	[0.00356]***
Inactive	0.08131	0.12793	0.01399
	[0.00907]***	[0.00813]***	[0.00269]***
Unemployed	0.20448	0.22963	0.0617
	[0.00825]***	[0.00725]***	[0.00248]***
Employer	0.06007	0.02433	0.02785
	[0.02213]***	[0.02175]	[0.00489]***
Self-employed	0.029	0.03264	0.00644
	[0.00705]***	[0.00610]***	[0.00216]***
Informal sector worker	0.08725	0.11759	0.01316
	[0.00674]***	[0.00617]***	[0.00197]***
Public sector worker	0.00324	0.03523	-0.00067
	[0.01035]	[0.00956]***	[0.00280]
Level of qualification: Operative	-0.03878	-0.0421	-0.00697
	[0.00574]***	[0.00518]***	[0.00169]***
Level of qualification: Technical / Professional	-0.06805	-0.08	-0.01679
	[0.01307]***	[0.01622]***	[0.00363]***
Primary Education – Complete	-0.02666	-0.05328	0.0026
	[0.00549]***	[0.00480]***	[0.00169]
Secondary Education – Incomplete	-0.03212	-0.06173	-0.01483
	[0.00677]***	[0.00608]***	[0.00203]***
Secondary Education - Complete	-0.16102	-0.18975	-0.02457
	[0.01064]***	[0.01116]***	[0.00261]***
Further Education - Incomplete	-0.11621	-0.07938	-0.04006
	[0.02494]***	[0.02436]***	[0.00705]***
Further Education - Complete	-0.14017	-0.16669	-0.04981
	[0.02096]***	[0.01772]***	[0.00885]***
University Education	-0.17906	-0.14143	-0.05126
	[0.01684]***	[0.01279]***	[0.00474]***

(continued)	Total Poverty	Chronic	Transient
Spouse characteristics			
Inactive	0.04692	0.0569	0.01223
	[0.01155]***	[0.01017]***	[0.00368]***
Unemployed	0.13502	0.12663	0.02476
	[0.01315]***	[0.01152]***	[0.00416]***
Employer	0.22281	0.07813	0.03661
	[0.03064]***	[0.02825]***	[0.00991]***
Self-employed	-0.01644	-0.01411	0.00677
	[0.01070]	[0.00957]	[0.00325]**
Informal sector worker	0.02914	0.01824	0.00537
	[0.01276]**	[0.01122]	[0.00406]
Level of qualification: Operative	-0.01686	-0.03378	-0.01042
	[0.01071]	[0.01032]***	[0.00337]***
Level of qualification: Technical	-0.08941	-0.12389	-0.01978
	[0.02607]***	[0.01913]***	[0.00626]***
Level of qualification: Profesional	-0.0852	-0.031	-0.01728
	[0.02886]***	[0.02357]	[0.01172]
Public sector worker	-0.11584	0.05596	-0.01236
	[0.02169]***	[0.01616]***	[0.00537]**
Primary Education – Complete	-0.06353	-0.05894	-0.02344
	[0.00621]***	[0.00532]***	[0.00196]***
Secondary Education – Incomplete	-0.14017	-0.16398	-0.03052
	[0.00757]***	[0.00714]***	[0.00229]***
Secondary Education - Complete	-0.16016	-0.19071	-0.03345
	[0.01019]***	[0.01065]***	[0.00273]***
Further Education - Incomplete	-0.04291	-0.09544	-0.043
	[0.02247]*	[0.01927]***	[0.00859]***
Further Education - Complete	-0.0921	-0.33523	-0.02125
	[0.02013]***	[0.01912]***	[0.00514]***
University Education	-0.33934	-0.13979	-0.06746
	[0.02516]***	[0.01405]***	[0.01014]***
Cohort controls			
95-2 to 97-1	0.07824	0.15982	-0.01241
	[0.01138]***	[0.01103]***	[0.00303]***
96-1 to 97-2	0.05245	0.0811	-0.00191
	[0.01219]***	[0.01251]***	[0.00310]
96-2 to 98-1	0.04365	0.09046	-0.00526
	[0.01135]***	[0.01128]***	[0.00291]*
97-1 to 98-2	0.05176	0.1155	-0.00235
	[0.01181]***	[0.01159]***	[0.00310]
97-2 to 99-1	0.05642	0.11633	0.00237
	[0.01160]***	[0.01135]***	[0.00298]
98-1 to 99-2	0.10109	0.16046	0.00464
	[0.01121]***	[0.01117]***	[0.00290]
98-2 to 00-1	0.05722	0.12879	0.00256
	[0.01141]***	[0.01099]***	[0.00288]
99-1 to 00-2	0.07769	0.14167	-0.00607
	[0.01158]***	[0.01101]***	[0.00302]**
99-2 to 01-1	0.09595	0.18423	0.00658
	[0.01152]***	[0.01107]***	[0.00292]**
00-1 to 01-2	0.09066	0.14889	0.00282
	[0.01145]***	[0.01101]***	[0.00302]
00-2 to 02-1	0.17291	0.2458	0.02856
	[0.01117]***	[0.01092]***	[0.00280]***
Constant	-0.05622	-0.20806	0.01912
	[0.01877]***	[0.01884]***	[0.00572]***
Observations	2439	1409	3275
Pseudo R-Squared	0.2606	0.2646	0.1089

Standard errors in brackets (significant: * at 10%; ** at 5%; *** at 1%)

Source: Author's estimations based on EPH household survey data (INDEC).

for the head of household, and the negative and significant impact on T_i for the spouse. A similar effect is found with respect to changes in income by Corbacho et al. (2003), who use EPH data from the 1999-2002 period.

In the P_i regressions, all education and qualification indicators were associated with lower poverty. This is also true for the lowest level of education of the head (completed primary school) and its effect on chronic poverty. However, the lack of a significant effect of this variable on transient poverty (and its positive sign) indicates that little education may help in terms of reducing the level of poverty, but not in moderating its variability.

The positive and significant effect of the head's employer indicator on transient poverty, and its lack of effect on chronic poverty, may explain the puzzle discussed above: small scale entrepreneurs may not face higher levels of chronic poverty, although the risky nature of their businesses implies higher variability and thus higher transient measures. The same explanation probably applies to the self-employed indicator for the spouse, which has a (non-significant) negative effect on total and chronic poverty, but a positive and significant effect on its transient component.

The positive and significant values of the cohort indicators for the total and chronic measures have a clear upward trend, which reflects the fall in household income over the 1995-2002 period. Interestingly, these indicators only have a statistically significant effect on T_i for a few cohorts, indicating that while the increase in the depth of poverty was unambiguous, its transient dimension varied over the period. The excluded cohort is the first one (covering May 1995 to October 1996). The coefficients of the October 1995-May 1997 and the October 1996-May 1998 cohorts in the transient poverty regression are negative and significant, indicating that the period of recovery after the Mexican crisis was marked by a fall in the variability of well-being over time. The indicator corresponding to the May 1999 to October 2000 is also negative and significant in the T_i regression, due to the slight but short-lived recovery in income and unemployment for October 2000 (Figure 1.3). In contrast, the cohort indicators for these three cohorts are positive and strongly significant for the P_i and C_i regressions. The large fall in income during the recession of 1999-2001 and the 2001-2002 crisis, however, are reflected in the positive and highly significant values of the indicators for cohorts 10 and 12 in the three regressions.

Finally, the results on the determinants of chronic and transient poverty can be compared to those of the risk adjusted income regressions of Section 3.3 (page 89). As noted in the Introduction to this Chapter, the methodology presented in Chapter 3 concentrates on the effects of income risk at every point of the income distribution, while the transient-chronic decomposition deals only with the level and variability of well-being among the poor, so the two sets of results can be considered complementary.

The results for income and poverty levels are consistent: employment status, education and qualifications have the largest impacts on both. The comparison between the analysis of risk – the difference between average and risk adjusted income – and that of differences between transient and chronic poverty is certainly the most interesting. The regressions of Section 3.3 (Table 3.2, page 98) indicated that households with elderly members faced lower levels of risk, which is consistent with the negative effect of older household heads on transient poverty in Table 4.3. The informality indicators contributed to higher levels of risk and higher levels of poverty, although the employer and self-employed variables, which affect transient poverty, have no significant effect on average income or risk. Another coincidence is that education and qualifications reduce both risk and the transient component of poverty. Finally, the results in Tables 3.2 and 4.3 capture the fall in income and the increase in its variability induced by the 2001-2002 crisis.

4.4 Conclusion

This Chapter presented a decomposition of intertemporal poverty that accounts for the large fluctuations of poverty and household income in Argentina for the period 1995-2002. This methodology was critically assessed in Chapter 2 in the context of the evaluation of income fluctuations over time.

The partition of the population into different groups, according to their average income over time and their exposure to poverty, complemented the decomposition of a poverty measure in its transient and chronic components. The analysis of the trend in these two elements revealed that the increasing deterioration of living standards over this period was not only reflected in its level, but also in its variability. However, given the large fall in household income due to the 2001-2002 crisis, the largest share of poverty was due to its chronic component.

The decomposition also allows for the study of the correlates of total, transient and chronic poverty. This type of regression analysis represents a step forward with respect to the simple poverty profiles, since the differences in the impact of variables on chronic and transient poverty reveals their effect not only on the level of well-being, but also on its variability. These results are broadly consistent with those of the risk adjusted income regressions presented in Chapter 3. They complement that Chapter's approach and the results from the longitudinal studies for Argentina reviewed in Section 1.4.

Part II

Fertility and Women's Labour Supply in Argentina: Identification of Causal Effects Through Sex Preferences

CHAPTER 5

EFFECTS OF FERTILITY ON WOMEN'S LABOUR SUPPLY: METHODOLOGY, ESTIMATION STRATEGY AND DATA FOR ARGENTINA

5.1 INTRODUCTION TO PART II: POVERTY, FERTILITY, AND WOMEN'S LABOUR SUPPLY

In the previous discussion of poverty, risk and income fluctuations in Argentina, larger households (and especially those with more children) were found to be poorer and more prone to suffering from income fluctuations. At the same time, the employment status of the head of household and the spouse was established as a strong correlate of chronic and transient poverty.

Studies of this type provide a valuable input for the analysis of poverty and its alleviation, and constitute a step towards understanding the mechanisms underlying deprivation and vulnerability. However, the recovered correlations do not imply causality, at least not without further assumptions: causal relations are blurred by the endogeneity and simultaneity of the different factors at stake. For instance, household size and fertility might be "causing" poverty by the simple mechanical effect of dividing income among a larger number of people,[1] but also by hampering the opportunities of income-generating activities of some household members. At the same time, poverty itself may induce a rise in fertility, because of a lower opportunity cost of a parent's time, or because of reduced access to family planning

[1] In the case of poverty measurement in Argentina, this is manifested in the number of household members k_i in the denominator of Equation 1.2.

possibilities.[2] Similar concerns about the direction of causality also arise in the relationship between poverty and labour market outcomes.

The next step after the regression results of Chapters 3 and 4 consists in establishing the nature of the causal links underlying the identified correlations.

The results of Part I on the positive correlations between poverty and fertility, on the one hand, and poverty and joblessness, on the other, motivate the research presented in this Part, which establishes the determinants of the income-generating process of women as primary and secondary earners in the household. Specifically, the following Chapters study the effects of fertility on female labour supply, prompted not only by their correlation with poverty measures, but also by their evolution in Argentina: Figure 5.1 shows that female labour force participation increased by almost 60 percent in the 1980-2000 period, while fertility fell significantly by almost 25 percent during the same years and is expected to reach replacement levels by 2010-2015 (Pantelides, 2002; Binstock, 2004; CELADE, 2004).[3] The following pages will attempt to establish whether the change in fertility can explain the large increase in female labour force participation.

Fertility transitions of this type, and an even higher incorporation of women into the labour force in developed countries during the twentieth century, prompted a continuous interest in the relationship between childbearing and women's labour supply in the labour economics and demography literatures.[4]

However, endogeneity issues are pervasive in applied empirical research. Concerns about the endogeneity of fertility and work decisions imply that much of this literature has been devoted to disentangle the causal mechanisms linking childbearing and women's labour supply. In a review of the literature, Willis (1987) wrote that "...it has proven difficult to find enough well-measured exogenous variables to permit cause and effect relationships to be extracted from correlations among factors such as [...] the decline of childbearing [...] and increased female labour participation." Since the

[2] See Anand and Morduch (1998) and Lipton (1998) for a discussion of these points.

[3] Replacement level fertility implies a total fertility rate usually between 2.1 and 2.2 children per woman, depending on a country's level of mortality.

[4] See, among others, Gronau (1973), Rosenzweig and Wolpin (1980), Killingsworth and Heckman (1986), Willis (1987), and Browning (1992).

Figure 5.1: Female Labour Force Participation (Women Aged 14 and Older) and Fertility (Children per Woman), Argentina 1960-2010

Source: CELADE (2004).

publication of that review, however, substantial progress has been made in labour economics by means of "natural experiments," which exploit the exogenous dimension of naturally occurring events as sources of variation (Angrist and Krueger, 1999, 2001).

The aim of Chapters 5 to 8 is to provide a baseline measure of the impact of fertility on women's labour supply in Argentina. The following Chap-

"cause and effect relationships."

It is argued, however, that whether the identification strategy can be applied to developing countries or not must first be established. The empirical results for Argentina constitute the first contribution of the following pages. The application to Argentina establishes whether the causal effect of childbearing on female labour supply holds in developing countries, where fertility is typically higher, and female education and labour force participation levels are lower than in developed countries (United Nations, 2002).

The second contribution, presented in this Chapter and the following, consists in the discussion of the "same sex" strategy in the context of developing countries, and in the proposed interpretation of a set of auxiliary evidence for the evaluation of the identifying assumptions. Chapter 6 maintains that since the exclusion restrictions of instrumental variables are inherently non-testable, their plausibility must be evaluated on a case by case basis by means of indirect evidence. In particular, it is argued that the type and degree of sex preferences have to be assessed to establish the validity of the exclusion restrictions. Finally, the third contribution, presented in Chapter 8, is the derivation of a new test to support the generality of instrumental variable results.

The present Chapter provides an econometric framework for the application of the "same sex" estimation strategy to Argentina. Section 5.2 illustrates the theoretical relationship between fertility and female labour supply. It then describes the potential outcomes framework and the conditions for identification of causal effects. Section 5.3 studies in detail the "same sex" strategy within this framework. Section 5.4 describes the data employed for the analysis and presents a set of summary statistics of the main variables. Some brief conclusions follow.

5.2 Theory and Methodology

5.2.1 *Theoretical framework: fertility and labour supply*

The analysis of women's labour supply is intrinsically connected to the economic models of fertility, time allocation and household decision making

household survey data from Korea, and Cruces and Galiani (2003) present additional data and estimates from Mexico.

(Becker, 1991, summarises the developments in this field).

The essence of the economic analysis of fertility and labour supply is that the two are usually considered joint decisions: while children provide utility to their parents, they also enter the household's budget constraint since they involve considerable costs, both in terms of goods (e.g., food and school materials) and time devoted to childcare.

These relations are captured in this Section by means of a stylised static model of a nuclear household adapted from Browning (1992). This model concentrates on the woman's side of the problem, taking other variables, such as the spouse's income, hours of work at home and in the market as fixed.

The woman's utility function is defined as $U = U(x_m, x_c, l, h_h, c)$, and is assumed to be increasing in all its arguments: x_m and x_c denote the consumption of the mother and the children, l is the time devoted to leisure, h_h is the time spent at home, and c is the number of children. The woman divides her total time T between work at home h_h, leisure l and work in the market h_m, for which she is compensated with a wage w. Finally, the budget constraint is completed by a fixed quantity I, representing the household's other sources of income, the price p_x of consumption goods and a cost per child given by p_c. The woman chooses the optimal quantities of her choice variables to solve the following maximisation problem:

$$\begin{aligned} \max_{x_m, x_c, l, h_h, c} U &= U(x_m, x_c, l, h_h, c) \text{ subject to} && (5.1) \\ & I + wh_m = p_x(x_m + x_c) + p_c c \quad && \text{(budget constraint)} \\ & T = h_h + h_m + l && \text{(time constraint)} \end{aligned}$$

The two constraints can be summarised as $I + wT = (wl + p_x(x_m + x_c)) + (p_c c + wh_h)$, which describes the allocation of the household's full income between the woman and the child, if work at home is considered mainly as childcare and household chores.

This stylised model highlights the main theoretical relationships needed for the discussion of this Part. The shape of the utility function U and the first and second order conditions of the optimisation problem in Equation 5.1 define the demand for children, the labour force participation and the labour supply of the woman. Killingsworth and Heckman (1986), Montgomery and Trussell (1986) and Browning (1992) present more elaborate models covering single-parent households, labour supply dynamics, private childcare, household production (Becker, 1965; Gronau, 1977), joint allocation of hours of man and woman (Gronau, 1973), and the quantity-quality of children interaction (Becker and Lewis, 1973). Cigno (1991) and Ermisch (2003) provide full treatments of all these aspects of the economics of the family.

The simple setting of Equation 5.1 illustrates some important considerations. Firstly, the labour supply, childcare and fertility decisions are simultaneous, although this is partially due to the static nature of the model: dynamic models capture the irreversibility of fertility decisions and their subsequent effects on time allocation. Secondly, while the model of Equation 5.1 is too general for the derivation of demands for the different goods (and their interactions) without functional form assumptions, it still captures the essence of the causal relation between fertility and female labour supply: the utility function and the budget and time constraints imply a trade-off between "pure" utility from children, wage-income and the time and goods needs of children. Dynamic models often result in a negative causal effect of fertility on short-run labour supply through the time needs of children in the time constraint. Finally, the model can be used to illustrate the endogeneity that arises in the empirical estimation of labour supply models.

The objective of this Part is to obtain estimates of the direct effect of children c in the labour supply of women, represented by $h_m^* = T - l^* - h_h^*$. Following Browning (1992), the model from Equation 5.1 results in a conditional labour supply – either in terms of hours, or as a binary participation indicator – defined as $Y = f(\mathbf{K}, D)$, where $\mathbf{K}$ is a vector that contains the variables in the model of Equation 5.1 and some exogenous characteristics, and D is a measure of fertility – such as the number of children, or an indicator of more than c children in a sample of women with c or more children.

The parameter of interest is the labour supply response to changes in the fertility variable, f_D. This parameter, however, is difficult to recover by simple statistical methods as illustrated by the derivative of Y with respect to D. Ignoring the effects of fertility on all the other variables in Equation 5.1 (present in $\mathbf{K}$), which requires a series of highly implausible assumptions (Browning, 1992), but considering the potential effects of fertility on wages, for example, this derivative is equal to:

$$\frac{\partial Y}{\partial D} = \frac{\partial w}{\partial D} f_w + f_D \tag{5.2}$$

Childbearing might have an effect on wages, for instance because of the foregone appreciation in the woman's "stock of experience" during maternity leave (Cigno, 1991, Chapter 7). This would imply that $\partial w / \partial D \neq 0$. Moreover, the wage w is determined by ability and motivation factors that are unobservable and that may be correlated with fertility decisions through the childbearing and leisure preferences in the utility function U. Taking into account all the variables of the model in Equation 5.1 would add partial derivatives (in Equation 5.2) of the components of $\mathbf{K}$ with respect to D.

This discussion implies that a fertility indicator D would be endogenous in a labour supply model – a regression of Y on D is flawed because "variables that are explicitly or implicitly assumed to be fixed are [...] within the control of mothers" (Browning, 1992). An additional factor is that unobserved factors might be driving both decisions.

An alternative is to evaluate the structural parameters implied by the utility function and the constraints, but models of this type rely on a large number of assumptions, since preferences are not observable. As pointed out by Willis (1987), a solution to these endogeneity problems resides in finding a variable Z that induces variation in fertility but does not affect the labour supply decision directly, which allows the derivation of a reduced form relationship between fertility and labour supply.

Continuing the example presented in Equation 5.2, which only considers the endogenous effect of fertility on the wage rate, if Z is not related to the factors that account for $\partial w / \partial D$ then:

$$\frac{\partial Y}{\partial Z} = \frac{\partial w}{\partial Z} f_w + \frac{\partial D}{\partial Z} f_D, \text{ resulting in } f_D = \frac{\partial Y}{\partial Z} / \frac{\partial D}{\partial Z} \tag{5.3}$$

since the exogeneity of Z with respect to w implies that $\partial w / \partial Z = 0$. The parameter of interest, the response of the labour supply to changes in fertility, is thus identified. This intuitive idea is the basis of the statistical framework and identification strategy presented in the following pages.

5.2.2 *The potential outcomes framework*

Instrumental variables techniques, based on variables like Z in the previous Section, have been used since the 1920s to identify causal effects by exploiting exogenous variations in the variables of interest (Wright, 1928; Angrist and Krueger, 2001). This section presents the potential outcomes framework, a general setting for causal inference within which instrumental variables estimators can be given a causal interpretation without functional form assumptions.[6]

The objective is to evaluate the causal effect of some treatment over an outcome of interest: in this Part, the "treatment" denotes a measure of fertility D, and the outcome Y is related to the employment status of a woman. This Section focuses on the case of binary treatments and outcomes:[7] Y_i is equal to 1 if the woman i is employed, and 0 if she is not, while D_i is an indicator of whether i has more than two children in a sample of women with at least two offspring, which corresponds to the Angrist and Evans (1998) setting discussed in the following Section.

As observed in the discussion of Equation 5.2, the direct effect of D on Y in empirical models of women's labour supply is difficult to obtain because of simultaneity and endogeneity concerns. The potential outcomes framework attempts to solve endogeneity problems of this type. Its starting point is the definition of a causal effect, which relies on the notion of potential – as opposed to observed – outcomes Y_d (Abadie, 2003a): Y_{0i} is the potential outcome without treatment for individual i, and represents the level of Y that i would attain if not exposed to the treatment. Y_{1i} is defined analogously: it represents the outcome that the same individual i would attain if exposed to the treatment. The key feature is that potential outcomes refer to unobserved counterfactuals. An individual i has either been exposed ($D_i = 1$) or not exposed to the treatment ($D_i = 0$), and Y_i represents i's actual observed outcome. However, both Y_{0i} and Y_{1i} are defined for i: they represent the outcome that would have been observed in the two alternative situations, one of which is necessarily a counterfactual. In the case of fertility and wo-

[6] This Section draws mainly on Abadie's (2003a) presentation of results by Imbens and Angrist (1994), Angrist et al. (1996), Angrist (2001) and Abadie (2002, 2003b), among others.

[7] Most of the results hold in models with variable treatment intensity (Angrist and Imbens, 1995), as discussed below. The empirical results in Chapters 7 and 8 deal with both cases.

men's labour supply, the employment status of a woman i who has more than two children ($D_i = 1$) is Y_{1i}, which is equal to the observed Y_i, and Y_{0i} represents the same woman's counterfactual employment status which would have been observed if she had only two children ($D_i = 0$).[8]

The causal effect of the treatment D for individual i is defined in terms of counterfactuals as the difference between the two potential outcomes, $Y_{1i} - Y_{0i}$ (Abadie, 2003a). In the previous example, the causal effect of childbearing is the divergence in employment status between having two or more than two children – this difference is due only to childbearing, and thus it is not contaminated by other endogenous factors as in Equation 5.2.

Since causal effects are defined in terms of inherently unobserved counterfactuals (i.e., what labour supply would have been in another situation), the problem of identification is to find a way of expressing the parameter of interest in terms of observable quantities. Moreover, since Y_{0i} and Y_{1i} cannot both be observed at the same time for i, causal effects cannot be computed at the individual level: the identified parameter refers necessarily to the average causal effect $E[Y_1 - Y_0]$.

A first naive approach, corresponding to that of Equation 5.2, consists in comparing the average outcomes by treatment status. However, the simple comparison between the treated ($E[Y|D = 1]$) and the non treated ($E[Y|D = 0]$), as given by an ordinary least squares regression of Y on D, is unlikely to identify any meaningful causal effect. This can be shown by re-writing the difference of these expectations in terms of potential outcomes:

$$\begin{aligned} & E[Y|D=1] - E[Y|D=0] = \\ & = E[Y_1|D=1] - E[Y_0|D=0] + E[Y_1 - Y_0] - E[Y_1 - Y_0] \\ & = E[Y_1 - Y_0] + \underbrace{\{E[Y_0] - E[Y_0|D=0]\} - \{E[Y_1] - E[Y_1|D=1]\}}_{bias} \end{aligned} \tag{5.4}$$

where $E[Y_1 - Y_0]$ is the average treatment effect, and the last term represents the bias. The elements in the first line of Equation 5.4 are observable, but since the bias term is composed of non-observable counterfactuals the average treatment effect cannot be distinguished from the simple difference

[8]Formally, the observed outcome Y_i is a function of potential outcomes and the treatment indicator D_i: $Y_i = Y_{0i}(1 - D_i) + Y_{1i}D_i$.

in average outcomes.[9]

The identification of the causal effect $E[Y_1 - Y_0]$ in Equation 5.4 can still be attained in situations where the bias is equal to zero, although this is unlikely to be the case in most applications due to problems of selection and endogeneity like those described in the previous Section. For instance, individuals might choose whether to enter the treatment by estimating their own potential outcomes, resulting in a non-zero bias term in Equation 5.4 – Section 5.3.1 discusses this in detail in the context of fertility and female labour supply.

A well-known exception in which the left hand side of Equation 5.4 successfully estimates the average causal effect is the case of random assignment, which plays a central role in identification. When the population is randomly divided into treatment ($D_i = 1$) and control ($D_i = 0$) groups, the expectations of Y_1 and Y_0 are independent of D. Intuitively, the assignment ensures that individuals do not self-select into treatment, and thus the bias in Equation 5.4 is forced to be 0 by the experimental design.

While randomised experiments are difficult to carry out in economics, and infeasible in the study of fertility and women's labour supply, the problems of selection and endogeneity can be overcome by finding a setting akin to random assignment. The next Section discusses the case of instrumental variables, in which identification is attained with a variable, correlated with the treatment, which is "as good as randomly assigned" (Angrist, 2004).

5.2.3 *Identification by instrumental variables: LATE and the Wald estimator*

A solution to the endogeneity problem in the theoretical model described above was given in Equation 5.3 by means of exogenous variation in the causing variable. Imbens and Angrist (1994) translate the intuition of that

[9] Alternatively, the bias can be expressed in terms of the average treatment effect on the treated, as done by Abadie (2003b) and Angrist (2004):

$$\begin{aligned} E[Y|D=1] - E[Y|D=0] &= E[Y_1|D=1] - E[Y_0|D=0] \\ &= E[Y_1 - Y_0|D=1] \\ &\quad + \{E[Y_0|D=1] - E[Y_0|D=0]\} \end{aligned}$$

where $E[Y_1 - Y_0|D=1]$ is defined as the average causal effect on the treated, and the term $E[Y_0|D=1] - E[Y_0|D=0]$ is the bias. Equation 5.4 seems better for presentational purposes since instrumental variables identify the average treatment effect and not necessarily the effect on the treated.

Equation into the potential outcomes framework, showing that the identification of causal effects when the treatment is non-random can be attained with an instrumental variable (IV) Z which induces exogenous variation in the treatment. The condition, as in Equation 5.3, is that Z must be correlated with the treatment but only affect the outcome Y through its effect on D: in the Angrist and Evans (1998) example, the instrument Z is an indicator for women whose first two children are of the same sex, which, as discussed in the next Section, is correlated with having more than two children, but does not have a direct impact on the mother's labour supply.

Some additional notation and definitions are needed to derive the instrumental variables identification result. Given a binary instrument Z, D_z represents the potential treatment status given $Z = z$: $D_z = D_0$ if $Z = 0$ and $D_z = D_1$ if $Z = 1$. Just as Y_1 and Y_0 represent the potential outcomes in terms of the treatment D, D_z represents the treatment status that would be observed for different values of the instrument. With this notation, the potential outcomes can be re-defined in terms of the treatment status and the instrument as Y_{zd}. As in the case of potential outcomes, just one treatment status is observable for each individual, either D_0 or D_1, but both counterfactuals are defined.[10]

Following Angrist et al. (1996), this setting allows the partition of the population into four mutually exclusive categories according to the values of D_z:

1. *Compliers*: $D_0 = 0$ and $D_1 = 1$. These individuals receive the treatment when the instrument is 1, but do not receive it when it is 0.

2. *Always takers*: $D_0 = 1$ and $D_1 = 1$. These individuals are always exposed to the treatment, regardless of the value of the instrument.

3. *Never takers*: $D_0 = 0$ and $D_1 = 0$ These individuals are never exposed to the treatment, regardless of the value of the instrument.

4. *Defiers*: $D_0 = 1$ and $D_1 = 0$. These individuals receive the treatment when the instrument is 0, but do not receive it when it is 1.

[10]Formally, the observed treatment D_i is a function of potential treatment and the instrument Z_i: $D_i = D_{0i}(1 - Z_i) + D_{1i}Z_i$.

Compliers are those whose treatment status is changed by the instrument. In terms of the childbearing example, compliers are women who would have had an additional child if their first two children were of the same sex, but would not have had it if the first two were of different sex. Always takers always have more than two children irrespective of the sex of the first two, whereas never takers stop at two in any circumstance. Finally, defiers are simply those who behave in the opposite way of compliers: two children of the same sex induce them to stop having children, while two children of different sex encourage them to have more than two. Since these definitions are based on unobservable potential treatments, it is impossible to assign a single individual to any of these four groups from observable characteristics.

The following assumptions represent a set of nonparametric conditions[11] in terms of Y_{zd}, D_z and Z under which the instrumental variables estimators identify causal effects for the subpopulation of compliers (Abadie, 2003b):

Assumption 5.1 *Independence: the vector* $(Y_{00}, Y_{10}, Y_{01}, Y_{11}, D_0, D_1)$ *is independent of the instrument* Z.

Assumption 5.2 *Exclusion:* $Y_{1d} = Y_{0d}$ *for* $d = 0$ *and* $d = 1$.

Assumption 5.3 *First stage:* $0 < \Pr(Z = 1) < 1$ *and also*
$\Pr(D_1 = 1) > \Pr(D_0 = 1)$.

Assumption 5.4 *Monotonicity:* $D_1 \geqslant D_0$.

The independence Assumption 5.1 refers to the treatment assignment mechanism with respect to Z, requiring that the instrument is randomly assigned.

