THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Culture, Fertility, and Son Preference

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Declaration

I certify that the thesis I have presented for examination for the MPhil/PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorization does not, to the best of my belief, infringe the rights of any third party.

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Abstract

My thesis comprises three papers on individuals' preferences over family composition and the degree to which these are culturally determined, or learnt.

Prices, Norms and Preferences: The Influence of Cultural Values on Fertility

This paper investigates the influence of cultural values on fertility. High country of origin fertility is associated with high fertility in the UK, in line with previous results. This is consistent with fertility preferences being a transmissible (learnable) cultural value. However, I find that high fertility in the country of origin is also associated with earlier childbearing. If timing is not accounted for, this phenomenon could lead to an upward bias when estimating the importance of cultural values.

Son Preference and Culture

I measure the sex preferences of immigrant women in the United Kingdom by estimating the effect of family composition on birth hazard rates. International comparisons of son preference are constructed, the first known to the author. A theoretical model suggests that costs (eg, dowries) are unlikely to explain the variation in outcomes between groups. Finally, women arriving in the UK at a young age appear to have less distinct tastes, also consistent with a primarily cultural, rather than economic, explanation for parental sex preferences.

Son Preference and Sex Ratios: How many 'Missing Women' are Missing?

When parents prefer sons, heterogeneity in the probability of having sons can lead to excess girls. I argue that this may lead to under-counting the number of 'missing women'. Parents show significant differences in son preference between countries. I exploit these differences to simulate sex ratios in the presence of measured heterogeneity. Parents' son preferences account for 1.5% of differences between sex ratios worldwide (significant at 10%). The presence of this effect may imply that sex ratios are more biased than previously estimated, since previous comparisons use benchmarks that already contain too few girls. Therefore there may be more women missing due to discrimination than we thought.

Executive Summary

My thesis comprises three papers on individuals' preferences over family composition and the degree to which these are culturally determined, or *learnt* (Chapters 2–4). The latter two papers form the major contributions: I find strong evidence that preference for sons is culturally driven, and show that son preference can affect the sex ratio at birth. My first chapter sets out definitions for the terms *culture*, *values*, and *norms*.

Prices, Norms and Preferences: The Influence of Cultural Values on Fertility

Cultural values appear to influence the fertility of immigrants in the UK, but birth timing effects may bias this result upward. I use the total fertility rate in a woman's country of origin as a proxy for her values. These rates significantly predict immigrants' fertility, supporting the findings of Fernández and Fogli [2006]. Without accounting for timing effects, I estimate that an extra child per woman in the country of origin is associated with 0.116 extra children for an immigrant in the UK.

This result would indicate that cultural values play a role in forming individuals' preferences over family size. However, immigrants from high-fertility countries start families younger, so at the time of measurement they have more children relative to their expected total. This leads to an upward bias on the coefficient on originating country fertility. Since a variety of other factors are also expected to contribute an upward bias, the absolute effect of cultural values would appear to be small. Such a conclusion would imply that the costs of childrearing are of primary importance in determining family size, according with Becker et al. [1990] and Galor and Weil [2000].

Son Preference and Culture

I present theoretical and empirical results that support a cultural, rather than economic, explanation for parents' sex preferences. This contribution innovates in the growing literature on cultural values since few authors have studied culturally-driven behaviour in environments where prices matter. To the extent that son preferences reflect discrimination more generally, my findings suggest that cultural barriers are an important factor in retarding development outcomes for girls.

This paper measures the sex preferences of immigrant women in the United Kingdom by estimating the effect of family composition on birth hazard rates. I know of no previous attempts to measure parents' preferences so that they can be compared between countries. I use hazard rate estimation to measure the difference in fecundity between women already having sons and those already having daughters; there are strong differences in behaviour between country groups, with some displaying strong preferences for sons (eg, India, Pakistan, Somalia), and others preferences for daughters (Germany).

My theoretical model [after Leung, 1991] suggests that costs (dowries or expected support in old age) are unlikely to explain the variation in behaviour between groups. A common explanation for son-preferring behaviour is that daughters are more expensive or can provide less support [Das Gupta et al., 2002]. If this were true, then women who already have daughters are poorer than those with sons. Since children are a normal good, those having daughters will have *fewer* children in the future. However, this contradicts the empirical findings, so I conclude that costs *do not* drive the observed behaviour. Moreover, women arriving in the UK at a young age appear to have less distinct tastes, which is consistent with parents' sex preferences being a cultural value that is acquired over time.

Son Preference and Sex Ratios:

How many 'Missing Women' are Missing?

When parents prefer sons, heterogeneity in the probability of having sons can lead to excess girls. Son preference implies that parents will reduce childbearing after having boys, the extreme case being a 'stopping rule' whereby a woman has children until a son is born. If all women have the same probability of having a son, the sex ratio (number of boys per girl) is not affected by this behaviour. However, if son-probabilities are heterogeneous, women who have boys with low probabilities will have larger families on average. Therefore the proportion of girls in a son-preferring population will be higher than the 'biological' level resulting with no son preference. Heterogeneity is necessary and sufficient for parental decisions to affect the aggregate sex ratio; homogeneous models cannot display this effect in large populations [Leung, 1988].

The key contribution is my estimation of the real-world implications of this finding. First, I derive a new econometric estimator to measure the underlying probabilities of women having boys, under the assumption that individuals have fixed probabilities of bearing sons. I measure significant heterogeneity: ten percent of women have probabilities of having boys that are less than 42% or more than 61%. Homogeneity is strongly rejected.

Finally, I simulate the effect of son preferences — as measured for immigrant women in the UK — on sex ratios worldwide. Under the heterogeneity I estimate, preferences account for 1.5% of differences in population sex ratios. The presence of this effect may imply that sex ratios are more biased than previously estimated, since previous comparisons [eg, Oster, 2005] use benchmarks that already contain too few girls. Therefore there may be more women missing due to discrimination and mortality than we thought. To the best of my knowledge, this is the first quantitative demonstration of the influence of cultural values on an important demographic outcome.

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I dedicate this thesis to my parents.

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Preface

> [N]o significant behaviour has been illuminated by assumptions of differences in tastes. [Stigler and Becker, 1977]

Since the inception of economics as a discipline, authors have regarded both differences in people's preferences and social interactions between individuals as crucial to their understanding of human behaviour. However, while other social scientists, notably sociologists, are well aware of the role tastes play and the importance of informal sanctions and rewards in people's lives, modern economists have largely neglected these topics. Broadly speaking, these are the *values*, or individual preferences, and *norms*, social equilibria, with which this thesis is concerned.

In general, economists have taken a 'beneath the lamp-post' approach, confining models to situations where values and norms can be easily ignored. Restrictions include representative agent assumptions and that people do not care about the actions of their peers. We have been massively successful in understanding the world with such models, and this success has fed the view that we need not expand our horizons. As a result, any economic investigation into tastes promises to be received with some scepticism, and combined with the inherent difficulty of such research, the rejection from Stigler and Becker is a handy justification to bypass the topic altogether.

Unfortunately, we have ignored many interesting cases. The fear is that, in dealing with more 'social' topics, economics will struggle to maintain its rigour. That concern is fair. However, I do not believe the correct approach is to let restrictions confine our research or prohibit us from investigating more complex sociological topics. Instead, as a discipline, we should be more open to applying the rigorous methods we have developed to culturally driven phenomena.

Fortunately, the discipline is now making progress on several fronts. Theorists are developing our ideas of socialisation, and there is a growing empirical literature trying to establish the impact of culture on outcomes, particularly in areas such as parental preferences. However, I believe there are three large holes in our current knowledge. I will describe each separately, though they are tightly interconnected issues.

Social Interactions

Thanks to work such as Bisin and Verdier [2000], economists are becoming more comfortable with the idea that parents may decide to socialise their children, and the decision optimises parents' utility. Such models have fruitful applications, such as describing the evolution of unemployment claimants in European countries since the second world war [Michau, 2008]. But this work still depends on a 'single meme' idea of culture: people are type-A by default, and one may choose to socialise one's child to type-B. Researchers have not cracked open the mechanism of the socialisation process, or how values are transmitted and assimilated. Our best guess is 'habit formation'. But, as an example, this explanation cannot inform us about how a young girl decides to wear a headscarf. Though we can model this choice as a taste (she receives utility from wearing it), a strategic decision (her family will punish her otherwise), or a combination of both, we do not yet have a conception of how these interact. Such a theory might explain how she disliked wearing it when young, but over time it became part of her identity. Understanding the mechanism may help explain the decisions she takes in bringing up her own daughter.

Macroeconomists understand the need for such explanations: witness the wealth of literature on 'social capital'. I propose this theory should have a coherent microfoundation based on interpersonal interactions.

Building that foundation will be a difficult task; Chapter 1 represents my attempt — not to *take* — but merely to *pave* the first step of the journey. The aim is to break apart the concept of a norm is and explore what it entails for its subjects. More than being a 'convention' or 'rule', I maintain that the actions of a follower of a norm must be utility-maximising. The outcome of the norm must then constitute an equilibrium in which both subjects and non-subjects optimise with respect to the sanctions and rewards imposed by each other.

The empirical components of this thesis unfortunately shed no light on whether or not behaviours are driven by values (individuals' preferences) or norms (social interactions based on individuals' preferences). For example, in Chapter 3, I cannot distinguish between the hypotheses that (a) women have preferences for sons and (b) women dislike shame *and* some communities are ashamed of women who bear only daughters.[1]

Costs and Culture

The majority of empirical work on culture has either attempted to control for or eradicate the influence of prices,[2] or have considered situations where costs are irrelevant.[3] Perhaps this was inevitable: the first priority was to establish whether people's backgrounds do indeed affect their behaviour. Culture *does* matter, and it is a topic worthy of economists' time. But what's the surprise?

From my perspective, the interaction between prices and preferences is key. When can behaviour be said to be driven by costs, and when do values matter? In Chapter 3, I look at son preference amongst immigrants to the UK. Under the assumption that children are a normal good, son-preferring behaviour cannot be driven by high costs of raising girls. If girls were expensive, women with

[1]In terms of utility functions, I cannot discern $u = u_B(B) + u_G(G)$ from $u = u_{B+G}(B + G) + v(r)$; $r = f(B)$. In the latter case, a woman only cares about the number of her children $(B + G)$, not the sex composition (B, G). However, she receives a social reward r for having boys.

[2]For example, in Chapter 2 I look at women from different backgrounds but who live in the United Kingdom. Costs of raising children are plausibly equal across groups, and educational dummies control for different levels of human capital.

[3]Fisman and Miguel [2007] consider diplomats whose parking tickets do not have to be paid; Manning and Roy [2007] investigate national identity, which is costless.

daughters rather than sons would be poorer. Thus, controlling for family size, normality implies that women with daughters would have *lower* fertility. The opposite is observed, so I conclude that a taste for sons, and not expensive daughters, drives the biased behaviour.[4]

One implication of Chapter 3 is that scholarships or other subsidies for girls might *promote* son-biased fertility behaviour. More work such as this is required to fully understand behaviour when preferences are put at odds with prices, since otherwise we cannot quantifiably predict the effects of our policy tools.

Implications

I intend 'implications' in two ways. First, cultural values shape the world we live in, and, as economists, purport to explain. It is therefore surprising that so little an attempt has been made to measure the impact and implications of those values.

Chapter 4 is such an attempt. I take the levels of son preference amongst immigrants in the UK and demonstrate that their behaviour significantly predicts sex ratios in their countries of origin. A preference for sons leads to an excess of girls.[5] The effect I measure is small (but probably a lower bound). However, we are likely to have underestimated the number of women missing due to discrimination.

This finding is minor, but non-trivial. There are countless other ways in which cultural values affect outcomes substantively: both for good (when they discourage corruption or support education, for example) but also for worse, when they engender discrimination or promote a lax attitude to sexual health. Examples abound. Quantitative research, alas, does not.

The second implication of cultural economics concerns policy. Suppose, as in the case of sexual discrimination, we determine an outcome is culturally driven.

[4]High costs/low benefits of raising girls *could* contribute to a social norm in which sons are required for 'honour', leading to a social preference for sons, as sketched in Footnote 1.

[5]Women are heterogeneous in the probability of having a boy at any given birth (call this p). Suppose women prefer sons, and have children until they have a son. Heterogeneity implies that low-p women expect larger families than high-p women. Thus more children are born to low-p women, and there are relatively more girls born than if parents had no sex preferences.

From a policy perspective, what are our options? Education is an obvious contender. But then the interactions between individuals must be properly understood. The well-meaning teacher might advocate sexual equality in the classroom, but what about the effect of discriminatory treatment at home or in the community? Until we have a coherent model of such situations, economics will confined to areas where cultural values are unimportant.

My larger point is more subtle: there are moral considerations to bear in mind when dealing with cultural phenomena. At some level, an individual is the product of his experiences, views, preferences and beliefs. If we seek to affect these, we must acknowledge that we will change the individual. The policy-maker now assumes a degree of moral authority, and, while I have no problem in principle, this represents a colossal shift from amorally setting economic policy. And in practice, problems appear swiftly.

Final thoughts

It was not my original intention to write a thesis about culture. However, as the results of each paper became clear, the next question simply stood out. I have therefore presented my work in chronological order, except for Chapter 1: as I worked on Chapter 2, I was struck by the need to put formal definitions to the concepts I was dealing with.

As this rough explanation tries to convey, I believe a rigorous theory of culture is possibly the biggest outstanding gap in economists' knowledge. Though minor in its reach, I hope this work will help others close that gap in the coming years.

Jas Ellis

London, September 2008

Chapter 1

Culture, Values and Norms

In this paper I formally define a social *norm* to be a general equilibrium outcome amongst agents who hold preferences over each others' behaviour. My definition makes clear the distinction between the substance of a norm and its embodiment. This approach makes clear the difference between cultural *values* and norms. I close with a brief discussion of the implications of norms and values when addressing policy questions.

1.1 Introduction

Of the many interpretations for the word 'culture', I take the broad definition provided by Cavalli-Sforza et al. [1982], defining it to be the 'activities, values, and behaviour of an individual that are acquired through instruction and imitation'. While many species exhibit such traits [Findlay et al., 1989], the extent to which cultural traits affect behaviour is undeniably unique to humans [Cavalli-Sforza et al., 1982; Higgs, 2000].[1]

The present paper builds a new definition of social norms and provides a framework for analysing cultural phenomena in an economic setting. In particular, I codify the distinction between cultural *values* and *norms.* I argue that a norm is best viewed as a general equilibrium outcome amongst agents who hold preferences over each others' behaviour.

[1] Perhaps unsurprisingly, social scientists seem much more ready than biologists to propose this uniqueness [See Tomasello, 1998, quoted in Dekker, 2001, p. 82].

The major contribution of this paper is the positive construction of a *norm basis*, which is a set of values that underlie the norm. These values may be thought of as preferences held by individuals. The *norm* is then the behavioural outcome within a community when some (or all) individuals hold the basis values. This is a very general definition which encompasses those of previous authors. I believe this definition will allow researchers to explicitly frame the quantitative modelling of cultural phenomena by making clear which aspects of normed behaviour are relevant in which cases. I provide two very simple examples.

While previous work by sociologists (particularly Morris [1956]) has provided a coherent definition of a norm for that discipline, to the best of my knowledge economists are yet to broach the topic substantively.[2] I therefore lean heavily on previous work to construct my new definition and do not lay claim to the broad ideas encompassed within this paper. The novelty of this work is to apply an axiomatic approach to build a framework that is amenable to microeconomic modelling. The construction is inspired by Allison [1992].

1.2 Culture

The definition of 'culture' given above comprises two components: a set of properties ('activities, values, and behaviour'), and a transmission mechanism ('acquired through instruction or imitation'). Considered in this fashion, culture has been the focus of a wide body of literature, spanning Biology, Economics, Anthropology, and Sociology, and particularly Memetics, for which this two-part definition is a founding concept. Memeticists attempt to explain cultural phenomena by considering the evolution of *memes*, which are small transmissible 'units' of culture, analogous to genes in Genetics (this concept is due to Dawkins [1989]).[3] Bisin and Verdier [2005] provide an inexhaustive summary of the

[2] Young [2008] outlines the topic informally.

[3] However, the status of Memetics as a discipline is as yet unresolved. Though the concept of a meme is not in itself unhelpful, Holdcroft and Lewis [2000] provide a thorough critique to the purely memetic view of culture, concluding 'there is a serious question whether there

literature.

By applying this analogy, Biologists have been particularly insightful.[4] In Genetics, traits (or *phenotypes*) pertaining to morphology and behaviour are controlled by genes, which are transmitted through sexual or asexual reproduction. (Florini [1996, pp. 367] provides a deeper discussion of these mechanisms.) This leads to a natural definition for a cultural property (ie, a *meme*): it is simply a phenotype that is transmitted through instruction or imitation [Cavalli-Sforza et al., 1982]. The analogy is completed by permitting mutation during transmission.[5]

The class of memes relevant to this discussion are those which I shall call *values*, following Morris [1956].[6] Whereas almost any kind of abstract idea can constitute a meme, a value imparts a behavioural constraint. From an economic perspective, this may be because the value affects one's utility function; or it may be better understood as a constraint on the choice set. Having the value 'I must have many children' might be best represented as the former, whereas 'thou shalt not steal' evokes the latter. However, stealing could also be thought of as yielding an arbitrarily large negative utility. This formulation recalls the 'economics of identity' of Akerlof and Kranton [2000].

For the purposes of this analysis, a *value* is the most basic component of preferences, since I am only concerned with memes that impart a behavioural outcome. Since the major objective here is to distinguish a value from a norm, I will follow the ethos of Set Theory and abstain from formally defining a value.

is available ... a theory of meaning that would afford to memes the kind of robust status that memetics demands of them'.

[4] See, eg, Cavalli-Sforza and Feldman [1981, 1983]; Cavalli-Sforza et al. [1982]; Findlay et al. [1989]; Guglielmino et al. [1995].

[5] Note that mutation of DNA base pairs is very rare [Florini, 1996, footnote 10, p. 372]; most of the variety across populations results from the recombination of several genes due to sexual reproduction. However, innovation resulting in the mutation of memes is very common [Dawkins, 1989, p. 323–4, in Florini, 1996].

[6] I shall explicitly define the terms under discussion; there are ambiguous definitions in the literature, and some authors appear to draw no distinction between values and norms. Morris [1956] provides a coherent picture; see page 25.

1.2.1 Cultural Transmission

Cavalli-Sforza et al. [1982] distinguish three transmission modes for memes between individuals, which they label following conventions in Epidemiology:

- *Vertical Transmission* from parents to their children.
- *Horizontal Transmission* between individuals of the same generation.
- *Oblique Transmission* from individuals of the parental generation to those in the filial generation who are not their children.

Plainly, Genetics is concerned with vertical transmission only, with genes passed on solely through DNA [Cavalli-Sforza and Feldman, 1983].

Though it has been argued [Harris 1998, in Dekker 2001] that vertical transmission of cultural traits is negligible, the empirical evidence strongly refutes this. Cavalli-Sforza et al. [1982] assess the correlations between the beliefs of young adults, their peers, and their parents, observing stronger vertical then horizontal transmission for several classes of value, especially religious belief.[7] The finding of Fernández and Fogli [2006] — that the number of one's siblings is significant in predicting one's own fertility — also points to vertical transmission of fertility values, though they fail to make this interpretation.

The different transmission mechanisms result in different distributional and dynamic outcomes, as can be seen in Table 1.1. These relate primarily to the rate of spread through the population and the equilibrium heterogeneity. The key insight of this literature is that cultural dynamics have the potential to produce more complex outcomes than genetic dynamics alone [Cavalli-Sforza and Feldman, 1983; Feldman and Cavalli-Sforza, 1984].

More recently, economists have modelled cultural transmission as purposeful socialisation decisions made within families.[8] Parents are usually assumed to be altruistic toward their offspring, and choose to socialise their children if

[7]Guglielmino et al. [1995] provide further examples, as does Shennan [2000, p. 813].
[8]Examples include Bisin and Verdier [2000, 2005]; Tabellini [2007b]; Michau [2008].

Table 1.1: Modes and rates of cultural transmission, reproduced from Cavalli-Sforza et al. [1982].

Ratio of transmitters to receivers:	Many to one	One to few (few to few)		One to many	
Example:	Social class or caste influences	Vertical (parent to child)	Horizontal	Social Hierarchies	Teacher/student Social Leaders Mass media
Rate of Cultural Change:	Lowest	⟶	⟶	⟶	Highest
Population heterogeneity:	Little acceptance of variants; between and within population heterogeneities are low.	Persistence of variation (stable polymorphic equilibrium not uncommon); between and within heterogeneities are high.		Rapid flux; between population heterogeneity high; within population heterogeneity low.	

they think this will maximise their welfare (often parents show 'imperfect empathy', and can only evaluate the effects of socialisation form their own socialised perspective).

1.3 From Values to Norms

1.3.1 Values

The discussion so far has focused on memes and individual values, and their transmission. In this section I relate this concept to norms, which are necessarily collective [Morris, 1956].

There exist many definitions of the term *norm*, and a considerable amount of disagreement: Gibbs [1965] cites no fewer than seven — somewhat contradictory — definitions (including those of Morris [1956] and Homans [1950]). Moreover, as Gibbs notes [p. 587], these are generally ambiguous. Here it is my intention to construct a more precise definition that is suitable as a micro-foundation for economic models.

Whereas values are not necessarily observable externally, it is generally held that norms must be [Morris, 1956; Allison, 1992; Florini, 1996]. That is, they need to involve values that are *made visible* through behaviour. However, norms are more than simply 'behavioural regularities' [Florini, 1996, p. 364]. Such a regularity might merely result from a commonly held *value*.

Succinctly, I take a norm to be "a set of intersubjective understandings readily apparent to actors that makes behavioural claims on those actors" [Finnemore, 1994, in Florini, 1996, p. 364]. Allison [1992] takes a very similar line (citing Homans [1950]). As a direct comparison, a value (as I define it) is merely an 'understanding that makes a behavioural claim on its subject'.

Morris [1956] provides a clear distinction between values and norms:

> [V]alues are individual, or commonly shared conceptions of the desirable, ie, what I and/or others feel we justifiably want — what it is proper to want. On the other hand, norms are generally accepted, sanctioned prescriptions for, or prohibitions against, others' behaviour, belief, or feeling, ie, what others *ought* to do, believe, feel—*or else.* Values can be held by a single individual; norms cannot. Norms must be shared prescriptions and apply to others, by definition. Values have only a subject—the believer—while norms have both subjects and objects—those who set the prescription, and those to whom it applies. Norms always include sanctions, values never do. [Morris, 1956]

It is clear then that visible behaviours are a fundamental component of norms: without observable actions being taken, sanctions cannot be applied. This fact prompts a first-principles construction of a norm from constituent values. I shall follow the approach taken by Allison [1992], who introduces the idea of splitting a norm into component parts.

1.3.2 Defining a Norm

Morris's description highlights the two major classes of values held by a norm's subjects. First, there is the observable behaviour, so there must be a value mandating or a taste for that behaviour. Second, the subject's behaviour towards others is dependent on whether *they* display that behaviour, and therefore there must be some values pertaining to those sanctions or rewards. This motivates the first two components of the following definition, which are necessary. As discussed in the previous section, the subjects of some norms also have a explicit taste for the spread of the norm, so transmission values may also be components of the norm's values. Finally, there also may (or may not) be unobservable values attached to the norm. I package these values as a single unit, which I call a *basis*, since they will define many of characteristics the norm.

Definition 1. *The* basis *of a norm is a set of values, N, consisting of the following components:*

- *One or more values mandating some observable behaviour (I denote the set of these by X).*
- *One or more values entailing sanctions against those in whom X is not observed and/or rewards for those in whom X is observed (Y).*
- *Zero or more values explicitly prescribing transmission of N (T).*
- *Zero or more non-observable values (Z).*

The basis of a norm is just a set of beliefs; one must mandate some observable behaviour and one must mandate sanctions or rewards of others, given their behaviour. The individual holding these beliefs acts as Morris describes.

Values corresponding to transmission of the norm (T) may be included, but need not be; they may either be observable or not observable. (Bisin and Verdier [2000, 2005]'s socialisation process fits in here.) Naturally, sanctioning or transmitting behaviours may either be observable or not observable, so $Y, T \subseteq X \cup Z (= N)$. It will be helpful to define the set of 'core' observable values (ie, not related to sanctions or transmission), $\tilde{X} = X \backslash (Y \cup T)$, and similarly $\tilde{Z} = Z \backslash (Y \cup T)$.

In economic terms, the components of this definition can be considered as facets of the utility function, with any sanctions or rewards being seen as alterations to the choice sets of other agents. Thus, the set of values imparts both behavioural restrictions on the subject directly, and also incentives on others.

Definition 2. *Amongst a number of individuals, a* norm *is the equilibrium behavioural outcome due to some (or all) agents holding a basis of values that satisfies Definition 1.*

Restated, the existence of a norm in a group requires some agents to hold some belief or otherwise have preferences about how they should behave, including behaviours that provide incentives for others (sanctions or rewards). Those not holding this set of beliefs are constrained in their behaviour by these incentives. The resulting outcome, with each agent taking into account their preferences and these incentives, is what I call a *norm*.

This definition is general enough to encompass those given by Morris [1956], Homans [1950], and others, and offers a clear direction for theoretical (modelling) work. In particular, the 'intersubjectivity' of Finnemore [1994] derives from the simultaneous imposition of the sanctions/rewards by subjects and the decisions taken by all objects who are aware of the norm. The resulting outcome must be an equilibrium in which all agents maximise their utility with respect to the constraints placed upon them by others.

Young [2008] makes a less formal definition, that a norm a "customary rule of behaviour that coordinates our interactions with others". However, my definition is more basic, in that coordination is a (possible) outcome, not a fundamental component. My more formal approach from first principles makes clear precisely where a norm is different to commonly held preferences or behavioural regularities: it is the beliefs about others' behaviour.

There are two non-neoclassical elements to my definition. First, I allow agents to have arbitrary preferences about each others' behaviour, and these preferences motivate the sanctions subjects apply to others. Fortunately, no new ideas will be needed to formally model such situations, since this can be treated as a type of externality. On the other hand, preferences must be malleable in some sense, which I have not defined. Habit-forming and deliberate socialisation are two possible mechanisms that have been modelled previously [Bisin and Verdier, 2000, for example].

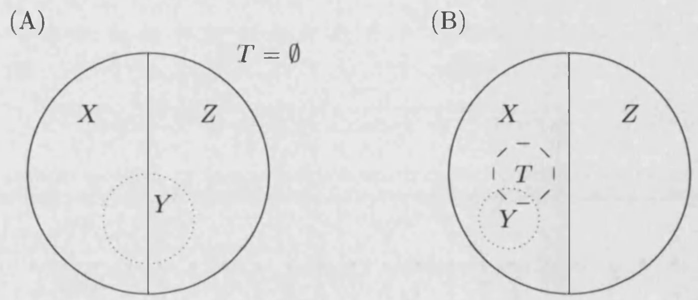
1.3.3 Examples

Two examples demonstrate the generality of my definition. First, it is rare for users of public transport in London to speak to one another. For some this results from a preference for travelling in silence, though this is not true for everyone. Consider this as a norm. The value mandating the observable behaviour is the preference for not talking: $\tilde{X} = \{$'travel in silence'$\}$, and this also applies when not observed by others: $\tilde{Z} = \{$'travel in silence'$\}$. Meanwhile, transgressors — regardless of their preferences — are punished, so $Y = \{$'respond rudely to those who talk to you'$\}$. This punishment may or may not be observed by others, depending on the context. Finally, $T = \emptyset$. T is empty since I make no explicit attempt to convey the norm to others: I don't necessarily want you to *like* travelling in silence. However, I may transmit these values to some by example. A Euler diagram representing the relationships between X, Y and Z can be found in Figure 1.1, Panel (A).

The norm then, is the equilibrium outcome within the population, some of whom hold values $N = X \cup Z$, and others who do not, but are nonetheless affected by the incentives imposed by those holding N. That is, if you attempt to speak to someone, you risk sanction if that person holds N. On public transport in London, there appear to be a sufficient number of 'holders' to support a no-talking equilibrium, with occasional infractions and sanctions. Elsewhere, though there may be individuals holding the basis N, they may not be enough to support such an outcome.

A second example would be the norm of a hypothetical religious group that is evangelical. Here, religious practice is observable, though of course the fundamental beliefs are not. Moreover, evangelism is prescribed *and is observable.* So here we have $\tilde{X} = \{$'practise religion'$\}$ (eg, attend worship); $Y = \{$'shun those not practising'$\}$; $Z = \{$'true religious belief'$\}$. $T = \{$'evangelise'$\}$ (and $T \subseteq X$). Supposing the sanction is also observable, we have $Y \subseteq X$, and $X = \tilde{X} \cup Y \cup T$. Panel (B) in Figure 1.1 demonstrates this example. Note that $Y \cap T \neq \emptyset$: evangelistic behaviour and sanctions may coincide. Here, the norm

Figure 1.1: Euler diagrams representing basis values for norms for (A) not talking to fellow passengers on public transport and (B) an evangelical sect. See Section 1.3.3 for details of the examples. X is those values that mandate observable practices; Y denotes values prescribing sanctions or rewards; Z is the set of unobservable values; and T is those values mandating transmitting behaviours.



is the equilibrium level of religious practise within a community.

1.4 Equilibrium Outcomes

Morris [1956] presents a typology of norms (reproduced in Table 1.2) breaking down 17 key dimensions along which norms may be compared. Many of these derive from the values comprising the norm as discussed above. However, not all do. For example, knowledge of the norm by objects (those to whom the norm applies) will depend on the number of subjects (those holding the values) in the population. In short, this is a property of the general equilibrium outcome (though it need not be static).

The innovation here is to draw a distinction between the set of values comprising the norm, the *basis*, and the *manifestation of the norm* within a population. A norm that is held by a small number of people in one society may constitute the same values as another norm prevalent elsewhere, but the effects on the behaviour of both subjects and objects may well be different, especially for objects who are not subjects.

In some sense, once can consider the basis of norm as exogenous to the

Table 1.2: Characteristics of norms, from Morris [1956]. The following annotations are mine: 'I' corresponds to properties intrinsic to the norm as a set of values, whereas 'G' denotes properties that will depend on general equilibrium effects in the population, or the manifestation of the norm. See the discussion on page 30.

	I. DISTRIBUTION OF THE NORM	
	Extent of knowledge of the norm	
(1)	By subjects (those who set the norm)	G
(2)	By objects (those to whom the norm applies)	I,G
	Extent of acceptance or agreement with the norm	
(3)	By subjects	I
(4)	By objects	I,G
	Extent of application of the norm to objects	
(5)	To groups or categories	I
(6)	To conditions	I
	II. MODE OF ENFORCEMENT OF THE NORM	
(7)	Balance of reward/punishment	I
(8)	Severity of sanction	I
(9)	Enforcing agency	I,G
(10)	Extent of enforcement (specialised or universal)	I
(11)	Source of authority	I
(12)	Degree of internalisation by objects	I,G
	III. TRANSMISSION OF THE NORM	
(13)	Socialisation process	I/I,G
(14)	Degree of reinforcement by subjects	I,G
(15)	Amount of conformity attempted by objects	G
	IV. CONFORMITY TO THE NORM	
(16)	Amount of deviance by objects	G
(17)	Kind of deviance	I,G

environment,[9] and the prevalence and outcomes of the norm as endogenous and depending on the environment in which the norm resides. Thus, in the final column in Table 1.2 I categorise each property. Either the property is intrinsic ('I') — that is, specified completely by the basis of the norm, or the property depends on the manifestation of the norm (the general equilibrium outcome, 'G') — these outcomes include the number of subjects holding the norm, their distribution amongst the general population, and other factors.