Assumption 5.2 means that $Y_{00} = Y_{10} = Y_0$ and $Y_{01} = Y_{11} = Y_1$, implying that for a given treatment status d, the potential outcome Y_{zd} is always the same, irrespective of the value of the instrument. Potential outcomes can then be defined in terms of the treatment D alone, Y_d, as in Section 5.2.2. This exclusion restriction means that any influence of the instrument on the

[11] Implicit in this notation is the "Stable Unit Treatment Value Assumption," which postulates that an individual i is not affected by the treatment received and instrument assigned to other individuals in the population (Angrist et al., 1996).

potential outcomes comes only through its effect on the treatment D: the instrument Z does not affect Y directly.

The first part of Assumption 5.3 rules out the possibility that either all or none of the individuals in the population have a positive value for the instrument indicator – any of the two extremes would render Z trivial. The second part of the Assumption states that the instrument affects the probability of treatment, which is required to be more likely to equal 1 for those with $Z_i = 1$ than for those with $Z_i = 0$.[12]

Finally, Assumption 5.4 requires that changing Z from 0 to 1 should not shift an individual from receiving the treatment to not receiving it. This effectively rules out the presence of defiers, which is not controversial in most applications.[13]

Given an instrument Z that satisfies Assumptions 5.1-5.4, Imbens and Angrist (1994) show that the causal effect of the treatment is identified for those whose treatment status is changed by the instrument ($D_0 = 0$ and $D_1 = 1$), the group of compliers:

Proposition 5.1 *Local Average Treatment Effect (Imbens and Angrist, 1994): If Assumptions 5.1, 5.2, 5.3 and 5.4 hold, then:*

$$E\left[Y_1 - Y_0 | D_0 = 0, D_1 = 1\right] = \frac{E[Y|Z=1] - E[Y|Z=0]}{E[D|Z=1] - E[D|Z=0]} \tag{5.5}$$

This estimator is the Local Average Treatment Effect (LATE). It is an identification result in the sense that a difference in unobservable potential outcomes can be expressed as a function of observable quantities. In the presence of an instrumental variable that fulfils the conditions set above, the causal effect of the treatment D for the group of compliers is the quotient in Equation 5.5.[14] This result is obtained without any functional form

[12]The "greater than" signs in Assumptions 5.3 and 5.4 can be reversed without loss of generality.

[13]This assumption is not specific to the potential outcomes framework: as noted by Angrist et al. (1996), it is implicit in standard instrumental variable models. The same authors provide a detailed discussion of these four assumptions and the consequences of their violations.

[14]While the discussion focuses on binary treatments, Angrist and Imbens (1995) show an equivalent identifying result in models with variable treatment intensity. When D is not binary, the parameter ϕ in Equation 5.5 captures the weighted average of causal responses to a unit change in treatment. In the fertility example, if the variable D is the number of

assumption.

Proposition 5.1 identifies the causal effect for the subpopulation of compliers, since for this group the treatment status D is determined by a random event Z. This rules out the issue of self-selection, making compliers akin to a group subject to an experiment with random assignment to treatment.

A limitation of the LATE parameter from Proposition 5.1 is that it can only be extrapolated as a causal effect for the whole population by assuming no heterogeneity in potential outcomes between compliers and other groups. Under that assumption, LATE is equal to the population average causal effect $E\left[Y_1 - Y_0\right]$. Chapter 8 addresses the plausibility of assumptions of this type in the context of fertility and women's labour supply.

The LATE parameter and its standard error can be recovered by means of an instrumental variable model with a dummy endogenous regressor. This coefficient is known as the "Wald" estimate, and is obtained by estimating the Equation:

$$Y_i = \gamma + \phi D_i + \varepsilon_i \tag{5.6}$$

where Y_i and D_i are defined as before, γ is a constant term, ε_i is an error term, and the treatment variable D_i is instrumented with Z_i.

In some cases, Assumptions 5.1, 5.2, 5.3 and 5.4 may only hold conditionally on some observable exogenous variables X_i. Alternatively, a researcher might be interested in controlling for these characteristics in the estimation of causal effects to extrapolate results to another group of the population with different values of X_i. In these cases, the simplest option is to estimate the causal effect is by means of a linear, constant-effects model of the form:

$$\begin{aligned} E[Y_{oi}|X_i] &= X_i'\beta \text{ and} \\ Y_{1i} &= Y_{oi} + \phi \end{aligned}$$

where X_i is a vector of control variables that influence the outcome Y independently of the treatment status, as described in the first Equation (Angrist, 2001). The second Equation implies that the causal effect of the treatment represents a shift in the outcome, as in the LATE setting above. These as-

own children, Y_j represents the potential labour supply for an individual at each value j of D, and the LATE parameter represents the average effect of an increase in the number of children by one.

sumptions lead to the following linear causal model:

$$Y_i = X_i'\beta + \phi D_i + \varepsilon_i \tag{5.7}$$

This model can be estimated by two-stage least squares, with Z_i as an instrument for D_i, to obtain the causal effect parameter ϕ. The instrumental variable Z_i must satisfy an extended version of Assumptions 5.1-5.4 that makes them conditional on the controls X_i (Abadie, 2003b).[15]

The two-stage least squares (2SLS) model in Equation 5.7 is equivalent to the canonical version of the instrumental variable model with one endogenous regressor. Moreover, it has been shown that this setting can be considered as a special case of the latent index model.[16] The advantages of the framework described in this Section are threefold. Firstly, it provides an alternative interpretation of these models in terms of causal inference. It also individualises the underlying assumptions, making conditions for identification explicit. Finally, these conditions do not depend on functional form assumptions. The following Section discusses the application of the framework to the case of fertility and women's labour supply, highlighting the endogeneity problems that arise in this context and the potential for identification by means of instrumental variables.

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[15]Abadie (2003b) points out that the introduction of covariates X_i implies that the parameter ϕ in Equation 5.7 is not exactly a LATE as defined in Proposition 5.1, and he proposes a weighted "Casual IV estimator" for ϕ that has a LATE interpretation. However, his own results, as well as estimations from Angrist (2001) and Cruces and Galiani (2003), find the "Casual IV" estimates of ϕ in Equation 5.7 almost indistinguishable from those obtained by two-stage least squares. This is due to the fact that the covariates used in the estimation are discrete with finite support (Abadie, 2003b).

[16]The model in Equation 5.7 can have an alternative interpretation as a latent index model where $Y_i^* = X_i'\beta + \phi D_i + \varepsilon_i$, with $Y_i = 1$ if $Y_i^* > 0$, $Y_i = 0$ if $Y_i^* \leq 0$, and $\varepsilon_i = \delta\theta_i + u_i$. Y_i^* is a latent outcome variable, and the error term is composed by a random component u_i and an unobservable parameter θ_i affecting the treatment and the outcome (Iacovou, 2001). Heckman et al. (2003) discuss the equivalence of the potential outcomes and latent index models, using a latent-variable framework "to unite the recent treatment-effect literature with the classical selection-bias literature." This issue is also explored at length by Angrist (2001, 2003).

5.3 Fertility, Women's Labour Supply and the "Same Sex" Estimation Strategy

5.3.1 *Fertility and women's labour supply: endogeneity and selection issues*

A variety of studies from different disciplines as well as casual observation indicate the presence of a negative correlation between childbearing and women's labour supply (see references in Section 5.2.1). However, this correlation cannot be interpreted as a causal effect without further (and debatable) assumptions on the nature, size and sign of the selection bias term.

The bias term in Equation 5.4 provides a simple illustration of selection as an obstacle to identification. The bias arises because expected potential outcomes may affect self-selection into treatment: this term would be 0 in Equation 5.4 (and thus identification achieved) only if the decision to have a child is independent of a women's potential labour market outcomes when not having any children. In that case, the treatment D becomes irrelevant for the expectation of potential outcomes, and the bias disappears:

$$\begin{aligned} Bias &= \{E[Y_0] - E[Y_0|D=0]\} - \{E[Y_1] - E[Y_1|D=1]\} \qquad (5.8) \\ &= \{E[Y_0] - E[Y_0]\} - \{E[Y_1] - E[Y_1]\} = 0 \end{aligned}$$

However, the theoretical results discussed in Section 5.2.1 and empirical evidence suggest that fertility and women's labour supply are jointly determined and that there is a causal link between the two, making this independence assumption implausible. Childbearing decisions take into account expected potential outcomes, career plans, comparative advantages, preferences and the division of labour within the household, implying that women with higher fertility are probably different in terms of potential outcomes from women with lower fertility.

For instance, women lacking opportunities for childcare arrangements, with stronger preferences for children, or who forecast relatively poor labour market outcomes (such as a low quality job, or low wages)[17] might decide to work at home and have children. These women self-select into treatment because they expect a relatively low Y_1, implying that their poten-

[17] This might be related to individual ability, but can also be affected by opportunities and by the extent of discrimination in labour markets, among other factors.

tial outcomes are lower than average: this results in $E[Y_1|D = 1] < E[Y_1]$. On the other hand, women who expect good labour market outcomes probably self-select into lower fertility (non treatment): the potential outcome of this group is above average, implying that $E[Y_0|D = 0] > E[Y_0]$.

A situation like this results in a negative bias term in Equation 5.4,[18] but this is due to the nature of the example: in other cases, the bias might be positive. For instance, this is the case if $E[Y_1]$ is very low within women who self-select into $D = 0$, and relatively high among those who chose $D = 1$. In a situation like this, women who chose lower fertility do so because of low expected outcomes when having children (Y_1), and not because of good outcomes without children as in the previous example.

While the framework outlined in the previous Section proposed a solution to the endogeneity problems of this type through instrumental variables, the problem remains in finding a suitable variable Z, which is discussed in the following pages.

5.3.2 *Identification through natural experiments*

As shown by Proposition 5.1, the identification of the causal effect in Equation 5.4 can be attained through an instrument Z that meets the requirements of Assumptions 5.1-5.4. However, finding a valid instrument in socioeconomic data is not evident: most of the observed individual characteristics are plausibly correlated with unobservable factors driving the outcome, making them endogenous to the relationship of interest in violation of Assumption 5.2. For instance, there is strong evidence of a link between the level of education and women's fertility decisions, but it is unlikely that education could make a good instrument for childbearing since it certainly affects labour supply through channels other than the number of children. Moreover, while most meaningful socioeconomic characteristics might be considered to be jointly determined, other plausibly exogenous individual attributes might not have an impact in the variable of interest, as required by Assumption 5.3.

[18]Using the alternative definition of the bias in terms of the average treatment on the treated given in footnote 9 (page 132), the bias is $E[Y_0|D = 1] - E[Y_0|D = 0]$. Women who expect high outcomes without the treatment self-select into $D = 0$, which results in a negative bias since $E[Y_0|D = 0] > E[Y_0|D = 1]$.

These problems with socioeconomic characteristics and the difficulties of carrying out randomised experiments in the social sciences imply that researchers often rely on "natural experiments," situations equivalent to random treatments that arise by chance. Some examples of naturally occurring events exploited in labour economics are birth date, gender composition of offspring and twin births – Angrist and Krueger (1999) review these applications, and Rosenzweig and Wolpin (2000) provide a critical assessment of the literature.

The main advantage of the natural outcomes of the previous paragraph is that, in the words of Rosenzweig and Wolpin (2000), they are "plausibly random with respect to at least two of the major sources of heterogeneity in human population, tastes and abilities." The consequence is that these natural outcomes are exogenous, as required by Assumption 5.2. If they influence the variable whose effect is of interest, they comply with Assumption 5.3 and they can be exploited as instruments if Assumptions 5.1 and 5.4 are also met.

5.3.3 *The "same sex" strategy: sex mix as a natural experiment*

This is the approach proposed by Angrist and Evans (1998) for the study of fertility and female labour supply. The "same sex" estimation strategy relies on the sex of a women's first two children as an instrument for fertility in a model of female labour supply. Its suitability as an instrument is given by two hypotheses. On the one hand, the gender of children is random. On the other hand, the gender mix has an impact on fertility as a consequence of parental sex preferences, but does not affect directly the parent's labour supply. These premises are discussed in detail for Argentina in the following Chapter.

In general terms, sex preferences can be defined as the utility that parents derive from the gender of their children. This issue, and its relationship to fertility behaviour, has been dealt with from different angles, from in-depth ethnographic studies to demographic statistical analysis (Williamson, 1983; Basu and Das Gupta, 2001) and models of rational utility maximising agents (Ben Porath and Welch, 1976; Leung, 1991; Ahn, 1995). While most studies concentrate on son or daughter preference, the "same sex" strategy exploits the parental predilection for a mixed sex composition of children, which is revealed as the desire to have at least one son and one daughter – a well-known stylised fact in the demography literature for developed countries (Williamson, 1983). When such preferences are present, parents of two children of the same sex exhibit a higher probability of having another child to attain their desired composition.

The "same sex" strategy relies on these preferences, and can be justified as follows. The sex composition of children, a naturally occurring random event,[19] affects fertility through parental sex preferences, as required by Assumptions 5.3 and 5.4. Since the sex mix is random, making the identifying assumption that it affects labour supply only through its effect on the number of children satisfies the requirements of Assumptions 5.1 and 5.2. In these circumstances, the sex mix constitutes an instrumental variable for fertility which can be used to identify causal effects on women's labour supply through models like Equations 5.6 and 5.7. Because of its reliance in the sex mix of children, the "same sex" strategy studies women with at least two children.

Angrist and Evans (1998) analyze the case of the United States in detail, and discuss the plausibility of the exogeneity of sex preferences (and their effects) in labour supply decisions in their study. They estimate their model for the United States' 1980 and 1990 Censuses. For both years, they report strong first-stage results of the effects of sex mix on fertility, and compelling evidence of a negative causal effect of fertility on women's labour supply in the second stage.

Besides this original application, the "same sex" estimation strategy has been used in other contexts. Carrasco (2001) uses the Panel Survey of Income Dynamics from the United States, adapting the instrumental variables estimators for the longitudinal structure of the data. Her results are consistent with previous estimates from Census data. In an application to the United Kingdom, Iacovou (2001) employs the "same sex" strategy with data from the British Household Panel Survey and the National Child Development Study. While she still finds negative effects of fertility on women's

[19]Sex screening techniques might affect the randomness of the gender composition because of selective abortion. While these techniques have made substantial progress in the last decade, they were not widely available in the United States in 1980 and 1990, the years Angrist and Evans (1998) use in their estimation. Section 7.2.2 discusses the case of Argentina.

labour supply, the instrumental variables coefficients are not very precisely estimated, which might be attributed to the relatively small sample size of her datasets.

In developing countries, Chun and Oh (2002) applied the "same sex" strategy to household survey data from Korea (the National Survey of Family Income and Expenditure), finding significant first- and second-stage effects roughly consistent with the Angrist and Evans (1998) results for the United States. Rosenzweig and Wolpin (2000) find similar results with a dataset of rural households in India. Finally, Cruces and Galiani (2003) present additional data and estimates for Mexico, which show that the significant casual effect of fertility on female labour supply accounts for most of the increase in female labour force participation in the 1970-2000 period in that country.

While the fertility effects of the sex mix of children can be established from the data, identifying assumptions are not universally valid and must be evaluated on a case by case basis. After the description of the data in the following Section, Chapter 6 studies the plausibility of the strategy's premises for Argentina.

5.4 Data and Summary Statistics

5.4.1 *Description of the main dataset*

The data used in this Chapter is from Argentina's 1991 Census of Population and Housing ("Censo Nacional de Poblaci6n y Viviendas") conducted by the Instituto Nacional de Estadísticas y Censos (INDEC).

This Census is divided into two sections. A basic questionnaire was administered to the whole population (32,245,467 individuals and 8,927,289 households), while an extended questionnaire covered a large random sample representative of the whole country. The analysis in this Chapter is based on the dataset gathered by the latter questionnaire, since it contains detailed demographic and labour force participation data. The sample is composed of a total of 16,023,180 individuals and 4,287,580 households.

The study of fertility and labour supply needed some adjustments to the data. Women with two children were selected from the total sample, and their characteristics were linked to those of their children and spouses (if present). As in Angrist and Evans (1998), the sample was limited to women between 21 and 35 years old whose oldest child was at most 18 years old at the time of the Census.[20]

Since the relationship variable in the Census dataset indicates kinship with respect to the head of the household, it was only possible to match children with women who were heads of households or spouses of the head. The observations for women spouses of the head were checked so that the number of own surviving children (as asked for in a specific question) was the same as the number of matched children in the household.[21] This ensured that children of a male head of household were not wrongly matched to a spouse who was not their mother. As shown in Appendix D, the empirical results of this Part are robust to all these adjustments.

Finally, in order to establish the generality of the results, the analysis was carried out on a series of variations of the total sample described in the previous paragraphs. The full sample consists of all women aged 21-35 with at least two children and whose oldest child was 18 or less (*Complete Sample*), whereas the *Married* sample corresponds to the subgroup of legally married women living with their spouses. Since Angrist and Evans (1998) exclude women whose second child was less than a year old from their estimations, this further adjustment was made to the two previous samples to obtain comparable datasets, resulting in the *AE* and *AE Married* categories. All variables, parameters and estimates of interest are reported separately for these four subgroups. The corresponding sample sizes are reported in the last row of Table 5.1.[22]

[20]There were a total of 766,572 women between 21 and 35 with at least two children whose oldest child was 18 or less. The observations for which the age at first birth was less than 14 were discarded, taking this as an indicator of data entry errors or misallocated children, since most of the ages were far too low (8,745 women were discarded in total, of which 2,952 had imputed ages at first birth of 11 or less). A small fraction (5,718 observations) of married women for which the husband's age at first birth was less than 14 was also discarded.

[21]This is by far the most important adjustment of the sample. A total of 106,001 women were discarded (13.83 percent of the original 766,572), corresponding to those whose declared number of surviving children did not correspond to the number of children matched in the household.

[22]These large sample sizes imply that the standard errors of the regression coefficients presented in Chapter 7 are virtually not affected by the use of Huber-White robust standard errors.

5.4.2 *Variables and descriptive statistics*

The outcome of interest for the estimations is the labour supply of women. In the Argentine Census data, individuals working for pay include employees (wage earners), the self-employed, owner-managers and civil and domestic servants, and exclude family workers without remuneration. The *Worked for pay* indicator is equal to 1 for this group, and 0 otherwise. Since income and hours of work were not collected in the Argentine Census, the analysis covers this employment status indicator only.

The fertility characteristics refer to the number and gender composition of children. The variable *Number of children* represents own children in the household, according to the allocation rules described above. The *More than two children* indicator is derived from this variable, and is defined as 1 for women with three or more children, and 0 otherwise. The *Same sex*, *Two boys* and *Two girls* variables refer to the sex of the first two children, and are equal to 1 if the first two were of the same sex, two males or two females respectively, and 0 otherwise in all cases.

Regarding individual characteristics, the *Age* and *Age at first birth* variables, measured in years, are self explanatory. The education indicators were constructed by dividing the sample into three homogeneous groups, composed of those with up to some primary schooling, those with some high school, and those with some higher education. Finally, all variables are defined analogously when referring to the spouses of married women.

As stated in the Introduction to this Chapter, demographic indicators in Argentina in 1991 were at a level consistent with an advanced fertility transition: the average number of children ever born for women in the 19-49 age group was 2.04 (and 2.83 for women with at least one child), with a mode of 2: these figures are in the 2-3 range, where the "same sex" strategy applies. Finally, for this age group, the labour force participation rose almost continuously during the twentieth century, reaching 35.4 percent in 1991 – Figure 5.1 presents these trends for women aged 14 and older.

These patterns are reflected in Table 5.1, which presents a set of summary statistics of the main variables used in the analysis for the four samples defined in Section 5.4.1 (*Complete Sample, Married, AE Sample, AE Married*), corresponding to women aged 21-35 with at least two children.

Table 5.1: Descriptive Statistics of Variables of Interest

Characteristics:	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**
Main variables:				
Worked for pay	0.314	0.305	0.315	0.305
(=1 if worked for pay, 0 otherwise)	(0.464)	(0.460)	(0.465)	(0.460)
More than 2 children	0.548	0.528	0.596	0.574
(=1 if more than two children, 0 otherwise)	(0.498)	(0.499)	(0.491)	(0.495)
Number of children	2.976	2.905	3.062	2.985
	(1.223)	(1.165)	(1.240)	(1.183)
Basic demographics:				
Age	29.410	29.679	29.660	29.928
	(3.868)	(3.755)	(3.770)	(3.652)
Age at first birth	20.830	21.127	20.641	20.932
	(3.434)	(3.436)	(3.337)	(3.340)
Fertility and sex mix:				
Same Sex	0.507	0.506	0.506	0.505
(=1 if first two children of same sex, 0 otherwise)	(0.500)	(0.500)	(0.500)	(0.500)
Two Boys	0.260	0.261	0.260	0.261
(=1 if first two children were boys, 0 otherwise)	(0.438)	(0.439)	(0.438)	(0.439)
Two Girls	0.246	0.245	0.246	0.244
(=1 if first two children were girls, 0 otherwise)	(0.431)	(0.430)	(0.431)	(0.430)
Boy 1st	0.508	0.510	0.508	0.510
(=1 if first child was a boy, 0 otherwise)	(0.500)	(0.500)	(0.500)	(0.500)
Boy 2nd	0.506	0.507	0.506	0.507
(=1 if second child was a boy, 0 otherwise)	(0.500)	(0.500)	(0.500)	(0.500)
Indicators of maximum education level:				
Some primary education	0.581	0.531	0.593	0.544
	(0.493)	(0.499)	(0.491)	(0.493)
Some secondary education	0.298	0.325	0.293	0.321
	(0.457)	(0.468)	(0.455)	(0.457)
Some tertiary eduaction	0.121	0.144	0.114	0.135
	(0.326)	(0.351)	(0.318)	(0.326)
Observations	653,213	497,194	599,941	456,437

Note: Means and standard deviations (in parentheses). The samples correspond to women aged 21-35 with two or more children aged 18 or younger from the extended questionnaire sample of the 1991 Census, as described in the text.

The labour force participation, as captured by the *Worked for pay* indicator, is in the 30.5-31.5 percent range, depending on the sample, with the lower rates corresponding to married women. The average fertility is substantially higher than for the 19-49 age group discussed above, because Table 5.1 refers to women with at least two children. The average number of children varies between 2.91 and 3.06, and it is slightly lower for married women. More than half of the women have more than two children, but unlike the case of the employment and number of children variables, there is a substantial variation between the four samples. This is due to the adjustment made to obtain the *AE* samples, which results in an average of 57.4-59.6 percent (*AE Sample* and *AE Married*, respectively) compared to a lower 52.8-54.8 percent for the *Complete* and *Married* samples.

The average age of the women in these samples is between 29 and 30 years old, and slightly higher for married women, while the age at first birth is around 21 years old for all samples. Regarding the sex composition of children, the proportion of males in first births is around 51 percent, and just above 50 percent of the women have two siblings of the same sex, with a slightly higher proportion of these cases corresponding to two boys (around 26 percent) than two girls (around 24 percent). These figures correspond to the stylised facts of the demography literature (Williamson, 1983).

Finally, the education level is relatively high in the four samples with respect to other Latin American countries, with more than 40 percent of the women with at least some secondary education. A noticeable difference between the samples is that married women have higher levels of secondary and further education than the corresponding overall samples.

5.5 Conclusion

This Chapter has discussed the theoretical and empirical problems for establishing a causal relationship between fertility and female labour supply. The discussion was carried out in terms of the potential outcomes framework, and it proposed instrumental variable techniques a possible solution to the endogeneity problems that invalidate simple estimation approaches.

The "same sex" strategy exploits the fertility effects of parental sex preferences as a natural experiment. While its necessary conditions were met in the original application to the United States (Angrist and Evans, 1998), the challenge for its application to another context is to show that the identification strategy is still valid. The data in Section 5.4 implies that Argentina in 1991 was substantially different from the United States in the two key variables: the average number of children ever born for women in the 19-49 age group was 2.04 (and 2.83 for women with at least one child), compared to 1.44 (and 2.23, respectively) for the equivalent United States sample of 1990, while the labour force participation for the same group was 52.8 percent in Argentina compared to 80.9 percent in the United States.[23]

The next Chapter discusses the conditions for application of the "same sex" strategy and the problems of this identification strategy in the context of a developing country, where son preferences, among other institutional factors, might affect the plausibility of the identifying assumptions. Their validity is critically assessed in the Argentine case, using the data described in this Chapter and other complementary sources.

[23]These figures were computed from Argentina's 1991 Census (as described in Section 5.4) and from the one percent Public Use Micro Sample from the United States 1990 Census, provided by Sobek et al. (2003).

CHAPTER 6

SEX PREFERENCES AND FERTILITY IN ARGENTINA

6.1 INTRODUCTION

The previous Chapter motivated the establishment of a link between fertility and female labour supply by noting that in Part I both variables were consistently associated with a household's poverty status in Argentina. While causal links are difficult to establish in applied empirical research, Chapter 5 discussed an instrumental variable estimation strategy for models of fertility and female labour supply based on the fertility effects of parental sex preferences.

This identification strategy was originally devised for the United States in the late twentieth century, and its justification is a priori valid only for that case. The analysis in this Chapter deals with the threats to the validity of the approach in its application to the Argentine census data of 1991, presenting evidence on the fertility effects of sex preferences and on their exogeneity with respect to labour market outcomes.

The Chapter is organised as follows. Section 6.2 discusses the threats to the validity of the strategy for developing countries. Section 6.3 presents evidence against these potential challenges, studying the nature and extent of sex preferences in Argentina, their fertility effects, and their institutional background. A brief conclusion follows.

6.2 Validity of the Identification Strategy in Developing Countries

6.2.1 *First stages: nature of sex preferences and the same-sex effect*

The "same sex" strategy is based on context-dependent evidence and assumptions that need to be considered on a case by case basis. This is especially relevant when attempting to apply the strategy to developing countries like Argentina, where the socioeconomic and cultural context differs substantially from the United States, where the original study was carried out.

The precondition for the application of the "same sex" strategy is the existence of a first-stage relationship between the sex mix of children and further childbearing in the context under study. A correlation between the treatment D and the instrument Z, as required by Assumption 5.3 (page 134), is easy to establish: it only requires to check if the sex mix of children has a significant effect on further childbearing. Angrist and Evans (1998) study the impact of a "same sex" indicator on further childbearing for women with at least two children, and Section 6.3.1 presents a detailed analysis of sex mix and fertility in Argentina by studying the probability of further childbearing conditional on the sex of previous children.

The basis of the "same sex" strategy is the fact that parents tend to have a preference for a balanced sibling sex composition, which implies that those with two children of the same sex are more likely to have another child than parents of a boy and a girl. These type of sex preferences, observed by Angrist and Evans (1998) in their United States data, are not uncommon. Based on multiple sources of attitudinal evidence on fertility, Basu and Das Gupta (2001) state that "in most regions of the world, parents express a preference for a gender-balanced family," usually mixed with "mild preferences for children of a particular gender." While stated preferences might not affect fertility behaviour in a significant manner, Williamson (1983) and Basu and Das Gupta (2001) report that there is compelling evidence that sex preferences result in differential fertility effects, either as a consequence of a gender-balanced preference or as a result of a preference for sons.

The evidence for developed countries is consistent with gender-balanced preferences: results from attitudinal surveys are confirmed by higher fertility for parents of children of the same sex. This is complemented with a minor son bias in some circumstances, which is characterised as a higher probability of further childbearing for parents of girls than for parents of boys. The United States provide a typical example for industrialised societies: Angrist and Evans (1998) report that for the 1980 and 1990 Census, parents of two children of the same sex had a significantly higher probability of having a third child than parents of a boy and a girl, and that mothers of two girls were slightly more likely to have a third child than were mothers of two boys. This is consistent with previous evidence from the United States (Ben Porath and Welch, 1976; Williamson, 1983). Iacovou (2001) reports similar results from two British datasets: in samples from the British Household Panel Survey, almost half of the mothers with two sons or two daughters had another child (with a difference between the two of only half a percentage point), compared to only 41.2 percent of mothers of a boy and a girl. These fertility patterns correspond to the effects of the conventional sex preferences observed by Basu and Das Gupta (2001).

In developing countries, sex preferences and their fertility effects are more heterogeneous, and can differ from the patterns of the previous paragraph. In general, the preference for a gender-balanced family coexists with stronger son preferences. For instance, Das (1987) finds for India that "at each parity a higher proportion of couples with no sons went on to have the next child than did those who already had one or more sons," but he also observes a positive effect on fertility when all living children are sons, "indicating that preference for sons is not to the exclusion of daughters." In a review of attitudinal evidence, family and population structures in Bangladesh, India and Pakistan, Nag (1991) concludes that the prevalent form is a "general preference of sons over daughters as well as a desire for at least one daughter."

In other developing countries, however, parental preferences indicate only a strong preference for sons. This implies that couples are more likely to stop having children when having at least one boy, and that parents of a certain number of girls are much more likely to have an additional child than parents of the same number of boys. Moreover, as reported by Das Gupta (2003) for China and Korea, extreme forms of son preference also result in abnormally high ratios of boys to girls in the population as a consequence of selective abortion, higher infant mortality for daughters, and even infanticide. In these cases, the sex composition of children cannot be considered to be purely random, and thus the independence Assumption 5.1 is not likely to hold.

In general, the fertility effects of sex preferences can be divided into three categories: gender-balanced, gender-balanced with moderate son preference, or strongly biased towards sons. It should be noted, however, that the presence of sex preferences other than the first case is not necessarily an impediment for the application of the "same sex" strategy in other contexts. If the gender composition of children can be considered as a random event and the sex preferences have some form of effect on childbearing, then the sex mix of children can still be exploited as a source of variation in fertility (i.e., as an instrument Z in Equations 5.6 or 5.7, pages 136 and 137).[1] However, this is only true if the exclusion and monotonicity Assumptions hold: a first-stage relationship is a necessary condition, but the crucial point is whether the variation in fertility induced by sex preferences can be considered to be exogenous. This is discussed in the following pages for developing countries.

6.2.2 *Sex preferences and the identifying assumption*

Establishing the case for the randomness of the instrument (Assumption 5.1, page 134) is relatively straightforward. The gender of a child is a naturally occurring random event, and the sex mix is thus "as good as randomly assigned" (Angrist, 2001). As discussed in the previous Chapter, a problem arises with extreme forms of son preference that lead to the neglect of daughters in basic healthcare, or when sex screening techniques are widely available and result in selective abortions. In those cases, the sex mix is manipulated and might be correlated with potential outcomes. The inspection of sex ratios by age, household consumption and school enrolment data provides evidence on extreme forms of son preferences that could cast doubts on the credibility of the independence assumption. This is accomplished in

[1]Note, however, that different instruments imply different types of compliers and thus identify causal effects for different subgroups of the population. Section 8.2 (page 191) discusses whether differences in the "complier" subpopulations are relevant for the estimation results.

Section 6.3 for Argentina.

The independence of the sex mix with respect to potential outcomes cannot be established directly, but while the assignment mechanism itself is not testable, its implications are. A simple test is to compare characteristics of parents of same-sex and mixed sex siblings – if truly random, there should not be systematic differences in exogenous attributes between the two groups.

Identification is not attained solely through first stages and independence: the basis of instrumental variable estimation is that the instrument Z, while correlated with the treatment D, does not have a direct effect on the outcome Y and is thus correctly excluded from the second stage. However, as an exclusion restriction, Assumption 5.2 (page 134) is inherently non-testable and its plausibility has to be evaluated on a case by case basis. In the context of the "same sex" strategy in the United States, Angrist and Evans (1998) show that there is almost no association between the sex of children and labour supply. Moreover, they review the evidence on norms and behaviour and the institutional setting, concluding that the sex mix only affects labour supply through its influence on fertility. Finally, they argue that the inclusion of the sex of the first two children among the covariates X in the estimation of Equation 5.7 controls for any secular effects of these variables.

While this may or may not be the case in other developed countries, the presence of moderate and extreme son preferences raises additional concerns in developing countries. If the bias towards sons is a pure preference with no other behavioural consequence than its impact on fertility, it constitutes an idiosyncratic characteristic of the population under study and the plausibility of the exclusion restriction is not affected.[2] The "same sex" strategy can still be applied, accommodating for the preference for sons in the first stage by including in X the sex of the first two children.

However, the identification strategy may be compromised if the preference for sons has socioeconomic roots and consequences that are conceivably related to the potential outcomes, in violation of Assumption 5.2,

[2] In terms of the theoretical model of Secion 5.2.1 (page 126), this holds under the condition of separability of leisure and the utility derived from children and their gender (Rosenzweig and Wolpin, 2000).

which is more likely to happen in developing countries. Basu and Das Gupta (2001) argue that beyond cultural and religious factors, some societies exhibit a strong son preference because of the gap between sons' and daughters' "ability to contribute to the physical, emotional and financial well-being of their parental household." This gap is determined by kinship systems: if women's links with their parents are cut off after marriage, it becomes more attractive to rear sons that will be able to provide for their parents in old age.

This observation has important implications for the "same sex" strategy. For instance, it is possible to imagine a situation where having two daughters is a random event (Assumption 5.1) that induces a higher probability of further childbearing through a combination of son and gender-balanced preferences (Assumption 5.3). If in this hypothetical setting there is no social insurance and women have low employment rates, parents might rely on their male children for old age support, and this might be at the origin of the preference for sons. Thus parents of two girls are relatively worse off, and will have to work more in order to compensate for the foregone income. In terms of the theoretical model of Section 5.2.1 (page 126), taking I as the permanent income of the household, using sons for old age support implies that the instrument Z (the sex mix of children) cannot identify the direct effect of fertility on labour supply, f_D, because of the effect of the sex mix of children on I. The derivative of Y (labour supply) with respect to Z is given by:

$$\frac{\partial Y}{\partial Z} = \frac{\partial I}{\partial Z} f_I + f_D$$

and the use of sons for old age support implies that

$$\frac{\partial I}{\partial Z} \neq 0$$

which in turn implies that Z has a direct effect on labour supply, over and above its effect on fertility. In terms of potential outcomes, irrespective of the treatment D, the sex mix of children implies that $Y_{1d} > Y_{0d}$, that is, those who had two girls will work more than others. This is a direct effect of Z on potential outcomes over and above its influence on further childbearing D, and as such, it invalidates Assumption 5.2. In terms of the canonical instrumental variables model, the preference for sons might induce a direct correlation of the sex mix with the labour supply or the unobservable factors that affect it, and in this case it is incorrectly excluded from the second stage.

There are other plausible problems for identification in contexts with non-extreme son preferences.[3] In some societies, parents are expected to pay substantial dowries for their daughters, which affects their permanent income and, potentially, their labour supply. These effects on potential outcomes are not verifiable: it is not possible to determine if the sex mix of children or related factors, like dowries, have a direct effect on labour supply. However, an examination of the social and institutional setting of each application might reveal or rule out the presence of problems of this type. Section 6.3 conducts this analysis for Argentina.

6.2.3 Direct effects of same sex

The identification problems discussed above arise from the presence of son preferences. However, direct effects of the sex mix of children, unrelated to parental sex preferences, might also invalidate the application of the "same sex" strategy. As discussed above, Angrist and Evans (1998) rule out the possibility that the secular effects of the sex of children contaminate their instrumental variables estimates for the United States. Rosenzweig and Wolpin (2000) attempt to question this aspect of the estimation strategy using data from rural India. They show that having two children of the same sex, which is likely to be random in their data, implies a higher probability of further childbearing, establishing the presence of a "same sex" first-stage relationship.

Rosenzweig and Wolpin's (2000) caveats are based on the expenditure data for the same households. By studying outlays on child-related goods, they find that same-sex siblings are associated with lower levels of expenditure. They attribute this effect to "hand-me-down" savings, which are more likely to arise for items such as clothing and footwear when there are children of the same sex in the household. Based on this effect of sex mix on expenditure, Rosenzweig and Wolpin (2000) presume that "the sex compo-

[3]As discussed above, extreme forms of son preferences that result in selective abortions or neglect of girls invalidate the randomness of the instrument, in addition to their effects on the exclusion restriction.

sition of children plausibly alters labour supply through mechanisms other than through fertility change alone." According to this interpretation, parents of same-sex children in their Indian data may need to work less because of these savings, implying in terms of potential outcomes that $Y_{0d} > Y_{1d}$. While the authors provide evidence of a link of sex mix and expenditure, they do not establish a direct effect of the instrument Z on labour supply. Moreover, the critique only applies to their Indian dataset: they state that "it is not possible to infer from this evidence whether hand-me-down economies associated with the sex-mix of births are an important phenomenon" in other situations. However, these valid concerns can be addressed by testing the presence of savings of this type with expenditure data, and this is done for Argentina in Section 6.3.

Despite the context-dependent nature of the identifying assumptions, most of the applications of the "same sex" strategy mentioned in Section 5.3.3 (page 140) are justified on the basis of a first-stage relationship, without studying the potential impediments to the exclusion restriction and the other identifying assumptions. The exceptions are Rosenzweig and Wolpin (2000), although they only deal with the concern raised in the previous paragraph, and Chun and Oh (2002), who briefly discuss the strong son preference observed in their Korean data. The originality of this Chapter lies in the detailed analysis of different data sources to assess the plausibility of the "same sex" identifying assumptions in the Argentine case.

6.3 Sex Preferences and Identification Assumptions in Argentina

6.3.1 *Independence of the instrument and fertility effects of sex preferences*

The purpose of this Section is to assess the plausibility of the identifying assumptions of the "same sex" strategy for Argentina, addressing the issues raised in the previous Section.

Assumption 5.1 requires the independence of the instrument with respect to the potential outcomes and treatments. While potential outcomes and treatments, by definition, cannot be observed, the randomness of the instrument can still be established by some of the implications of the independence assumption. One simple check is to compare the characteristics of

Table 6.1: Differences in Selected Characteristics by "Same Sex" Indicator

Characteristics:	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**
Age	-0.0285	-0.0234	-0.0213	-0.0195
	(0.0096)***	(0.0107)**	(0.0097)**	(0.0096)***
Age at first birth	0.0090	0.0134	0.0057	0.0081
	(0.0085)	(0.0097)	(0.0086)	(0.0085)
Residence in rural area	-0.0015	-0.0016	-0.0011	-0.0014
	(0.0012)	(0.0014)	(0.0013)	(0.0012)
Indicators of maximum education level:				
Some primary education	-0.0002	-0.0015	-0.0002	-0.0014
	(0.0012)	(0.0014)	(0.0013)	(0.0012)
Some secondary education	0.0003	0.0012	0.0001	0.0009
	(0.0011)	(0.0013)	(0.0012)	(0.0011)
Some tertiary eduaction	-0.0001	0.0003	0.0001	0.0005
	(0.0008)	(0.0010)	(0.0008)	(0.0008)
Observations	653,213	497,194	599,941	456,437

Note: Differences in means (mean of "same sex" mothers minus mean of mixed sex mothers) and their standard deviations (in parentheses). * significant at 10%; ** significant at 5%; *** significant at 1%. The samples correspond to women aged 21-35 with two or more children aged 18 or younger from the extended questionnaire sample of the 1991 Census, as described in the text.

women with same-sex and mixed-sex sibling compositions, i.e., according to the value of the instrument Z.

Table 6.1 presents the differences in selected variables between these two groups for the four samples of women with at least two children defined in Section 5.4 (page 142). With the exception of the *Age* variable, none of the differences is significant, not even at the 10 percent level, despite the extremely large sample sizes. Women whose first two children were of the same sex and mothers of mixed-sex children exhibit no differences in their ages at first birth, area of residence and education levels.

The only variable for which there is a significant difference is *Age*: the Table indicates that "same sex" mothers are about 0.02-0.03 years younger than mothers of mixed-sex siblings. While statistically significant, this effect is small, and it can be attributed to the high precision of the estimates for large sample sizes, since there does not seem to be a difference in the closely related *Age at firth birth* variable. Moreover, women in the groups defined by the *Same sex* indicator cannot be distinguished in terms of their education level, which is an important determinant of earnings and labour supply. In any case, two-stage least squares models like Equation 5.7 can accommodate covariates like the *Age* variable to control for any effects that this might have on the outcome of interest.

While the evidence from Table 6.1 supports the hypothesis of random assignment of the *Same sex* instrument Z, another prerequisite of the estimation strategy is the existence of a first-stage relationship, embodied in Assumption 5.3. The analysis below serves two purposes: it first establishes the existence of a first-stage relationship between sex preferences and fertility in Argentina, and it also provides a detailed study of the nature of these preferences in the data.

A first-stage relationship requires a significant correlation between the instrument Z and the indicator D, but as discussed in the previous Section, the correlation between childbearing and an indicator of having two children of the same sex may be due to different types of preferences. The mixed-sex sibling preference consists in a desire of having at least one child of each sex, which induces a higher probability of having more children ($D = 1$) in couples whose children are all boys or all girls ($Z = 1$). The preference for sons, in turn, implies that parents of a certain number of girls are more likely to have an additional child than parents of the same number of boys. To discriminate between these two types of preferences, it is necessary to disaggregate the effect of the *Same sex* variable.

In the demography literature, sex preferences and their effect on fertility are discussed in terms of "parity progression ratios." The parity is defined as the number of children, while the progression ratio refers to the probability of having $n + 1$ children, given n children. Much of this literature is devoted to the presence of son preference and their effects, implicitly assuming that a positive correlation between the number of daughters and subsequent childbearing (or a negative correlation with the number of sons) is an unambiguous sign of son preference. Leung (1991), however, develops a dynamic model of sex preferences and fertility decisions to show that such tests of sex preferences are only valid under certain conditions. He derives the optimal fertility behaviour for a couple as a value function defined over the effective number of children given by:

$$a_t B_t + b_t G_t$$

where B_t represents the number of sons, G_t the number of daughters, and a_t and b_t the relative weight attached to children of each sex. Values of a_t or b_t greater (smaller) than zero indicate a positive (negative) valuation of children of the respective sex. Son preference, no sex preference, and daughter preference are defined as cases where $a_t > b_t$, $a_t = b_t$ and $a_t < b_t$ respectively.

Leung (1991) questions the commonly held view according to which a negative effect of the number of sons on subsequent fertility is an unambiguous sign of boy preference. The main conclusion from the model is that a negative relationship between the probability of further births and the number of boys, holding parity constant, can be explained by either son or daughter preference: the only definite conclusion is that sex preferences of some sort are present since the gender of children affects the probability of birth. For this negative correlation to be consistent with daughter preference, however, Leung (1991) shows that parents must value boys negatively at every single parity.[4] In what follows, it is shown that this is unlikely to be the case in the Argentine data, so that this mild restriction allows the discussion of son and daughter preference in a way consistent with the previous literature.

Table 6.2 presents the progression ratios by parity and sex composition of children for the sample of married women – for completeness, the Table also includes those who had only one child. These results are similar for the other three samples previously defined.

The first row of the Table presents the results for parities one to two. More than 77 percent of the women went on to have another child, but those who had a girl in their first birth have a small but significantly higher probability of having a second child, while those who had a boy are less likely to have another child. It should be noted that, while significant, these effects are extremely small: the difference in the probability of further childbearing

[4] He shows that a negative effect of the number of sons on subsequent fertility can be observationally equivalent to cases of daughter preference, for instance if $a_t < 0$ and $a_t < b_t < 0$, but he notes that this requires $a_t < 0$ (a dislike of sons) at each parity.

Table 6.2: Parity Progression Ratios by Parity and Sex Mix of Children, Married Women

Parity	Obs.	Fraction that had another child							
		Overall PPR	Same sex	Mixed sex	PPR by number of boys: 0	1	2	3	4
1 to 2	644,084	0.7719	-	-	0.7737**	0.7703**			
2 to 3	497,194	0.5280	0.5460***	0.5096***	0.5568***	0.5096***	0.5359***		
3 to 4	262,525	0.4241	0.4422***	0.4176***	0.4499***	0.4229	0.4124***	0.4348***	
4 to 5	111,341	0.3941	0.4050***	0.3922	0.4031	0.3961	0.3909	0.3903	0.4070**

Note: *, ** and *** indicate that the number in the cell is different to the "Overall" category at the 10, 5 and 1% levels of significance respectively. The samples correspond to married women aged 21-35 with two or more children aged 18 or younger from the extended questionnaire sample of the 1991 Census, as described in the text (*Complete sample, married*).

between the two groups is only 0.34 percentage points. Although this is a sign of son preference, the size of the differences for higher parities (discussed below) indicates that this difference is not substantial and that its significance may be due to the precision granted by the large sample size.

The second row of Table 6.2 presents the transition probability between parities two and three, which is at the heart of the "same sex" strategy since it represents the first-stage relationship between the instrument Z (*Same sex*) and the treatment D (*More than two children* and *Number of children*). In the sample of married women with two children, 52.8 percent went on to have a third child, but as pointed by the two following columns, this group represented a larger fraction among women with two boys or two girls (54.6 percent) than among those with a son and a daughter (50.1 percent). This sizeable and significant difference of 4.5 percentage points indicates the presence of some form of sex preferences, which can be analysed with the help of the following columns. Mothers of two boys and of two girls both exhibit a significantly higher probability of further childbearing, but this probability is almost 2.1 percentage points higher for mothers of girls. The fact that mothers of two boys have a higher probability of having another child than mothers of a boy and a girl (53.6 percent compared to 50.1) suggests the presence of a strong gender-balanced preference with a moderate bias towards boys.

This conclusion is supported by the analysis of further parity progression ratios. The difference between same-sex and mixed-sex parents is only about 2.5 percentage points in the transition probabilities between three to four children, compared to the 4.5 for two to three, but the pattern is similar when observing the effect of boys and girls. This same-sex effect is still higher for parents of two girls than for parents of two boys.

In the transition from four to five children, the same-sex effect is still present, although the difference in the probability of further childbearing between parents of same-sex and mixed-sex children is reduced to 1.3 percentage points. An interesting point, however, is that at this parity the effect is driven by a preference for daughters, since the probability of further childbearing for those who have had no sons is not significantly different from the overall probability.[5]

Finally, it should be noted that the number of boys never has a negative effect on the probability of further childbearing, which is not consistent with a negative net value of sons at every parity. This addresses Leung's (1991) concern of observational equivalence between son and daughter preferences.

The results in Table 6.2 refer to the *Married* sample, but the magnitude and significance of the parity progression ratios are similar for the remaining three samples. However, it is possible that different groups in the population defined by some characteristics exhibit different types of sex preferences, which could bias the results with the pooled datasets if these characteristics are systematically related to labour market outcomes. While not presenting the full parity progression ratio analysis, Section 7.5 (page 187) discusses the first-stage relationship between the instruments *Same sex*, *Two boys* and *Two girls* and the treatments *More than two children* and *Number of children* for the groups defined by the women's education levels of Table 5.1 (page 145). This analysis indicates that the sex preferences identified in this Section are homogeneous across these three groups and among rural and urban populations, with only minor differences in the probabilities of

[5]A corollary of this analysis brings support to Assumption 5.4 (page 134). While monotonicity is not directly verifiable, because it is defined in terms of potential outcomes, Angrist and Imbens (1995) note that the assumption has a testable implication in the case of multivaried treatments such as the number of children: if the assumption holds, the cumulative density functions of D with $Z = 0$ and $Z = 1$ should not cross. Inspection of Table 6.2 indicates that this is the case for the Argentine data.

further childbearing.

This evidence implies that the first-stage Assumption 5.3 is valid, in the sense that the sex mix of children has an effect on fertility in Argentina. Moreover, sex preferences and their effect on fertility correspond to Section's 6.2.1 gender-balanced with moderate son preference category, and they are consistent with Basu and Das Gupta's (2001) widespread "preference for a gender-balanced family" with "mild preferences for children of a particular gender."

Given the presence of son preferences and the concerns raised in the previous Section about this phenomenon for the validity of the "same sex" strategy in developing countries, the following pages study the possibility of contamination of instrumental variable estimations by describing the institutional setting and presenting evidence on the exogeneity of the sex-mix for female labour supply decisions in Argentina.

6.3.2 *Institutional setting and effects of son preferences*

The analysis of the first-stage relationship revealed that the preference for a gender-balanced family is more intense for parents of girls, which was interpreted as a moderate bias for sons in Argentina. As discussed in Section 6.2, this might raise some concerns about the exclusion restriction in Assumption 5.2 in the context of a developing country: if son preferences are due to – or result in – economic factors that are correlated with the labour supply of the parents, the instrument Z has a direct effect on the outcome Y. In that case, instrumental variable results are biased and do not identify the causal effect in Proposition 5.1 (page 135). Since potential outcomes are not observable, exclusion restrictions are inherently non-testable, and their plausibility must be evaluated on a case by case basis by means of indirect evidence – the following Chapter presents direct evidence by means of Hausman-type overidentification tests.

As described in Section 6.2.2, Basu and Das Gupta (2001) attribute the extreme preference for sons in China and other developing countries to the gap between sons' and daughters' ability to contribute to the well-being of their parental household, which is determined by kinship systems. However, when reviewing the evidence for Latin America, they observe that "childbearing outside formal marriage or stable unions is common," a pattern that they find inconsistent with economic dependence of women on men. They conclude that despite a tradition of "male machismo [..] there are few rigid rules constraining women from participating actively in social and economic life, or from helping their parents" in the region.

This is consistent with the evidence from Argentina (INDEC, 2001). With respect to kinship systems, women stay in contact with their parents, and the lack of constraints pointed out by Basu and Das Gupta (2001) implies a relatively high labour force participation of women, as previously discussed. Moreover, dowries are unheard of, which implies that daughters are not necessarily more expensive to rear than sons, at least as far as marriage is concerned. Finally, the argument of children (and notably boys) as insurance for old age is weakened by the fact that since the middle of the twentieth century Argentina has had a fairly large social security system that supports retired workers but also destitute people in old age, regardless of their previous contributions,[6] which was reflected in the results in Part I on the relative income stability in households with pensioners.

The institutional setting suggests that the roots of the moderate predilection for boys in Argentina is eminently cultural. As discussed in Section 6.2.2, however, even if due to purely cultural factors in their origin, son preference may have consequences that might call into question the validity of the "same sex" strategy in developing countries.

One of the most prominent manifestations of extreme son preferences is the phenomenon of "missing girls," attributed to discrimination in the form of gender-based stopping rules, selective abortion, neglect of daughters and even infanticide. The effect of stopping rules was considered in the discussion of Table 6.2, and selective abortion can be ruled out in 1991 Argentina since sex screening techniques were practically not available at the time of the Census.[7]

Figure 6.1 presents the infant sex ratios – representing the ratio of boys to girls aged zero to four years old – for selected countries around 1990. The Figure indicates that this ratio is slightly lower in Argentina than in

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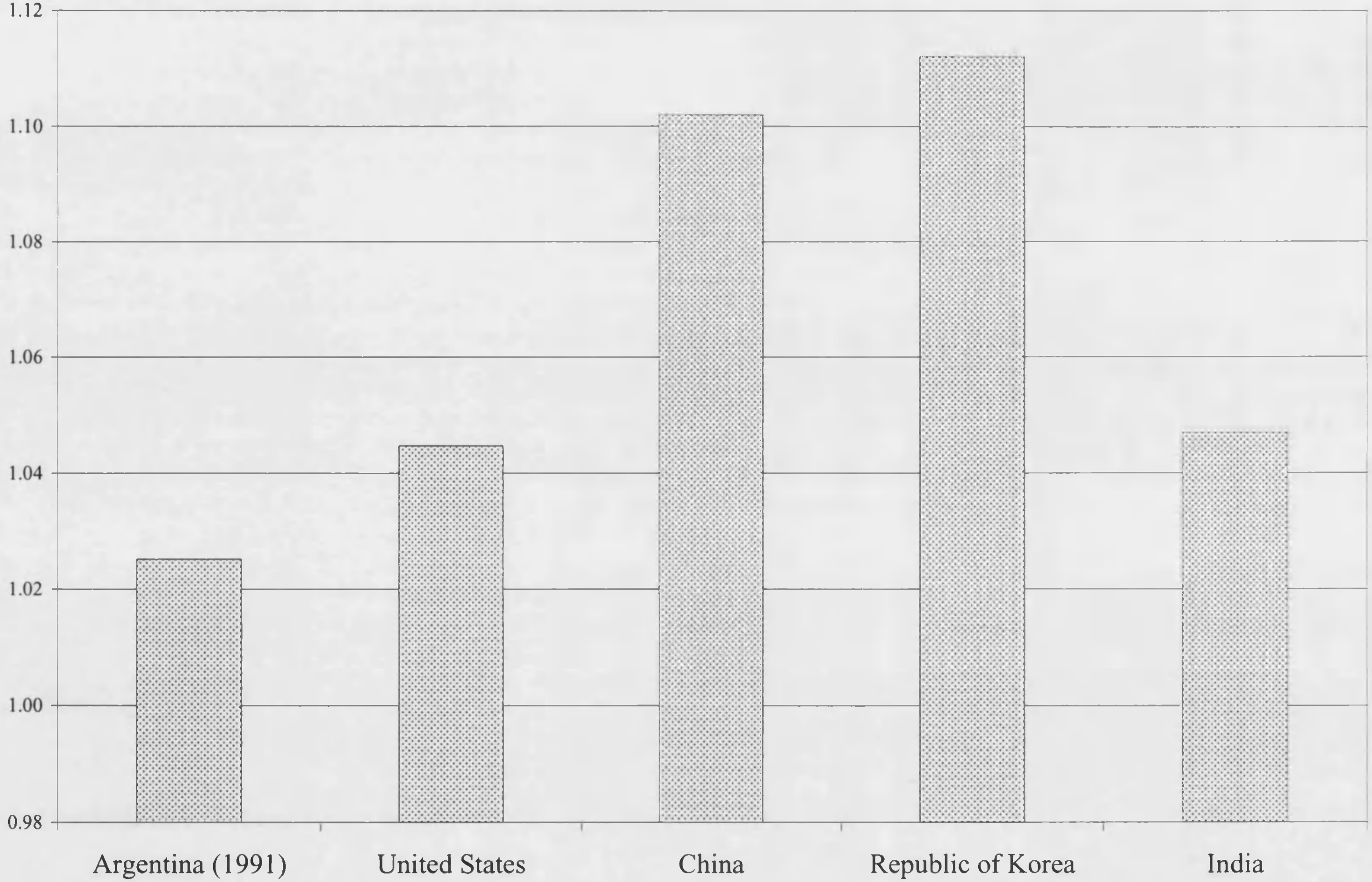
[6]See Arza (2004) for a thorough review of social security in Argentina.

[7]While screening techniques have made substantial progress in the last decade, access to them was limited (at best) in Argentina in 1991. Moreover, abortion was (and still is) illegal, further reducing the possibilities of selection of the sex of offspring. Das Gupta (2003) discusses selective abortion and their effects on gender mix in Korea.

Figure 6.1: Sex Ratios – Number of Boys / Number of Girls, 0 to 4 Years Old, Selected Countries, 1990



Source: Argentina and United States: author's calculations based on the respective censuses. China, Korea and India: Basu and Das Gupta (2003).

Table 6.3: School Enrolment, Children Aged 6 to 12

Age	Boys		Girls		Overall		Difference
	Population	Enrolment Rate	Population	Enrolment Rate	Population	Enrolment Rate	(percentage points)
6	319,150	96.17%	311,510	96.51%	630,660	96.34%	-0.346
7	323,530	97.30%	314,370	96.95%	637,900	97.13%	0.348
8	332,694	98.01%	326,251	98.18%	658,945	98.10%	-0.173
9	337,167	98.08%	330,052	98.20%	667,219	98.14%	-0.127
10	336,681	97.80%	327,912	98.12%	664,593	97.96%	-0.319
11	345,115	97.54%	336,835	97.76%	681,950	97.65%	-0.221
12	340,912	96.11%	331,430	96.42%	672,342	96.26%	-0.307
Total	2,335,249	97.29%	2,278,360	97.46%	4,613,609	97.38%	-0.167

Note: Data from the 1991 Census. The difference in attendance is the rate for boys minus the rate for girls.

the United States, which is considered a case of very mild son preference (Williamson, 1983), and substantially lower than in extreme cases like China and Korea, identified as cases of extreme son preferences (Basu and Das Gupta, 2001).

The infant sex ratio in Argentina is consistent with the small but relatively higher proportion of boys in births, which is an almost universal feature of demographic data. Figure 6.1 can thus be taken as evidence of no discrimination against girls in the form of neglect or reduced healthcare that results in higher mortality among girls, and it shows the lack of an aggregate effect of the preference for sons in the Argentine data.

Another manifestation of extreme forms of son preference is the neglect of daughters in other aspects than nutrition and healthcare. In most countries where girls are systematically discriminated against, the school enrolment rates of younger females are significantly lower than that of their male counterparts. In Argentina, however, Pantelides (2002) reports that in 1991 women exhibited higher rates of course completion than men, which is consistent with the evidence in Table 6.3. This Table presents the school enrolment rates for children aged six to twelve years old from the 1991 Census. These rates are very close for boys and girls, but slightly higher for girls on average and for almost every age group. This pattern is not consistent with discrimination against girls in education.

As discussed in the previous Chapter, further evidence on the effect of sex preferences can be deducted from household's consumption patterns and the budget spent on goods for children of different sex.[8] Table 6.4 presents evidence from the 1987 National Survey of Household Expenditure ("Encuesta Nacional de Gasto de los Hogares"–ENGH), carried out by INDEC.[9] The sample is representative of the 1991 Census data (with the exception of isolated rural areas), and it was constructed following the criteria set out in Section 5.4 (page 142). It consists of 6,808 married women aged 18 to 45, with two or more children aged 18 or younger.

Table 6.4 presents data on differences in budget shares for a series of goods by sex composition of children. If girls were neglected or discriminated against, parents of boys would spend a higher proportion of their budget on food, health, clothing or education, among other goods. The first panel in the Table points out that parents of two children of the same sex, and parents of two boys and two girls have the same budget shares in seven categories ranging from marginal expenditures, like "Entertainment," to more substantial items like "Food and beverages," including also categories of children related goods. None of the differences for parents of two boys or two girls are different from zero at the normal levels of significance. Moreover, the last column presents the coefficient of a regression of the respective share on the ratio of boys to total children in the household, and none is significant either. Finally, the bottom panel of the Table presents the total and per capita measures of income and expenditure and their differences by the same variables: the results indicates that these aggregates are not affected by the sex mix of children in the household.

The consistent lack of effect of the sex composition of children on the budget shares of child-related goods can be taken as further evidence of no discrimination against girls and of the lack of direct effects of sex mix on relevant economic variables.

The evidence presented so far states that demographic and fertility patterns in Argentina are consistent with preferences for a gender-balanced

[8]Deaton (1997, Chapter 4) and Case and Deaton (2003) review these issues.

[9]Expenditure surveys are only carried out every ten years by INDEC. The 1987 survey is the closest to the 1991 Census year employed in the empirical analysis of fertility and labour supply.

Table 6.4: Difference in Budget Shares, Income and Expenditure by Sex Composition of Children

	Total	First two children			Boys / Total
		Same sex	Two boys	Two girls	
Budget shares of:					
Food and beverages	42.0%	0.0105	0.0117	0.0019	-0.0006
		(0.0140)	(0.0159)	(0.0164)	(0.0229)
Clothing and footwear	8.4%	0.0037	0.0030	0.0019	0.0030
		(0.0022)*	(0.0025)	(0.0026)	(0.0037)
Clothing for children under 10	3.4%	0.0009	0.0003	0.0009	0.0002
		(0.0008)	(0.0009)	(0.0009)	(0.0013)
Health and related expenditures	4.6%	-0.0018	-0.0018	-0.0005	-0.0016
		(0.0021)	(0.0024)	(0.0025)	(0.0035)
Education, total	1.7%	-0.0031	-0.0017	-0.0025	0.0004
		(0.0022)	(0.0025)	(0.0026)	(0.0036)
School related materials	0.6%	-0.0002	-0.0007	0.0004	-0.0009
		(0.0005)	(0.0006)	(0.0006)	(0.0009)
Entertainment	6.1%	0.0002	0.0018	-0.0017	0.0043
		(0.0019)	(0.0022)	(0.0022)	(0.0031)
Income and expenditure measures:					
Total net income of the household	1085	9.0	27.3	-16.6	56.5
		(27.9)	(31.7)	(32.6)	(45.6)
Net income per capita	227	-1.8	4.1	-6.7	13.9
		(6.1)	(7.0)	(7.2)	(10.0)
Total expenditure	941	11.4	-2.7	18.4	-10.3
		(20.1)	(22.9)	(23.5)	(33.0)
Per capita expenditure	196	-0.7	-0.9	0.1	1.4
		(4.5)	(5.1)	(5.3)	(7.4)

Note: Differences in means (mean of the relevant group minus mean of the rest of the population) and their standard deviations (in parentheses), except for the last column which reports the regression coefficient of the ratio of boys (with the variable in column 1 as the dependent variable). * significant at 10%; ** significant at 5%; *** significant at 1%. The sample consists of 6,808 married women aged 18-45, with two or more children aged 18 or younger from the Encuesta Nacional de Gasto de los Hogares, INDEC, 1987. Income and expenditure in current Australes.

family with a moderate bias towards sons, and that these patterns are homogeneous across different groups of the population. Moreover, the institutional setting and the evidence presented in this Section supports the conclusion that these preferences are eminently cultural in their origins and limited in their effects. Data from sex ratios, school enrolment and household expenditure fail to reveal any significant form of discrimination against girls, supporting the hypothesis that the bias towards sons, observed in the parity progression ratios, is an idiosyncratic feature of the society under study which appears to be innocuous for the application of the "same sex" strategy in Argentina.