Extent of the norm amongst subjects (property 1) is necessarily a general equilibrium outcome, since this quantity is simply the number of people holding the values that constitute the basis of norm. The number of subjects will be a dynamic outcome of the transmission process, which will depend on the constituent values themselves — but only indirectly, through the prevalence rate.

Conversely, knowledge of the norm by objects (property 2) *will* depend directly on the intrinsic nature: if the values do not mandate strong sanctions against non-subject objects (perhaps if subjects are rewarded instead) and

[9] Exogeneity is highly unlikely in the strict sense — the basis must have originated from somewhere, and most likely evolved into its observed form for some reason. See the discussion on page 32 and in Young [2008].

prevalence is low, knowledge of the norm amongst these would be expected to be low. It should be evident that any measure relating to objects will depend somewhat on the prevalence of the norm at least, and is hence denoted 'G'. However, the intrinsic values of the norm will still matter: a rare norm that mandates evangelism would be better known than a rare norm mandating secrecy, say. Therefore 'I' applies here too.

Finally, the transmission process (property 13) is of note. Transmission certainly depends on the values of the norm, especially if there are values mandating efforts to teach the norm. However, it may also depend on the general equilibrium: some norms become institutionalised. Rather than being transmitted chaotically between individuals, there are structures formed specifically to (say) teach the constituent values. This institutionalisation changes the transmission process, and whether this happens (and how) will depend on the manifestation of the norm. However, many norms are not institutionalised, and continue to be transmitted in their endogenous fashion.

It is implicit in this discussion that, by my definition, the values of a norm *can* be held by a single individual; however, this does not contradict Morris's 1956 description (see page 25). All that is required is that there be only one subject that holding the constituent values. A *norm* itself, though, is a property of groups, corresponding to equilibrium behaviour. (But note that a single subject, if sufficiently powerful, may be able to impart sufficient incentives for a norm to be observed in a group).

In any case, it is unlikely that a norm's values can be held by only one individual in practice: the values must spread, otherwise the norm itself will become extinct before too long. One successful example is Mormonism, founded by Joseph Smith Jr. in the early 19$^{\text{th}}$ century. At its inception, the number of subjects was just one: Smith himself.

To summarise, I differentiate two concepts: the *value*, which is a belief that imposes a behavioural constraint, and the *norm* which is an equilibrium outcome in which some agents have several bundled values. Some of these values must imply observable behaviours, and some must mandate enforcing behaviour on others. There may also be allied non-observable values or values implying efforts to transmit or teach the norm.

At the population level, a norm's effects will depend on its prevalence. At any instant, the collective efforts of the subjects of the norm will impose a set of incentives for all in the society, and transmission will partly arise from this.

1.5 Development of Norms

One outstanding issue is the reason for the existence of any norms. The prevailing explanation is simple: evolutionary advantage.[10] The evolutionary process can be considered in the usual — Darwinian — sense [eg, Allison, 1992; Mark, 2002; Young, 2008], in which populations having certain norms are more successful than others. Hence the world we observe is populated by groups who are made more successful due to their norms.[11]

One rationale for such behaviour is the case of some externality, so that individual choices lead to a socially inefficient outcome. Several well known mechanisms allow the social surplus to be maximised, such as taxation schemes and the introduction of missing markets. But norms can also fulfil this role, with interacting sanctions ensuring each actor behaves cooperatively. If children exert an externality on others (either positive or negative), fertility norms may constitute a means of achieving the most efficient fertility rate for the society.

Additionally, norms may assist decision-making even when there are not coordination problems. If agents are unable to ascertain the full consequences of their actions, prevalent values and/or norms may entail that chosen behaviours are not detrimental. Naturally, societies having such values will be advantaged. Florini [1996, p. 379] cites the example of heuristic rules in chess; these provide

[10] Proponents include Cavalli-Sforza et al. [1982]; Allison [1992]; Florini [1996]; Henrich [2001]; Mark [2002].

[11] There is also a more sophisticated evolutionary interpretation: the memetic point of view applies the concept of natural selection to memes, values, and norms themselves. In this context, a successful norm is one which is prevalent. This view presents people as merely being the substrate for values, which may indeed harm its subjects, analogously to a parasite. See Holdcroft and Lewis [2000] for a full explanation and comments.

a short cut, allowing the player to avoid considering each possible branch of the game-tree. These rules can help successful decision making even if the player does not understand the reasoning behind the rule. Similarly, norms can impart knowledge very cheaply, to save individuals from costly experimentation.

1.5.1 Diversity

If one expects the evolution of norms that are adapted to benefit a society, it is not unreasonable to expect that different societies will develop different norms, according to the environment they face. One conceivable outcome is the divergence of fertility rates between different populations.

However, such reasoning is not essential in explaining differences in norms between populations. Theoretical and simulation-based work by Findlay et al. [1989] demonstrates that cultural systems exhibit more complicated dynamics than solely biological systems, often resulting in multiple stable equilibria. Though that research considers values alone, norms, via their incentive structures in equilibrium, create further potential for arbitrary self-sustaining (focal) equilibria, implying that differing environments are not a necessary requirement for differing norms. The existence of social norms are therefore likely to be strongly history-dependent.

1.6 Discussion

The arguments here highlight the distinct problems faced by the researcher seeking to explain social phenomena when cultural forces are in evidence. However, having acknowledged the distinction between values and norms allows the implications of each to be drawn more specifically. The difference lies in the fact that interactions affect individuals' behaviour within groups where norms are present. Values affect only the individual holding them.

One major question arises: do values-driven outcomes ever occur without norms? This question is an empirical one, and has thus far gone unanswered by social scientists. But I hypothesise that the answer is no. Without a norm, there is little opportunity for a value to be transmitted. Insofar as one's preferences are formed in a particular way by socialisation, rather than being physiologically determined, they must be picked up from — or moulded in reference to — one's social environment. As an example, it is hard to conceive that son preference is transmitted simply as a value alone without social interactions [Das Gupta et al., 2002].

If values alone drove a behaviour, policy implications would be simple in practice, despite the moral concerns raised when preferences are to be changed. For example, addressing discrimination due to son preference is relatively clear-cut: policy should strive to teach that boys and girls are of equal worth, and the time to implement this teaching would be at a young age, when preferences are more malleable. This is indeed a moral position, based on the axiom that discrimination due to gender is obscene. It is not hard to find a consensus on an issue such as this. However, what, if anything, should be done about son preference when it truly does not lead to discrimination? Some would argue that this too is obscene, though far less agreement would be found.[12]

The moral questions do not disappear when the policy question addresses norms, but the practical problems certainly increase. With a strong norm in place, a locally stable equilibrium exists, so any attempt to alter outcomes must overcome the stabilising forces. If, say, son preferences are strongly reinforced by all members of a community, education alone is unlikely to have a significant impact. Moreover, if a policy is implemented from outside the community, there may be a negative reaction to the external influence.

This paper's aim is to push forward our understanding of values and norms in a manner that is helpful for economists. The discipline is at last making great strides in the field of cultural interactions, particularly in theoretical work. Future empirical work should consider social forces in more detail, and particularly attempt to identify when social factors are quantitatively important, as in Chap-

[12]To my mind, the 'moral authority' wielded by the policy-maker becomes more obvious when one considers one's preferences as one's *identity*, as Akerlof and Kranton [2000] do.

ters 3 and 4. However, we must bear in mind the moral dilemmas that policy-making involves. Usually, policy action affects incentives: the costs people face. If values and norms are deemed to cause unwanted outcomes, policy-makers will find themselves needing to alter who people *are*.

Chapter 2

Prices, Norms and Preferences: The Effect of Cultural Values on Fertility

This paper investigates the influence of cultural values on fertility. First, I compare the fertility of immigrants in the UK with fertility in their countries of origin, before extending my analysis to consider the effect of differential birth timing on the measurement of fertility.
High country of origin fertility is associated with high fertility in the UK, in line with previous results. This is consistent with fertility preferences being a transmissible (learnable) cultural value. However, I find that high fertility in the country of origin is also associated with earlier childbearing. If timing is not accounted for, this phenomenon could lead to an upward bias when estimating the importance of cultural values.

2.1 Introduction

There are large differences in fertility rates between countries. In Somalia, the Total Fertility Rate (TFR) is over seven births per woman; in Hong Kong it is close to one.[1] Many explanations for these differences have been proposed, including: opportunity costs in childrearing and women's relative wages [Galor and Weil, 1996, 2000; Wolf, 2006], returns on human capital [Becker et al., 1990; de la Croix and Doepke, 2003], child mortality rates [Becker and Barro, 1988; Barro, 1991], family policies [Neyer, 2003], economic risks [Pommeret and Smith, 2004], 'altruistic' reasons [Becker and Tomes, 1976; Becker and Barro, 1988; Ellis, 2006], and provision for care in old age [Neher, 1971; Ehrlich and Lui, 1991; Morand, 1999; Ellis, 2006].

This paper investigates the influence of cultural values on fertility. That culture does — or at least, *has the ability to* — influence fertility decisions is self-evident: witness the Shaker movement, whose chastity led to eventual extinction. This is an extreme example; however, many societies have norms or otherwise prevailing values that influence choices about the number and timing of births.

Following Fernández and Fogli [2005, 2006], I compare the fertility of immigrants in the UK with fertility in their countries of origin. High country of origin fertility is associated with high fertility in the UK, in line with Fernández and Fogli's results and consistent with fertility preferences being a transmissible (learnable) cultural value. However, I then extend my analysis to consider the effect of differential birth timing on the measurement of fertility. I find that high fertility in the country of origin is also associated with earlier childbearing, possibly leading to an upward bias when estimating the importance of cultural values if timing is not accounted for.

When comparing high-fertility immigrants with low-fertility immigrants, the former have their children when younger. If children are counted when women are still fertile, high-fertility immigrants have had some of their children, and

[1] World Bank Development Indicators (1997); see Table 2.2.

are measured as having larger families, while low-fertility women are yet to have theirs. This biases up the estimated effect of cultural background on completed fertility, since the low-fertility women catch up in later years, and the final fertility gap is smaller than the gap that is measured.

2.1.1 Empirics

The methodology taken in this paper follows that of Fernández and Fogli [2005, 2006], matching data on immigrants into Britain from the UK Labour Force Survey with data (from World Development Indicators) from their country of origin. The basic specification regresses the fertility of the individual on the origin-country fertility rate. (Full details of methodology are to be found in Sections 2.2 and 2.3).

There are two identifying assumptions: first, I assert that these women have differing values regarding desired fertility, and the origin-country fertility rate proxies for this. The second assumption requires that prices and external incentives are the same for different immigrant groups. This is unlikely in practice, but several observable differences can be controlled for (eg, educational attainment gives an indication of the opportunity costs of childrearing).[2]

This paper presents several improvements on previous work. First, the LFS dataset is both larger and better suited to this task than the General Social Survey and US Census data used in Fernández and Fogli [2005] and Fernández and Fogli [2006] respectively. My base sample contains 11,081 observations, compared to their samples of 6,774 and 1,145. Moreover, all women in my dataset are first-generation immigrants, and I have information on their date of arrival into the UK. In Fernández and Fogli [2006], the women's antecedents may have been in the US for several generations. I discuss this further in Section 2.2. Also, a much wider selection of countries is represented in my sample.

Second, and more importantly, I consider heterogeneity in birth timing be-

[2]It should be observed that the majority of the unaccounted mechanisms would lead to an upward bias of the estimated coefficients for cultural values. See Sections 2.3 and 2.4.

tween different groups. As my analysis in Section 2.4 indicates, this is likely to bias *up* Fernández and Fogli's estimates, since they interpret these coefficients as differences in completed fertility. The strength of cultural norms provides an upper bound for the role of policy in shaping fertility trends — if these norms are very strong, policy will be ineffective. My results, indicating less importance for cultural norms, suggest a greater role for policies acting through price channels.

2.1.2 Identification

The benefit of this methodology is that, by studying women of different 'cultural origins' within the same environment, greater validity is lent to comparisons between groups. Were those groups observed in differing environments (their original countries), they would face different prices and norms and no comparison would be readily appropriate. The same idea is applied by Fisman and Miguel [2007] to another cultural sphere: corruption, or adherence to protocol. Their quasi-experiment depends on agents (UN diplomats) being separated from their cultural brethren and placed in a common environment (New York). Because of diplomatic immunity, parking fines levied on diplomatic cars were unenforceable; payment depended on diplomats' own values. Most importantly, decisions to pay fines are taken without facing the pressures of any norms prevalent in their home environment.

There are two essential components for interpreting such work. The first is the existence of a *norm* in the country of origin, or at least a prevailing *value* that is transmitted to the agent. The value prescribes a fertility behaviour, or can alternatively be considered as instilling particular preferences. Since women take their values from their originating countries, there is a diversity of values amongst the subjects of the study and, moreover, these values are correlated with the values held in their origin countries. The second component is observation in a common environment. This (hopefully) entails that, when the agents come to act, they face a common set of prices and norms, and the differing effects of the values they hold can be ascertained.

2.1.3 Related Work

This work links several strands of research. Lam [1986], Kremer and Chen [2000] and De la Croix and Doepke [2003] suggest that, besides the aggregate fertility rate, *fertility differentials* between groups matter for both social mobility and income inequality. These authors concentrate on differentials by income. However, differences between ethnic groups may play a similar role, especially if they reinforce income-driven effects. For example, (poor) immigrants may choose to have many children for both cultural and financial reasons. This could feasibly be perceived as problematic by the native majority, especially in countries with generous social welfare systems.

A second strand includes work on social norms such as Manning and Roy [2007], who investigate the degree to which immigrants describe themselves as British (they too use data from the LFS). They measure (predictably) that immigrants are more likely to call themselves British over time, but they find the perhaps surprising result that those from poorer countries seem to do so at a faster rate.

This raises the question of whether other social determinants, such as fertility norms, also converge over time. However, the age-specific nature of fertility may make analysis difficult. This matter is further complicated by the effects found by Andersson [2001] of elevated birth probabilities for most immigrant groups shortly after arrival in Sweden. His interpretation is that "migration and family building are interrelated processes" [Andersson, 2001, p. 1], though citizenship eligibility might be expected to play a role in this.

2.1.4 Implications

The empirical work presented in this paper has implications in a number of areas. The effects of the fertility rate on macroeconomic growth are highlighted by Young [2005a,b], who studies the implications of the fertility response to the HIV/AIDS epidemic in sub-Saharan Africa. Young states that the fertility decline he observes could simply be a price effect in response to labour scarcity [2005a, p. 424]. Regardless, his long run predictions for per-capita consumption depend on this fertility decline, and even a small influence via cultural channels could have non-trivial long-term effects.

Conversely, many developed countries currently face below-replacement fertility (see eg, Billari and Kohler [2002]; Neyer [2003], and Table 2.2 in this paper). Dixon and Margo [2006] highlight some of the implications of low fertility in Britain, and discuss some of the remedial options available to policy-makers. The first pillar of their argument is that, *regardless of intent*, government policy affects fertility decisions, and that fertility 'side effects' should be borne in mind. Indeed, they go on to suggest the government should be more direct in 'promoting' fertility. Such a policy was introduced in Quebec and is studied by Milligan [2002]. However, if culturally-derived preferences or incentives play a large role in fertility choices, price-based policies may be infeasible or too expensive.

2.2 Data and Methodology

2.2.1 Variables

The objective of this paper is to quantify the effects of culture — in the forms of individual values and collective norms — on fertility decisions.[3] For this, three key things are needed: a sample exhibiting a variety of cultural values, some quantification of these values, and some measurement of the outcome in a common — or at least, comparable — environment. I shall address each in turn.