6.3.3 *Identification concerns beyond sex preferences: direct effects of "same sex"*

The indirect evidence presented above supports the hypothesis that son preferences do not invalidate the exclusion restriction in Assumption 5.2, since it seems unlikely that they induce a direct effect on the labour supply of women over and above their effect on fertility. It must still be established, however, that beyond the issue of son preference the sex mix of children (the instrument Z) does not have a direct effect on potential outcomes.

A possible threat to the validity of the "same sex" identification strategy is posed by Rosenzweig and Wolpin (2000), as discussed in Section 6.2.3. Studying outlays per children in rural India, they find that same sex siblings are related to substantially lower levels of expenditure on some child-related goods. They attribute this effect to hand-me-down savings, which are more likely to arise for items such as clothing and footwear when there are children of the same sex in the household. Since these items represent a sizeable fraction of the household's expenditures, they note that the sex composition of children plausibly alters labour supply through mechanisms other than through fertility change alone.

Whether or not the effect identified by Rosenzweig and Wolpin's (2000) is present in other settings is a verifiable matter, and Table 6.4 presents evidence on the effects of sex mix on household consumption patterns in Argentina. Using expenditure data from the ENGH survey (described above), the Table reports the budget share of seven categories of goods (top panel) and the sample means of income and expenditure (bottom panel). It also presents the difference in those variables between the whole sample and households with same sex children, two boys and two girls (columns 3, 4 and 5 respectively). In the last column, it reports the regression coefficient of the ratio of boys when the budget shares, income and expenditure variables are used as dependent variables.

The budget shares of clothing, footwear, and school-related goods, among other categories, are not significantly affected by the sex composition of children in the household. Only one of the figures in the Table is significant at the 10 percent level: households with two children of the same sex have a 0.3 percentage points higher budget share of clothing and footwear. Moreover, the sign of this difference contradicts the presence of hand-me-down savings, since those with same-sex children spend a significantly higher share of their budget in clothing and footwear. The evidence in Table 6.4 reflects the lack of hand-me-down savings or other effects of sex mix on the expenditure patterns of households in Argentina.

Finally, aggregate data from the ENGH suggests that hand-me-down effects not reflected in Table 6.4 are unlikely to have a noticeable effect on total expenditure. Argentine households in the full 1987 ENGH sample devoted 6.7 percent of their budget to the clothing and footwear (for all members), and only 2.8 percent on those items for children aged 10 or less (INDEC, 2000).

Meanwhile, Rosenzweig and Wolpin (2000) find in their Indian data that clothing expenditures on children under 18 represents 11 percent of household income, and their estimated hand-me-down savings for these goods amounts to 1.3 percent of average earnings. Even assuming that savings of this type exist in Argentina (and that they imply a direct effect on labour supply), their size would be too small to account for a meaningful reduced form relationship between a same sex indicator and parental labour supply. The results for India are specific to the nature of the setting, which consists of extremely poor households in rural areas that devote a large share of their resources to child-related goods.

The indirect evidence presented in this Section is thus consistent with the validity of the exclusion restriction of Assumption 5.2. The following Chapter presents further evidence on the exogeneity of the same sex variable in the labour supply decision based on Hausman-type overidentification tests of the instrumental variables regressions.

6.4 CONCLUSION

The discussion and the evidence presented in this Chapter indicates that the sex mix of children, as captured by the "same sex" instrument Z, has an effect on fertility D and probably no direct effect on the labour market outcome Y, and it is thus correctly excluded from the second-stage estimation in Argentina. While the preference for a gender-balanced family is complemented by a moderate bias for sons, this secular effect is not endogenous to the labour supply decision of the parents and can be controlled for by adding covariates in two-stage least squares estimations.

In the following Chapter, the significant and plausibly exogenous effect of the sex mix of children on further childbearing in Argentina is exploited to produce instrumental variables estimates of the causal effect of fertility on labour supply.

CHAPTER 7

FERTILITY AND WOMEN'S LABOUR SUPPLY IN ARGENTINA

7.1 INTRODUCTION

As discussed in the Introduction to Part II (page 123), labour market variables are strong correlates of poverty measures, but little is known about their determinants in Argentina. While the negative correlation between childbearing and labour force participation is an almost universal phenomenon, its interpretation in terms of causality is often marred by self-selection, endogeneity and simultaneity issues, as discussed with the help of a stylised model of female labour supply in Section 5.2.1 (page 126).

This Chapter establishes the causal nature of the link between fertility and female labour supply in Argentina by means of the "same sex" identification strategy. This strategy is based on the observation that parents of two children of the same sex exhibit a higher propensity to have another child to obtain a gender-balanced sibling composition. Under certain conditions, analysed in Chapters 5, the sex mix of children can thus be used as an instrument for further childbearing, and as shown in Chapter 6, the exogeneity requirements for the instrument are met in the Argentine case.

The data employed in this Chapter was described in Section 5.4 (page 142) and consists of a large sample of women from the 1991 Census, aged 21 to 35 and with two or more children. As discussed in Introduction to Part II, the period 1980-2000 was characterised by a large increase in female labour force participation and by a fall in fertility rates towards replacement levels. Moreover, as discussed in Section 1.1 (page 18), the year 1991 marked the beginning of a period of market oriented reforms that changed the structure of Argentine labour markets and the economy as a whole. The post-Second World War period was characterised by relatively high levels of unionisation (about half of the labour force in 1990), job security and high employment protection (Galiani and Gerchunoff, 2003). The structural reforms of the 1990s affected the labour market directly, by modifying employment regulations and reducing the power of unions through labour laws, and indirectly, through the impact of trade liberalisation on unemployment and participation. The main effects were a deterioration of job stability and the growth of the informal sector[1] from 28.9 percent of workers in May 1991 EPH to almost 45 percent in May 2003,[2] which resulted in a dual market with relatively well paid workers in secure jobs, on the one hand, and self-employed and small-firm employees with no benefits and high de facto job flexibility on the other (Moreno and Roca, 2002).

The unemployment rate had an upward trend before and after the period under study. It raised from less than 3 percent in 1980 up to 6.9 percent in May 1991, with a relatively higher level for women than for men (7.3 and 6.9 percent, respectively). However, these figures are low when compared to the evolution of the 1990s, depicted in Figure 1.3 (page 30) – the unemployment rate eventually peaked at 21.5 percent in May 2002. This trend was simultaneous to a substantial increase in female labour force participation, from 35.4 in 1990 to 38.4 percent in 2000, compared to 66.5 to 67.7 for men (CELADE, 2004, based on Census data). The high levels of unemployment, however, imply that employment rates did not grow as much during this period for women, and decreased substantially for men and the overall population during the crisis of 2001-2002 (Cortés, 2003).

With respect to the distribution of hours, part-time work was relatively uncommon in Argentina. In May 1991, only 5.7 percent of employed men worked less than 30 hours. This modality was more common for women, with 10.8 percent worked less than 20 hours, and 26.1 percent less than 30 hours, but still relatively low when compared to the United Kingdom, for instance, where 40.5 percent of women worked part time in 2000 (ILO, 2003). The low participation of women and the low levels of part time work were

[1]See the definition of informality in Section 3.3 (footnote 5, page 95).

[2]Unless stated otherwise, the figures in this Introduction correspond to EPH indicators presented by Cortés (2003). The May 1991 data is almost contemporaneous to the Census, but the EPH covers only major urban centres.

attributed, among other factors, to the limited supply of childcare facilities for children under school age and to the lack of free provision for poor households (Cortés, 2003). This issue is discussed later in this Chapter in the light of the results from the model of fertility and female labour supply estimated below.

This Chapter is organised as follows. Section 7.2 presents the benchmark results from the Wald and two-stage least squares instrumental variable estimations of fertility and female labour supply in Argentina. Section 7.3 extends these results to parents of at least three children, and provides an analysis of the effects of fertility for different groups defined by their education level. Conclusions follow.

7.2 Wald and Two-Stage Least Squares Estimates

7.2.1 *Wald estimates*

This Section studies the causal effect of fertility on female labour supply. The estimations are based on the utility maximisation problem presented in Equation 5.1 (page 127). This model results in a labour supply function $Y = f(\mathbf{K}, D)$, where $\mathbf{K}$ is a vector of characteristics and choice variables, and D is a measure of fertility. The parameter of interest is the labour supply response to changes in the fertility variable, f_D, which may be difficult to recover due to the potential effects of D on the components of $\mathbf{K}$. As discussed in Section 5.2.1 (page 126), a solution to these endogeneity problems resides in finding an instrumental variable Z that induces variation in fertility (D) but does not affect the labour supply decision directly. Defining K as a generic component of $\mathbf{K}$, the derivative of Y (labour supply) with respect to Z is given by:

$$\frac{\partial Y}{\partial Z} = \frac{\partial K}{\partial Z} f_K + \frac{\partial D}{\partial Z} f_D$$

Since the exogeneity of Z ensures that $\partial K / \partial Z = 0$, the effect of fertility on labour supply is identified:

$$f_D = \frac{\partial Y}{\partial Z} / \frac{\partial D}{\partial Z} \tag{7.1}$$

Previous work on fertility and labour supply found that parental sex preferences provide valid instruments for models of this type in the United States (Angrist and Evans, 1998). The evidence presented in Chapter 6 for Argentina indicated that the sex mix of children, as captured by the "same sex" instrument Z, has an effect on further childbearing in women with at least two children (D), and no direct effect on the labour market outcome Y.

The simplest way to estimate the parameter in Equation 7.1 is by instrumental variables, in a model with a constant and one endogenous regressor like Equation 5.6:

$$Y_i = \gamma + \phi D_i + \varepsilon_i$$

This regression is estimated with Z as an instrument for D with a first-stage regression of the form:

$$D_i = \gamma_f + \theta Z_i + \epsilon_i \tag{7.2}$$

The parameter ϕ estimated in this way corresponds to the Local Average Treatment Effect of Proposition 5.1 (page 135), since by definition ϕ obtained by IV represents the difference in means of the outcome variable for the two values of the instrument Z divided by θ, which is equal to the difference in the expectation of the treatment D at the two values of Z.[3]

The Assumptions 5.1-5.4, required by Proposition 5.1, were the object of the previous Chapter, which presented evidence on their plausibility in the Argentine case. It can then be assumed that the parameter ϕ identifies a Local Average Treatment Effect (LATE) for the group of compliers.

Table 7.1 reports the results of the unconditional IV model of Equation 5.6, the LATE-Wald coefficient ϕ, for the four samples defined in Section 5.4 (page 142). For comparison purposes, the Table also presents the corresponding OLS results for ϕ, obtained by estimating the model in Equation 5.6 without instrumenting D.[4]

[3]While the discussion is in terms of a binary treatment D (*More than two children*), this Chapter also presents results obtained with D set to the *Number of children* variable. These two regressors correspond to the binary and variable treatments, respectively, as discussed in Section 5.2.3 (page 132). The case of variable treatment intensity requires only minor adjustments to the interpretation of the LATE parameter, as described in the same Section (footnote 14, page 135).

[4]While useful for comparison purposes, it should be noted that the OLS and instrumental variables coefficients are not necessarily comparable without further homogeneity assumptions. As discussed in Section 5.2.3 (page 132), instrumental variables estimates identify the causal effect only for the subpopulation of compliers, while OLS coefficients,

Table 7.1: Wald Estimates of the Effect of Fertility on Women's Labour Supply

	Complete Sample				**Married**			
	Proportion of sample	**Worked for pay**	**Number of children**	**More than two children**	**Proportion of sample**	**Worked for pay**	**Number of children**	**More than two children**
Overall mean		0.3138	2.9763	0.5480		0.3050	2.9050	0.5280
Same sex (1)	0.5066	0.3124	3.0047	0.5637	0.5056	0.3034	2.9365	0.5460
Mixed sex (2)	0.4934	0.3153	2.9472	0.5318	0.4944	0.3067	2.8729	0.5096
Difference (1)-(2)		-0.0029	0.0574	0.0320		-0.0034	0.0636	0.0364
Wald estimate			-0.0511	-0.0917			-0.0529	-0.0924
Standard error			[0.0199]**	[0.0358]**			[0.0205]***	[0.0357]***
OLS estimate			-0.0352	-0.0783			-0.0392	-0.0800
Standard error			[0.0005]***	[0.0011]***			[0.0006]***	[0.0013]***
Observations			653,213				497,194	

	AE Sample				**AE Sample, married**			
	Proportion of sample	**Worked for pay**	**Number of children**	**More than two children**	**Proportion of sample**	**Worked for pay**	**Number of children**	**More than two children**
Overall mean		0.3155	3.0619	0.5955		0.3046	2.9848	0.5741
Same sex (1)	0.5062	0.3139	3.0935	0.6131	0.5053	0.3025	3.0196	0.5940
Mixed sex (2)	0.4938	0.3171	3.0295	0.5775	0.4947	0.3066	2.9492	0.5538
Difference (1)-(2)		-0.0032	0.0640	0.0356		-0.0041	0.0704	0.0403
Wald estimate			-0.0503	-0.0905			-0.0584	-0.1021
Standard error			[0.0187]***	[0.0336]***			[0.0193]***	[0.0337]***
OLS estimate			-0.0383	-0.0913			-0.0410	-0.0875
Standard error			[0.0005]***	[0.0012]***			[0.0006]***	[0.0014]***
Observations			599,941				456,437	

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. The Wald estimates represent the difference (1)-(2) of the *Worked for pay* indicator divided by the difference (1)-(2) of the *Number of children* and *More than two children* variables. The OLS estimates represent the coefficients of these two variables in the respective regressions with *Worked for pay* as the dependent variable. The samples correspond to women aged 21-35 with two or more children aged 18 or younger from the extended questionnaire sample of the 1991 Census, as described in the text.

The Wald estimates of the effect of the total number of children and having more than two children on the probability of working for pay is obtained with the following variables: the instrument Z is the binary indicator *Same sex*, the dependent variable Y is *Worked for pay*, and the endogenous regressor D is either the *Number of children* variable or the *More than two children* indicator.

Given the interpretation of OLS regressions with one binary independent variable as simple differences in the mean of the dependent variable, Table 7.1 presents the overall means of Y and D, and their values conditional on $Z = 1$ (same sex) and $Z = 0$ (mixed sex). The Table also reports the difference of the conditional means, which in the case of the variables *Number of children* and *More than two children* can be interpreted as the coefficient θ in the first-stage regression of Equation 7.2.

The Table has four panels, one for each of the samples on which the analysis is carried out. The first row within each panel contains the means of the variables of interest, as already presented in Table 5.1 (page 145). The first column indicates that among parents of at least two children there is a marginally higher probability of having the first two children of the same sex (about 50.5-50.6 percent) than one son and one daughter.

The reduced form effect of the *Same sex* instrument on the outcome variable *Worked for Pay*, denoted by the difference in the conditional means, is very small, as expected from the discussion of the previous Chapter. This difference, which represents the numerator of the LATE coefficient of Equation 5.5 (page 135), is of the expected sign: mothers of *Same sex* children have a lower probability of working for pay of about 0.3 to 0.4 percentage points, which can be attributed to the impact of the instrument on the endogenous fertility variables. The third and fourth columns of each panel report the means of *Number of children* and *More than two children* conditional on *Same sex*, and their differences. Women whose first two children were of the same sex had on average between 0.057 and 0.0584 more children, and a 0.032-0.0403 higher probability of having a third child, depending on the sample. These numbers represent the estimate of the parameter θ in the first-stage Equation 7.2, and correspond to the parental preference for

as given by Equation 5.4 (page on 132), provide a (potentially biased) estimate of the average effect for the whole population.

a gender-balanced family in the transition from two to three children, presented in Table 6.2 and discussed in Section 6.3.1 (page 155).

The bottom part of each panel in Table 7.1 reports the OLS and Wald (IV) estimates of the effects of fertility on women's labour supply, represented by ϕ in Equation 5.6. The Wald coefficients indicate that an additional child reduces women's labour supply by about 5 percentage points, while having more than two children has a negative impact of about 9-10 percentage points. The results are very similar for the *Complete* and *AE Samples*, although the coefficients are slightly higher (in absolute value) for married women. Moreover, all estimates are strongly significant, with six of the eight Wald coefficients different from zero at the 1 percent level. Finally, for both instrumented variables, *More than two children* and *Number of children*, the Wald point estimates are higher than the OLS coefficients in absolute value, implying that OLS estimates might be underestimating the negative effect of additional children on women's labour supply if the compliers are similar in their characteristics to the rest of the population. The following Section presents a formal test of these differences.

The Wald estimates and their statistical significance represent strong evidence of a causal effect of fertility on labour supply in the Argentina data. However, as discussed in general in Section 6.2 and specifically for Argentina in Section 6.3 (page 155), the concerns raised by a mild son preference in the sample indicate the need for controlling for the secular effect of the sex of the first two children in the estimations. Moreover, other plausible exogenous demographic characteristics can be included as regressors in the second stage. The following Section addresses these issues, presenting the results of the two-stage least squares estimation of the fertility and labour supply model that accommodates a set of covariates.

7.2.2 *First stages and two-stage least squares: benchmark results*

The first-stage effect of the instrument was evident in the tabulations of Table 6.2, and it was confirmed in Table 7.1. However, the results from Table 6.2 point out the presence of a mixed-sex sibling preference complemented with a moderate bias for boys, so that the model could be improved by adding covariates to control for any secular independent of the sex of the first two children, and by distinguishing between the *Two boys* and *Two girls* components of the *Same sex* instrument. While the Wald setup of Equation 5.6 provides a compact model for causal effects, its drawbacks are the lack of controls for other exogenous characteristics and its reliance on a single instrument. This Section deals with the constant effect model of Equation 5.7:

$$Y_i = X_i'\beta + \phi D_i + \varepsilon_i$$

This model is estimated by two-stage least squares, with Z as an instrument for D, which implies a first-stage regression of the form:

$$D_i = X_i'\beta_f + \theta Z_i + \epsilon_i \tag{7.3}$$

The set of covariates X includes plausibly exogenous characteristics like the age of the woman and her age at first birth. Given the possibility of effects of the gender of children on omitted variables, the vector X also includes indicators for the sex of the first two children. As discussed in the robustness checks presented in Appendix D (page 232), the main results of this Section are not affected by the inclusion of other covariates in X, but the evidence suggests that some of them, like the indicators of the education level, might be endogenous. For this reason, this Section only reports results with a minimum of demographic variables in X.[5]

Finally, with respect to the mild son preference found in the data, the estimation is also carried out by decomposing the *Same sex* indicator into the indicators *Two boys* and *Two girls*, since a further advantage of two-stage least squares is that it allows for more than one instrument to be included in the estimation: these two variables can be used as an instrument for D in Equation 5.7. The estimation with two separate instruments implies a first-stage model of the form:

$$D_i = X_i'\beta_f + \theta_1 Z_{1i} + \theta_2 Z_{2i} + \epsilon_i \tag{7.4}$$

where Z_1 and Z_2 represent the *Two boys* and *Two girls* indicators, and D and

[5] It should be noted that the regressions implicitly control for the age of the first child, equal to the difference of *Age* and *Age at first* birth. The ages of other children were not included because of the potential endogeneity of birth intervals, which are left for further research.

X are defined as before.[6]

Table 7.2 reports the coefficients θ from Equation 7.3 and θ_1 and θ_2 from Equation 7.4. These OLS first-stage regressions are estimated for the two instrumented variables D, *Number of children* and *More than two children*, and the Table reports only the coefficients and standard errors of the instruments.

Columns one to four contain the results for an OLS regression with *Number of children* as the dependent variable, and columns five to eight present the same information with *More than two children* as the dependent variable. The first row indicates that women in the complete sample with two children of the same sex have on average 0.0633 more children after conditioning on the characteristics X, and have a 0.0341 higher probability of having more than two children, with slightly higher numbers for the *AE* samples and for married women. It should be noted that all the coefficients presented in the Table are significant at the 1 percent level.

The results for the *Same sex* instrument in Table 7.2 are a weighted average of the effect of having two girls and two boys. These are presented in the second and third rows. For the whole sample, women with two girls have on average 0.0894 more children, and a 0.0439 higher probability of having more than two children. As observed previously in Table 6.2 (page 155), these figures are lower for women who had two boys (0.0372 and 0.0243 respectively). Finally, the panel at the bottom of the Table presents the results of the same first-stage regressions, but using the covariates corresponding to the women's spouse. The coefficients are similar to those for married women, which are higher than those for the overall sample.

Table 7.2 represents a multivariate version of the parity progression ratios of Table 6.2 for the transition from parity two to three, and the conclusions from that Table still hold conditional on the covariates X: the sex mix of the first two children has a strongly significant effect on fertility variables, and this first-stage relationship reveals a preference for a gender-balanced family with a moderate bias for sons.

Based on the effects of the instrument Z (and its components Z_1 and Z_2)

[6]When using these two instruments instead of *Same sex*, it is not possible to control for the sex of the first two children in the regression because of perfect multicollinearity. As in Angrist and Evans (1998), the results presented here control for the sex of the first child when using *Two boys* and *Two girls* as instruments.

Table 7.2: First Stages: Effect of Sex Composition on Further Childbearing

Dependent variable:		**Number of children**				**More than two children**			
		Complete Sample	**Married**	**AE Sample**	**AE Sample, married**	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**
Coefficient of:									
Same Sex	Same Sex	0.0633	0.0695	0.0683	0.0750	0.0341	0.0387	0.0370	0.0419
Controls for sexes of 1st & 2nd children		[0.0026]***	[0.0029]***	[0.0028]***	[0.0031]***	[0.0011]***	[0.0013]***	[0.0012]***	[0.0014]***
Two Boys and Two Girls	Two Boys	0.0372	0.0436	0.0402	0.0466	0.0243	0.0286	0.0265	0.0306
Control for sex of 1st child		[0.0037]***	[0.0040]***	[0.0040]***	[0.0043]***	[0.0016]***	[0.0018]***	[0.0017]***	[0.0019]***
	Two Girls	0.0894	0.0954	0.0964	0.1033	0.0439	0.0488	0.0475	0.0531
		[0.0038]***	[0.0041]***	[0.0040]***	[0.0044]***	[0.0016]***	[0.0018]***	[0.0017]***	[0.0019]***
Spouse worked for pay									
Same Sex	Same Sex		0.0657		0.0753		0.0354		0.0420
Controls for sexes of 1st & 2nd children			[0.0027]***		[0.0031]***		[0.0012]***		[0.0014]***
Two Boys and Two Girls	Two Boys		0.0408		0.0475		0.0256		0.0310
Control for sex of 1st child			[0.0038]***		[0.0044]***		[0.0016]***		[0.0019]***
	Two Girls		0.0906		0.1032		0.0451		0.0531
			[0.0039]***		[0.0045]***		[0.0016]***		[0.0019]***
Observations		653,213	497,194	599,941	456,437	653,213	497,194	599,941	456,437

Note: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include the age and the age at first birth of the woman or her spouse, in addition to the sex of the first and second children (where indicated). The samples correspond to women aged 21-35 with two or more children aged 18 or younger from the extended questionnaire sample of the 1991 Census, as described in the text.

on the endogenous regressors D, and given the plausibility of the identifying assumptions in the Argentine case as discussed in the previous Chapter, Table 7.3 presents the results of the estimation of Equation 5.7 by ordinary and two-stage least squares. The Table reports the coefficient ϕ by OLS and using *Same sex* or *Two boys* and *Two girls* as instruments for *Number of children* (columns 1-4) and *More than two children* (columns 5-8), with *Worked for pay* as the dependent variable.

The first panel of the Table presents the OLS results. Since the use of *Two boys* and *Two girls* as instruments implies that it is not possible to control for the sex of the first two children, due to multicollinearity, the panel presents the OLS estimations when controlling alternatively for the sex of the first child and the sex of the first two. These OLS results are unaffected by the exclusion of the second child, and are all strongly significant at the 1 percent level, indicating that an additional child reduces the mother's probability of working by 0.0415-0.0469, while the *More than two children* indicator has an impact of 0.0792-0.0984 on labour supply, depending on the samples. The impact is lower (in absolute terms) for married women, and for the *AE* samples.

The second panel of Table 7.3 presents the instrumental variables estimates of Equation 5.7. The first set of coefficients corresponds to the use of the *Same sex* variable as the sole instrument. Instrumental variables estimates for married women are higher (in absolute value) than the correspondent OLS coefficients for both *Number of children* and *More than two children* (around -0.04/-0.05 and -0.07/-0.09, respectively), but they are lower for the overall samples (*Complete* and *AE*). It should be noted that all these coefficients are significant at least at the 5 percent level, indicating that the instrument provides enough variation in the endogenous variables.

The next set of results in the second panel of Table 7.3 presents the estimation when the *Same sex* instrument is decomposed into its *Two boys* and *Two girls* components. The pattern of differences with OLS estimates is now much simpler: using the two instruments, IV coefficients are consistently smaller (in absolute value) than OLS, in contrast with the pattern of differences with the Wald estimates of Table 7.1. The differences are relatively large: *More than two children* OLS coefficients are in the -0.0793/-0.0985 range, but are restricted to -0.061/-0.0801 for the instrumental variables es-

Table 7.3: OLS and Two-Stage Least Squares Estimates of Fertility and Women's Labour Supply

	Instrumented: Number of children				Instrumented: More than two children			
Dependent variable: Worked for pay	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**
OLS estimates								
OLS	-0.0459	-0.0415	-0.0469	-0.0424	-0.0936	-0.0792	-0.0984	-0.0826
Control for sex of 1st child	[0.0005]***	[0.0006]***	[0.0005]***	[0.0006]***	[0.0013]***	[0.0014]***	[0.0013]***	[0.0015]***
OLS	-0.0459	-0.0415	-0.0469	-0.0424	-0.0936	-0.0793	-0.0985	-0.0826
Controls for sexes of 1st & 2nd children	[0.0005]***	[0.0006]***	[0.0005]***	[0.0006]***	[0.0013]***	[0.0014]***	[0.0013]***	[0.0015]***
IV Estimates								
IV: Same Sex	-0.0397	-0.0461	-0.0419	-0.0520	-0.0737	-0.0828	-0.0775	-0.0931
Controls for sexes of 1st & 2nd children	[0.0178]**	[0.0185]**	[0.0173]**	[0.0179]***	[0.0331]**	[0.0332]**	[0.0319]**	[0.0320]***
DWH p-value	0.7262	0.8021	0.7724	0.5906	0.5474	0.9145	0.5105	0.7425
IV: Two Boys and Two Girls	-0.0287	-0.0364	-0.0288	-0.0404	-0.0610	-0.0722	-0.0621	-0.0801
Control for sex of 1st child	[0.0166]*	[0.0174]**	[0.0161]*	[0.0168]**	[0.0320]*	[0.0322]**	[0.0309]**	[0.0311]***
Sargan p-value	0.0949	0.1148	0.0391	0.0540	0.1432	0.1760	0.0653	0.0941
DWH p-value	0.2989	0.7702	0.2596	0.9041	0.3072	0.8278	0.2391	0.9371
Spouse worked for pay								
OLS		-0.0076		-0.0066		-0.0116		-0.0090
Controls for sexes of 1st & 2nd children		[0.0002]***		[0.0003]***		[0.0006]***		[0.0006]***
IV: Same Sex		0.0029		-0.0017		0.0054		-0.0031
Controls for sexes of 1st & 2nd children		[0.0080]		[0.0075]		[0.0148]		[0.0134]
DWH p-value		0.1869		0.5163		0.2496		0.6596
Observations	653,213	497,194	599,941	456,437	653,213	497,194	599,941	456,437

Note: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include the age and the age at first birth of the woman or her spouse, in addition to the sex of the first and second children (where indicated). The samples correspond to women aged 21-35 with two or more children aged 18 or younger from the extended questionnaire sample of the 1991 Census, as described in the text.

timates; the pattern is similar for *Number of children*. For both variables, the coefficients for the whole samples are smaller than those for married women, and their level of significance is somewhat smaller than when using *Same sex* as an instrument, but still significant overall (three at the 10 percent level, four at 5 percent and one at 1 percent).

As noted by Angrist and Evans (1998), an advantage of decomposing the *Same sex* instrument is that the model becomes overidentified, with two instruments for one endogenous regressor, and thus a standard Sargan test of over-identifying restrictions can be applied. These results provide further evidence in favour of the exogeneity of the instrument, discussed in Section 6.3: the validity of the instruments is not rejected by the tests' results, as indicated by their p-values in Table 7.3. This implies that the instruments are uncorrelated with the error term and correctly excluded from the estimated equation. For only one case (*Number of children - AE Sample*), the test's null is rejected at the 5 percent level. Moreover, Angrist and Imbens (1995) show that this test also measures the difference in the coefficient ϕ when the estimation is carried out with the two instruments separately. The causal effect of childbearing for *Two boys* compliers is thus not significantly different from the effect for the *Two girls* compliers, providing further evidence that the moderate bias towards sons in the gender-balanced preferences is not a cause of concern, as discussed at length in Section 6.3.2 (page 155).

The last panel in Table 7.3 presents the results for *Spouse worked for pay* as the dependent variable, with the corresponding controls for the sex of the first two children, the spouse's age and age at first birth. While there seems to be a small but strongly significant effect in the OLS regressions (-0.0066/-0.0076 for *Number of children*, -0.0116/-0.009 for *More than two children*), none of the instrumental variables coefficients are significantly different from zero at the standard levels of confidence. This can be taken as evidence of no effect of the number of children on the spouses' labour supply, which might be explained by the small variation in the dependent variable: more than 95 percent of the male spouses work for pay. It should be noted, however, that the IV estimates are statistically indistinguishable from the OLS estimates, so that the instrument might not contain enough information to isolate the impact of children on this outcome.