Variation: The focus of this study is immigrant women. Coming from different cultural backgrounds, it is hoped that they hold different cultural values, transmitted to them in their original countries. This transmission could act

[3] I use the term 'decision', although it is not expected that this is always made consciously; by this I mean only that people choose between different behaviours (eg, contraceptive use or abstinence) that affect the probability of a birth at different costs.

via any of the vertical, horizontal and oblique modes (from parents, peers or the community, respectively; see Cavalli-Sforza et al. [1982]), either simply as a learnt value, or through incentives existing due to a norm.

Quantification: In any country, the total fertility rate (TFR) represents the number of women choosing to have children at the time of measurement.[4] Each parental decision is itself the outcome of a process that involves parents' preferences, the prices they face (including the institutional framework), and non-price incentives imposed by others — not to mention chance. Variations in TFR between countries will be driven by all of these factors.

However, it would be surprising if the true underlying values were not positively correlated with the number of births. Thus, TFR represents, to some degree, the fertility preferences — that is, values — of the population, and those which we expect the immigrant to hold. Therefore, following Fernández and Fogli [2005, 2006], I use country of origin TFR as a measure for these values.

Naturally, there will be heterogeneity in the values held by individuals of the country; indeed, there will be considerable variation in actual fertility outcomes. But empirically this heterogeneity is hard to separate from unobservable factors or stochastic components. Therefore I take the TFR to be merely indicative of the individual's preferences, and so appropriate care must be taken when making inferences.

Environment: While the quantification of fertility preferences is vague, other factors relevant to individuals' fertility can be measured more directly. One of the most commonly cited fertility determinants is the opportunity cost of childrearing. This underlies the human capital and wage arguments of Becker et al. [1990], de la Croix and Doepke [2003], Galor and Weil [1996, 2000], and many others. If children require a considerable amount of maternal time, higher wage rates mean a higher level of forgone income.

Estimating this forgone income (effectively the price of a mother's time)

[4]TFR represents the total number of children born to a hypothetical woman whose behaviour at any age is the current behaviour of women that age. It will coincide with the completed fertility rate (total children born to the cohort currently ending their fertile years) when fertility patterns are stable over time.

presents considerable difficulties, since it is a joint outcome with the fertility decision itself. However, educational attainment is unaffected by one's fertility, and presents a measure of the mother's human capital, and hence opportunity costs. The literature cited suggests that a mother's human capital will be negatively correlated with her fertility. Since women are, in general, more likely to remain at home to raise children, husbands' income is more often used as a measure for household income. The same arguments can be made for fathers' forgone income as for mothers, but here income effects may be expected to be dominant [Becker et al., 1990; Galor and Weil, 1996, 2000]. That is, higher income and higher wage rates make children more affordable (presuming children are a normal good). However, there may be concerns that paternal income is endogenous because of assortative matching between high-capital partners.

Other factors that might be expected to affect fertility, such as access to family planning technologies or infant mortality (as suggested by Barro [1991]) can reasonably be neglected when considering women in a developed country such as the UK. Contraceptives and abortion are available widely, and so use of these can be expected to be a woman's own choice, even if norms — perhaps enforced by husbands — may discourage such behaviour in some communities. In addition, infant mortality is low in the UK (though it is feasible the some groups from developing countries have higher rates than the native population [Troe, 2008]).

In sum, the identifying assumption is that the economic costs of raising children are equal for all groups in my sample, or at least that these costs are not correlated with fertility in the country of origin. I will consider the validity of this assumption in Section 2.5.

2.2.2 Existing Work

Fernández and Fogli [2005, 2006] suggest that cultural values matter in women's fertility decisions. The former paper uses data from the United States' 1970 Census, focusing on women born in the US but whose fathers were not. They define 'country of origin' to be the father's country of birth. They restrict their sample to married women aged 30–40, resulting in 6,774 observations after omitting women from various countries.[5] Their remaining sample contains women having origins in 25 different countries. However, 16 of these are European, and four of the others are members of the OECD.[6]

In the latter paper, they use data from the US General Social Survey (GSS). This dataset contains variables covering fertility and ethnic origins, in the form of a question *"From what countries or part of the world did your ancestors come?"* They restrict attention to women born in the US to control for country differences such as educational systems. Taking observations from 1977, 1978, 1980 and 1982–1987, they select their sample to include only married women aged 29–50. They again make restrictions on country of origin, similar to those discussed in footnote 5. Here they are reduced to 14 countries, of which 11 are European, a further two OECD but not European (Canada and Mexico), and finally Russia.

The proxy Fernández and Fogli use for 'cultural values' is 1950 Total Fertility Rate (TFR) in country of origin.[7] They state that this is the earliest data appropriate, and it is intended to represent TFR at the time of respondents' ancestors' migration. In this case, timing assumption is arguable; respondents ancestors may have migrated hundreds of years previously. Indeed, only 8% of respondents claimed "American" or "American Indian" heritage [Fernández and Fogli, 2006, footnote 7, p. 554]. However in mitigation, the authors indicate that the distribution of national TFRs is highly stable [Fernández and Fogli, 2006, pp. 560].

[5]They exclude all women whose fathers born in countries that became centrally planned economies after World War II, reasoning that these women's parents must have been in the US by 1940. Therefore their emigrating parents would not have experienced the transformation to communism, and TFR in 1950 does not 'capture the correct culture for these individuals' [Fernández and Fogli, 2005, p. 10]. They also exclude countries with fewer than 15 observations.

[6]The remainder are Cuba, China, Lebanon, the Philippines and Syria.

[7]TFR attempts to measure the number of children a woman is expected to have 'by the end of her childbearing years'. It is be calculated as the sum of age-specific fertility rates, weighted by the probability of reaching each given age. It does not, however, denote the completed (ie, actual) fertility of any cohort of women, and is affected by changes in birth timing, as highlighted by Bongaarts and Feeney [1998]. I will discuss timing further in Section 2.4.

2.2.3 The Labour Force Survey

I use household data obtained from the UK Labour Force Survey (LFS) between 1996 and 2005 and proxy data from the World Bank Development Indicators dataset. The LFS is a rolling panel conducted every quarter with each household appearing in five 'waves', and contains variables detailing employment, education, income, family status, ethnicity and religion.[8] Whilst there are some disadvantages, the LFS data are superior to the US Census data and GSS in several ways.

2.2.3.1 Disadvantages of the LFS

First and foremost, the LFS does not contain data on respondents' ancestry; in my data, country of origin is known only for first generation immigrants. I believe that this disadvantage of the LFS data is more than compensated by the ability to focus solely on a single generation of immigrants who have a relatively consistent history in the UK. Fernández and Fogli [2005] focus on second generation immigrants, but if there were heterogeneity in matching between groups (ie, some nationalities are more likely to find a partner within their own group), then the cultural transmission would also feasibly be heterogeneous, since women reporting some nationalities would be more likely to have both parents of that nationality.[9] The reporting of origin in Fernández and Fogli [2006] is even more restricted, because the GSS data cannot discern how long ago respondents' ancestors arrived. In some cases this may have been hundreds of years ago, so 1950 TFR may be an inappropriate proxy for their cultural values. By taking only first-generation immigrants, I ensure that the women in question have comparable circumstances.

A second disadvantage is that the LFS does not contain 'raw' fertility data,

[8] I take household responses from the first wave only.

[9] I am able to test for heterogeneity in matching rates. In my sample, 46% of women have husbands from the same country of origin. Across countries, the average proportion of husbands of the same origin is 0.40 with a standard deviation of 0.24. Singapore is lowest (0.028) and Albania is highest (1.00). This suggests there may be heterogeneity in transmission of values.

for example in the form of birth histories or a number-of-births variable. To circumvent this, an identifying assumption must be made: I assume that all children live with their mothers [as in Gangadharan and Maitra, 2003].[10] That is, I take the number of a woman's children in the household to be the number of that she *has had*. Implicitly, childhood mortality is assumed to be zero. Non-trivial mortality will only cause identification problems if there is heterogeneity in mortality rates amongst immigrants from different countries.[11] It is likely that infant mortality would be higher for those immigrants from less-developed countries, where fertility is typically higher [Troe, 2008]. This would tend to bias down the coefficient on country of origin TFR, making it harder to find a significant positive result. However, since mortality is low in general, this is unlikely to be problematic.

2.2.3.2 Censoring

To reiterate, I define a woman's fertility to be the number of her children and stepchildren aged below 15 who live in her household. I label this variable CHILDREN. This is likely to be accurate for younger women: they are not old enough to have children who are older than fifteen. However, attenuation may occur with older women, particularly for those groups who have children earlier. This could have implications when considering birth timing factors (see Section 2.4). The effect can be considered as a 'censoring' of the data (cf. Greene [1997, §19.9.2, pp. 936]).

In several regression specifications (see Tables 2.3, 2.6 and 2.8) large squared-age coefficients indicate declining completed fertility with age at the upper end of the sample range. Possibly older cohorts simply had fewer children. However, this finding is more likely to reflect either censoring of the data as older children leave home, or that the a quadratic model is unsuitable for such a wide age sample. The former is more likely and the results in Fernández and Fogli

[10] I treat stepchildren in exactly the same way as children, reasoning that for each woman living with a stepchild, there is a woman not living with her child.

[11] In computing TFR estimates I also neglect adult mortality. Therefore I simply compute TFR as a sum of age-specific fertility rates.

[2006] do not show this effect (Fernández and Fogli [2005] does not report age coefficients). Further, as can be seen in Figure 2.2, women appear to have children swiftly once they begin a family, and then childbearing tails off. Thus, the total number of children is increasing, but at a diminishing rate, suggesting a quadratic is appropriate. However, all results presented here are robust to eliminating women over 39. I attempt to address some of these issues in Section 2.4.

2.2.3.3 Advantages of the LFS

Most importantly, the LFS is a large survey. The years 1996–2005 record 1.15 million people, of which almost 80,000 were born abroad. I present results using almost all 11,081 married women in aged 30–49; this compares favourably with Fernández and Fogli's samples of 6,774 from the US Census [2005] and of 1,177 from the GSS [2006].[12] Various summary statistics can be seen in Table 2.1. GTFR is my proxy for fertility norms, the Total Fertility Rate in the country of origin, taken from the World Bank Development Indicators (1997), and DEGREE, FE, AL and GCSE are indicators of highest educational attainment, taken from the LFS variable HIQUALD. Husband's gross pay is measured in thousands of pounds per annum, and is derived from the LFS variables GRSSWK and GRSSWK2 (gross weekly pay in first and second jobs respectively).

The LFS also captures immigrants from many more countries than the GSS: 89 compared with fourteen. Moreover, my sample includes a wide variety of currently developing countries (see Table 2.2); in the GSS sample the majority of original countries — and the majority of sample respondents — are from western Europe. Only one has a instrumented TFR of above four (Mexico, with 6.87 children per woman), and only a further three have values above three. The mean 1950 TFR is 3.01, with a standard deviation of 1.20. In my sample

[12]Following Fernández and Fogli, I disregard countries with fewer than ten observations (though all results are robust to their inclusion). However, I have not eliminated women from the former communist bloc as those authors do: their reasoning is not applicable for the time periods relevant to my sample.

Table 2.1: Summary statistics, women born abroad aged 30–49, Labour Force Survey 1996–2005. GTFR is my proxy for fertility norms, taken from the World Bank Development Indicators. DEGREE, FE, AL and GCSE are indicators of highest educational attainment. Husband's gross pay measured in thousands of pounds per annum.

Variable	Mean	Std. Dev.	Min.	Max.	N
CHILDREN	1.48	1.264	0	9	11081
GTFR	3.126	1.498	1.087	7.25	11081
AGE	39.179	5.654	30	49	11081
DEGREE	0.123	0.328			11081
FE	0.062	0.241			11081
AL	0.065	0.246			11081
GCSE	0.086	0.28			11081
Husband's DEGREE	0.201	0.4			11081
Husband's FE	0.048	0.214			11081
Husband's AL	0.12	0.326			11081
Husband's GCSE	0.056	0.229			11081
Husband's gross pay	29.497	26.388	0.26	663.416	4370

the values are 3.13 and 1.50, respectively. Figure 2.1 shows the relationship between my sample's mean fertility and country of origin TFR.

For simplicity, I use 1997 TFR as my proxy for fertility preferences. The window for arrivals in the LFS sample is 1946–2005.[13] This is certainly smaller than the 'arrival window' Fernández and Fogli [2006] are faced with, which is feasibly several hundred years since they cannot focus on a single generation of immigrants. Fernández and Fogli [2005]'s sample also has a large arrival window.

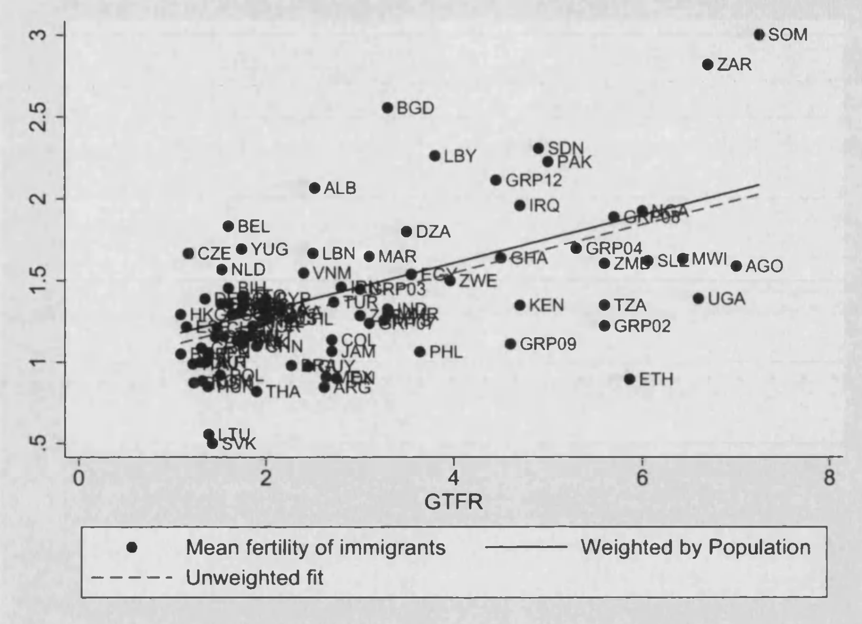
Unfortunately the resolution of the country of origin data is not perfect: not all countries may be identified uniquely. I therefore take means of TFRs for 'grouped' countries. The groupings are given in Appendix A.1, page 145.

[13] Women aged 29–50, interviewed between 1996 and 2005. Restricting by age at arrival would further reduce this window.

Table 2.2: Country Statistics. See note on Table 2.1. Fertility denotes the mean number of children of immigrants from each country, as plotted in Figure 2.1. Country groups are explained in Appendix A.1.

Code	Obs.	GTFR	Fert.	Code	Obs.	GTFR	Fert.
AGO	17	7.00	1.58	MEX	22	2.64	0.90
ALB	15	2.52	2.06	MLT	87	1.83	1.16
ARG	13	2.62	0.84	MMR	17	3.30	1.29
AUS	233	1.77	1.35	MUS	86	2.04	1.26
AUT	18	1.36	1.00	MWI	60	6.43	1.63
BEL	30	1.60	1.83	MYS	167	3.26	1.25
BGD	536	3.30	2.55	NGA	204	6.00	1.92
BGR	20	1.09	1.05	NLD	88	1.53	1.56
BIH	11	1.60	1.45	NOR	27	1.86	1.22
BRA	49	2.27	0.97	NZL	108	1.96	1.25
BRB	24	1.75	1.33	PAK	1034	5.00	2.22
CAN	183	1.55	1.15	PHL	235	3.64	1.06
CHE	43	1.48	1.20	POL	126	1.51	0.92
CHI	18	1.75	1.38	PRT	102	1.46	1.15
CHL	15	2.25	1.26	ROM	26	1.32	0.88
CHN	132	1.90	1.09	RUS	55	1.23	0.87
COL	51	2.70	1.13	SDN	26	4.90	2.30
CYP	198	2.00	1.38	SGP	181	1.63	1.29
CZE	18	1.17	1.66	SLE	29	6.06	1.62
DEU	522	1.35	1.38	SOM	31	7.25	3.00
DNK	43	1.75	1.11	SVK	12	1.43	0.50
DZA	20	3.50	1.80	SWE	53	1.52	1.35
EGY	39	3.55	1.53	THA	61	1.90	0.81
ESP	97	1.15	1.21	TTO	54	1.75	1.40
ETH	19	5.86	0.89	TUR	152	2.72	1.36
FIN	32	1.75	1.15	TZA	126	5.60	1.34
GHA	122	4.50	1.63	UGA	195	6.60	1.38
GRC	23	1.31	1.08	UKR	22	1.30	1.00
GUY	39	2.45	0.97	USA	428	1.97	1.32
HKG	239	1.08	1.29	VNM	53	2.40	1.54
HRV	15	1.69	1.13	YUG	75	1.74	1.69
HUN	20	1.38	0.85	ZAF	301	3.00	1.28
IDN	20	2.75	0.90	ZAR	11	6.70	2.81
IND	1529	3.30	1.32	ZMB	91	5.60	1.60
IRN	113	2.80	1.46	ZWE	144	3.96	1.50
IRQ	49	4.70	1.95	GRP02	36	5.60	1.22
ITA	170	1.22	0.98	GRP03	29	3.00	1.44
JAM	193	2.70	1.06	GRP04	109	5.30	1.69
JPN	137	1.38	1.05	GRP07	46	3.10	1.23
KEN	577	4.70	1.34	GRP08	99	5.70	1.88
KOR	39	1.60	1.35	GRP09	27	4.60	1.11
LBN	27	2.50	1.66	GRP10	203	1.72	1.31
LBY	38	3.80	2.26	GRP12	35	4.45	2.11
LKA	207	2.15	1.30				
LTU	18	1.39	0.55	Av.	124.5	2.89	1.38
MAR	37	3.10	1.64	Std.	214.4	1.63	0.45

Figure 2.1: Mean fertility of immigrants in UK versus TFR in country of origin. Fit lines are (a) weighted by size of country group in my sample, and (b) unweighted.



2.3 Regression Specifications and Results

2.3.1 Ordinary Least Squares

Fernández and Fogli [2006] run several ordinary least-squares (OLS) regressions of the following form:

$$Z_{isjt} = \beta_0 + \beta_1' X_i + \beta_2' \tilde{Y}_i + \beta_3' \tilde{Z}_j + f_s + \gamma_t + \epsilon_{isjt}.$$

Here, Z_{isjt} is the fertility of a woman i, who lives in region s, is of ancestry j, and is interviewed in year t. X_i contains individual characteristics depending on the specification and $\tilde{Z}_j$ is the cultural values proxy: country of origin TFR (I label this variable GTFR). γ_t is the year-of-survey fixed effect. Here, I do not consider regional effects (f_s). Y_i is the number of siblings the woman herself has, a factor which I also do not investigate here.

2.3.1.1 Regression Model

My comparable regression model is:

$$Z_{ijt} = \beta_0 + \beta_1' X_i + \beta_2' \tilde{Z}_j + \gamma_t + \epsilon_{ijt}.$$

The terms are:

- Z_{ijt} The number of children of a woman i, who lives in region s, is of ancestry j, and is interviewed in LFS wave t. I label this variable CHILDREN.
- X_i Individual characteristics of woman i, depending on the specification.
- $\tilde{Z}_j$ My proxy for fertility norms, the Total Fertility Rate of country j. This variable is labelled GTFR.
- γ_t Survey-wave fixed effect.
- ϵ_{ijt} Error term.

Control variables used include AGE and AGE2, the woman's age and squared age; indicators DEGREE, FE, AL and GCSE denoting the woman's education (a degree, further education, A-Level and GCSE attainment (or equivalent) respectively); husband's educational attainment indicators; and her husband's gross pay (measured in thousands of pounds sterling per annum).[14]

The coefficient of interest is β_2, which measures the power of the fertility proxy in explaining fertility outcomes amongst the women in my sample.

β_0, the constant term, is a measure of the baseline number of children that the women in my sample have. If age controls are included in X_i, it will reflect the number of children a woman has had at age 30, since the sample contains women of age 30–49. The actual expected number of children will be a linear transformation also involving the age coefficients from β_1. It must be noted that this is a *completed fertility* measure. I will return to this in Section 2.4.[15]

[14] Husbands' income is chosen to avoid endogeneity between fertility and women's income. See the discussion on Page 43.

[15] In particular, see the discussion on page 65 concerning the interpretation of coefficients.

2.3.1.2 Results

Table 2.3 presents OLS results, with robust standard errors accounting for clustering at the country of origin level. With only the cultural proxy included in the regression (column (1)), Fernández and Fogli [2006] find it to be statistically significant at better than 1%, with a coefficient of 0.166. In the same specification I estimate this coefficient to be 0.146, also significant at 1%. (Time dummies are included for all 40 waves, as is a constant term, though these coefficients are not reported).

Where available, I use the same controls as Fernández and Fogli: age (AGE), squared age (AGE2) and dummies for highest educational attainment (derived from the LFS variable HIQUALD). These are DEGREE, FE, AL and GCSE, representing degree level, further education level, A-Level or GCSE attainment respectively. Controlling for age and education (Table 2.3, column (2)) they find this falls slightly to 0.117 (still significant at 1%); I find a value of 0.144, significant at 0.1%.

Quantitatively, this coefficient value corresponds to an increase of 0.23 children for a standard deviation increase in GTFR (1.63). This is about half of the standard deviation of the fertility across country groups (0.45).

The age controls are also significant at 0.1% as would be expected and have the expected signs: the age coefficient is positive — older women have had more children, and the squared-age coefficient is negative suggesting (predictably) that the rate of childbearing declines with age.

The education dummies all have negative signs and are jointly significant at 5%. However, only DEGREE and AL are individually significant, at the 1% and 5% level respectively. Note that these two coefficients are quantitatively quite large (-0.282 and -0.244), suggesting that women having these qualifications tend to have a quarter of a child fewer.

With GTFR ranging between 1.087 and 7.25 (Table 2.1), country of origin fertility is the largest factor in predicting individuals' fertility besides age, dominating education. These findings support the argument that cultural values are

Table 2.3: Ordinary Least-Squares regressions, family size on TFR rate in country of origin. A constant term and wave dummies are included in each regression. Standard errors account for clustering at the country of origin level (White) [Greene, 1997, pp. 503].

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
GTFR	0.146**	0.144***	0.140***	0.116**
	(0.0452)	(0.0419)	(0.0405)	(0.0379)
AGE		0.720***	0.723***	0.749***
		(0.0347)	(0.0339)	(0.0483)
AGE2		-0.00992***	-0.00996***	-0.0101***
		(0.000394)	(0.000383)	(0.000579)
DEGREE		-0.282**	-0.236**	-0.265**
		(0.105)	(0.0745)	(0.0824)
FE		-0.144	-0.0968	-0.0153
		(0.105)	(0.0818)	(0.0937)
AL		-0.244*	-0.192*	-0.136
		(0.112)	(0.0896)	(0.0915)
GCSE		-0.126	-0.0737	-0.0698
		(0.104)	(0.0855)	(0.0743)
Husband's DEGREE			-0.0948	-0.0436
			(0.0757)	(0.0979)
Husband's FE			-0.145	-0.0678
			(0.0805)	(0.107)
Husband's AL			-0.189*	-0.169
			(0.0834)	(0.100)
Husband's GCSE			-0.138	-0.0834
			(0.0865)	(0.122)
Husband's gross pay				0.00118
				(0.00114)
Observations	11081	11081	11081	4370
R^2	0.035	0.166	0.169	0.144

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.4: Correlations between educational controls for women and their husbands. Note that the indicator is 1 for the highest level of qualification only. NONE corresponds no qualification.

Variables	DEGREE	FE	AL	GCSE	NONE
Husband's DEGREE	0.45	0.09	0.06	-0.02	-0.38
Husband's FE	0.03	0.12	0.05	0.07	-0.15
Husband's AL	-0.03	0.03	0.11	0.13	-0.13
Husband's GCSE	-0.04	0.04	0.05	0.12	-0.10
Husband's NONE	-0.34	-0.17	-0.17	-0.16	0.50

significant in determining family size preferences.

My estimates of the GTFR and age coefficients are robust to including women's husbands' characteristics (Table 2.3, columns (3) and (4)). Dummies for husbands' education all appear negatively, with A-Level attainment having 5% significance (column (3)). This finding is unexpected, since if fathers do not undertake childcare, higher paternal earnings would expand the household budget set without increasing opportunity costs, as in Galor and Weil [1996, 2000]. However, there is a high level of correlation between husbands' and wives' education (Table 2.4) — there is some degree of assortative matching.

Assortative matching entails that the coefficients on husbands' education partly identify their wives' education. In Table 2.3, column (3), women's education dummies are all reduced in magnitude (they become more positive) when husbands' education is included, though significance levels are unchanged. The minor increase in the R^2 statistic is consistent with this story. As such, husband's education may act negatively because educated men marry educated women (who have fewer children), even though husbands' human capital may have a positive effect on fertility in itself.

In Table 2.3, column (4), husbands' income is included in the regression. Husband's gross pay enters positively but insignificantly. This mirrors the finding by Fernández and Fogli [2006]. The positive effect is previously documented [Butz and Ward 1979; Heckman and Walker 1990, in Galor and Weil 1996] and is predicted by the models of Galor and Weil [1996, 2000]. Though insignificant, the positive coefficient is consistent with paternal education having a positive effect on fertility which is dominated by assortative matching with educated women.

The influence of women's age and education are robust to inclusion of husbands' income, and small changes to the education coefficients are attributable to the smaller subsample. Results are very similar when specification (3) is run on the sample of model (4) (regression not reported).

2.3.1.3 Fixed Effect Models

Table 2.5 presents OLS results with country of origin dummies included, rather than country of origin fertility. The fit of each model (measured by the R^2 statistic) can be used to infer the explanatory power of the culture proxy. With each set of controls, the more general specification improves model fit by around 8 percentage points, with the country of origin dummies being significant at better than 0.1% in each case. On its own, the proxy GTFR explains 3.5% of fertility differences between women (Table 2.3, column (1)), or roughly a third of the differences between country groups. Other factors make up two-thirds of between-group differences.

Standard deviations of the country dummies lie in the range 0.41–0.47 for the various specifications in the table. As in the previous specification, differences in fertility between country groups are larger than the effects of any other factor in the regressions, except age.

In the alternative models with country dummies, coefficients on women's education all become less negative, with A-Level education becoming insignificant and both DEGREE and GCSE increasing by around 0.13, about half their magnitude. This result suggests there are differences in levels of education between country groups that are not correlated with GTFR. The country dummies identify some of the educational differences.

Husbands' education coefficients also become more positive; they are statistically insignificant (column (3)). Moreover, these coefficients are essentially insignificant *economically.* In this case, including husbands' education does not

Table 2.5: Ordinary Least-Squares regressions, family size on country of origin dummies. Wave dummies are included in each regression. Standard errors account for clustering at the country of origin level (White) [Greene, 1997, pp. 503].

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Country Dummies	Yes	Yes	Yes	Yes
AGE		0.737***	0.739***	0.745***
		(0.0307)	(0.0304)	(0.0473)
AGE2		-0.0101***	-0.0101***	-0.01000***
		(0.000353)	(0.000351)	(0.000569)
DEGREE		-0.153**	-0.160**	-0.221**
		(0.0502)	(0.0484)	(0.0728)
FE		-0.0125	-0.00719	0.0399
		(0.0500)	(0.0495)	(0.0677)
AL		-0.125	-0.114	-0.116
		(0.0643)	(0.0613)	(0.0782)
GCSE		0.00128	0.0157	-0.00218
		(0.0454)	(0.0444)	(0.0600)
Husband's DEGREE			0.00521	0.0217
			(0.0406)	(0.0763)
Husband's FE			-0.0509	-0.0138
			(0.0548)	(0.0892)
Husband's AL			-0.0738	-0.0901
			(0.0428)	(0.0673)
Husband's GCSE			-0.0462	-0.0214
			(0.0463)	(0.0811)
Husband's gross pay				0.00205**
				(0.000752)
Observations	11081	11081	11081	4370
R^2	0.119	0.241	0.241	0.224

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

increase the R^2 statistic at all, suggesting a high correlation in educational attainment both within couples and within country groups.

With country fixed effects, husbands' income is significant at the 1% level (Table 2.3, column (4)). Relative to the baseline model with the culture proxy, the point estimate coefficient is almost doubled, and all the educational dummies are more positive. As with education, income levels are likely to be different between country groups. Across the whole sample, income is statistically insignificant, but once group differences are accounted for with fixed effects, income is significant.

The magnitudes of the fixed effect coefficients, along with the lesser importance of education is consistent with significant differences in family size preferences across groups. Transmitted values, as proxied by country of origin fertility, appears to comprise a non-trivial component of these differences. Nonetheless, there are sizeable group-specific factors that are not captured by the proxy. Future work will investigate these differences more fully, particularly with respect to sample selection issues.

2.3.1.4 Problems

Econometrically, a linear specification is unsatisfactory. The number of children a woman has is likely to be better modelled as a discrete, count-based data generating process. I shall now consider some of these specifications, following the discussion in Greene [1997, §19.9] and Wooldridge [2002, §19.2]. Young [2005a,b] demonstrates some applications of this model to fertility.

2.3.2 Poisson Count

2.3.2.1 Regression Model

In the Poisson count model, the dependent variable takes a Poisson distribution with mean (and hence variance) whose logarithm is a linear combination of the independent variables.[16] That is,

$$\begin{aligned} Z_{ijt} &\sim \text{Poisson}(\mu_{ijt}) \\ \text{Where } \log \mu_{ijt} &= \beta_0 + \beta_1' X_i + \beta_2' \tilde{Z}_j + \gamma_t. \end{aligned}$$

Conveniently, the estimates have the same interpretation as those in a log-linear regression.

The coefficient estimates may computed numerically by the maximum likelihood method. It should be noted the Poisson model necessarily implies heteroskedasticity, since if $Z \sim \text{Poisson}(\mu)$, then $\text{Var}(Z) = \text{E}(Z) = \mu$.

Even in the case that the dependent process is not Poisson, the coefficient estimates found by (pseudo-)maximum likelihood estimation are robust to a number of misspecifications. Particularly, they are unchanged under the generalisation that $\text{Var}(Z) = \sigma^2\,\text{E}(Z)$ for constant σ^2. If $\sigma^2 > 1$ this is described as 'over-dispersion' Wooldridge [2002, p. 647]. However, although the coefficient estimates are unchanged, the standard errors must be adjusted upwards.

Conversely, if $\sigma^2 < 1$ (under-dispersion), the standard errors derived by pseudo-maximum likelihood are robust. There are a number of tests for over-dispersion (recorded in Wooldridge [2002, pp. 655] and Greene [1997, §19.9.3, pp. 937]). I have found no evidence of over-dispersion in my sample; most tests indicate a small degree of under-dispersion.

2.3.2.2 Results

Tables 2.6 and 2.7 records the results of these Poisson regressions with the same independent variables as the OLS regressions in Tables 2.3 and 2.5 respectively, again with clustered errors at the country of origin level. In each case the fit is slightly better than its OLS counterpart, according to the predicted values test (Pseudo-R^2) given by Wooldridge [2002, p. 653].

The coefficients cannot be compared directly with those from the OLS but

[16] The Poisson distribution with parameter μ has probability mass function $f(k) = \frac{e^{-\mu}\mu^k}{k!}$.

Table 2.6: Poisson regressions, family size on TFR rate in country of origin. A constant term and wave dummies are included in each regression. Standard errors account for clustering at the country of origin level (White) [Greene, 1997, pp. 503].