Regarding the differences between IV and OLS, it is worth remembering that the "same sex" strategy identifies the average effect of having more than two children on those whose fertility decisions are changed by the instrument, the group of compliers, while OLS is suspected to fail at identifying the same effect averaged over the whole population. While the two methods do not estimate results for the same groups without further assumptions (see the discussion of compliers in Chapter 8), they can still be compared and their differences can be tested for statistical significance: under homogeneity assumptions, this difference is the selection bias from OLS in Equation 5.4 (page 131). Table 7.3 reports the results from a Durbin-Wu-Hausman test for the two-stage least squares models. Most of the OLS coefficients in Table 7.3 are higher (in absolute value) than their IV counterparts, but the opposite is true for the Wald estimates of Table 7.1, pointing to upward and downward biases as discussed in Section 5.3.1 (page 155). However, while the instrumental variable coefficients are significant at the 5 percent level, their confidence intervals are still broad, and this is reflected in the failure to reject the Durbin-Wu-Hausman null hypothesis of significant differences between IV and OLS coefficients for all the models in the Table and in Table 7.1 (tests not reported).

7.3 Additional Results

7.3.1 More than three children

This Section provides additional findings, and some robustness checks of the benchmark results of this Chapter. A first extension to the "same sex" strategy is based on the evidence from the parity progression ratios in Table 6.2 (page 159), which indicates that the preference for a gender-balanced family in Argentina is not limited to the two to three children range: parents of three boys or three girls have a significantly higher probability of having a fourth child than parents of mixed sex siblings. The higher fertility implies that the decision to go from three to four children is more relevant in the Argentine case than in the other applications reviewed in Section 5.3.3 (page 140). In 1991, 33.8 percent of women aged 19-49 had three or more children, compared to only 20.5 percent in the United States in 1990. This allows the estimation of a 2SLS model like Equation 5.7 for the impact of childbearing at higher parities on women's labour supply by limiting the samples to women with three children or more, which none of previous studies has attempted.

The first-stage, OLS and IV results from this model are presented in Table 7.4. The instrument *Same sex* indicates that the first three children were of the same sex, and it is decomposed into its *Three boys* and *Three girls* indicators. The endogenous regressors are *Number of children* and *More than three children*, and the covariates X include controls for age, age at first birth and the sex of the first two or three children.

In accordance with the evidence in Table 6.2, the first stages are strongly significant. The *Same sex* indicator has an effect of about 0.041-0.046 more children and 0.025-0.029 higher probability of having a fourth child. While significant, these coefficients are substantially lower than the *Same sex* effect on the two to three children decision, again as expected from Table 6.2.

The OLS results in Table 7.4 suggest that the impact of childbearing on labour supply is relatively homogeneous, not varying widely with the number of children: the coefficients of *Number of children* are in the 0.036-0.038 range, lower but close to those in Table 7.3. The same is true for the coefficients of *More than three children*: at around 0.07-0.073, they are not far below than those for *More than two children*.

Although the sample size is smaller and the effect of the instruments is weaker, the instrumental variables coefficients of *Number of children* and *More than three children* in Table 7.4 are still significant at the 10 percent level for married women. Compared to the results of Table 7.3, these IV coefficients indicate that the negative causal effect of fertility on labour supply is higher for a fourth child than for a third child. When instrumenting *Number of children*, the estimate is around 0.07 for married women, above the 0.029-0.052 range for the two to three children effect, while the results for *More than three children*, at around 0.11, are higher than those of *More than two children* in Table 7.3 (0.061-0.093).

Finally, the Sargan null fails to be rejected in all the estimations, supporting the exogeneity of the *Three boys* and *Three girls* indicators, but as in Table 7.3, the Durbin-Wu-Hausman tests indicate that the differences between IV and OLS estimates are not significant.

Table 7.4: OLS and Two-Stage Least Squares Estimations for Three or More Children

	Instrumented: Number of children				Instrumented: More than three children			
Dependent variable: Worked for pay	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**
First stages								
Coefficient of Same sex	0.0410	0.0463	0.0410	0.0462	0.0249	0.0295	0.0250	0.0296
	[0.0040]***	[0.0044]***	[0.0040]***	[0.0044]***	[0.0018]***	[0.0020]***	[0.0018]***	[0.0021]***
OLS estimates								
OLS	-0.0377	-0.0362	-0.0378	-0.0363	-0.0728	-0.0704	-0.0728	-0.0705
	[0.0007]***	[0.0009]***	[0.0007]***	[0.0009]***	[0.0016]***	[0.0018]***	[0.0016]***	[0.0018]***
IV Estimates								
IV: Same Sex	-0.0538	-0.0708	-0.0540	-0.0712	-0.0886	-0.1111	-0.0885	-0.1112
	[0.0409]	[0.0418]*	[0.0409]	[0.0419]*	[0.0673]	[0.0654]*	[0.0671]	[0.0653]*
DWH p-value	0.6938	0.4063	0.6911	0.4022	0.8135	0.5340	0.8144	0.5321
IV: Three Boys and Three Girls	-0.0493	-0.0695	-0.0492	-0.0698	-0.0846	-0.1094	-0.0843	-0.1094
Controls for sexes of 1st & 2nd children	[0.0406]	[0.0418]*	[0.0406]	[0.0419]*	[0.0672]	[0.0655]*	[0.0669]	[0.0653]*
Sargan p-value	0.3267	0.2921	0.3097	0.2757	0.3568	0.2967	0.3387	0.2792
DWH p-value	0.7756	0.4251	0.7770	0.4216	0.8600	0.5509	0.8639	0.5503
Observations	357,933	262,525	357,273	262,049	357,933	262,525	357,273	262,049

Note: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include controls for the age and the age at first birth of the women and the sex of the first two or three children. The samples correspond to women aged 21-35 with three or more children aged 18 or younger from the extended questionnaire sample of the 1991 Census, as described in the text.

7.3.2 Heterogeneous effects: results by education level

The results in the previous Sections of this Chapter captured the average causal effect of fertility on women's labour supply for the population as a whole. However, subgroups of the population can be expected to have different propensities to participate in the labour market, and the effect of childbearing might differ substantially for them.

In Table 7.5, the two-stage least squares model given by Equation 5.7 was estimated separately for three mutually exclusive subgroups of the population defined by the level of education of women: those with up to some primary education, those with some high school education, and those with some tertiary or university education. The first stages (not reported) for these three groups are remarkably close, and consistent with the gender-balanced preferences with a moderate bias for sons in all three cases: the fact that the same fertility effects are observed for very different groups of the population reinforces the conclusions of Section 6.3.1 (page 155) on the nature of the group of compliers.[7]

The results in Table 7.5 correspond to OLS and IV regressions of *Worked for pay* on the standard set of controls, with *Number of children* and *More than two children* instrumented by the *Same sex* indicator.

For the less educated group, the results are similar to those in Table 7.3 for the overall population, although the IV estimates are significant at the standard levels for the married samples only. For the group of women with some high school education, the effects of fertility in the IV regressions are significantly different from zero (for six of the coefficients at the 10 percent level, and at 5 percent for the other two), and they are higher than those in Table 7.3: for *Number of children*, the coefficients (in absolute value) stand around 0.07 (compared to 0.04-0.05), while the *More than two children* coef-

[7] The unconditional effects of *Two boys* and *Two girls* in a regression with *More than two children* as the dependent variable are 0.0223 and 0.0423, and the effect of the *Same sex* indicator is 0.0320 (as in Table 7.1) for the *Complete sample*. The same coefficients estimated for the primary education group are 0.0201, 0.0407 and 0.0301; for the high school sample 0.0254, 0.0440 and 0.0344; and for the further education group, 0.0284, 0.0422 and 0.0350. All these coefficients are similar, and only the *Two boys* coefficient for the further education sample is outside the 95 percent confidence intervals of the full sample coefficients, indicating that for this group the preference for boys is smaller than for the other two. However, this group still exhibits preferences for a gender-balanced family with a (more) moderate bias for sons. The same type of decomposition reveals that the first-stage effects are statistically equal between rural and urban households.

Table 7.5: Heterogeneous Effects: Results by Education Level

	Instrumented: Number of children				**Instrumented: More than two children**			
Dependent variable: Worked for pay	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**
	Education Level: Completed primary or less							
IV: Same Sex	-0.0299	-0.0508	-0.0293	-0.0497	-0.0629	-0.1028	-0.0613	-0.1004
	[0.0197]	[0.0197]**	[0.0194]	[0.0194]**	[0.0416]	[0.0399]**	[0.0407]	[0.0393]**
DWH p-value	0.7804	0.3624	0.7187	0.4101	0.7403	0.4094	0.5967	0.5150
OLS with same controls	-0.0354	-0.0329	-0.0362	-0.0338	-0.0767	-0.0699	-0.0828	-0.0749
	[0.0006]***	[0.0007]***	[0.0006]***	[0.0007]***	[0.0015]***	[0.0018]***	[0.0016]***	[0.0018]***
Observations	379,290	264,142	355,560	248,477	379,290	264,142	355,560	248,477
	Education Level: high school, complete or incomplete							
IV: Same Sex	-0.0655	-0.0683	-0.0680	-0.0755	-0.1063	-0.1107	-0.1100	-0.1219
	[0.0353]*	[0.0363]*	[0.0341]**	[0.0351]**	[0.0573]*	[0.0588]*	[0.0551]**	[0.0567]**
DWH p-value	0.6976	0.5515	0.6442	0.4198	0.8062	0.5847	0.7803	0.4620
OLS with same controls	-0.0518	-0.0468	-0.0523	-0.0472	-0.0923	-0.0786	-0.0946	-0.0803
	[0.0013]***	[0.0014]***	[0.0013]***	[0.0014]***	[0.0023]***	[0.0025]***	[0.0023]***	[0.0025]***
Observations	194,683	161,631	176,000	146,492	194,683	161,631	176,000	146,492
	Education Level: some university or tertiary							
IV: Same Sex	0.0196	0.0505	-0.0271	-0.0072	0.0280	0.0700	-0.0386	-0.0100
	[0.0663]	[0.0671]	[0.0613]	[0.0616]	[0.0945]	[0.0928]	[0.0875]	[0.0852]
DWH p-value	0.2515	0.1268	0.6386	0.4809	0.2985	0.1485	0.7141	0.5302
OLS with same controls	-0.0559	-0.0508	-0.0558	-0.0505	-0.0698	-0.0629	-0.0707	-0.0633
	[0.0025]***	[0.0026]***	[0.0025]***	[0.0027]***	[0.0037]***	[0.0039]***	[0.0038]***	[0.0040]***
Observations	79,240	71,421	68,381	61,468	79,240	71,421	68,381	61,468

Note: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include the age and the age at first birth of the women or her spouse, in addition to the sex of the first and second children (where indicated). The samples correspond to women aged 21-35 with two or more children aged 18 or younger from the extended questionnaire sample of the 1991 Census, as described in the text.

ficients, at around 0.10-0.12, are higher than the previous 0.08-0.09. Given the wide IV confidence intervals, however, the equality of coefficients in the two Tables cannot be rejected.

As expected, the OLS coefficients are significantly different from zero for all samples and education groups. Despite this fact, none of the IV estimates for the higher education group are even marginally significant. This might be due to a lack of precision, since the smaller sample size may not provide enough variation to isolate a causal effect of children on labour supply (see the discussion of significance and sample sizes in Appendix D, page 236). Alternatively, there might be no effect at all for this group. A possible reason for this is that richer households (as proxied by the education level) may be able to afford market-provided childcare, which attenuates the fertility effect on labour supply. This hypothesis is supported by the data. The 1991 Census covered members of the household and their domestic employees living in the same dwelling, which can be taken as a lower bound for childcare services consumption. Overall, 1.03 percent of the women in the final sample had a domestic employee living in the house. The proportion for the lowest education group was only 0.19 percent, in contrast with 1.02 percent for those with some high school and a relatively high 4.51 percent for women with some higher education. While not conclusive, this result is consistent with the idea that access to childcare attenuates the negative effect of childbearing on women's labour supply. Moreover, it is also consistent with previous findings: as discussed in the Introduction to this Chapter, Cortés (2003) states that the lack of free childcare for children under school age was a major impediment for the labour force participation of women in poorer households in Argentina.

The heterogeneity in the impact of fertility on women's labour supply in Argentina is further analysed in terms of potential outcomes in the following Chapter.

7.4 Conclusion

Building on the results from Chapter 6, which revealed a significant and plausibly exogenous effect of the sex mix of children on further childbearing in Argentina, this Chapter exploited this source of variation to produce instrumental variables estimates of fertility on female labour supply.

The results of this Chapter indicate the presence of a strongly significant negative causal effect of fertility on the labour supply of women with at least two children. This result is robust to different specifications of the model, the variables and the underlying datasets, and it was shown to hold for women with three or more children. The strongest negative impact of fertility was on the labour supply of women with low education levels, while the effect on women with higher education was not significantly different from zero.

The findings of this Chapter indicate that childbearing leads to a reduction in female labour supply in Argentina – but how much of the increase in labour force participation in the last three decades can be explained by the large changes in fertility observed in Figure 5.1 (page 125)? According to CELADE (2004), fertility fell by 24 percent in Argentina between 1980 and 2000, while female labour force participation increased by 14.3 percentage points (just under 60 percent). Using the Wald estimates for the complete sample in Table 7.1, one fewer child implies a fall in female labour force participation of about 5.11 percentage points. The fall of 0.82 children in Argentina between 1980 and 2000 accounts for an increase of 4.2 percentage points in participation, which is 29.4 percent of the increase in female employment during the same period.

It should be noted, however, that the identified causal effect holds only for the group of compliers (defined in Chapter 5) without further assumptions: the calculation of the previous paragraph is only valid if the estimated elasticity can be generalised from compliers to the whole population of women with at least two children (and from this group to all women). The following Chapter discusses the generality of these Local Average Treatment Effects, and establishes whether the identified causal link can be extrapolated from compliers to the population. It also expands the results by education levels by applying additional identification results within the potential outcomes framework.

The robust causal link between fertility and female labour supply, the substantial magnitude of its effects and its stronger impact on the poorest group of the population have important policy implications, which are discussed in the Conclusion to Part II (page 212).

CHAPTER 8

POTENTIAL OUTCOMES AND EXTRAPOLATION OF RESULTS FOR COMPLIERS

8.1 INTRODUCTION

The previous three Chapters presented the "same sex" identification strategy, which consists of using the sex composition of children as instruments for childbearing in a model of fertility and female labour supply. The strategy exploits parental preferences for a mixed-sex sibling composition, which induce higher fertility in couples with two children of the same sex. The validity of the strategy was discussed in Chapter 6 by means of a detailed analysis of the identifying assumptions and their plausibility in the Argentine case, studying the institutional context and the testable implications of the assumptions set out in Chapter 5. The evidence supported the validity of the strategy for Argentina, and this allowed the estimation of the causal effect of fertility on women's labour supply in Chapter 7.

The aim of this Chapter is to extend and generalise these findings by specifying additional identification results in the context of instrumental variable estimation, and using the Argentine data on fertility and female labour supply to illustrate how these results can be applied. The motivation is twofold. On the one hand, without further assumptions, IV results like those obtained in the previous Chapter are only valid for the group of compliers (Imbens and Angrist, 1994). In the model of fertility and female labour supply, this group is composed of women who had an additional child because the first two were of the same sex. The issue is whether the results obtained for compliers are representative and can be extrapolated to the whole population, since the parameter of interest is how women in general (and not only compliers) adapt their labour supply to changes in fertility. On the other hand, the estimation of the labour supply model by education group, presented in Section 7.3 (page 183), revealed the presence of heterogeneous effects of fertility: childbearing only affected the labour supply of women with lower levels of education. The following pages present additional identification results within the potential outcomes framework to study the nature of heterogeneous effects beyond the simple estimation of causal effects for different subgroups of the population. While IV coefficients estimate the difference between outcomes (for instance, labour supply) in two counterfactual situations (for instance, low and high fertility), the analysis developed in this Chapter focuses on the outcome levels in these two situations, and not only in the difference between the two.

The Chapter is organised as follows. Section 8.2 discusses the nature of the group of compliers, presenting additional identification results and proposing an auxiliary test to verify to what extent the LATE estimates can be generalised to the whole population. Section 8.3 presents the main results on fertility and female labour supply broken down by education group, and carries out the discussion beyond causal effects by concentrating on potential outcomes. The issue of extrapolation of results for compliers is then discussed with respect to the three education subgroups, and the auxiliary test proposed in Section 8.2 is illustrated with the Argentine labour supply data and with a job training programme dataset from the United States. Conclusion follows.

8.2 "SAME SEX" COMPLIERS AND THE GENERALITY OF LATE RESULTS

8.2.1 *"Same sex" compliers and extrapolation*

The potential outcomes framework, presented in Section 5.2.2 (page 130), addresses problems of endogeneity in the estimation of causal effects. The definition of causal effects relies on the notion of potential – as opposed to observed – outcomes Y_d with respect to a binary treatment D: Y_{0i} and Y_{1i} represent the outcome that would have been observed for individual i in the two alternative situations $D_i = 0$ and $D_i = 1$, one of which is necessarily a counterfactual. In the case of fertility and women's labour supply, the employment status of a woman i who has more than two children ($D_i = 1$) is

Y_{1i}, which is equal to the observed Y_i, and Y_{0i} represents the same woman's counterfactual employment status which would have been observed if she had only two children ($D_i = 0$). The causal effect of the treatment D for individual i is defined in terms of counterfactuals as the difference between the two potential outcomes, $Y_{1i} - Y_{0i}$ (Abadie, 2003a). Since Y_{0i} and Y_{1i} cannot both be observed at the same time for the same individual i, causal effects cannot be computed at the individual level: the identified parameter refers necessarily to the average causal effect $E[Y_1 - Y_0]$.

As discussed in Section 5.2.3, the LATE identification result of Proposition 5.1 (page 135) establishes that when an instrument Z is available, and satisfies Assumptions 5.1-5.4 (page 134), this average causal effect is identified (i.e., can be expressed in terms of observable quantities) for the group of compliers. The proposition results in Equation 5.5, which defines the Local Average Treatment Effect (LATE):

$$E\left[Y_1^c - Y_0^c\right] = \frac{E[Y|Z=1]-E[Y|Z=0]}{E[D|Z=1]-E[D|Z=0]}$$

This result, however, holds only for compliers, those whose treatment status is changed by the instrument. In the case of the "same sex" instrument, compliers consist of two groups: namely, women who had another child because their first two children were of the same sex, but who would have stopped at two if the children were of different sex, and the reciprocal group, women who did not have additional children because they had one boy and one girl, but would have had more children if the first two were of the same sex.

These two subgroups are akin to a randomised treatment-control setup, which is why compliers play such an important role in identification: their treatment status is solely determined by a random factor, the sex of the first two children. But even if the instrument Z plausibly complies with Assumptions 5.1-5.4, resulting in a valid instrumental variable estimation, the relevance and generality of the results depends on the nature of the group of compliers. The plausibility of homogeneity assumptions, the limits of extrapolation of results from compliers, and their relevance as a subgroup of the population are all matters that need to be considered with respect to specific applications.

The first point to raise is whether compliers are per se an interesting subset of the population. This is certainly true in some applications: for instance, in the JTPA job training programme in the United States, individuals were offered labour market oriented courses through a random mechanism. While not all of those assigned attended training sessions, the assignment itself provides a good instrument in randomised experiments with imperfect compliance (Abadie et al., 2002; Abadie, 2003b). Compliers in the JTPA case were those who attended training sessions because they were offered the opportunity of doing so, but would not have attended in the absence of an offer.

The identified causal effect for this group consists in the change in outcomes induced by the offer of training, which is an interesting result for policy and for the evaluation of programmes of this type.

In the "same sex" case, however, compliers only represent individuals with a type of sex preference that modifies their fertility behaviour in a specific way. "Same sex" compliers do not represent an especially interesting group in terms of economic theory or policy as far as their complier status is concerned, because their "experimental treatment" is driven by genetics and not an economic programme. For this reason, "same sex" compliers have an advantage for the extrapolation of results to the whole population. In the job training example, the identified effect is interesting per se, but it does not represent the average effect of the programme for the overall population because compliers represent a particular subset, i.e. those who reacted positively to the offer of training. On the other hand, generalising the effects for compliers in the "same sex" case seems less controversial: while exhibiting stronger effects of sex preferences in their fertility decisions, there is no a priori reason to argue that they are substantially different from the rest of the population in terms of labour supply behaviour.

This Section presents and derives additional identification results which can be used to test assertions of this type: while the extrapolation of causal effects for compliers remains intrinsically untestable, as in the case of the exclusion restriction (see Section 6.3, 155), its plausibility can be assessed with auxiliary evidence.

8.2.2 Proportion of compliers in different samples

The extrapolation of results from compliers to the whole population cannot be directly verified: since they are defined in terms of their counterfactual treatment status, it is not possible to assign any individual to this group, and thus their characteristics cannot be observed. For this reason, it is not possible to say whether compliers are representative of the whole population, and thus parameters like the LATE coefficient defined in Proposition 5.1 cannot be extrapolated without further assumptions.

However, if it is plausible to assume that compliers are not intrinsically different from the rest of the population except in their behaviour with respect to the instrument, this homogeneity warranties that estimates like LATE represent the average causal effect for the overall population (and not only for compliers). In the "same sex" case, compliers are women who had more children because the first two where of the same sex: if they are deemed similar to other women in other dimensions, then their labour supply parameters can be extrapolated to the rest of the population.

While homogeneity cannot be tested directly, some of its implications can be verified, as in the discussion of the exclusion restriction in Chapter 6. For instance, if homogeneity holds, then compliers should represent constant fractions of the population among subgroups distinguished by some exogenous characteristic X. This can be verified by means of an additional identification result due to Imbens and Rubin (1997) for the case of binary treatments:

Proposition 8.1 *Proportion of compliers (Imbens and Rubin, 1997): if Assumptions 5.1, 5.2, 5.3 and 5.4 hold, then the proportion of compliers in the population is identified and given by:*

$$\begin{aligned}\Pr(D_0 = 0, D_1 = 1) &= \Pr(D_i = 1|Z_i = 1) - \Pr(D_i = 1|Z_i = 0) \\ &= E[D|Z = 1] - E[D|Z = 0] \qquad (8.1)\end{aligned}$$

This result follows from the definition of the different groups by potential treatment in Section 5.2.2 (page 130): the fraction of individuals with $D_i = 1$ and $Z_i = 1$ estimates the combined population of always-takers (those who would always be treated, independently of the instrument) and compliers. Moreover, the group with $D_i = 1$ and $Z_i = 0$ is composed only of always takers: the monotonicity Assumption 5.4, which rules out the presence of defiers, implies that the proportion of compliers given in Proposition 8.1 can be obtained as a residual between these two proportions of the sample when D is binary.

The difference in Equation 8.1 is the denominator of the LATE-Wald estimator (right hand side of Equation 5.5, page 135), and it is equivalent to the coefficient of Z in a first-stage regression of D on a constant and Z.[1]

The unbiased estimator of the proportion of compliers given in Equation 8.1 can be calculated for different subsets of the population defined by exogenous characteristics: the rationale for this is that if the proportions vary significantly among groups, the status of complier would be associated with the discriminating characteristic, weakening the case for extrapolation of results to the whole population. Section 8.3.2 carries out this analysis with samples defined by education level in Argentina.

8.2.3 *Identification of outcomes for compliers*

The analysis of proportions of compliers in different subpopulations is useful as a check of homogeneity assumptions, but it does not provide a formal test to support claims about extrapolation. An auxiliary test can be derived from additional identification results for compliers.

As described in detail in Section 5.2 (page 126), causality and the LATE estimate are defined in terms of differences in potential outcomes of the form $E[Y_1 - Y_0]$. However, the nature of compliers[2] allows for more general identification results: Abadie (2002, Lemma 2.1) shows that the whole marginal distribution of potential outcomes is identified for this group. In particular, the average potential outcomes are given by Equations 8.2 and 8.3 in the following Proposition:

[1] Abadie (2003b, Lemma 2.1) provides an additional formal proof and extends this result to the case of covariates X.

[2] To ease the reading of the Equations in this Chapter, the superscritp "c" is used to indicate a variable for the groups of compliers only, and the conditioning of an expectation to this group: for instance, the outcome for compliers is written as:
$Y^c \equiv Y|D_0 = 0, D_1 = 1$, and its expectation is given by:
$E^c[Y] \equiv E[Y^c] \equiv E[Y|D_0 = 0, D_1 = 1]$.

Proposition 8.2 *Potential outcomes for compliers (Abadie, 2002): If Assumptions 5.1, 5.2, 5.3 and 5.4 hold, then:*

$$E[Y_0^c] = \frac{E[Y(1-D)|Z=1] - E[Y(1-D)|Z=0]}{E[(1-D)|Z=1] - E[(1-D)|Z=0]} \tag{8.2}$$

$$E[Y_1^c] = \frac{E[YD|Z=1] - E[YD|Z=0]}{E[D|Z=1] - E[D|Z=0]} \tag{8.3}$$

Proposition 8.2 allows the decomposition of the causal effect for compliers, the LATE $E^c[Y_1 - Y_0]$, into its two components. By providing the baseline upon which the causal effect operates, this result facilitates the study of heterogeneous effects in the population. An analysis of this type for Argentina is presented in Section 7.3.2.[3]

Finally, the results from Propositions 8.1 and 8.2 allow the derivation of a new identification result, central to the discussion of the extrapolation of results for compliers.

The following proposition is the main result of the Chapter. It builds on Abadie's (2003b) proof that the expectation of functions of Y, D and Z are identified for compliers. Using this result and Equations 8.2 and 8.3, the Proposition shows that beyond the counterfactuals, the actual expected outcome is identified for compliers:

Proposition 8.3 *Identification of average outcomes for compliers: if Assumptions 5.1, 5.2, 5.3 and 5.4 hold, then:*

$$\begin{aligned} E[Y^c] &= E[Y_1^c]\Pr(Z=1) + E[Y_0^c]\Pr(Z=0) \qquad (8.4)\\ &= \tfrac{E[YD|Z=1]-E[YD|Z=0]}{E[D|Z=1]-E[D|Z=0]} - \tfrac{E[Y|Z=1]-E[Y|Z=0]}{E[D|Z=1]-E[D|Z=0]} E[1-Z] \end{aligned}$$

The proof of Proposition 8.3 is based on the fact that the average outcome for compliers is a weighted sum of the potential outcomes for this group:

Proof. The expected outcome can be expressed as a weighted sum according to the values of the instrument Z: $E[Y] = E[Y|Z=0]\Pr(Z=0) + E[Y|Z=1]\Pr(Z=1)$. This is also true for compliers:

$$E[Y^c] = E[Y^c|Z=0]\Pr(Z=0) + E[Y^c|Z=1]\Pr(Z=1) \tag{8.5}$$

[3]The details for the computation of the parameters in Equations 8.2 and 8.3 and their standard errors are provided in Appendix E.

Since for compliers $D = Z$, the independence of Z implies that:

$$E[Y^c|Z=0] = E[Y_0^c|Z=0] = E[Y_0^c] \tag{8.6}$$

A similar argument shows that:

$$E[Y^c|Z=1] = E[Y_1^c|Z=1] = E[Y_1^c] \tag{8.7}$$

Replacing 8.6 and 8.7 into 8.5 gives:

$$E[Y^c] = E[Y_1^c]\Pr(Z=1) + E[Y_0^c]\Pr(Z=0)$$

Using the identification results for Y_0 and Y_1 for compliers (Equations 8.2 and 8.3, Proposition 8.2) in the previous Equation results in:

$$\begin{aligned} E[Y^c] &= \tfrac{E[YD|Z=1]-E[YD|Z=0]}{E[D|Z=1]-E[D|Z=0]}\Pr(Z=1) + \\ &\quad \tfrac{E[Y(1-D)|Z=1]-E[Y(1-D)|Z=0]}{E[(1-D)|Z=1]-E[(1-D)|Z=0]}\Pr(Z=0) \end{aligned}$$

Since Z is a binary variable, $\Pr(Z=0) = E[1-Z] = 1-E[Z]$ and $\Pr(Z=1) = E[Z]$. Using this and the fact that $E[Y(1-D)] = E[Y] - E[YD]$ and $E[1-D] = 1 - E[D]$, some manipulation of the previous Equation results in:

$$E[Y^c] = \tfrac{E[YD|Z=1]-E[YD|Z=0]}{E[D|Z=1]-E[D|Z=0]} - \tfrac{E[Y|Z=1]-E[Y|Z=0]}{E[D|Z=1]-E[D|Z=0]}E[1-Z]$$

which is the result of the proposition. ■

An alternative and conceptually equivalent proof can be constructed using Theorem 3.1 in Abadie (2003b). This Theorem states that under the LATE identifying assumptions the expectation of any function $g(Y, D, X)$ is identified for compliers. Proposition 8.3 can be thought of as the case in which $g(Y, D, X) = Y$. The alternative proof uses this Theorem and the results from Proposition 8.2.

Intuitively, the proof states that the expected outcome is a weighted sum of the potential outcomes for compliers with different values of the instrument, since this group is akin to a randomised experiment and thus there is no self-selection bias.

This Proposition can be used to assess the plausibility of the homogeneity of compliers with respect to the population. It is possible to verify if the average outcome for compliers differs from that of the overall population, with a test given by:

$$\lambda = E[Y] - E[Y^c] \tag{8.8}$$

The idea is that the extrapolation of LATE results from compliers to the overall population is less credible if $\lambda = 0$ is rejected.[4] In that case, compliers would differ significantly from the overall sample in a crucial aspect, namely the expectation of the outcome variable.

Equation 8.8 is an auxiliary test for extrapolation, and it can be conducted for different subgroups defined by observable characteristics. The following Section provides examples of this test for the model of labour supply in Argentina, and for the JTPA training programme mentioned above, since the two were identified as opposed cases with respect to the extrapolation of results for compliers in the discussion of this Section.

8.3 Potential Outcomes and Heterogeneous Effects

8.3.1 Decomposition of LATE estimates by potential outcomes

The definition of a causal effect in Chapter 5 referred to the difference between observed and counterfactual outcomes. For instance, in the labour supply example, the causal effect of fertility is obtained by comparing the labour supply of women with three or more children with the labour supply of the same women if they had only two children. While IV coefficients like LATE concentrate on this difference, represented by parameters like ϕ in Equation 5.7, the identification results in Proposition 8.2 show that, subject to Assumptions 5.1-5.4, it is possible to study the counterfactual levels themselves. The study of causal effects can be complemented by the analysis of the full set of potential outcomes for compliers: the LATE and IV coefficients, which present the difference $\phi = E^c[Y_1 - Y_0]$, may be masking important differences in the levels of $E[Y_1^c]$ and $E[Y_0^c]$. The results below concentrate on the levels of $E[Y_1^c]$ and $E[Y_0^c]$, and constitute a complement of the IV estimates of the previous Chapter because they measure the baseline upon which the causal effect operates.

Table 8.1 presents the decomposition of the LATE coefficients in potential

[4]The details for the computation of the test in Equation 8.4 with regression software are provided in Appendix E.

Table 8.1: Effect of "More than two children" on "Worked for pay": Expected and Potential Outcomes by Education Level, Married Women

	Outcome variable: Worked for pay	Overall	Some primary education	Some secondary education	Some tertiary education
	Overall outcomes:				
(1)	**Expected outcome**	0.305	0.214	0.301	0.681
(2)	**Expected outcome with D=0**	0.355	0.237	0.330	0.703
(3)	**Expected outcome with D=1**	0.267	0.201	0.272	0.653
(4)	**OLS Estimate (3)-(2)**	-0.088	-0.035	-0.058	-0.050
	Potential outcomes for compliers:				
(5)	**Y_0: Potential outcome with D=0**	0.350	0.245	0.340	0.780
	Standard error	(0.023)	(0.025)	(0.043)	(0.064)
(6)	**Y_1: Potential outcome with D=1**	0.248	0.125	0.212	0.753
	Standard error	(0.025)	(0.033)	(0.041)	(0.059)
(7)	**Wald-LATE estimate (6)-(5)**	-0.102	-0.120	-0.128	-0.026
	Standard error	(0.034)***	(0.042)***	(0.059)**	(0.086)
	Outcomes for compliers:				
(8)	**Proportion in the sample**	0.040	0.040	0.040	0.044
(9)	**Expected outcome**	0.298	0.184	0.275	0.766
	Standard error	(0.017)	(0.021)	(0.030)	(0.044)
(10)	**P-value of the test (1)=(9)**	0.699	0.158	0.380	0.060
Observations		456,437	248,477	146,492	61,468

Note: All potential outcomes and OLS coefficients are different from zero at the 1% level. For the Wald estimate, superscripts denote significance as in previous tables. The samples correspond to married women aged 21-35 with two or more children aged 18 or younger from the extended questionnaire sample of the 1991 Census, as described in the text (*AE sample, married*).

outcomes for the same education groups as in Table 7.5 (page 187) for the *AE sample, married* (the results for other samples are quantitatively similar and qualitatively the same).

The first panel of the Table presents the unconditional expectation of the outcome variable, $E[Y]$ (row 1), and its value conditional on the instrument Z, $E[Y|D=0]$ (row 2) and $E[Y|D=1]$ (row 3). The average in the *Worked for pay* indicator, 0.305, conceals important differences in the population. In the lowest educated group only a fraction 0.214 of the women work for pay, while in the middle education group this proportion is 0.301, just below the population average. For the relatively small group with some higher education, however, the average of the *Worked for pay* indicator is much higher at 0.681.

The Table also presents the expected outcomes conditional on $D = 0$ and $D = 1$ and the difference between the two, which is the simple OLS coefficient of D when this variable is regressed on Y, as presented in Table 7.1 (page 174) for all samples. As in that Table, the coefficients are all negative and strongly significant.

The second panel of the Table breaks down the LATE-Wald estimate $E^c[Y_1 - Y_0]$ (row 7) into its components $E[Y_0^c]$ (row 5) and $E[Y_1^c]$ (row 6), which are identified for compliers (Proposition 8.2). These potential outcomes represent the counterfactual probabilities of employment under the two values of the treatment. The LATE coefficients, which represent the difference between $E[Y_0^c]$ and $E[Y_1^c]$, are relatively close in the 0.10-0.13 range (in absolute value) for the overall sample and the low and middle education groups.

The compliers in the middle education group exhibit a counterfactual probability of working of 0.34 if not having a third child, while their average labour supply would be only 0.212 if they did have a third child. While resulting in a similar difference in absolute terms, the potential outcomes for the low education compliers are 0.245 and 0.125, respectively, substantially lower than those in the middle group. The 0.12-0.128 difference in potential outcomes given by the LATE estimates gives the impression of a relatively homogeneous impact of childbearing on labour supply in these two education groups: while this is true in absolute terms, the impact is much larger for the low education group when relative to the baseline potential outcomes.

Finally, as with the expected outcome, the potential outcomes for the higher education group are much higher than for the population as a whole, but the Wald estimate is not significantly different from zero, which might indicate a lack of precision given the smaller sample size.

Since regression coefficients of binary indicators represent differences in the expectation of variables, evidence like that of Table 7.5 might overlook important disparities in their levels. The breakdown presented in Table 8.1 is an important complement of the analysis of heterogeneity in the impact of childbearing on women's labour supply, and provides a clear picture of the differences between the three subgroups.

8.3.2 Are compliers different? Extrapolation and homogeneity assumptions

The division of the sample by education group can also be exploited to address the issue of extrapolation of results for compliers by means of the additional identification results discussed in Sections 8.2.2 and 8.2.3.

The bottom panel of Table 8.1 presents estimates of the proportion of compliers (row 8) for the different subpopulations (Proposition 8.1), which are given by the first-stage coefficients of Z when this variable is regressed on D. Compliers represent about 4 percent of the *AE married* sample, with about the same proportion in the low and middle education groups, and 4.4 percent of the higher education group.

The Table shows that the proportion of compliers is uniform across subpopulations with large differences in the outcome variable and other observable characteristics. Moreover, this also indicates that the first-stage effect of *Same sex* on *More than two children* is roughly constant in the population (as discussed in Section 7.3.2, page 186), which supports the hypothesis that compliers are not substantially different from the rest of the population in the "same sex" application to Argentina and suggests that the LATE results can be extrapolated.

Further evidence in this regard is provided by row 9 in the bottom panel of Table 8.1, which presents the computation of the expected outcome for compliers $E[Y^c]$, and its standard error, as defined in Proposition 8.3. For the three groups, these expectations seem to be close to the average outcomes for the respective complete populations. This is formally confirmed by the results in row 10, which presents the p-value of the test derived from Proposition 8.3 and given by Equation 8.8. The hypothesis of equality of mean outcomes between compliers and the overall population cannot be rejected at the standard levels of significance for the complete sample nor for any of the three groups.

The intuition of Section 8.2.1 is right: compliers are important in the "same sex" application because they are not substantially different from the rest, and thus the causal effects identified for this group may be considered as representative of the whole population.

For comparison purposes, the test in Equation 8.8 is also computed with participants in the JTPA programme, since the discussion in Section 8.2.1 hy-

Table 8.2: Effect of Training on Earnings: Expected and Potential Outcomes, JTPA Participants

	Outcome variable: Annual earnings (US dollars)	Men	Women
	Overall outcomes:		
(1)	**Expected outcome**	19,147	13,029
(2)	**Expected outcome with D=0**	17,485	12,078
(3)	**Expected outcome with D=1**	21,456	14,211
(4)	**OLS Estimate (3)-(2)**	3,970	2,133
	Potential outcomes for compliers:		
(5)	**Y_0: Potential outcome with D=0**	19,830	12,311
	Standard error	710	419
(6)	**Y_1: Potential outcome with D=1**	21,655	14,253
	Standard error	624	385
(7)	**Wald-LATE estimate (6)-(5)**	1,825	1,942
	Standard error	(945)*	(569)***
	Outcomes for compliers:		
(8)	**Proportion in the sample**	0.612	0.640
(9)	**Expected outcome**	21,046	13,612
	Standard error	(479)	(293)
(10)	**P-value of the test (1)=(9)**	0.000	0.046
Observations		5,102	6,102

Note: All potential outcomes and OLS coefficients are different from zero at the 1% level. For the Wald estimate, superscripts denote significance as in previous tables. The treatment D is attending training sessions. The samples correspond to participants in the JTPA training programme, as described in Abadie et al. (2002).

pothesised that compliers in that application were fundamentally different from other groups.

Table 8.2 presents the same set of statistics as in Table 8.1 for men and women participating in the JTPA experiment, using the data from Abadie et al. (2002). Based on a random selection procedure, two thirds of the participants in the programme were assigned to training courses, while a further third was not allowed to attend them. The treatment in this case is the training received, and a random, exogenous instrument is provided by the offer of training.[5] Abadie et al. (2002) find that the programme had a positive and

[5]The instrumentation is needed because even in randomised experiments the identification by simple differences in means only holds if all individuals assigned to treatment are indeed treated, and those in the control group are completely excluded – that is, if

significant causal effect on women's earnings, but only a marginally significant effect for men. These results correspond to the Wald-LATE estimates in Table 8.2 (row 7).

The decomposition of the LATE estimate $E^c[Y_1 - Y_0]$ in row 7 into its components $E[Y_0^c]$ and $E[Y_1^c]$, presented in the second panel of the Table (rows 5 and 6), shows that the similar causal effects for men and for women ($1,825 and $1,942 respectively) operate on very different baselines, with potential outcomes substantially lower for women than for men.

Finally, as discussed in Section 8.2.1, compliers in this randomised experiment can be expected to differ substantially from the overall population. The evidence in Table 8.2 supports this hypothesis: for both men and women, compliers exhibit a significantly higher level of expected earnings than the overall population, as revealed by test of equality of $E[Y]$ (row 1) and $E^c[Y]$ (row 9) given by Equation 8.8. The results in row 10 state that this hypothesis can be rejected at the 5 percent level of significance for women and at the 1 percent level for men in the JTPA experiment.

The discussion of the results in Tables 8.1 and 8.2 illustrates the use of the additional identification results derived in Section 8.2. Besides the useful information provided by the decomposition of causal effects into counterfactual potential outcomes, the computation of the test in Equation 8.8 for two different samples provides further support to the conjecture that "same sex" compliers are not significantly different from the overall population. This is because the result of the test in Table 8.2 captures the intuition that compliers in JTPA programme are fundamentally different from other groups.

8.4 Conclusion

This Chapter studied the issue of heterogeneity in the effects of fertility on female labour supply, and presented additional identification results to test the generality of the benchmark results of Chapter 7.

The analysis of LATE estimates broken down by education groups revealed the presence of some heterogeneity in the effect of childbearing on labour supply by education level. By studying the potential outcomes for

compliance with the experimental protocol is perfect.

each subgroup, the negative causal effect of fertility on female labour supply was found to be stronger among the lowest educated group. Since these women had the lowest levels of labour force participation, the reduction in labour supply induced by an increase in fertility was found to be larger, in proportional terms, than for women in the middle education category. These results also confirmed the finding (presented in Chapter 7) that women in the higher education group were not significantly affected by fertility in their labour supply decisions. The analysis in terms of potential outcomes, however, provided an explanation of this result: the labour force participation of women with some tertiary education was found to be very high regardless of the number of children, and thus the reduction in labour supply induced by a third child was not significant.

Finally, regarding the generality of the baseline findings of Chapter 7 in terms of the causal effect of fertility on female labour supply in Argentina, the evidence indicates that "same sex" compliers are not substantially different from the overall population in some key characteristics. This implies that the benchmark IV estimates of the previous Chapter can be generalised and extrapolated from the group of compliers to the whole population. It is then possible to say, with some confidence, that the significant negative effect of fertility on women's labour supply is not confined to a small subgroup but that it is representative of the population average causal effect for women with two or more children.

CONCLUSIONS

The following pages review the main findings and contributions of the previous Chapters. The discussion focuses on the practical lessons on some key questions about the welfare evaluation of income dynamics in a time of crisis, and labour supply decisions and income prospects in Argentina. The two Sections below also draw attention to the policy implications that can be derived from the empirical results in Parts I and II of this thesis.

CONCLUSION TO PART I: POVERTY AND INCOME FLUCTUATIONS

Methodological contributions: accounting for income fluctuations

The Chapters in Part I focused on poverty as a dynamic phenomenon. The motivation was the recurring economic crises that affect developing countries and the incidence of the resulting income fluctuations on household welfare. Indeed, a striking finding from Chapter 1 was that relatively modest changes in poverty rates between two periods were the result of large but offsetting movements into and out of poverty in Argentina. Moreover, the results from Chapters 2 and 3 indicate that these large fluctuations of income over time have a significant negative effect on household welfare even during periods of aggregate growth.

The use of panels revealed some features of the data that could not have been captured with the cross-sectional datasets usually employed in poverty analysis. Chapters 1 to 4 went beyond the simple analysis of poverty transitions, and explored the theoretical basis for the incorporation of income fluctuations into the measurement of poverty and well-being over time.

Chapter 2 presented a general framework for the welfare evaluation of income dynamics, based on extensions of the existing methodology for static distributional analysis. An analogy with the concept of risk aversion provided a rationale for the incorporation of income fluctuations into the measurement of household well-being. This welfare criterion was rationalised using intuition derived from the risk literature: households prefer a steady stream of income to a variable one with the same mean, at least in a second-best world with incomplete insurance and capital markets. The indicators derived from this evaluation framework accounted not only for the level of poverty, but also for the effects of income variability on welfare.

Moreover, existing alternative approaches for measuring well-being based on panel data, such as the literatures on transient-chronic poverty and on vulnerability, were interpreted as special cases of this evaluation framework. The following two Chapters presented variations of these special cases. Chapter 3 introduced a simple methodology to derive risk adjusted measures of income, and Chapter 4 analysed poverty over the same period based on a decomposition of a household's intertemporal poverty into its transient and chronic components. In both Chapters, regressions were used to identify a number of characteristics related to the income risk and the persistence of poverty faced by Argentine households.

These methodologies were illustrated with a panel dataset from the Greater Buenos Aires region for the 1995-2002 period, but the analysis carried out in Chapters 2, 3 and 4 can be applied to other contexts where panel data on household income or expenditure is available. The following pages deal with the main empirical findings and their policy implications for Argentina.

Empirical findings: fluctuations matter

The empirical findings of Chapters 1 to 4 imply that income fluctuations matter in at least four important dimensions.

The first dimension refers to the nature and extent of poverty analysis. As mentioned above, Chapter 1, which documented different aspects of household welfare over the 1995-2002 period in Argentina, found that changes in poverty rates between two periods were the result of large offsetting movements into and out of poverty. Moreover, these movements, which were not apparent in the simple analysis of changes in poverty rates between two periods, were not confined to economic crises: a substantial fraction of the population was found to enter poverty even when rates were falling on aggregate.

The high proportion of individuals who changed poverty status in a relatively short period of time (about six months in the Argentine data), and the fact that these changes occurred in all stages of the business cycle, imply that traditional poverty studies based on cross-sectional data might be missing some fundamental information.

The second dimension refers to the relative importance of income fluctuations for household well-being. The framework developed in Chapter 2 provided a rationale, based on an analogy with the concept of risk aversion, for imputing a negative impact of fluctuations on welfare. However, the magnitude of this effect is an empirical question.

The evidence for Argentina in Chapters 2 and 3 demonstrated that income fluctuations substantially reduced household welfare under relatively mild assumptions. There is, however, a trade-off: when income observations over time are aggregated at the household level, welfare measures increase and poverty evaluations decrease when compared to indices based on punctual observations. This is because the averaging mitigates the impact of negative shocks. This smoothing effect, however, was more than offset once the disutility from income fluctuations was taken into account, assuming only moderate levels of risk aversion in line with most estimates of the uncertainty literature.

Most importantly, the sizeable effects of fluctuations on welfare and poverty were not limited to periods of crisis or downturns. The findings from Chapter 2 and 3 indicate that income fluctuations at the household level have substantial effects on well-being even during periods of aggregate growth, for instance during the 1996-1998 period in Argentina (see Figures 1.2 and 1.3, pages 21 and 30 respectively). This result reflects the finding that a substantial fraction of the population entered poverty even when aggregate rates were falling.

The third dimension refers to the effects of an economic crisis from a dynamic perspective. The empirical results in Part I indicate that major macroeconomic shocks, like the 2001-2002 crisis in Argentina, not only reduce income levels, but also increase income risk, which magnifies their overall negative impact on poverty and well-being. Moreover, the decomposition of a household's intertemporal poverty into its transient and chronic components, presented in Chapter 4, found that the chronic component accounted for most of the large increase in poverty over the period. While income levels fell and their variability increased, the deterioration in living standards had a larger effect than the rise in fluctuations during this turbulent period.

This evidence on the increase of chronic poverty is compatible with the results on short-term dynamics presented in Chapter 1: over the 1995-2002 period, the fraction of the poor population staying in poverty increased almost constantly, while the proportion of those escaping poverty between two periods fell significantly.

Finally, the fourth dimension refers to the heterogeneity of the effects of income fluctuations on household welfare. The increase in chronic and transient poverty and the fall in risk adjusted income was not constant among households: the regression analyses in Chapters 3 and 4 identified some of the characteristics associated with income risk and poverty variability in Argentina.

The first result that stands out from both Chapters is that the education levels of the head of household and of the spouse were systematically correlated to lower levels of income risk, and of transient and chronic poverty. Households with better-educated members were found to have higher incomes and to face lower income risk, and all education and qualification indicators were associated with lower measures of intertemporal poverty (with no education and no qualification as the excluded category).

The larger effects in the income and poverty regressions, however, were related to labour market variables. Households with inactive or unemployed members bore a larger share of income risk than any other group. The indicators for relatively stable sources of income, such as pensions and public sector jobs, had a negative impact on transient poverty, whereas the opposite was true for variables reflecting more precarious jobs: the informality indicators contributed to higher levels of risk and poverty, and being self-employed was found to have a positive effect on transient poverty. Finally, the demographic variables indicated that households with children were more prone to suffer from income risk, and experienced higher levels of intertemporal, chronic and transient poverty. The following Section derives some policy lessons from these results.

Policy implications: safety nets for rainy (and sunny) days

These household characteristics allow us to derive some recommendations for public interventions in times of crisis. In broad terms, however, these results confirm the policy consensus in Latin America on the importance of labour market outcomes and family composition as strong predictors of poverty (de Ferranti et al., 2000a). This consensus was reflected in the two major public intervention programmes in Argentina, reviewed in Chapter 1: the *Plan Trabajar*, introduced in the wake of high unemployment levels after the Mexican financial crisis of 1995, and the *Plan Jefes y Jefas de Hogar Desempleados*, implemented during the crisis of 2001-2002.

The designs of both programmes took into account, implicitly or explicitly, the household characteristics identified in the previous Section. *Trabajar* provided short-term jobs at low wages, usually related to public works in poor areas (Ravallion and Jalan, 2003). For practical purposes, *Trabajar* operated as a poverty alleviation programme targeted through unemployment (de Ferranti et al., 2000b), and thus recognised labour market outcomes as proxies of poverty. In the *Plan Jefes y Jefas*, unemployed heads of households with dependent children received direct income support (Galasso and Ravallion, 2003). The programme design took into account the importance of labour market outcomes and also the demographic composition of the household as proxies for vulnerability.

At first glance, then, these results on the household characteristics associated with higher levels of income risk and poverty variability do not seem particularly original. The main point, however, is that the regression analyses in Chapters 3 and 4 included years of crisis but also periods of recovery. Labour market outcomes, education levels and family structure were correlated with the substantial income fluctuations observed during the whole 1995-2002 period in Argentina.

While the importance of dealing with the effects of aggregate shocks has long been recognised, the main conclusion from Chapters 1-4 is that safety nets and other social protection mechanisms, while vital during major crises, should also be implemented on a continuous basis, irrespective of the short term evolution of macroeconomic aggregates.

This conclusion is based on the empirical findings of Part I on the incidence of income fluctuations on household welfare. While the results indicate that major macroeconomic shocks substantially reduce income levels and increase income risk, the detrimental effect of income fluctuations at the household level was also found to be significant during periods of stability or recovery. Moreover, irrespective of changes in GDP, during the whole 1995-2002 period in Argentina a substantial proportion of the population entered poverty between two periods of time, even when poverty rates were falling, and a significant proportion of observed poverty was attributed to its transient component.

This conclusion is reinforced by recent figures that have uncovered some hysteresis of poverty in Argentina: the strong recovery in GDP growth observed in 2003 (see Figure 1.2, page 21) has reduced unemployment levels, but poverty rates are not falling as fast (INDEC, 2004). The implication for future interventions is that it is as important to insure households against income risk and to avoid entry into poverty on a continual basis as it is to provide coping mechanisms during future crises.

Given the importance of labour market outcomes for poverty dynamics and income risk, the design of a permanent social protection scheme in Argentina could draw on relatively successful welfare systems that manage to balance work incentives with income support in developed countries (Gregg and Wadsworth, 1999b, review the recent experience for the United Kingdom). However, the peculiarities of labour markets in developing countries introduce further complications. For instance, the existing unemployment insurance programme in Argentina only covers a fraction of the population in formal employment, the least vulnerable group: beneficiaries tend to be more numerous among middle and upper-middle income groups, as in most Latin American countries with programmes of this type (de Ferranti et al., 2000b). The challenge resides in designing unemployment insurance and other permanent social protection policies within economies with high levels of informality in the labour market. In the following pages, the Conclusion of Part II discusses the impact of fertility on female labour supply, and draws attention to the importance of childcare and early schooling programmes for the income prospects of poorer households.

Beyond the need for short term emergency interventions in times of crisis and for long term insurance mechanisms, the evidence in Chapters 3 and 4 confirms the importance of education and qualifications for poverty alleviation in the long run. Moreover, the results of this thesis suggest that human capital investments pay off in terms of increased returns but also in lower levels of risk. In this area, public interventions are also concentrated on periods of crises: for instance, the *Plan Jefes y Jefas* introduced some conditionality on school attendance for the children of beneficiaries. While primary school enrolment rates are relatively high in Argentina (see Table 6.3, page 164), the much needed long term initiatives on education (for instance, in terms of incentives for completion of secondary schooling) are scattered among different levels of government.

Finally, the results in Part I indicate that the design of long term policies for social protection must draw both on traditional static poverty profiles and on studies of income dynamics. Panel datasets, though not without their problems, provide vital information about the underlying movements that result in aggregate poverty changes, and thus their collection should be given a higher priority within statistical agencies in developing countries.

Conclusion to Part II: Fertility and Women's Labour Supply

Methodological contributions: female labour supply, fertility and endogeneity in developing countries

The Chapters in Part II discussed the determinants of the income generating process at the household level in Argentina, focusing on the potential causal effect of fertility on female labour supply. This research was motivated by two main factors. The first consisted of the results of Part I on the correlations between poverty and fertility, on the one hand, and poverty and labour market indicators, on the other. The second factor was the significant fall of total fertility rates and the rise in female labour force participation in Argentina in the last twenty years, discussed in Chapter 5.

While the negative correlation between childbearing and labour force participation is an almost universal phenomenon, its interpretation in terms of causality is often marred by self-selection, endogeneity and simultaneity issues. The main results of Part II (presented in Chapter 7) were significant because they established the causal nature of this correlation in Argentina.

The methodological contributions of the Chapters in Part II were all related to the endogeneity problems that arise in models of fertility and female labour supply, and on how to deal with them with the "same sex" identification strategy in the context of developing countries. This strategy is based on the observation that parents of two children of the same sex exhibit a higher propensity to have another child to obtain a gender-balanced sibling composition. Under certain conditions, analysed in Chapters 5, the sex mix of children can thus be used as an instrument for further childbearing.

Chapter 6 provided a detailed discussion of the identification strategy and its application to developing countries, where female participation is lower and fertility is higher than in the developed economies. The Chapter presented evidence on the effects of parental sex preferences on fertility, the first of its type for Argentina,[1] and on the exogeneity of this relationship with respect to labour supply. Moreover, it presented a study of parental demographic and expenditure data, which failed to reveal any significant bias against girls in Argentine households. Based on these results, Chap-

[1]Personal communication, Georgina Binstock and Alejandra Pantelides, Centro de Estudios de Población (CENEP), Buenos Aires, Argentina.

ter 7 presented the main instrumental variable estimates of the causal effect of fertility on female labour supply. Finally, Chapter 8 made two methodological contributions. On the one hand, it presented a test for the generality of instrumental variable estimates, establishing the conditions under which these estimates can be considered representative of the population under study. On the other hand, it presented an original decomposition of IV coefficients, which was applied to the study of the effects of fertility by education level in Argentina.

Empirical findings: childbearing matters

The main conclusion from Part II, presented in Chapter 7, is that in Argentina children significantly reduce the labour supply of their mothers. Using the estimated coefficients, the fall in fertility between 1980 and 2000 accounted for almost a third of the large increase in female labour force participation during the same period.

This finding was further qualified by the analysis conducted in Chapter 8, which divided mothers into three groups according to their education levels – those with some primary, some secondary or some higher education.

The participation rate among women in the higher education group was just below 70 percent, higher than the overall averages in developed countries with high female participation like the United Kingdom and the United States (ILO, 2003). For this group of women, the reduction in labour supply induced by childbearing was small and not significantly different from zero. Moreover, women in this group were found to have a much higher propensity towards employing live-in domestic help, which was interpreted as a proxy for childcare services consumption.

Meanwhile, the causal effect of childbearing was found to be stronger among women with lower education levels than in any of the other two groups. Women in poorer households (as proxied by the education level) experienced a large and significant reduction in labour supply: a third child implied a reduction of about 12 percentage points in participation. The analysis in Chapter 8 added a new dimension to this finding: it revealed that this effect operated at already low levels of participation. Those 12 percentage points represented a counterfactual reduction in participation from

24.5 to 12.5 percent, both lower than the average of 30.5 percent for women in the three groups.

These results provide a rationale for the correlations between household size and poverty, and poverty and labour market outcomes. The sizeable causal effect of children on labour supply and the fact that it was stronger for women with lower education levels support the hypothesis that childbearing hampers crucial income-generating opportunities, which contributes to poverty at the household level. This conclusion is backed by alternative data sources: for instance, the May 1991 EPH indicates that 39.9 percent of households with women aged 21-35 with two or more children were poor, compared to 31.1 percent for the whole population.[2] Imputing the average income of poor women who worked for pay to poor women who did not work for pay reduces the incidence of poverty to 23 percent, a decrease in the rate of more than 40 percent. While this is an upper bound of the effect of fertility on poverty, it highlights the importance of women's labour force participation for the welfare of the household: even if the majority of these women were second earners, their income would still be decisive in a society where one average full-time salary does not always cover the basic needs of a typical family. These back of the envelope calculations are consistent with other sources. For instance, Gasparini and Marchionni (2003) perform microsimulation exercises and find that the reduction of family size among poorer households in the Greater Buenos Aires area in the 1990s reduced poverty, a factor mainly driven by the "weakening of the relationship between the hours of work and the number of children in the case of female spouses."

Policy implications: childcare provision and social protection

The policy implications of this analysis are far-reaching. The robust causal link between fertility and female labour supply in Argentina rules out other explanations of the observed correlation. Most notably, the issue of self-selection, often invoked to prove the futility of policy interventions in this

[2]This dataset contains women aged 21-35 with two or more children, as described in Appendix D (footnote 2, page 238). The poverty figures, based on equivalised household income, were constructed with the Greater Buenos Aires poverty line, since official national poverty lines are not available for 1991. See the discussion in Section 1.2 (page 22).

area, can be discarded. In this context, self-selection implies that women with low expected labour market outcomes choose to specialise in housework and childbearing. If the observed correlation is due to self-selection, policies promoting work would fail because of the nature of the target group. The results of Part II, however, established that this is not the case in Argentina: the analysis of counterfactuals implies that a significant fraction of non-working mothers would work with lower fertility – or with better ways to accommodate childbearing and work. Since fertility levels are relatively low and falling, and family planning is freely available and well developed in Argentina, policy should concentrate on accommodating childbearing and work.

There is thus scope for policy interventions to promote work among women with children, especially considering the evidence on a stronger effect of fertility on the female labour supply of poorer women. In broad terms, the policy objective is to reduce the size of the coefficient linking fertility and female labour supply.

Recent policy developments in some industrialised countries, such as the working and family tax credits in the United States and the United Kingdom, focus specifically on improving work incentives for women and families with children. Initiatives such as the New Deal for Lone Parents have shown significant effects on employment levels among women in the UK (Dickens et al., 2004). While the scope for applying policies of this type is limited in countries lacking a comprehensive welfare system like Argentina, there still exist ways to ease the labour market participation of disadvantaged groups.

One option for reducing the negative link between fertility and female labour supply, especially for poorer women, is to provide free or low-cost childcare. In Argentina, the State only offers preschool facilities for children aged three to five, with no free childcare and no subsidies for newborns and children aged one or two (Cortés, 2003). The evidence presented in Part II suggests that a better supply of nurseries and day-care centres would improve the situation of the poorer sector of the population by easing the transition towards work.

The analysis presented in Chapters 5-8 also has important implications for market-oriented reforms in developing countries. Labour market reform in Latin America has been associated with the reduction of job security and of other forms of labour protection (Heckman and Pages, 2003), without substantial improvements so far: one of the main conclusions of an IADB (2004) report on the region is that "structural reforms did not produce the changes that were expected in labour markets." The wave of reforms of the 1990s concentrated on market deregulation, but neglected other aspects of labour market flexibility. For instance, the evidence presented in Part II suggests that poorer households could benefit from measures that increase the opportunities for part-time work, which is relatively infrequent in Argentina, and from the promotion of flexible work arrangements for parents.

Nevertheless, these policies are second order considerations with respect to macroeconomic stability and growth: an increase in labour supply might not be met by a labour demand in a context of high unemployment, as observed in Argentina over the 1999-2002 period.

Appendices and Bibliography

APPENDIX A

ABBREVIATIONS AND NOTATION

Table A.1: List of Abbreviations

INDEC:	Instituto Nacional de Estadísticas y Censos, Argentina.
GBA:	Greater Buenos Aires region.
US:	United States.
EPH:	Encuesta Permanente de Hogares.
ENGH:	Encuesta Nacional de Gasto de los Hogares.
OLS:	Ordinary Least Squares.
2SLS:	Two-stage least squares.
IV:	Instrumental Variables.
LATE:	Local Average Treatment Effect (Proposition 5.1, page 135).
SUR:	Seemingly Unrelated Regressions (Equation 3.8, page 88).
FGT:	Foster et al.'s (1984) class of poverty measures (Equation 1.6, page 35).
CPI:	Consumer Price Index.