	(1)	(2)	(3)	(4)
	Poisson	Poisson	Poisson	Poisson
GTFR	0.0950***	0.0937***	0.0912***	0.0804***
	(0.0259)	(0.0237)	(0.0231)	(0.0232)
AGE		0.637***	0.640***	0.670***
		(0.0559)	(0.0550)	(0.0451)
AGE2		-0.00877***	-0.00881***	-0.00908***
		(0.000724)	(0.000712)	(0.000567)
DEGREE		-0.200**	-0.167***	-0.191***
		(0.0660)	(0.0478)	(0.0567)
FE		-0.103	-0.0695	-0.0149
		(0.0695)	(0.0553)	(0.0651)
AL		-0.172*	-0.136*	-0.100
		(0.0707)	(0.0575)	(0.0627)
GCSE		-0.0891	-0.0533	-0.0419
		(0.0647)	(0.0541)	(0.0497)
Husband's DEGREE			-0.0681	-0.0325
			(0.0471)	(0.0649)
Husband's FE			-0.106*	-0.0501
			(0.0515)	(0.0704)
Husband's AL			-0.134*	-0.125
			(0.0535)	(0.0684)
Husband's GCSE			-0.0968	-0.0650
			(0.0546)	(0.0812)
Husband's gross pay				0.000829
				(0.000871)
Observations	11081	11081	11081	4370
Pseudo R^2	0.034	0.175	0.178	0.151

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.7: Poisson regressions, family size on country of origin dummies. A constant term and wave dummies are included in each regression. Standard errors account for clustering at the country of origin level (White) [Greene, 1997, pp. 503].

	(1) Poisson	(2) Poisson	(3) Poisson	(4) Poisson
Country Dummies	Yes	Yes	Yes	Yes
AGE		0.650***	0.651***	0.667***
		(0.0496)	(0.0495)	(0.0445)
AGE2		-0.00892***	-0.00894***	-0.00901***
		(0.000644)	(0.000644)	(0.000569)
DEGREE		-0.109**	-0.113***	-0.163**
		(0.0346)	(0.0335)	(0.0520)
FE		-0.0119	-0.00726	0.0243
		(0.0348)	(0.0343)	(0.0453)
AL		-0.0883*	-0.0799	-0.0846
		(0.0428)	(0.0409)	(0.0542)
GCSE		0.00112	0.0120	0.00818
		(0.0286)	(0.0284)	(0.0418)
Husband's DEGREE			0.00178	0.0176
			(0.0278)	(0.0514)
Husband's FE			-0.0430	-0.0134
			(0.0380)	(0.0583)
Husband's AL			-0.0575	-0.0730
			(0.0300)	(0.0475)
Husband's GCSE			-0.0360	-0.0206
			(0.0302)	(0.0516)
Husband's gross pay				0.00149**
				(0.000530)
Observations	11081	11081	11081	4370
Pseudo R^2	0.120	0.254	0.0254	0.233

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

the pattern of significance is very similar, as are the relative magnitudes. GTFR is statistically significant at 0.1% in each specification.

Quantitively, these results suggest that a one (group) standard deviation increase in GTFR (1.63) explains an increase in fertility of 13–14%. As with the OLS regressions, the economic significance of the culture proxy dominates all other factors except age. Again, country fixed effects improve the fit of the model by around 8 percentage points, with GTFR alone explaining 3.4% of family size differences, consistent with a role for cultural values in determining fertility preferences.

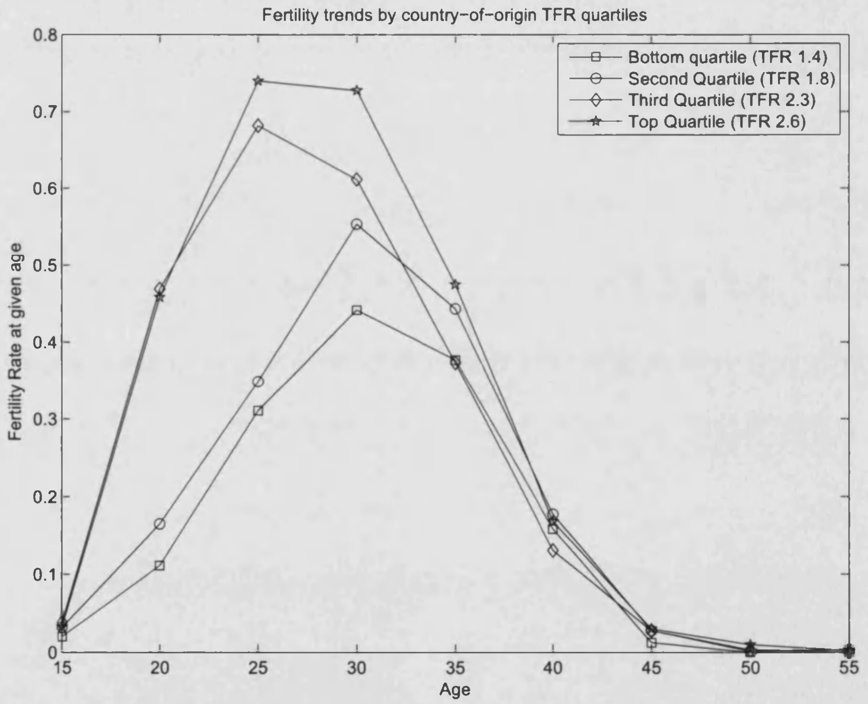
2.4 Heterogeneous Birth Timing

Fernández and Fogli [2006] take some steps to address the dynamic nature of fertility: they restrict the sample to older women (ages 29–50), and they incorporate age and squared-age controls. In Fernández and Fogli [2005] they consider only women aged 30–40. Ideally one would consider only 'completed fertility', looking at older women, so that any timing differences would be accounted for. However, in the sample age range, women are still fertile. Hence, coefficient estimates may be biased or misleading if birth *timing* is heterogeneous and systematically correlated with the cultural proxy.

Figure 2.2 indicates this may be the case: it appears that women from high-TFR countries reach their highest fertility in the 20–25 age band, whereas women from low-TFR countries reach their peak between 25 and 30. This comparison does not control for factors such as education, but this illustration suggests that further investigation is appropriate.

There is another potential problem deriving from birth timing: differing patterns of fertility *after thirty* are seen, implying heterogeneity in birth rates in the 30–40 age band. This is likely to bias the measurement of completed fertility differences, because age coefficients will not correctly capture continuing fertility for all groups. It is not clear that Fernández and Fogli [2006] will be

Figure 2.2: Trends in birth timing. Data plotted are the age-specific fertility rates for immigrants, grouped by TFR in their country of origin.
TFR estimates for each group are the sum of the 5-year rates (see the discussion in Footnote 11, page 46). This is equal to the integral of the relevant curve. Not only do high-TFR countries (third and top quartiles) have more children, their peak fertility appears to be earlier (25–30 as opposed to 30–35).
Note that raw data is plotted: there are no controls for educational attainment or other factors; these may be correlated with the TFR proxy.



immune from this problem if similar trends were shown in their data. Indeed, is possible that Fernández and Fogli [2005] will be more susceptible, since their sample includes only women in that age range.

Here, I test for this effect by including the interaction between age and the TFR instrument as a regressor in a Poisson regression. An alternate specification would allow different countries of origin to have different age coefficients (a random growth model).

2.4.1 Concerns

Birth timing may be heterogeneous for several reasons. Education might be expected to be a major factor, since women may defer childbearing until it is completed. Earnings and the expected path of future income may also play a role, and this may be ambiguous: women might decide to have children when their financial constraints are less, but also they may delay childbearing if the present opportunity cost is very high.

These effects are also likely to work though husbands' earnings, recalling the contribution of Galor and Weil [1996]. In their model, increases in women's wages increase the opportunity cost of childrearing and reduce fertility. Conversely, men's wages relate only to the size of the budget set, and higher male wages make children more 'affordable': fertility increases in male earnings.

Finally, another reason for heterogeneous birth timing may be differing preferences — that is, cultural values. It is appropriate for any work considering culture and fertility preferences to consider preferences regarding timing; however neither Fernández and Fogli [2005] nor Fernández and Fogli [2006] mentions this.

2.4.2 Implications

If women from low-TFR countries have children earlier, this will bias *up* the estimated differences in completed fertility. The mechanism for this is simple: selecting a sample of women aged 30 and older, the regression model used entails that the constant term and coefficient on GTFR together reflect fertility *at age 30*, with the age coefficients reflecting time trends *as if common to all women.*

As an example, consider the hypothetical case that the cultural proxy was entirely uncorrelated with completed fertility, but a high proxy were related to *early* fertility. A regression including only women in the middle of their fertile years would record a positive coefficient on GTFR, since those with a high proxy would have ad their children early, before the time of measurement and the others would not yet have had their children. Conversely, a regression with only older women would report zero: the true effect of GTFR on fertility. The positive estimate is only due to timing, not aggregate fertility. If between-group timing differences are present in the data, the interpretation of the GTFR coefficient must be re-examined.

2.4.3 Testing

Here, I test for a time-shift correlated with GTFR by including the interaction between age and the TFR instrument as a regressor in a Poisson regression. I append two terms, GTFR*AGE, and GTFR*AGE2, taking account of the interactions with age and squared age respectively.

First, the AGE coefficient is likely to increase, since the baseline woman (low GTFR) is expected to have children at a faster rate in the sample age range. The interaction coefficient will correspondingly take a negative sign, since high-GTFR women are expected to have fewer children between 30 and 50.

By allowing separate trends for high- and low-GTFR women, I expect the former to be fitted a flatter cumulative fertility with age, and the latter a steeper profile. This results in a wider gap between the predicted fertilities at age 30 — ie, a larger GTFR coefficient. But since the trends converge, the gap in completed fertility is now smaller. The effect on the constant term will depend on the identity 'baseline' woman, ie, the normalisation used. I will return to this in Section 2.4.3.3.

2.4.3.1 Normalisation

Up to this point, I have followed Fernández and Fogli [2005, 2006] to allow a direct comparison of my results. However, the interpretation of the constant term is not immediately obvious in their framework. I therefore make a number of normalisations.

First, I normalise the cultural proxy GTFR by subtracting the value for Britain (1.73) to construct the variable GTFRN. The objective is to put in context the constant term and age coefficients for a hypothetical British woman.[17]

Secondly, I normalise age by subtracting 30, the lower bound of my sample, constructing the variable AGEN, squaring this to make AGEN2. Along with the above, this now gives a very simple interpretation of the constant term. In a linear regression it is the expected number of children a British woman aged 30, and in a Poisson regression it is the logarithm of this expectation.

Note that these linear transformations do not alter the fundamental regression framework. To see this, observe that the spans $\langle \text{GTFR}, \text{AGE}, \text{AGE2}, 1\rangle$ and $\langle(\text{GTFR}-1.73), (\text{AGE}-30), (\text{AGE}-30)^2, 1\rangle$ are the same, since $(\text{AGE}-30)^2 = \text{AGE2} - 60(\text{AGE}) + 900$. Another way of putting this is that the new coefficients will be bijection of the old coefficients.[18]

2.4.3.2 Results

Columns (2) and (4) of Table 2.8 records the results from OLS and Poisson regressions with interaction terms between age and my cultural proxy. Columns (1) and (3) show results from regression without interactions. These two are transformations of the regressions in Table 2.3 column (2) and Table 2.6 column (2) respectively, following the preceding discussion. All regressions here include educational controls and sample wave dummies (not reported).

While interaction terms themselves are only significant in the Poisson model,

[17] This woman is hypothetical in the sense that she has 'British preferences' but was born abroad. The baseline woman might alternately be considered to be from France (inc. Monaco) (TFR 1.73) or Serbia and Montenegro (TFR 1.74).

[18] A simple algebraic manipulation shows that estimated coefficients on GTFR and GTFRN will be the same, as will the coefficients on AGE2 and AGEN2. $\beta_{\text{AGEN}} = \beta_{\text{AGE}} + 60\beta_{\text{AGE2}}$.

Table 2.8: OLS and Poisson regressions with fertility rate-age interaction. Wave and educational dummies are included in each regression. Standard errors account for clustering at the country of origin level (White).
For reference, columns (1) and (3) record analogous regressions to those in Table 2.3 column (2) and Table 2.6 column (2) respectively; refer to the discussion on normalisation (page 65).

	(1) OLS	(2) OLS	(3) Poisson	(4) Poisson
GTFRN	0.144***	0.246***	0.0937***	0.156***
	(0.0419)	(0.0707)	(0.0237)	(0.0378)
AGEN	0.125***	0.141***	0.111***	0.135***
	(0.0126)	(0.0125)	(0.0132)	(0.0124)
AGEN2	-0.00992***	-0.00999***	-0.00877***	-0.00982***
	(0.000394)	(0.000513)	(0.000724)	(0.000705)
GTFRN*AGEN		-0.0118		-0.0150**
		(0.00642)		(0.00507)
GTFRN*AGEN2		0.0000423		0.000646*
		(0.000242)		(0.000277)
Constant	1.391***	1.255***	0.260***	0.158*
	(0.116)	(0.0956)	(0.0768)	(0.0744)
Observations	11081	11081	11081	11081

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.9: Predicted fertility deriving from regressions (2) and (4) from Table 2.8; no educational dummies are used. Note that predicted fertility declines between 35 and 40; this follows from large squared age coefficients relative the age coefficients, and may reflect censoring in the data (see page 45).

	Age	30	35	40
OLS	'Britain' (GTFRN = 0)	1.26	1.71	1.67
	Kenya (GTFRN = 1.97)	1.74	2.08	1.93
	Difference	0.48	0.37	0.26
Poisson	'Britain' (GTFRN = 0)	1.17	1.80	1.69
	Kenya (GTFRN = 1.97)	1.59	2.18	1.94
	Difference	0.42	0.38	0.25

they are jointly significant at 0.1% in the OLS model and at 0.5% in the Poisson model.

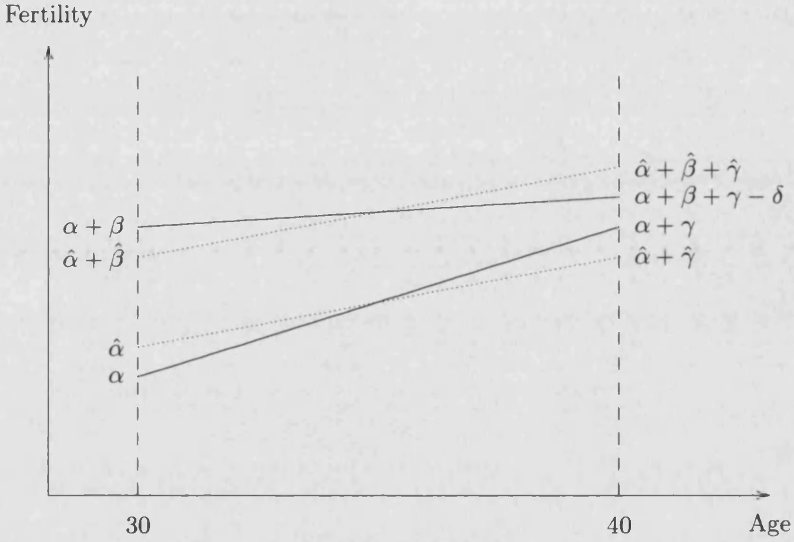
When the interaction terms are added, the GTFRN coefficients increase by roughly 70%. Also in line with predictions, the AGE coefficient increases with the interaction terms having opposite signs to the age terms. It remains significant in each specification. This might be taken as evidence that the cultural proxy is more important than previously thought. However, a more careful consideration these results suggests the opposite is true for completed fertility.

Table 2.9 shows predicted fertility for two women, one being a hypothetical British woman (GTFRN = 0), and the other being, say, Kenyan (GTFRN $\approx$ 2). (No educational dummies are applied.) It is predicted that the fertility difference is less for older women than those aged 30. This reflects the fact that the GTFRN interaction terms have the opposite signs to the plain age coefficients. However, these figures must be treated with caution, since declining total fertility suggests data problems, for example the censoring of children of older women (see page 45).