Table A.2: Main Variables: Definitions and Usual Notation, Part I

y_{it}	Total equivalised household's i income, normalised by the contemporaneous poverty line (Equation 1.3, page 27).
q_{ij}	Coefficient of equivalent adult for member j in household i (Table 1.3, page 26).
X_i	Household i's characteristics.
z_t, z_t^I	Poverty line and extreme ("indigent") poverty line at time t.
$\mathbf{y}_i$	Vector of observed incomes over time $[y_{i1}, ..., y_{iT}]$ for i.
$\bar{y}_i, \sigma_i$	Average and standard deviation of income y_{it} over the period $t = 1, ..., T$.
T	Total number of periods over which a household is observed $(t = 1, ..., T)$.
$P(y, z)$	Poverty measure as a function of income y and poverty line z.
u, U	Household's ex-post and expected utility function defined over an income aggregate.
v, V	Evaluation functions defined over an income aggregate.
ρ	Arrow-Pratt coefficient of risk (or variability) aversion.
$\tilde{y}_{se}$	Stability equivalent income, defined by the evaluation function V and derived from observed incomes $[y_{i1}, ..., y_{iT}]$.
π_v, Π	Variability and proportional variability premia for i, defined by Equations 2.8 and 2.9 respectively (page 61).
Note:	A simple variable (y) designates a fixed quantity, a variable with a hat ($\hat{y}$) indicates an ex-ante prospect (a random variable), and a variable with a wiggle ($\tilde{y}$) denotes a (fixed) counterfactual quantity. Finally, a bar as ($\bar{y}$) indicates the average of the underlying variable. When not required, the subscripts i and t are dropped for ease of exposition.

Table A.3: Usual notation, Part II

Y:	Outcome variable: labour supply.
X:	Set of individual characteristics.
D:	Endogenous treatment variable.
Z:	Instrument for the endogenous treatment variable D.
Y_0, Y_1:	Y_z represents the potential treatment status given $Z = z$: $Y_z = Y_0$ if $Z = 0$ and $Y_z = Y_1$ if $Z = 1$.
D_0, D_1:	D_z represents the potential treatment status given $Z = z$: $D_z = D_0$ if $Z = 0$ and $D_z = D_1$ if $Z = 1$.
Note:	To ease the reading of the Equations in this Part, the superscritp "c" is used to indicate a variable for the groups of compliers only, and the conditioning of an expectation to this group: for instance, the outcome for compliers is written as $Y^c \equiv Y\|D_0 = 0, D_1 = 1$ and its expectation as $E^c[Y] \equiv E[Y^c] \equiv E[Y\|D_0 = 0, D_1 = 1]$.

APPENDIX B

ARGENTINA'S STATISTICAL REGIONS AND URBAN AREAS

B.1 REGIONS AND URBAN AREAS

The map in this Appendix (Figure B.1) depicts the 23 provinces and one autonomous city (Buenos Aires) of Argentina and their division into six statistical regions as defined by INDEC (1996). Each of these regions contains the following urban areas:

Greater Buenos Aires (GBA) region: Ciudad de Buenos Aires, Partidos del Conurbano.

Noroeste region: San Salvador de Jujuy-Palpalá, Gran Catamarca, Santiago del Estero-La Banda, La Rioja, Salta, Gran Tucumán.

Noreste region: Formosa, Gran Resistencia, Corrientes, Concordia, Posadas, Gran Paraná.

Pampeana region: Gran Córdoba, Gran La Plata, Mar del Plata, Río Cuarto, Bahía Blanca-Cerri, Gran Rosario, Gran Santa Fe, Santa Rosa-Toay.

Cuyo region: Gran Mendoza, San Luis, Gran San Juan.

Patagonia region: Río Gallegos, Ushuaia, Comodoro Rivadavia, Neuquén-Plottier.

Figure B.1: Map of Argentina's Statistical Regions, INDEC

Table B.1: Poverty, Income and Labour Market Indicators by Region, Argentina, October 1998

	Population Covered by EPH	Poverty and Income			Labour Market Indicators			Qualifications	
		Total Poverty	Extreme Poverty	Total Household Income	Active Population	Unemployment	Informality	No Job Qualification	Illiteracy
GBA	12,225,209	25.9%	6.9%	1,124	59.9%	13.4%	34.4%	24.4%	1.4%
NOROESTE	2,109,612	42.4%	11.9%	825	52.9%	12.3%	41.9%	29.6%	3.3%
NORESTE	1,140,157	50.3%	17.6%	725	51.7%	9.2%	42.3%	28.1%	3.7%
CUYO	1,445,808	32.7%	7.7%	852	52.2%	6.1%	42.8%	29.6%	2.3%
PAMPEANA	5,255,024	29.3%	8.5%	843	54.0%	12.7%	37.9%	24.0%	2.1%
PATAGONIA	591,652	22.4%	8.0%	1,270	60.1%	10.6%	32.6%	24.7%	2.2%
Total	22,767,462	29.9%	8.4%	998	57.1%	12.5%	36.5%	25.2%	1.9%

Source: Author's estimations based on EPH household survey data (INDEC). Household income is in current pesos. Active labour market status is defined as being 15 years or older, employed or actively looking for a job. The unemployment, informality and no job qualification indicators refer to active individuals. The illiteracy rate refers to individuals aged 25 and older.

B.2 Regional Heterogeneity

INDEC (1996) describes the sampling frame for the EPH, and divides the 28 urban areas covered by the survey in the six regions depicted in Figure B.1. These six regions are highly heterogeneous from a socioeconomic perspective, as illustrated by indicators presented in Table B.1.

The Greater Buenos Aires is by far the largest, with more than 53 percent of the population covered by EPH. The following in size is the Pampeana region: its urban areas covered by EPH contain more than 5.2 million inhabitants. The Noroeste, Cuyo and Noreste regions cover between 1.1 and 2.1 millions each. Finally, the four urban areas of the Patagonia region included in the EPH sampling frame cover less than 600,000 inhabitants.

Most of the regional heterogeneity is captured by the differences in poverty rates. While almost 29.9 percent of the population in all urban areas covered by EPH in October 1998 lived below the poverty line, the rate was much higher in the northern regions (50.3 percent for the Noreste and 42.4 for the Noroeste), around the average in the Cuyo and Pampeana regions (32.7 and 29.3 percent, respectively), and below the national figure in the GBA (25.9 percent) and Patagonia regions (22.4 percent). The ranking in terms of extreme poverty (third column) is similar, and both partially reflect the large regional variation in average total household income (fourth column), from 725 pesos in the Noreste region up to 1,270 pesos in Patagonia.

In terms of labour market indicators, the three richer regions (GBA, Patagonia and Pampeana) have higher rates of activity and lower rates of informality,[1] but also the highest rates of unemployment. Of the three poorest regions (Noroeste, Noreste and Cuyo, only the Noroeste has unemployment levels similar to the national average of October 1998. In terms of qualifications, the three poorest regions have the higher levels of active workers with no job qualifications, at 28.1-29.6 percent of the working populations, compared to around 24-24.7 percent for the three regions with higher income. Finally, illiteracy is lower in the GBA region (1.4 percent of those aged 25 or older), with much higher levels in the Noroeste and Noreste regions (3.3 and 3.7 percent respectively).

For further references, SIEMPRO (2003) presents a broader set of indicators of human development, covering demographics, health and education, by region, province and urban areas. INDEC (2003a) also covers some of these aspects, and contains a thorough analysis of the different sectors of the economy in every province.

[1]See the discussion of informality in footnote 5, page 95.

APPENDIX C

DETAILED POVERTY FIGURES, ARGENTINA 1995-2002

Tables C.1 and C.2 present detailed prices, poverty lines and poverty measures as described in Chapter 1. The price index and the official poverty lines are based on INDEC (2002; 2003a).

Tables C.3-C.6 present some characteristics of the population broken down for the non-poor, the moderately poor and the extremely poor for four of the fifteen periods under study. These descriptive statistics are for illustration only – for detailed poverty profiles, see Cruces and Wodon (2003a) and World Bank (2000a; 2001; 2003). The Tables correspond to the following four waves: October 1995 (corresponding to a recession period), October 1998 (peak of the recovery), October 2001 (after three years of recession), and May 2002 (a few months after the crisis of 2001-2002). The characteristics of the households presented in these tables include (a) household level variables, including the number of babies, children, adults, and elderly household members, and their square; whether the household head has a spouse; whether the household head is a woman; indicators for the age and the migration status of the head (in the last five years); (b) characteristics of the household head, including his/her level of education; whether he/she is unemployed or inactive; whether he/she is an employer, a self-employed worker, or a wage worker; the type of his/her qualification, and whether he/she works in the public/is an informal worker; and (c) the same set of characteristics for the spouse of the household head, when there is one. Geographic indicators for five of the six regions are reported, with the GBA area as reference category.

Table C.1: Detailed Prices, Poverty Lines and Income Figures, Urban Argentina, 1995-2002

Consumer Price Index	**May 95**	**Oct. 95**	**May 96**	**Oct. 96**	**May 97**	**Oct. 97**	**May 98**	**Oct. 98**	**May 99**	**Oct. 99**	**May 00**	**Oct. 00**	**May 01**	**Oct. 01**	**May 02**
Base 9/2001=100	101.9	102.0	101.7	102.2	102.3	102.8	103.5	104.0	102.8	101.9	101.7	101.1	101.4	**100.0**	120.1
Inflation	-	0.14%	-0.35%	0.56%	0.09%	0.48%	0.68%	0.42%	-1.15%	-0.89%	-0.19%	-0.51%	0.28%	-1.41%	20.05%
Implicit poverty line deflactor, GBA	-	1.96%	0.08%	0.96%	-0.45%	1.30%	1.36%	0.89%	-3.00%	-0.89%	-1.32%	-1.19%	2.12%	-2.72%	29.09%
Description	CPI provided by INDEC (2003). Values in real terms throughout the paper are based on Sept. 2001 prices. The implicit poverty line deflactor is obtained from														
Nominal Poverty line	**May 95**	**Oct. 95**	**May 96**	**Oct. 96**	**May 97**	**Oct. 97**	**May 98**	**Oct. 98**	**May 99**	**Oct. 99**	**May 00**	**Oct. 00**	**May 01**	**Oct. 01**	**May 02**
GBA	*151.7*	*154.7*	*154.8*	*156.3*	*155.6*	*157.6*	*159.8*	*161.2*	*156.4*	*155.0*	*152.9*	*151.1*	*154.3*	*150.1*	*193.8*
NOROESTE	131.4	133.9	134.0	135.3	134.7	136.5	138.3	139.5	135.3	134.1	132.4	130.8	*133.6*	*130.0*	*167.6*
NORESTE	134.6	137.3	137.4	138.7	138.1	139.9	141.8	143.0	138.7	137.5	135.7	134.1	*136.9*	*133.2*	*171.8*
CUYO	132.6	135.2	135.3	136.6	136.0	137.8	139.6	140.9	136.6	135.4	133.6	132.1	*134.9*	*130.8*	*168.7*
PAMPEANA	137.1	139.8	139.9	141.3	140.6	142.4	144.4	145.7	141.3	140.0	138.2	136.5	*139.4*	*135.9*	*175.2*
PATAGONIA	144.5	147.3	147.4	148.9	148.2	150.1	152.1	153.5	148.9	147.6	145.6	143.9	*146.9*	*142.7*	*183.6*
GBA-Real	148.9	151.6	152.3	152.9	152.1	153.3	154.3	155.0	152.1	152.1	150.4	149.4	152.1	150.1	161.4
Description	Poverty lines in nominal terms (italics indicate official values). Note: GBA values only are official (INDEC, 2002) for the whole period. Regional values are INDEC's for 2001 and 2002, and constructed for 1995-2000 applying the GBA poverty lines rate of change to regional May 2001 values. See														
Extrene Poverty Line	**May 95**	**Oct. 95**	**May 96**	**Oct. 96**	**May 97**	**Oct. 97**	**May 98**	**Oct. 98**	**May 99**	**Oct. 99**	**May 00**	**Oct. 00**	**May 01**	**Oct. 01**	**May 02**
GBA	*64.8*	*66.1*	*65.9*	*67.4*	*65.4*	*67.4*	*68.3*	*69.8*	*66.0*	*64.6*	*62.9*	*62.4*	*63.2*	*61.0*	*81.8*
NOROESTE	57.1	58.3	58.1	59.4	57.6	59.4	60.2	61.5	58.1	56.9	55.5	55.0	*55.7*	*53.7*	*72.0*
NORESTE	58.3	59.5	59.3	60.6	58.8	60.6	61.4	62.8	59.4	58.1	56.6	56.2	*56.9*	*54.8*	*73.4*
CUYO	58.3	59.4	59.2	60.6	58.8	60.6	61.4	62.7	59.3	58.1	56.6	56.1	*56.9*	*54.5*	*73.0*
PAMPEANA	60.7	61.9	61.7	63.1	61.2	63.1	64.0	65.4	61.8	60.5	59.0	58.5	*59.2*	*57.6*	*77.2*
PATAGONIA	67.1	68.4	68.2	69.8	67.7	69.7	70.7	72.2	68.3	66.8	65.1	64.6	*65.5*	*63.2*	*84.6*
Description	Indigence or extreme poverty line, nominal terms. See text for details. Note: GBA values only are official (INDEC's) for the whole period. Regional values are INDEC's for 2001 and 2002, and constructed for 1995-2000.														
Equivalised income	**May 95**	**Oct. 95**	**May 96**	**Oct. 96**	**May 97**	**Oct. 97**	**May 98**	**Oct. 98**	**May 99**	**Oct. 99**	**May 00**	**Oct. 00**	**May 01**	**Oct. 01**	**May 02**
GBA	401.1	406.1	388.7	393.1	406.5	419.3	448.0	444.9	424.7	413.8	395.0	404.3	387.0	369.2	329.5
NOROESTE	236.9	236.8	223.5	215.5	242.6	237.7	256.6	257.9	239.3	239.5	229.5	227.8	223.2	214.3	194.0
NORESTE	227.2	225.0	221.5	211.2	220.1	226.2	238.4	230.3	230.1	212.9	200.1	201.1	200.8	185.8	167.9
CUYO	291.2	256.3	279.4	268.6	266.9	302.1	295.0	285.6	286.5	284.9	260.2	272.4	255.1	246.5	229.4
PAMPEANA	296.3	304.7	300.0	274.1	304.8	310.3	318.8	321.0	318.7	307.7	303.0	305.2	290.7	269.1	244.1
PATAGONIA	468.4	411.7	410.6	403.0	407.8	420.8	441.3	422.5	411.6	398.6	400.0	394.7	400.4	381.9	373.2
Total	354.6	346.6	336.7	336.4	349.0	358.9	378.5	375.6	361.8	351.6	337.3	343.2	329.4	311.6	280.7
Description	Equivalised household income in nominal terms. Adult equivalence scale used by INDEC - see Moreles (1988).														

Source: Author's estimations based on EPH household survey data (INDEC).

Table C.2: Detailed Poverty Figures, Urban Argentina, 1995-2002

Indigent individuals headcount	**May 95**	**Oct. 95**	**May 96**	**Oct. 96**	**May 97**	**Oct. 97**	**May 98**	**Oct. 98**	**May 99**	**Oct. 99**	**May 00**	**Oct. 00**	**May 01**	**Oct. 01**	**May 02**
GBA	0.0567	0.0629	0.0694	0.0760	0.0569	0.0644	0.0534	0.0687	0.0759	0.0674	0.0755	0.0765	0.1032	0.1218	0.2267
NOROESTE	0.0875	0.1120	0.1160	0.1313	0.1096	0.1187	0.1181	0.1186	0.1298	0.1107	0.1252	0.1331	0.1454	0.1615	0.2947
NORESTE	0.1343	0.1261	0.1480	0.1717	0.1479	0.1494	0.1499	0.1761	0.1769	0.1776	0.1848	0.1968	0.2302	0.2693	0.3876
CUYO	0.0558	0.0858	0.0783	0.0883	0.0922	0.0878	0.0701	0.0765	0.0795	0.0739	0.0843	0.1063	0.1102	0.1231	0.2471
PAMPEANA	0.0905	0.0746	0.0856	0.1073	0.0751	0.0793	0.0768	0.0851	0.0800	0.0838	0.0881	0.0902	0.1132	0.1367	0.2510
PATAGONIA	0.0310	0.0721	0.0699	0.0756	0.0602	0.0621	0.0654	0.0799	0.0690	0.0779	0.0757	0.0714	0.0692	0.0734	0.1534
Total	0.0676	0.0755	0.0823	0.0931	0.0732	0.0790	0.0715	0.0838	0.0877	0.0822	0.0899	0.0938	0.1163	0.1363	0.2477
Description	Headcount of indigent (extremely poor) individuals.														

Poor individuals headcount	**May 95**	**Oct. 95**	**May 96**	**Oct. 96**	**May 97**	**Oct. 97**	**May 98**	**Oct. 98**	**May 99**	**Oct. 99**	**May 00**	**Oct. 00**	**May 01**	**Oct. 01**	**May 02**
GBA	0.2217	0.2476	0.2668	0.2795	0.2629	0.2595	0.2427	0.2588	0.2711	0.2673	0.2973	0.2889	0.3267	0.3542	0.4965
NOROESTE	0.3783	0.4149	0.4419	0.4446	0.4066	0.4204	0.4023	0.4238	0.4558	0.4137	0.4455	0.4365	0.4742	0.4831	0.6355
NORESTE	0.4440	0.4531	0.4623	0.4889	0.4878	0.4837	0.4861	0.5026	0.5010	0.5061	0.5301	0.5314	0.5644	0.5730	0.6981
CUYO	0.2924	0.3599	0.3126	0.3496	0.3647	0.3204	0.3291	0.3274	0.3380	0.3342	0.3663	0.3917	0.3875	0.3966	0.5492
PAMPEANA	0.2848	0.2715	0.2916	0.3271	0.2921	0.2840	0.2863	0.2927	0.2936	0.2927	0.3092	0.3040	0.3387	0.3712	0.5271
PATAGONIA	0.1297	0.2203	0.2079	0.2269	0.2198	0.2183	0.2103	0.2242	0.2215	0.2476	0.2314	0.2417	0.2380	0.2325	0.3917
Total	0.2577	0.2870	0.3011	0.3200	0.3003	0.2954	0.2856	0.2991	0.3102	0.3048	0.3304	0.3262	0.3591	0.3831	0.5301
Description	Headcount of poor individuals.														

Total poverty gap	**May 95**	**Oct. 95**	**May 96**	**Oct. 96**	**May 97**	**Oct. 97**	**May 98**	**Oct. 98**	**May 99**	**Oct. 99**	**May 00**	**Oct. 00**	**May 01**	**Oct. 01**	**May 02**
GBA	0.0867	0.0979	0.1059	0.1147	0.1033	0.1042	0.0930	0.1081	0.1098	0.1071	0.1235	0.1219	0.1440	0.1632	0.2656
NOROESTE	0.1463	0.1637	0.1830	0.1875	0.1635	0.1732	0.1645	0.1693	0.1890	0.1699	0.1901	0.1877	0.2117	0.2211	0.3315
NORESTE	0.1875	0.1889	0.2008	0.2231	0.2108	0.2054	0.2120	0.2289	0.2292	0.2366	0.2501	0.2638	0.2863	0.3034	0.4139
CUYO	0.1010	0.1338	0.1221	0.1337	0.1429	0.1285	0.1162	0.1213	0.1313	0.1261	0.1424	0.1618	0.1607	0.1751	0.2812
PAMPEANA	0.1212	0.1081	0.1229	0.1410	0.1180	0.1158	0.1123	0.1171	0.1186	0.1207	0.1294	0.1322	0.1524	0.1780	0.2772
PATAGONIA	0.0474	0.0930	0.0882	0.0928	0.0849	0.0817	0.0885	0.0943	0.0889	0.1033	0.0973	0.0988	0.0964	0.1004	0.1830
Total	0.1019	0.1137	0.1228	0.1335	0.1200	0.1198	0.1119	0.1230	0.1270	0.1247	0.1390	0.1407	0.1604	0.1794	0.2822
Description	Poverty gap - FGT measure with alpha=1. See text for details.														

Total squared poverty gap	**May 95**	**Oct. 95**	**May 96**	**Oct. 96**	**May 97**	**Oct. 97**	**May 98**	**Oct. 98**	**May 99**	**Oct. 99**	**May 00**	**Oct. 00**	**May 01**	**Oct. 01**	**May 02**
GBA	0.0520	0.0578	0.0641	0.0690	0.0576	0.0606	0.0524	0.0628	0.0646	0.0622	0.0714	0.0712	0.0889	0.1041	0.1826
NOROESTE	0.0785	0.0896	0.1031	0.1080	0.0908	0.0970	0.0922	0.0939	0.1092	0.0963	0.1097	0.1101	0.1256	0.1357	0.2182
NORESTE	0.1085	0.1081	0.1182	0.1341	0.1215	0.1161	0.1224	0.1379	0.1382	0.1452	0.1541	0.1690	0.1845	0.2033	0.2933
CUYO	0.0502	0.0718	0.0662	0.0726	0.0793	0.0727	0.0590	0.0632	0.0711	0.0667	0.0778	0.0913	0.0929	0.1060	0.1846
PAMPEANA	0.0751	0.0636	0.0737	0.0881	0.0689	0.0695	0.0638	0.0685	0.0686	0.0727	0.0776	0.0804	0.0948	0.1164	0.1894
PATAGONIA	0.0271	0.0556	0.0550	0.0558	0.0506	0.0454	0.0524	0.0580	0.0500	0.0631	0.0576	0.0590	0.0560	0.0627	0.1176
Total	0.1019	0.1137	0.1228	0.1335	0.1200	0.1198	0.1119	0.1230	0.1270	0.1247	0.1390	0.1407	0.1604	0.1794	0.2822
Description	Poverty gap squared - FGT measure with alpha=2. See text for details.														

Source: Author's estimations based on EPH household survey data (INDEC).

Table C.3: Poverty Profile, Urban Argentina, October 1995

	Total	Non-poor	Poor	Extreme Poor
Log Normalised Income	0.599	0.978	-0.327	-2.273
Normalised Income	2.863	3.467	0.739	0.211
Demographic Composition				
Number of Infants (ages 0-5)	0.389	0.288	0.701	0.961
Number of Infants squared	0.708	0.468	1.391	2.248
Number of Children (ages 6-14)	0.587	0.418	1.150	1.409
Number of Children Squared	1.287	0.780	2.827	4.245
Number of Youths (ages 15-24)	0.632	0.569	0.869	0.858
Number of Youths Squared	1.275	1.120	1.872	1.806
Number of Adults (ages 25-64)	1.547	1.506	1.719	1.650
Number of Adults Squared	3.270	3.182	3.685	3.338
Number of Elderly (ages 65+)	0.357	0.392	0.255	0.125
Number of Elderly Squared	0.532	0.586	0.389	0.167
Household Head				
Age - 19 and younger	0.005	0.005	0.008	0.004
Age - 20-29	0.102	0.098	0.107	0.143
Age - 30-39	0.201	0.184	0.260	0.276
Age - 50-59	0.176	0.181	0.152	0.175
Age - 60 and older	0.299	0.330	0.199	0.125
Female	0.246	0.258	0.186	0.243
Recent migrant	0.061	0.061	0.055	0.068
Inactive	0.298	0.314	0.250	0.203
Unemployed	0.076	0.045	0.123	0.386
Primary - Complete	0.340	0.318	0.417	0.444
Secondary - Incomplete	0.158	0.158	0.163	0.150
Secondary - Complete	0.152	0.171	0.091	0.056
Further Education - Incomplete	0.008	0.009	0.003	0.001
Further Education - Complete	0.028	0.033	0.012	0.004
University Education	0.137	0.166	0.030	0.037
Boss	0.039	0.048	0.008	0.006
Self Employed	0.158	0.149	0.195	0.189
Informal Worker	0.242	0.223	0.320	0.292
Public Sector	0.101	0.112	0.070	0.032
Qualification: Operative	0.283	0.286	0.304	0.172
Qualification: Technician	0.142	0.156	0.098	0.063
Qualification: Professional	0.067	0.084	0.002	0.007
Spouse Not Present	0.326	0.350	0.212	0.306
Household Spouse				
Unemployed	0.044	0.034	0.070	0.109
Primary - Complete	0.238	0.211	0.346	0.322
Secondary - Complete	0.127	0.140	0.084	0.055
Secondary - Incomplete	0.099	0.092	0.137	0.092
Further - Complete	0.033	0.040	0.010	0.001
Further - Incomplete	0.008	0.008	0.006	0.005
University	0.062	0.076	0.012	0.006
Boss	0.007	0.008	0.005	0.000
Self Employed	0.055	0.056	0.052	0.044
Informal Worker	0.104	0.101	0.121	0.101
Public Sector	0.049	0.058	0.016	0.006
Qualification: Operative	0.055	0.061	0.032	0.021
Qualification: Technician	0.052	0.062	0.017	0.007
Qualification: Professional	0.023	0.028	0.001	0.000
Geographic location				
Noroeste	0.079	0.067	0.126	0.127
Noreste	0.044	0.036	0.073	0.079
Cuyo	0.061	0.056	0.082	0.072
Pampeana	0.239	0.242	0.220	0.237
Patagonia	0.025	0.026	0.018	0.026

Source: Author's estimations based on EPH household survey data (INDEC).

Table C.4: Poverty Profile, Urban Argentina, October 1998

	Total	Non-poor	Poor	Extreme Poor
Log Normalised Income	0.634	1.028	-0.338	-2.014
Normalised Income	3.033	3.712	0.731	0.232
Demographic Composition				
Number of Infants (ages 0-5)	0.368	0.262	0.673	0.948
Number of Infants squared	0.653	0.402	1.327	2.175
Number of Children (ages 6-14)	0.571	0.389	1.122	1.501
Number of Children Squared	1.233	0.705	2.691	4.344
Number of Youths (ages 15-24)	0.627	0.552	0.881	0.931
Number of Youths Squared	1.264	1.062	1.944	2.117
Number of Adults (ages 25-64)	1.529	1.487	1.697	1.630
Number of Adults Squared	3.213	3.131	3.594	3.262
Number of Elderly (ages 65+)	0.348	0.384	0.262	0.108
Number of Elderly Squared	0.520	0.571	0.409	0.147
Household Head				
Age - 19 and younger	0.005	0.004	0.005	0.005
Age - 20-29	0.109	0.106	0.114	0.145
Age - 30-39	0.195	0.177	0.254	0.277
Age - 50-59	0.185	0.190	0.163	0.189
Age - 60 and older	0.293	0.323	0.204	0.127
Female	0.266	0.276	0.209	0.292
Recent migrant	0.056	0.059	0.043	0.057
Inactive	0.284	0.296	0.241	0.229
Unemployed	0.060	0.035	0.102	0.297
Primary - Complete	0.313	0.283	0.432	0.386
Secondary - Incomplete	0.174	0.171	0.190	0.168
Secondary - Complete	0.152	0.175	0.080	0.049
Further Education - Incomplete	0.009	0.010	0.005	0.002
Further Education - Complete	0.027	0.033	0.005	0.005
University Education	0.156	0.191	0.031	0.026
Boss	0.036	0.045	0.005	0.003
Self Employed	0.161	0.153	0.182	0.212
Informal Worker	0.256	0.231	0.348	0.328
Public Sector	0.107	0.116	0.084	0.044
Qualification: Operative	0.336	0.326	0.406	0.262
Qualification: Technician	0.111	0.135	0.032	0.012
Qualification: Professional	0.069	0.088	0.004	0.001
Spouse Not Present	0.354	0.376	0.242	0.369
Household Spouse				
Unemployed	0.029	0.021	0.054	0.074
Primary - Complete	0.219	0.189	0.341	0.289
Secondary - Complete	0.115	0.128	0.076	0.046
Secondary - Incomplete	0.113	0.107	0.150	0.096
Further - Complete	0.033	0.040	0.007	0.005
Further - Incomplete	0.009	0.010	0.008	0.002
University	0.072	0.090	0.011	0.002
Boss	0.007	0.008	0.001	0.000
Self Employed	0.058	0.059	0.053	0.052
Informal Worker	0.107	0.107	0.109	0.102
Public Sector	0.054	0.064	0.023	0.004
Qualification: Operative	0.064	0.071	0.044	0.025
Qualification: Technician	0.055	0.068	0.008	0.007
Qualification: Professional	0.024	0.030	0.001	0.000
Geographic location				
Noroeste	0.080	0.068	0.121	0.122
Noreste	0.044	0.034	0.074	0.100
Cuyo	0.061	0.058	0.075	0.053
Pampeana	0.230	0.231	0.227	0.234
Patagonia	0.026	0.028	0.018	0.027

Source: Author's estimations based on EPH household survey data (INDEC).

Table C.5: Poverty Profile, Urban Argentina, October 2001

	Total	Non-poor	Poor	Extreme Poor
Log Normalised Income	0.452	1.024	-0.360	-2.254
Normalised Income	2.771	3.650	0.718	0.195
Demographic Composition				
Number of Infants (ages 0-5)	0.364	0.246	0.607	0.772
Number of Infants squared	0.618	0.365	1.111	1.546
Number of Children (ages 6-14)	0.579	0.352	1.018	1.420
Number of Children Squared	1.281	0.624	2.378	4.063
Number of Youths (ages 15-24)	0.642	0.516	0.942	0.998
Number of Youths Squared	1.324	0.972	2.079	2.479
Number of Adults (ages 25-64)	1.529	1.436	1.805	1.681
Number of Adults Squared	3.260	3.036	4.027	3.442
Number of Elderly (ages 65+)	0.345	0.413	0.208	0.110
Number of Elderly Squared	0.512	0.617	0.296	0.154
Household Head				
Age - 19 and younger	0.006	0.006	0.006	0.005
Age - 20-29	0.108	0.102	0.109	0.154
Age - 30-39	0.196	0.181	0.225	0.259
Age - 50-59	0.188	0.186	0.199	0.174
Age - 60 and older	0.289	0.337	0.185	0.133
Female	0.287	0.306	0.227	0.266
Recent migrant	0.055	0.062	0.036	0.038
Inactive	0.288	0.320	0.212	0.191
Unemployed	0.100	0.050	0.156	0.370
Primary - Complete	0.315	0.272	0.420	0.436
Secondary - Incomplete	0.162	0.155	0.192	0.152
Secondary - Complete	0.170	0.199	0.106	0.077
Further Education - Incomplete	0.011	0.013	0.007	0.004
Further Education - Complete	0.034	0.043	0.007	0.012
University Education	0.159	0.209	0.039	0.019
Boss	0.032	0.042	0.011	0.006
Self Employed	0.159	0.141	0.199	0.210
Informal Worker	0.256	0.222	0.351	0.324
Public Sector	0.107	0.121	0.080	0.053
Qualification: Operative	0.307	0.299	0.373	0.240
Qualification: Technician	0.109	0.139	0.037	0.016
Qualification: Professional	0.061	0.084	0.002	0.002
Spouse Not Present	0.370	0.402	0.276	0.322
Household Spouse				
Unemployed	0.039	0.029	0.058	0.076
Primary - Complete	0.207	0.162	0.327	0.305
Secondary - Complete	0.118	0.135	0.084	0.057
Secondary - Incomplete	0.104	0.089	0.143	0.137
Further - Complete	0.041	0.053	0.014	0.003
Further - Incomplete	0.010	0.011	0.009	0.003
University	0.077	0.101	0.017	0.010
Boss	0.007	0.010	0.001	0.000
Self Employed	0.051	0.046	0.065	0.060
Informal Worker	0.103	0.089	0.139	0.135
Public Sector	0.056	0.069	0.027	0.020
Qualification: Operative	0.066	0.075	0.051	0.031
Qualification: Technician	0.055	0.072	0.014	0.004
Qualification: Professional	0.025	0.034	0.002	0.000
Geographic location				
Noroeste	0.087	0.076	0.119	0.115
Noreste	0.047	0.036	0.066	0.094
Cuyo	0.064	0.062	0.073	0.059
Pampeana	0.236	0.239	0.225	0.233
Patagonia	0.030	0.034	0.020	0.018

Source: Author's estimations based on EPH household survey data (INDEC).

Table C.6: Poverty Profile, Urban Argentina, May 2002

	Total	Non-poor	Poor	Extreme Poor
Log Normalised Income	0.029	0.871	-0.379	-2.137
Normalised Income	1.975	3.039	0.704	0.202
Demographic Composition				
Number of Infants (ages 0-5)	0.368	0.201	0.527	0.699
Number of Infants squared	0.627	0.280	0.930	1.349
Number of Children (ages 6-14)	0.572	0.276	0.802	1.224
Number of Children Squared	1.269	0.473	1.693	3.269
Number of Youths (ages 15-24)	0.640	0.454	0.831	0.988
Number of Youths Squared	1.310	0.859	1.697	2.256
Number of Adults (ages 25-64)	1.534	1.400	1.729	1.713
Number of Adults Squared	3.304	2.977	3.878	3.613
Number of Elderly (ages 65+)	0.346	0.438	0.279	0.136
Number of Elderly Squared	0.517	0.651	0.444	0.183
Household Head				
Age - 19 and younger	0.006	0.005	0.005	0.008
Age - 20-29	0.118	0.104	0.128	0.151
Age - 30-39	0.192	0.166	0.218	0.240
Age - 50-59	0.189	0.186	0.194	0.189
Age - 60 and older	0.289	0.364	0.218	0.141
Female	0.287	0.323	0.225	0.253
Recent migrant	0.053	0.061	0.048	0.035
Inactive	0.289	0.341	0.233	0.196
Unemployed	0.124	0.052	0.137	0.339
Primary - Complete	0.311	0.250	0.393	0.403
Secondary - Incomplete	0.163	0.138	0.207	0.186
Secondary - Complete	0.173	0.211	0.142	0.093
Further Education - Incomplete	0.014	0.018	0.008	0.009
Further Education - Complete	0.035	0.050	0.019	0.009
University Education	0.162	0.239	0.068	0.036
Boss	0.025	0.038	0.009	0.003
Self Employed	0.150	0.127	0.162	0.207
Informal Worker	0.251	0.206	0.303	0.327
Public Sector	0.115	0.135	0.097	0.072
Qualification: Operative	0.294	0.277	0.372	0.249
Qualification: Technician	0.101	0.144	0.057	0.021
Qualification: Professional	0.058	0.097	0.007	0.002
Spouse Not Present	0.372	0.432	0.266	0.319
Household Spouse				
Unemployed	0.041	0.025	0.047	0.081
Primary - Complete	0.208	0.143	0.294	0.306
Secondary - Complete	0.122	0.137	0.118	0.080
Secondary - Incomplete	0.099	0.072	0.148	0.125
Further - Complete	0.041	0.058	0.022	0.011
Further - Incomplete	0.011	0.013	0.013	0.005
University	0.074	0.110	0.031	0.014
Boss	0.005	0.008	0.000	0.000
Self Employed	0.049	0.037	0.062	0.068
Informal Worker	0.103	0.078	0.136	0.141
Public Sector	0.057	0.073	0.035	0.033
Qualification: Operative	0.068	0.075	0.062	0.054
Qualification: Technician	0.050	0.076	0.018	0.008
Qualification: Professional	0.021	0.035	0.002	0.000
Geographic location				
Noroeste	0.086	0.069	0.111	0.109
Noreste	0.049	0.034	0.060	0.082
Cuyo	0.067	0.063	0.074	0.069
Pampeana	0.236	0.236	0.238	0.236
Patagonia	0.030	0.035	0.025	0.019

Source: Author's estimations based on EPH household survey data (INDEC).

APPENDIX D

FERTILITY AND LABOUR SUPPLY: ROBUSTNESS CHECKS

D.1 ROBUSTNESS CHECKS WITH DIFFERENT COVARIATES, SAMPLES AND VARIABLE DEFINITIONS

This Appendix provides additional findings and robustness checks of the benchmark results of Chapter 7 on the effects of fertility on female labour supply in Argentina. This Section corroborates that the results presented in Section 7.2.2 (page 176) are robust to differences in the underlying samples, in the specification of the model and in the definition of the variables.

The first set of robustness checks consists of adding covariates X to the estimation of Equation 5.7 (page 137). Table D.1 estimates the same model with two instruments as in Table 7.3 (page 181), with *Two boys* and *Two girls* as the instruments, and *Age, Age at first birth,* and the sex of the first two children as exogenous covariates, but it adds indicators for Argentina's 522 municipalities. These geographic controls capture the wide variation of socioeconomic conditions within the country, with a few relatively rich cities and extremely poor urban and rural areas. The results in Table D.1 are very close to those discussed in Section 7.2.2 (page 176): the coefficients are slightly smaller (in absolute value) once the geographic controls are introduced, but the differences are not significant. This finding reinforces the plausibility of the randomness of the instrument, since it indicates that it is orthogonal to the additional geographic controls, as indicated by the similarity of the coefficients with those in previous Tables and by the p-values of the Sargan overidentification tests.

Table D.2 presents the estimation of the same 2SLS model with demo-

Table D.1: Robustness Checks: OLS and Two-Stage Least Squares Results with Geographic Controls

	Instrumented: Number of children				Instrumented: More than two children			
Dependent variable: Worked for pay	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**
OLS estimates								
OLS	-0.0435	-0.0393	-0.0443	-0.0401	-0.0886	-0.0752	-0.0931	-0.0781
Control for sex of 1st child	[0.0005]***	[0.0006]***	[0.0005]***	[0.0006]***	[0.0013]***	[0.0014]***	[0.0013]***	[0.0015]***
OLS	-0.0435	-0.0393	-0.0443	-0.0401	-0.0886	-0.0752	-0.0931	-0.0782
Controls for sexes of 1st & 2nd children	[0.0005]***	[0.0006]***	[0.0005]***	[0.0006]***	[0.0013]***	[0.0014]***	[0.0013]***	[0.0015]***
IV Estimates								
IV: Same Sex	-0.0424	-0.0450	-0.0455	-0.0525	-0.0786	-0.0807	-0.0841	-0.0940
Controls for sexes of 1st & 2nd children	[0.0177]**	[0.0183]**	[0.0171]***	[0.0177]***	[0.0328]**	[0.0329]**	[0.0316]***	[0.0317]***
DWH p-value	0.9499	0.7552	0.9447	0.4821	0.7588	0.8667	0.7767	0.6159
IV: Two Boys and Two Girls	-0.0317	-0.0359	-0.0331	-0.0417	-0.0666	-0.0709	-0.0701	-0.0821
Control for sex of 1st child	[0.0165]*	[0.0173]**	[0.0159]**	[0.0167]**	[0.0318]**	[0.0320]**	[0.0306]**	[0.0308]***
Sargan p-value	0.0978	0.1253	0.0437	0.0621	0.1545	0.1888	0.0778	0.1075
DWH p-value	0.4746	0.8443	0.4798	0.9219	0.4875	0.8932	0.4520	0.8961
Spouse worked for pay								
OLS		-0.0059		-0.0051		-0.0085		-0.0065
Controls for sexes of 1st & 2nd children		[0.0002]***		[0.0003]***		[0.0006]***		[0.0006]***
IV: Same Sex		0.0029		-0.0014		0.0053		-0.0026
Controls for sexes of 1st & 2nd children		[0.0079]		[0.0074]		[0.0147]		[0.0132]
DWH p-value		0.2680		0.6189		0.3444		0.7655
Observations	653,213	497,194	599,941	456,437	653,213	497,194	599,941	456,437
Geographic Controls	522 Municipalities							

Note: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include the age and the age at first birth of the women or her spouse, in addition to the sex of the first and second children (where indicated). The samples correspond to women aged 21-35 with two or more children aged 18 or younger from the extended questionnaire sample of the 1991 Census, as described in the text.

graphic and geographic controls, with the age variable replaced by cohort dummies and with additional covariates in X. The first panel in the Table presents the results with the three education level indicators of Section 7.3.2 (page 186) included as right hand side variables. Most of the coefficients are lower in absolute value than their counterparts in Table 7.3, but again these differences are not statistically significant. The main difference is that the Sargan exogeneity null is now rejected (at the 5 percent level) for four of the eight coefficients estimated, indicating that the education variables are probably endogenous in the labour supply model. The results in the other three panels are substantially the same: in the second panel, an indicator for rural areas is added to the demographic, educational and geographic controls, while the third panel adds a household indicator of structural poverty constructed by INDEC. Finally, the last panel computes the model with the woman and her husband's education status as right hand side variables. All these models are consistent with the findings presented in Table 7.3, although the overidentification tests indicate that the extra covariates are, in most cases, endogenous.

While the addition of covariates does not affect the essence of the benchmark results, there might still be an impact from the definitions of the underlying samples and the variables, and from measurement error. These issues are addressed in Table D.3.

In the first panel of Table D.3, the dependent variable *Worked for pay* was replaced by an indicator of labour force participation, *Active labour force status*, equal to 1 for women who worked for pay or were unemployed during the reference week, and 0 otherwise. It is thus possible to test the robustness of the main results with respect to the definition of the dependent variable. In the main results of Chapters 7 and 8, the *Worked for pay* indicator was employed because it was considered to be more reliable, since the distinction between unemployment and inactivity might not be reflected correctly in the data. This is because the 1991 Census data was collected mostly by teachers and other civil servants, unlike smaller household surveys like EPH that are carried out by specialised staff who are better trained and use a more specific questionnaire on labour market issues. Gregg and Wadsworth (1999a) provide a discussion of the sometimes subtle distinction between the unemployed and the inactive. In any case, the difference between the

Table D.2: Robustness Checks: OLS and Two-Stage Least Squares Results with Additional Covariates

	Instrumented: Number of children				**Instrumented: More than two children**			
Dependent variable: Worked for pay	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**
IV: Two Boys and Two Girls	-0.0261	-0.0342	-0.0303	-0.0420	-0.0561	-0.0679	-0.0652	-0.0828
Controls: education level and birth cohort	[0.0157]*	[0.0161]**	[0.0153]**	[0.0156]***	[0.0301]*	[0.0298]**	[0.0292]**	[0.0288]***
Sargan p-value	0.0436	0.0777	0.0144	0.0354	0.0677	0.1212	0.0264	0.0651
DWH p-value	0.4751	0.9916	0.6158	0.6367	0.4740	0.9853	0.5765	0.6840
OLS with same controls	-0.0373	-0.0340	-0.0380	-0.0347	-0.0776	-0.0684	-0.0814	-0.0711
	[0.0005]***	[0.0006]***	[0.0005]***	[0.0006]***	[0.0012]***	[0.0013]***	[0.0012]***	[0.0014]***
IV: Two Boys and Two Girls	-0.0265	-0.0344	-0.0307	-0.0422	-0.0571	-0.0684	-0.0658	-0.0832
Controls: education level, birth cohort and urban dummy	[0.0157]*	[0.0161]**	[0.0153]**	[0.0156]***	[0.0300]*	[0.0297]**	[0.0291]**	[0.0288]***
Sargan p-value	0.0433	0.0780	0.0141	0.0352	0.0677	0.1221	0.0260	0.0649
DWH p-value	0.5034	0.9721	0.6421	0.6235	0.4984	0.9993	0.5973	0.6745
OLS with same controls	-0.0370	-0.0339	-0.0377	-0.0346	-0.0774	-0.0684	-0.0812	-0.0711
	[0.0005]***	[0.0006]***	[0.0005]***	[0.0006]***	[0.0012]***	[0.0013]***	[0.0012]***	[0.0014]***
IV: Two Boys and Two Girls	-0.0271	-0.0348	-0.0311	-0.0426	-0.0574	-0.0685	-0.0661	-0.0833
Controls: education level, birth cohort, NBI and urban dummy	[0.0159]*	[0.0162]**	[0.0154]**	[0.0157]***	[0.0302]*	[0.0298]**	[0.0292]**	[0.0288]***
Sargan p-value	0.0445	0.0800	0.0144	0.0365	0.0684	0.1220	0.0262	0.0651
DWH p-value	0.4621	0.9968	0.5744	0.6614	0.4965	0.9952	0.5899	0.6717
OLS with same controls	-0.0388	-0.0349	-0.0398	-0.0358	-0.0779	-0.0683	-0.0819	-0.0711
	[0.0005]***	[0.0006]***	[0.0005]***	[0.0006]***	[0.0012]***	[0.0014]***	[0.0012]***	[0.0014]***
IV: Two Boys and Two Girls		-0.0297		-0.0416		-0.0621		-0.0820
Controls: woman and spouse education, spouse age		[0.0155]*		[0.0156]***		[0.0294]**		[0.0288]***
Sargan p-value		0.0277		0.0365		0.0434		0.0667
DWH p-value		0.7961		0.6742		0.8105		0.7085
OLS with same controls		-0.0337		-0.0351		-0.0691		-0.0713
		[0.0005]***		[0.0006]***		[0.0012]***		[0.0014]***
Observations	653,213	497,194	599,941	456,437	653,213	497,194	599,941	456,437
Geographic Controls	522 Municipalities							

Note: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include the age (as cohort indicators in this Table) and the age at first birth of the women or her spouse, in addition to the sex of the first child. The education level indicators correspond to some primary, some secondary and some tertiary education. NBI is an indicator of structural poverty (basic needs) defined by INDEC. The samples correspond to women aged 21-35 with two or more children aged 18 or younger from the extended questionnaire sample of the 1991 Census, as described in the text.

two measures is relatively small, with 31.38 percent of the women in the complete sample working for pay and 33.82 percent in the labour force. The results with *Active labour force status* as the dependent variable are close (and qualitatively the same) to those using *Worked for pay* (as in Table 7.3), both in terms of levels and significance.

Another source of concern might be the narrow age group – 21 to 35 years old – for women in the final samples. The second panel in Table D.3 presents the results obtained by adding women in the age group 36-45 that complied with the selection criteria of Section 5.4.1 (page 142). This implies an additional 330,000 extra observations in the full samples, and around 280,000 in the married samples. These results (with *Worked for pay* as the dependent variable) are again similar to the those in Table 7.3. In fact, it can be noted that the increase in sample sizes boosts the precision of the estimates, since all the coefficients are significant at least at the 5 percent level. This suggests that the inclusion of the extra age group does not attenuate nor bias the results, but instead increases their precision.

Finally, some important adjustments were made to match women with their children in the Census data: Section 5.4.1 states that around 100,000 observations were discarded from the final sample because the total number of surviving children did not correspond to the number of matched children in the household. This was the most important adjustment in the sample, due to the lack of detail of the kinship variable. The final panel in Table D.3 estimates the same model as in Table 7.3 without discarding these 100,000 observations. The coefficients are smaller in absolute value than those in Table 7.3, but in the same range as those discussed in this Section. The measurement error in the fertility variables does affect the results in an important manner. Alternatively, this might be suggesting that children in the household seem to affect the labour supply of women even if they are not their own children.

D.2 ESTIMATION WITH AN ALTERNATIVE DATASET

Instrumental variables estimation with a relatively weak instruments such as the *Same sex* indicator usually requires large sample sizes to obtain coefficients estimated with precision, which is why Angrist and Evans (1998)

Table D.3: Robustness Checks: Alternative Dependent Variable and Different Sample Definitions

	Instrumented: Number of children				Instrumented: More than two children			
Dependent variable: Worked for pay	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**
	Using labor force status instead of worked for pay as dependent variable							
IV: Same Sex	-0.0403	-0.0457	-0.0438	-0.0530	-0.0748	-0.0820	-0.0809	-0.0948
	[0.0182]**	[0.0188]**	[0.0176]**	[0.0182]***	[0.0338]**	[0.0338]**	[0.0326]**	[0.0327]***
DWH p-value	0.7211	0.8587	0.8189	0.5963	0.5396	0.9779	0.5430	0.7584
OLS with same controls	-0.0468	-0.0423	-0.0478	-0.0433	-0.0956	-0.0811	-0.1007	-0.0847
	[0.0005]***	[0.0006]***	[0.0005]***	[0.0007]***	[0.0013]***	[0.0015]***	[0.0013]***	[0.0015]***
Observations	653,213	497,194	599,941	456,437	653,213	497,194	599,941	456,437
	Women 21-45							
IV: Same Sex	-0.0386	-0.0462	-0.0403	-0.0499	-0.0719	-0.0840	-0.0749	-0.0907
	[0.0126]***	[0.0129]***	[0.0123]***	[0.0127]***	[0.0235]***	[0.0236]***	[0.0229]***	[0.0231]***
DWH p-value	0.7802	0.4824	0.8241	0.3464	0.7344	0.3551	0.6995	0.2641
OLS with same controls	-0.0421	-0.0371	-0.0431	-0.0379	-0.0798	-0.0622	-0.0838	-0.0649
	[0.0004]***	[0.0005]***	[0.0004]***	[0.0005]***	[0.0010]***	[0.0012]***	[0.0011]***	[0.0012]***
Observations	989,113	774,059	932,166	730,542	989,113	774,059	932,166	730,542
	Women with mismatching surviving children and children in household							
IV: Same Sex	-0.0350	-0.0442	-0.0378	-0.0501	-0.0698	-0.0827	-0.0732	-0.0920
	[0.0171]**	[0.0179]**	[0.0167]**	[0.0174]***	[0.0341]**	[0.0335]**	[0.0328]**	[0.0323]***
DWH p-value	0.8000	0.7852	0.9089	0.5567	0.4325	0.9721	0.3897	0.8243
OLS with same controls	-0.0393	-0.0394	-0.0397	-0.0399	-0.0966	-0.0816	-0.1015	-0.0848
	[0.0004]***	[0.0005]***	[0.0004]***	[0.0005]***	[0.0012]***	[0.0014]***	[0.0012]***	[0.0014]***
Observations	748,157	541,529	690,103	499,000	748,157	541,529	690,103	499,000

Note: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include the age and the age at first birth of the women or her spouse, in addition to the sex of the first and second children (where indicated). The samples correspond to women aged 21-35 (except where noted) with two or more children aged 18 or younger from the extended questionnaire sample of the 1991 Census, as described in the text.

use datasets from the United States Census, and this Part employs the 1991 Census from Argentina. Applications of the "same sex" strategy to smaller datasets, as in Iacovou's (2001) study of the United Kingdom, tend to produce instrumental variables estimates with high standard errors.

This can be shown by following Dee and Evans' (2003) analysis of the power of the statistical significance test for IV coefficients. When a reduced form OLS regression of Y on Z generates unbiased estimates, the coefficient is $\phi_{RF} = E[Y|Z = 1] - E[Y|Z = 0]$. This estimate is statistically significant if the ratio of ϕ_{RF} and its standard error σ_{RF} is greater than a cut-off value η from the normal distribution – for instance, $\eta = 1.96$ for a 5 percent level of significance in a two-sided test. Defining $p_1 = E[Y|Z = 1]$ and $p_0 = E[Y|Z = 0]$, and with treatment and control groups defined by Z with $\frac{1}{2}N$ observations each, σ^2_{RF} is approximately equal to $[p_1(1 - p_1) + p_0(1 - p_0)]/\frac{1}{2}N$. Since by definition $p_1 = p_0 + \phi_{RF}$, using these expressions in $|\phi_{RF}/\sigma_{RF}| > \eta$ allows to solve for the minimum number of observations N needed for a statistically significant value of ϕ_{RF}. For the Argentine Census dataset employed in Part II, there are just enough observations for testing the IV coefficients at the 1 percent level of significance for most samples, and there are largely more than enough observations for the usual 5 percent tests for all four samples.[1]

However, using smaller alternative datasets covering the same region and period is valuable as a validation exercise, since at least the results from first-stages and OLS estimations can be compared with the main application. While no other Census dataset is available for Argentina, Table D.4 presents the estimation of a model equivalent to the one in Table 7.3 (page 181), but using a sample from INDEC's 1987 Expenditure Survey ("Encuesta Nacional de Gasto de los Hogares"–ENGH), which is the basis of the expenditure figures in Table 6.4 (page 166). While this survey did not cover smaller rural areas, it only excluded very small and isolated communities. It is thus broadly representative at the national level, and comparable to the 1991 Census data.[2] The four samples in the Table were constructed fol-

[1]The ratios of available to needed observations for a two-sided 1 percent test are 0.98, 1.01, 1.09 and 1.37 for the *Complete*, *Married*, *AE Sample* and *AE Sample, married* respectively. For a two-sided 5 percent test, the ratios are 1.7, 1.73 ,1.88 and 2.37.

[2]The data from the May 1991 Household Survey ("Encuesta Permanente de Hogares," presented in Section 1.2, page 22), corresponding to the month of the 1991 Census, is

lowing the criteria set in Section 5.4.1 (page 142), resulting in about 6,500 women in total and 4,500 in the married categories, which as discussed in the previous paragraph are not enough observations for obtaining precise IV estimates.

In Table D.4, the *Same sex* indicator has sizeable and significant first-stage effects on both the *Number of children* and *More than two children* variables. Moreover, these effects are close in size to those reported for the 1991 Census in Table 7.2 (page 179). The same is true for the OLS estimations of the effect of fertility on labour supply, where these two variables appear to have a significant negative effect on women's labour supply (*Worked for pay*). These effects are also within the range of the OLS coefficients in Table 7.3.

Finally, as expected from the small sample size, none of the instrumental variables estimates are significant, either with *Same sex* or *Two boys* and *Two girls* as instruments, but despite the lack of precision, the two-stage least squares coefficients are also in range with those in Table 7.3. These results suggest that the low significance of instrumental variables estimates is probably due to a problem of precision rather than the lack of a causal effect in the ENGH, and that the benchmark results of Section 7.2.2 (page 176) are not confined to one particular dataset for Argentina.

limited, with only seven urban areas with complete information (INDEC, 1996): Greater Buenos Aires, Greater Mendoza, Greater Córdoba, Neuquén, Jujuy, Río Gallegos and Santa Rosa. The resulting dataset of women with two children is too small, and it is not representative of the country. However, some of the results are still remarkably similar to the benchmark of this Chapter: in a sample of 1,398 women aged 21-35 with two or more children aged 18 or less, the average of the *Worked for pay* indicator is 0.38. The first-stage coefficient of *Same sex*, significant at the 5 percent level, is 0.0539, while the OLS coefficient of *More than two children* is -0.0438. The Conclusion to Part II (page 212) uses this data to discuss the implications of the main results in terms of poverty.

Table D.4: OLS and Two-Stage Least Squares Results, 1987 Expenditure Survey

	Instrumented: Number of children				**Instrumented: More than two children**			
Dependent variable: Worked for pay	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**	**Complete Sample**	**Married**	**AE Sample**	**AE Sample, married**
First stages								
Coefficient of Same sex	0.0738	0.0542	0.0772	0.0575	0.0535	0.0518	0.0552	0.0530
	[0.0290]**	[0.0321]*	[0.0303]**	[0.0335]*	[0.0113]***	[0.0133]***	[0.0117]***	[0.0137]***
OLS estimates								
OLS	-0.0553	-0.0491	-0.0567	-0.0502	-0.1023	-0.0731	-0.1080	-0.0778
	[0.0052]***	[0.0065]***	[0.0053]***	[0.0066]***	[0.0134]***	[0.0158]***	[0.0137]***	[0.0161]***
IV Estimates								
IV: Same Sex	-0.0686	-0.0079	-0.0717	-0.0345	-0.0945	-0.0083	-0.1004	-0.0374
	[0.1632]	[0.2619]	[0.1605]	[0.2532]	[0.2257]	[0.2747]	[0.2254]	[0.2756]
DWH p-value	0.9351	0.8745	0.9250	0.9507	0.9722	0.8129	0.9731	0.8834
IV: Two Boys and Two Girls	-0.0716	-0.0863	-0.0648	-0.0735	-0.0987	-0.0171	-0.0906	-0.0444
Controls for sexes of 1st & 2nd children	[0.1611]	[0.2443]	[0.1587]	[0.2344]	[0.2223]	[0.2745]	[0.2230]	[0.2752]
Sargan p-value	0.9082	0.4042	0.7622	0.6860	0.9126	0.3670	0.7628	0.6285
DWH p-value	0.9194	0.8787	0.9591	0.9208	0.9871	0.8378	0.9379	0.9031
Observations	6,355	4,589	6,028	4,361	6,355	4,589	6,028	4,361

Note: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include controls for the age and the age at first birth of the women and the sex of the first two children. The samples correspond to women aged 21-35 with two or more children aged 18 or younger from the Encuesta Nacional de Gasto de los Hogares, INDEC, 1987. The subsamples are analogous to those defined for the 1991 Census.

APPENDIX E

COMPUTATION OF RESULTS FOR COMPLIERS

E.1 COMPUTATION OF OUTCOMES FOR COMPLIERS BY REGRESSION METHODS

This Appendix provides the details of the computation of the parameters and tests presented in Chapter 8.

Proposition 8.2 (page 195) identifies the expectation of potential outcomes Y_1 and Y_0 for compliers, while Proposition 8.3 (page 196) shows how to compute the expectation of Y for the same group. Obtaining these averages and of the test in Equation 8.8 (page 198) from observed data is straightforward, but finding the correct standard errors of the estimates can prove more difficult. The results below are based on an analogy with LATE-Wald estimates of a binary instrument and one endogenous regressor by instrumental variables.

For any variable Ψ, with Z and D binary, the coefficient γ is given by:

$$\gamma = \frac{E[\Psi|Z=1] - E[\Psi|Z=0]}{E[D|Z=1] - E[D|Z=0]} \tag{E.1}$$

This coefficient can be obtained by means of an instrumental variable regression of Ψ on D and a constant with Z as an instrument for D (Proposition 5.5, page 135). The advantage of using a regression instead of Equation E.1 for finding γ is that the statistical software computes the standard errors for the parameter automatically.

$E[Y_1^c]$ in Equation 8.3 can be obtained by setting Ψ in Equation E.1 to $\Psi = YD$: this provides the potential outcome and its standard error.

The parameter $E[Y_0^c]$ in Equation 8.2 can also be computed by defining

$\tilde{D} = 1 - D$, using $\Psi = Y\tilde{D}$ and instrumenting $\tilde{D}$ instead of D. However, a variable transformation ensures that it can also be obtained by instrumenting D, as shown by the following result:

$$\begin{aligned} E[Y_0^c] &= \frac{E[Y(1-D)|Z=1]-E[Y(1-D)|Z=0]}{E[(1-D)|Z=1]-E[(1-D)|Z=0]} \\ &= -\frac{E[Y(1-D)|Z=1]-E[Y(1-D)|Z=0]}{E[D|Z=1]-E[D|Z=0]} \\ &= \frac{E[Y(D-1)|Z=1]-E[Y(D-1)|Z=0]}{E[D|Z=1]-E[D|Z=0]} \end{aligned}$$

The same reasoning applies by setting $\Psi = Y(D-1)$ in Equation E.1.

This result is useful for the computation of the average outcome for compliers from Proposition 8.3 and its standard error. Using the previous results:

$$\begin{aligned} E[Y^c] &= E[Y^c|Z=0]E[1-Z] + E[Y^c|Z=1]E[Z] \\ &= \frac{E[Y(D-1)|Z=1]-E[Y(D-1)|Z=0]}{E[D|Z=1]-E[D|Z=0]}E[1-Z] + \frac{E[YD|Z=1]-E[YD|Z=0]}{E[D|Z=1]-E[D|Z=0]}E[Z] \\ &= \frac{E[\tilde{Y}|Z=1]-E[\tilde{Y}|Z=0]}{E[D|Z=1]-E[D|Z=0]} \end{aligned}$$

where $\tilde{Y} = Y(D-1)E[1-Z] + YDE[Z]$. With large sample sizes, $E[Z]$ and $E[1-Z]$ can be considered non-stochastic. The last line in the previous Equation is analogous to Equation E.1, which implies that the expected outcome for compliers, $E[Y^c]$, can be obtained by setting $\Psi = \tilde{Y}$ and computing γ. Alternatively, it can be computed by a regression of $\tilde{Y}$ on D and a constant with Z as an instrument for D.

E.2 COMPUTATION OF THE AUXILIARY TEST FOR COMPLIERS BY REGRESSION METHODS

Finally, Chapter 8 also presented a test for the generality of IV results for compliers. The test exploited the additional identification result presented in Proposition 8.3 (page 196), which identified the expected potential outcome for compliers. The intuition is that if the expected outcome for the general population is not different from that of compliers, then the two are similar in one important dimension, and it is thus more likely that other results for compliers concerning the outcome variable can be extrapolated to the whole population. The test is in Equation 8.8, and given by:

$$\lambda = E[Y] - E\left[Y^c\right]$$

This test can be performed by means of the instrumental variable estimation described in the previous paragraph: the parameter γ in Equation E.1 estimates $E\left[Y^c\right]$ when $\Psi = \tilde{Y}$, which amounts to regressing $\tilde{Y}$ on D with Z as an instrument for D. Using this regression, a t-test of whether $\gamma = E[Y]$ is equivalent to testing the hypothesis $\lambda = 0$ in Equation 8.8.

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STATEMENT CONCERNING CONJOINT WORK

CRUCES, GUILLERMO ANTONIO - LSE
POVERTY, INCOME FLUCTUATIONS AND WORK: ARGENTINA, 1991-2002.

As required in the "UNIVERSITY OF LONDON REGULATIONS FOR THE DEGREES OF MPhil AND PhD," I hereby state that a part of Chapters 1, 3 and 4 of my thesis stems from joint research with Dr. Quentin Wodon from the World Bank, Washington DC, which have been published or submitted to publication to scholarly journals.

The Chapters as submitted represent adaptations and additions to this joint work with Dr. Wodon, and they form an integral part of the thesis. They consist of my own account of my investigations. The part that corresponds to me is two thirds of each of the three Chapters.

Signed by the candidate: G. CRUCES

Date: 18/11/2004

Certified by the supervisor: F. COWELL

Date: 18/11/2004