2.4.3.3 Explanation

It appears that the model of Fernández and Fogli [2005, 2006] is insufficient to explain the fertility trends observed in my data. The evidence presented here suggests that a part of the measured fertility differences across groups may result from differences in birth timing and not differences in total fertility.

Figure 2.3: A simple model of fertility dynamics.
α represents the constant term in found in the regression, β the coefficient on GTFRN and γ the coefficient on age. δ denotes the GTFRN-age interaction. Quadratic age terms are ignored.
The $\hat{\alpha}$, $\hat{\beta}$ and $\hat{\gamma}$ terms stylise the fitted coefficient values if an interaction term is not included in the regression.



Though it appears that immigrants from high-TFR countries have had more children at the age of 30, this trend is reversed as immigrants from low-TFR countries catch up later. Figure 2.3 shows a stylised model of this. The dark lines represent linear fertility trends for women from a low-TFR country and a high-TFR country. At age 30, the fertility difference is β. However, by age 40 the gap narrows to $\beta - \delta$.

The dotted lines in Figure 2.3 represent the model that Fernández and Fogli fit, with a fixed fertility gap at all ages. The same age profile is fitted for both groups: this is too steep for the high-TFR women, and too shallow for the low-TFR women. The fitted profiles are then too close at 30 and too far apart at 40 ($\beta - \delta < \hat{\beta} < \beta$). In this example, the predicted difference in both completed and age-30 fertility is $\hat{\beta}$. However, the true difference in completed fertility is $\beta - \delta$. We see that interpretation of the GTFR coefficient is dependent on the timing of fertility within the sample.

With the normalisation I use in my regressions (explained in Section 2.4.3.1), the constant term corresponds to predicted fertility at 30 for a 'British' woman. Her fertility was previously overestimated. In the diagram, this corresponds to $\hat{\alpha} > \alpha$.

2.4.3.4 Simulation

I conduct a simple simulation to estimate the effects of misspecifying the regression model. If the interaction terms formed part of the true data-generating process, what would be the estimated coefficients if it was estimated without interaction terms?

To try and answer this hypothetical question, I generated 1000 predicted values using the constant, GTFRN, age and interaction coefficients for both the OLS and Poisson models. I took AGEN and GTFRN drawn from $U[0, 10]$ and $U[0, 2]$ respectively (corresponding to ages 30–40 and GTFR between 1.73 and 3.73). I ignore education and wave coefficients.

I then regressed these predicted values on a constant, GTFRN and the age terms only. This gives predicted coefficients for Fernández and Fogli's specification, assuming the data-generating process truly involves the interaction terms.

Table 2.10 records the results of this exercise. While not matching the original estimates exactly, in each case the bias is towards that found in the 'No Interaction' regressions. This further suggests that birth timing and not absolute differences in completed fertility rates may be driving Fernández and Fogli's results and my earlier estimates.

2.4.3.5 Summary

There is evidence that heterogeneity in birth timing may result in misleading results if it is not controlled for. Indeed, if cultural values act systematically on birth timing, the effect of the those norms on family size may have been

Table 2.10: Actual and simulated regression coefficients, indicating bias in estimates without controls for birth timing. 'Predicted' estimates derive from regressions (2) and (4), Table 2.8. AGE and GTFRN are drawn from U[0, 10] (corresponding to ages 30–40) and U[0, 2] respectively with no education or wave coefficients.
'No Interaction' estimates are repeated from regressions (1) and (3), and 'Interaction' estimates are repeated from regressions (2) and (4).

		No Interaction	Predicted	Interaction
OLS	GTFRN	0.144	0.187	0.246
	AGEN	0.125	0.129	0.141
	AGEN2	-0.00992	-0.00993	-0.0999
	Constant	1.391	1.320	1.255
Poisson	GTFRN	0.0937	0.0997	0.156
	AGEN	0.111	0.119	0.135
	AGEN2	-0.00877	-0.00915	-0.00982
	Constant	0.260	0.221	0.158

overestimated in previous work.

2.5 Conclusion

My results indicate that culture (as instrumented by country of origin TFR from the World Bank Development Indicators) does play a role in the fertility decisions of immigrants in the UK (recorded in the Labour Force Survey). I extend the linear regression model used by Fernández and Fogli [2005, 2006] to a Poisson specification which is better suited to count data.

By including culture-age interaction terms in my regressions, I test for systematic differences in birth timing that are correlated with the culture proxy, and find statistically significant evidence for this. I argue that failure to account for timing can result in overestimation of the influence of culture on completed fertility.

Survival analysis would provide a robust way to deal with such timing issues. Hazard rate estimation has been used extensively to study son preference.[19] In that literature, the method takes women with a given number of children and assesses the likelihood that a woman has a further child, given the number of

[19]Examples include Leung [1988]; Gangadharan and Maitra [2003], and Chapters 3 and 4 of this thesis.

sons so far. Here, the dependent variable would be fertility rate in the country of origin. An additional benefit is the reduction in censoring problems when children leave home, since it is the age gaps between children that are relevant.

In sum, whilst cultural values do have a significant predictive effect for fertility, they do not appear to explain the whole story, since immigrants' fertility is certainly different to that in their countries of origin. There are also differences in fertility rates between groups that are not attributable directly to fertility norms, though these may relate to other cultural institutions, such as childrearing practices. Institutional structure may act by affecting implicit prices and surely play a significant role; further study is required to properly establish the importance of fertility values amongst these other factors.

Chapter 3

Son preference and Culture

This paper measures the sex preferences of immigrant women in the United Kingdom by estimating the effect of family composition on birth hazard rates. International comparisons of son preference are constructed, the first known to the author. I argue that aggregate sex ratio statistics, as exploited in existing research, are inadequate for cross-sectional comparisons.

I construct a theoretical model which suggests that costs (eg, dowries) are unlikely to explain the variation in outcomes between groups. Both the model and data are supportive of a cultural, rather than economic, explanation for cross-country variation in sex preferences. Finally, women arriving in the UK at a young age appear to have less distinct tastes, also consistent with a primarily cultural explanation of parental sex preferences.

3.1 Introduction

Parental sex preferences are considered to be a primary factor in retarding development outcomes for girls [United Nations, 1994, 2000; Das Gupta et al., 2002]. However, the underlying causes of preferential behaviour are still subject to much debate, with some researchers finding a primary role for cultural and social influences [see, for example, Das Gupta et al., 2002; Das Gupta, 2005], though others suggest economic factors are the major cause [eg, Burgess and Zhuang, 2000; Qian, 2006].[1]

[1] A third strand of research highlights the potential of biological explanations for skewed sex ratios [Graffelman and Hoekstra, 2000; Norberg, 2004; Oster, 2005, 2006; Matthews et al.,

This paper assesses the fertility outcomes due to the sex preferences of immigrant women in the United Kingdom. By estimating birth hazard rates for country groups, I provide the first comparable microeconometric estimates of son preference for a range of countries. I argue that aggregate sex ratio statistics, as exploited in previous research, are an inadequate measure of sex preferences, and cross-sectional comparisons in particular are untenable.

Considerable differences in son preference are observed between groups in the sample, and income does not appear to account for these differences. In addition, a neoclassical model of fertility indicates that relative costs of boys and girls are unlikely to explain the findings. Finally, women arriving in the UK at a young age appear to have less distinct tastes. The data and theory are consistent with a primarily cultural explanation of parental sex preferences.

I identify variation in 'cultural values' by grouping women by country of origin. This assumes that, to some degree, their preferences or expectations are formed at an early point in life and retained from then on.[2] I estimate the birth hazard rates of women with fixed effects (country dummies) for each group. Then, by interacting the country dummies with the number of boys already in each family, estimates of son preference are found for each group. The coefficients on these interaction terms measure the *reduction in the hazard rate due to having an extra son*, keeping family size constant.[3]

The identifying assumption is that the *relative* costs of girls and boys are equalised across groups — likely to be the case for women living in the UK. However, the overall cost of children need not be equalised across groups. The inclusion of non-interacted country dummies accounts for differing fertility trends between the groups, including differences due to costs.

Many groups I observe *do* reduce their fertility after having sons.[4] I term

2008].

[2]Similarly to Fernández and Fogli [2005, 2006] and Fisman and Miguel [2007]. Chapter 2 considers the caveats to this approach in more detail. I make no attempt to fully capture cultural effects; 'country of origin' merely provides a source of variation in women's values.

[3]The theoretical model of Section 3.2 rationalises this approach to measuring son preferences.

[4]Almost all authors find that parents have preferences for sons when measured this way [eg, Leung, 1988; Gangadharan and Maitra, 2003; Das Gupta, 2005].

this the 'Big Sister Effect' (BSE), since more children will end up with older sisters than older brothers. If prices are equal, greater preference for sons does result in a positive Big Sister Effect since the marginal value of a future child is higher for women with daughters.

Conversely, higher costs for girls lead to a 'big *brother* effect', contrary to what is observed in the data. As my theoretical model demonstrates, if girls are more costly, women having girls are poorer, all else equal. Thus, if children are a normal good, onward fertility should be lower for the women with girls. Das Gupta et al. [2002] argue that girls are indeed more expensive due to dowries or a lesser ability to provide care in old age; this argument applies particularly in son-preferring countries such as India or China. So if the price differential is positively correlated with a son preference, my measure of the big sister effect is downward biased. Thus, given the significant differences in the BSE between groups (robust to controlling for income) cultural values are likely to play an important role — they outweigh the price effects. This story is consistent with the weaker effects observed for young arrivals to the UK, who had less time immersed in their originating country.

In summary, I observe strong levels of son preference amongst some country groups, such as Bangladesh, India, Kenya and Pakistan. Conversely, women from most rich countries (eg, Germany), show insignificant preferences or a slight preference for daughters (Australia, Canada). I contend that this preferential behaviour cannot be explained by differences in the relative prices of girls, and so must derive from differences in individuals' preferences.

Literature

To date, few studies have attempted to find explanations for the differences in parental sex preferences across countries. Indeed, to best of my knowledge, no study even measures the *levels* of son preferences accurately. This stems chiefly from a lack of appropriate data. An exception is Das Gupta et al. [2002], though this sociological study only surveys India, China and South Korea.

Most studies assessing sex preferences focus on single countries. However, as Goodkind [1999] and Hank and Kohler [2002] note, findings are not usually comparable due to the variety of methodologies used.[5] However, macro-level sex ratio statistics are readily available for many countries and regions, and these have been used by authors such as Oster [2005]; Qian [2006] and Dubuc and Coleman [2007]. Unfortunately aggregate measures are difficult to interpret in terms of parental sex preferences, since they are subject to ambiguous biases when birth-progression decisions are accounted for. This caveat is raised by Leung [1988]; the result dates back to Weiler [1959] and Goodman [1961]. In Chapter 4, I simulate the effect of observed behaviour on sex ratios, and conclude that population sex ratios are inappropriate for comparing son preferences between countries.

I follow the example of Leung [1988] and Gangadharan and Maitra [2003] in estimating the effect of existing family composition (number of sons) on birth hazard rates for different groups. Whereas they consider only a few ethnic groups, I am able to study women originating from a large number of countries. I believe my estimates are the first internationally comparable measures of son preference.

In contrast to sex preferences, fertility behaviour has received a considerably greater amount of attention.[6] The most recent addition to our understanding of worldwide fertility differences is the recent work by Fernández and Fogli [2005, 2006] on the relevance of cultural factors. These papers, like Chapter 2, use surveys of immigrant women in given country, exploiting country of origin to provide variation in cultural background. Though culture is a robustly significant predictor of influence, the estimated effects are not great, suggesting that

[5] Microeconometric techniques include surveying attitudes to sons [Hank and Kohler, 2002; Pande and Astone, 2007], birth parity progression analysis [Leung, 1988; Heckman and Walker, 1990; Gangadharan and Maitra, 2003; Das Gupta, 2005], family expenditure studies [Bhalotra and Attfield, 1998; Burgess and Zhuang, 2000]. The latter two techniques assess the effect of family composition on parental decisions over future fertility and household spending, respectively.

[6] Examples abound: Barro [1991]; Galor and Zang [1997]; Ahn and Mira [2002]; Billari and Kohler [2002]. Along with many within-country studies at the micro level, these studies have allowed fertility trends to be comparatively well understood. Fertility is a component of many mainstream macroeconomic models.

prices dominate the differences in preferences regarding quantity of children. I apply the approach of these papers to investigate the influence of cultural values on son preference.

Despite the growing theoretical literature on cultural values,[7] empirical research on this topic lags behind. Apart from the work on fertility described above, work such as Manning and Roy [2007] and Fisman and Miguel [2007] has considered the influence of cultural background on national identity and car parking habits, respectively. However, these studies consider non-costly behaviours.[8] I believe this paper is the first to explicitly consider the interaction between cultural values and the economic environment.

3.2 Theory

This paper seeks to establish the cultural influences on parental sex preferences. The model presented here has two aims: first, to outline the interaction between prices and the measurement of son preference, and second to rationalise the econometric framework used in Section 3.4.

3.2.1 Micro-founding fertility models

Fertility decisions are taken sequentially, and at any point, the sex composition of the family is known. Then, if parents have preferences over the sex of their offspring, the probability of having another child will depend on the current composition.

This concept encompasses a range of 'stopping rule' models, which suppose that parents continue to have children until some criterion is met: having a son, say. These models have been studied at length by Sheps [1963]. One general result is that, in a population with homogeneous probability of a male birth, the aggregate sex ratio converges to that probability as the population becomes

[7] Eg, Bisin and Verdier [2000, 2005]; Tabellini [2007b,a].

[8] Fisman and Miguel's diplomats are not required by law to pay parking fines.

large [Leung, 1988].[9]

Leung [1991] proposes an alternative modelling approach: parents choose, in each period, the probability that they have a child at that time. He constructs a neoclassical consumption model which is then solved as a standard dynamic programming problem.

Without differentiating between the sexes, Leung's model provides some plausible predictions. Generally, the probability of birth increases with income and decreases with the cost of children. This is borne out empirically by Heckman and Walker [1990], and reflects the findings of Galor and Weil [1996, 2000]. Children are a normal good, with fertility increasing with income when all else is equal.[10]

When girls and boys are distinguished, parents may be allowed to prefer one sex over the other. Under some conditions, if parents prefer boys, then *having had more boys reduces the probability of birth*, holding the current number of children constant [see Leung, 1991, p. 1082].

Intuitively, diminishing marginal returns for each sex imply that, at a given family size, having more boys reduces the marginal return to a further boy. Son preference entails that each boy makes a greater contribution to parental utility than each girl. Although having more boys also increases the marginal return to a further girl, the son preference means that this is more than more than offset by the decrease in the marginal return of a extra boy. Hence the marginal benefit of an extra child diminishes, and so does the optimal birth probability. Another way to see this is to observe that boys carry more weight when considering the *effective* number of children. Thus, increasing the number of boys increases the effective number of children, holding the total number of children constant. The implication of this result for the birth probability is

[9] In small populations, a male-favouring stopping rule in fact leads to higher numbers of females. However, simulated results suggest that convergence is fast [Leung, 1988]. In Chapter 4, I prove that in the case of heterogeneous probabilities, excess girls will be present also in large populations.

[10] Higher wages increase the costs of rearing children, and this effect dominates to give low fertility in rich households and economies [Wolf, 2006]. This finding does not contradict the assumption that children are normal, as in the models of Leung [1991]; Galor and Weil [1996, 2000]; Kim [2005].

testable, and underlies the sex-preference tests using the progression ratio, OLS birth intervals and hazard rates.

Leung is forced to make several unintuitive assumptions on the parental utility function in order to solve for the parents' value function algebraically. Further, since both boys and girls are perfect complements for consumption, questions concerning prices and preferences cannot be answered. His model yields few predictions that can be taken to the data.

Rather than taking a particular form for the utility, I simplify the model by eliminating the dynamic component. This does not change the economic intuition behind the model, but simplifies matters considerably. As a result, I need only assume that parental utility is additively separable in its arguments. This reduced model is analogous to the final period of Leung's model without his restrictive assumptions.[11] However, I am able to derive the effect of differing prices for boys and girls.

3.2.2 Model

I construct a one-period model in which parents maximise their expected utility with respect to the probability of having a further child (h). Initially, they have an endowment of $(B_0, G_0, Y) \in \mathbb{R}^3_+$, where B_0 and G_0 are the initial numbers of boys and girls respectively, and Y is income. Girls and boys cost $P_G \in \mathbb{R}_+$ and $P_B \in \mathbb{R}_+$ respectively.[12]

Utility comprises two additive components: a standard utility part relating to the number of children (B and G) and consumption (C), and a component representing the disutility of fecundity. This latter term is expressed as a function W of the birth probability h, as in Leung [1991] and Kim [2005].

Assumption 1. *$U\colon \mathbb{R}^3_+ \to \mathbb{R}$ and $-W(.)\colon [0,1] \to \mathbb{R}$ are bounded, twice continuously differentiable and strictly concave. U is increasing in each of its ar-*

[11]The intuition behind my model is not affected by the static formulation. I am able to construct a simulation of a dynamic extension, which confirms that my analytical results hold more generally.

[12]Following the literature, I take the existing number of children to be continuous. Note, however, that childbearing *outcomes* are discrete.

guments.

Assumption 2. *For some $h^* \in (0,1)$, $W'(h) < 0$ for all $h \in [0, h^*)$ and $W'(h) > 0$ for all $h \in (h^*, 1]$. Further, let $W' \to \infty$ as $h \nearrow 1$ and $W' \to -\infty$ as $h \searrow 0$.*

Assumption 2 follows from the notion that it is costly to set the fertility probability at extreme values. h^* represents the 'natural' fecundity rate. The latter criterion of the assumption ensures that corner solutions are ruled out.

A child is born with probability h and this will be a boy with known exogenous probability π. Therefore the final family composition is given by the following rule:

$$\begin{pmatrix} B \\ G \end{pmatrix} = \begin{pmatrix} B_0 \\ G_0 \end{pmatrix} + H \left[\begin{pmatrix} 0 \\ 1 \end{pmatrix} + \Pi \begin{pmatrix} 1 \\ -1 \end{pmatrix} \right]$$

Where $H \sim \text{Bernoulli}(h)$ is a random variable indicating childbirth, and $\Pi \sim \text{Bernoulli}(\pi)$ is a random variable (latently) indicating a boy.

To summarize, parental utility is $\tilde{U} \stackrel{def}{=} U(B, G, C) - W(h)$. The budget constraint is standard: $P_B B + P_G G + C \leq Y$, with P_B and P_G being the prices of having children of either sex. Consumption is numeraire. To ensure that expected utility is defined, a further assumption is required, providing that a child of either sex is affordable.

Assumption 3. *$Y - P_B(B_0+1) - P_G G_0 > 0$ and $Y - P_B B_0 - P_G(G_0+1)) > 0$.*

Parents' problem

As stated, parents maximise their expected utility with respect to the probability of childbirth, subject to a budget constraint. Thus, the parents' problem is:

$$h(B_0, G_0) = \arg\max_h \left\{ \begin{array}{l} \mathrm{E}[U(B, G, C) - W(h)] \\ \quad \text{s. t. } P_B B + P_G G + C \leq Y \end{array} \right\}$$

This expression may be rewritten to remove the expectation operator. By Assumption 1, the budget constraint will always hold, so this may also be substituted. Let $Y_0 \stackrel{def}{=} Y - P_B B_0 - P_G G_0$ denote initial disposable income.

$$h(B_0, G_0) = \arg\max_h \left\{ \begin{array}{l} h\pi U(B_0 + 1, G_0, Y_0 - P_B) \\ \quad + h(1-\pi)U(B_0, G_0 + 1, Y_0 - P_G) \\ \quad + (1-h)U(B_0, G_0, Y_0) \\ \quad - W(h) \end{array} \right\}$$

The first three terms within the braces are the probabilities of having a boy ($h\pi$), girl ($h(1-\pi)$), or no child ($1-h$), respectively, multiplied by the utility obtained in each case. The fourth term is the fecundity penalty.

The first order condition (FOC) is therefore

$$\begin{aligned} W'(h) = \ & \pi U(B_0 + 1, G_0, Y_0 - P_B) \\ & + (1-\pi)U(B_0, G_0 + 1, Y_0 - P_G) \\ & - U(B_0, G_0, Y_0) \end{aligned}$$

Assumption 2 provides that there will be a solution with $h \in (0,1)$. The second order condition for this to be a maximum is $-W''(h) < 0$, which follows from the concavity of $-W(.)$ (Assumption 1).

The reasoning behind this condition is simple: the marginal disutility of fecundity must equal the expected marginal utility of an extra child. W' is monotonically increasing by Assumption 1, so a higher expected marginal utility of an extra child is associated with higher fertility.

In order to derive predictions from this model, I make the use of the following separability criterion.

Assumption 4. *Let* $U(B, G, C) \stackrel{def}{=} \alpha_B u(B) + \alpha_G u(G) + u(C)$ *for some increasing, bounded, twice continuously differentiable and strictly concave function* $u\colon \mathbb{R}_+ \to \mathbb{R}$ *and* $\alpha_B, \alpha_G \in \mathbb{R}_+$.

The coefficients α_B and α_G reflect the parents' underlying preferences for sons and daughters. Under Assumption 4, the first order condition becomes:

$$\begin{aligned} W'(h) = \;& \pi\left[\alpha_B u(B_0+1) + \alpha_G u(G_0) + u(Y_0 - P_B)\right] \\ & + (1-\pi)\left[\alpha_B u(B_0) + \alpha_G u(G_0+1) + u(Y_0 - P_G)\right] \\ & - \alpha_B u(B_0) + \alpha_G u(G_0) + u(Y_0) \end{aligned}$$

The separability criterion simplifies my analysis but is not necessary for my major result, Prediction 3.

3.2.3 Model Predictions

Definition 3. *The 'Big Sister Effect' (BSE) is*

$$\Delta(B_0) \overset{def}{=} -\left.\frac{\partial h}{\partial B_0}\right|_{B_0+G_0=N_0}$$

The object of interest is Δ, which gives the marginal decrease in the probability of birth with an extra son, *for a given total number of children.*[13] This is the object that is observed when progression rates or hazard rates are compared between women having different family compositions after a given number of children. It is usually measured to be positive, with more children having older sisters than older brothers. Women having more sons are less likely to have further children, implying that the expected marginal value of an extra child is lower when a woman has more sons.

The implications of the model hence depend on the sign of Δ. Taking the derivative of the FOC with respect to B_0 results in the following:

$$\Delta(B_0) = \frac{-1}{W''(h)}\left\{\begin{aligned} & \alpha_B\pi\left[u'(B_0+1) - u'(B_0)\right] \\ & \quad - \alpha_G(1-\pi)\left[u'(N_0 - B_0 + 1) - u'(N_0 - B_0)\right] \\ & \quad\quad + \alpha_C(P_G - P_B)\left[\pi u'(Y_0 - P_B)\right. \\ & \quad\quad\quad \left. + (1-\pi)u'(Y_0 - P_G) - u'(Y_0)\right] \end{aligned}\right\} \tag{3.1}$$

[13]The Effect can also be considered as the marginal increase in the probability of birth with an extra daughter: $\Delta = \left.\frac{\partial h}{\partial G_0}\right|_{B_0+G_0=N_0}$

Thus, the sign of Δ is the opposite to the term in parentheses, since $-W(.)$ is concave. The first two terms in square brackets are negative, since $u(.)$ is concave (Assumption 4). Therefore $u'(x+1) < u'(x)$ for all $x \in \mathbb{R}_+$, and so Δ depends positively on α_B and negatively on α_G. This leads to the first two predictions of this model.

Prediction 1. *Ceteris paribus, the Big Sister Effect is higher when sons yield higher utility (higher α_B).*

Prediction 2. *Ceteris paribus, the Big Sister Effect is lower when daughters yield higher utility (higher α_G).*

The intuition in each case is simple. When a family of given size (N_0) contains fewer boys, the marginal value of a future boy $(u(B_0+1) - u(B_0))$ is higher. At the same time, there are more girls, so the marginal value of a future girl $(u(N_0 - B_0 + 1) - u(N_0 - B_0))$ is lower. The change in marginal value of a future child is thus ambiguous. However, if boys are more preferred (larger α_B), the change in marginal value of a future child becomes dominated by the boys term. That is, it becomes more positive: the Big Sister Effect increases. The situation is symmetric for girls.

Returning to Equation 3.1, it can be seen that the third term in square brackets is positive. Girls and boys have positive prices, so $u'(Y_0 - P_B), u'(Y_0 - P_G) > u'(Y_0)$. Therefore the weighted sum $\pi u'(Y_0 - P_B) + (1-\pi)u'(Y_0 - P_G)$ is greater than $u'(Y_0)$. Therefore we have:

Prediction 3. *The Big Sister Effect is* ***decreasing*** *in the girl-boy price differential ($P_G - P_B$).*

Prediction 3 says that if girls cost more than boys, the Big Sister Effect is lower than when costs are equal. When girls are more expensive, families having more girls are poorer than those of the same size but with more boys. Children are a normal good, so the richer family has higher fecundity. The Effect is *negative.*

It must be noted that this implication depends only on the formulation of the utility function with respect to consumption. Thus this result is robust to the relaxation of Assumption 4 so that $U(B, G, C) \stackrel{def}{=} u(B, G) + v(C)$ for neoclassical u and v.

The generality of the intuition behind Prediction 3 suggests that price-based explanations for son preference in fertility decisions, such as the existence of dowries, are unlikely to dominate. It requires only that children are a normal good. If large dowries are required for daughters, families already having many girls should be expected to have *fewer* further children. The opposite is seen to be true in the data, suggesting that underlying preferences may be even stronger than have previously been measured.

3.2.4 Testing the predictions

The quantity Δ, the Big Sister Effect, is the marginal decrease in fecundity with an extra son, controlling for the total number of children. This formulation provides the basis for the empirical tests used in this paper. At a given birth parity (number of children), I test for the change in the birth hazard rate with an extra son.

With several distinct groups in my dataset, son preferences can be measured for each by including interactions between group dummy variables and the number of sons. The resulting coefficient can be interpreted as a change in the hazard associated with having one more boy. Negative coefficients imply a positive Effect.

As can be seen in Equation 3.1 (page 81) and Predictions 1–3, a more positive Big Sister Effect in one group implies a combination of the following: (a) the group has a stronger taste for sons (Prediction 1); (b) a weaker taste for daughters (Prediction 2); or (c) the group faces a lower girl-boy price differential $(P_G - P_B)$ (Prediction 3), that is, girls are relatively *cheaper*.

The advantage of conducting empirical work with UK data is that childrearing costs are generally high [Wolf, 2006], and not obviously different for boys and girls. Equivalently, the girl-boy price differential is feasibly nil. This would leave inter-group differences in the BSE entirely down to variation in preferences due to different cultural values.

It is possible to argue that relative costs of raising girls and boys may not be equal amongst different cultural groups, such as immigrants from different countries. Indeed, it is usually argued that groups displaying strong son preferences face relatively higher prices for girls (positive girl-boy differential) [Das Gupta et al., 2002]. This is due to dowries or less ability to provide old-age support.[14]

However, Prediction 3 gives that the effect of a positive girl-boy price differential will be to reduce the Big Sister Effect. The implication is that under equalised prices the Effect would be even stronger. If there is a correlation between higher prices for girls and stronger innate preference for sons, cross-cultural differences as estimated later in this paper will be downward biased.

Finally, it should be noted that these price-based arguments pertain only to son preference as measured by onward fertility measures. If neonatal mortality or educational attainment differentials are used as a measure of son preference, as in Qian [2006], a positive response to the price differential would be expected, as is found in that paper: when female wages rise, girls' mortality decreases.

3.3 Data

3.3.1 The Labour Force Survey

The source of data for this study is the UK Labour Force Survey (LFS). This is a quarterly survey of households, typically recording data for some 120,000 individuals. The LFS is conducted as a rolling panel with households appearing for five consecutive quarters, or waves.

From 1996, a family relationship matrix is available for each household,

[14]Das Gupta et al. state that greater costs for girls are actually a cause of son preference, a claim which cannot be reconciled at the individual level with the neoclassical intuition presented here. Nonetheless, it is conceivable that some general equilibrium model might support this hypothesis.

allowing children to be matched to their parents. Hence, birth histories may be constructed for each woman, by sorting her children by date of birth.[15]

Amongst the LFS data are various personal attributes, including country of origin and year of arrival for immigrants. Also present are variables recording education, jobs, income, religion and ethnicity. Where a spouse or cohabiting partner lives in the household, he can be identified using the household relationship tables and his records paired up with the woman's.

In the LFS, some questions are only asked once. Since the time between first and last waves is small in terms of fertility cycles (12 months), and many of the variables of interest are constant, I take only replies from first-wave responses from quarter 1, 1996 to quarter 4, 2005. This records 1,157,739 individuals, of which 27,544 are born abroad, female and aged 16–55.

3.3.2 Summary statistics

Summary statistics are listed in Table 3.1, grouped by birth parity. Throughout this study, comparisons are restricted to women with a given number of children, or 'parity level'. This is common in the literature and negates the influence of general birth spacing effects. Women are included in the sample at all parities up to the total number of their children at the time of survey.

In order to reduce the incidence of spurious country coefficients, only countries represented by more than 100 women are included in these tables and any calculation. This does not greatly reduce the overall sample size but significantly drops the number of coefficients in the regressions. This has the added benefit of reducing computation time: including dummy variables for small country groups makes the estimation problem difficult to solve, since the objective function has a shallow curvature at the maximum.[16]

Reported ages (variable AGE) correspond to the age at entry into the rele-

[15] These birth histories are necessarily net of mortality. The oldest child younger than 16 will be considered the woman's first, ie, of parity one. Gangadharan and Maitra [2003] take the same approach, concluding that the implications are negligible [see p. 383] provided that standard errors are computed to account for arbitrary heteroskedasticity (frailty).

[16] Not all countries of origin in the LFS are identified uniquely. Three groups of countries appear in my regressions. They are:

Table 3.1: Summary statistics, women born abroad, aged 16–55 (UK Labour Force Survey 1996–2005).

(a) Parity 1

Variable	Mean	Std. Dev.	Min.	Max.	N
AGE	26.34	5.22	14	51.5	13223
AGECAME	20.29	11.03	0	55.58	13112
GRSSPAY	27.25	26.59	0.26	663.42	3915
SONS	0.53	0.5	0	1	13223
EXPOSURE	60.9	76.83	1	472	13223
PROGRESSED	0.69	0.46	0	1	13223
DEGREE	0.09	0.29	0	1	13223
FE	0.06	0.24	0	1	13223
AL	0.07	0.25	0	1	13223
GCSE	0.1	0.3	0	1	13223

(b) Parity 2

Variable	Mean	Std. Dev.	Min.	Max.	N
AGE	28.56	5	15.42	48	7704
AGECAME	19.6	10.85	0	54.25	7630
GRSSPAY	26.96	28.76	0.26	663.42	2215
SONS	1.05	0.72	0	2	7704
EXPOSURE	73.99	71.72	1	396	7704
PROGRESSED	0.45	0.5	0	1	7704
DEGREE	0.08	0.27	0	1	7704
FE	0.06	0.23	0	1	7704
AL	0.06	0.24	0	1	7704
GCSE	0.1	0.29	0	1	7704

(c) Parity 3

Variable	Mean	Std. Dev.	Min.	Max.	N
AGE	29.37	4.81	17	47.83	2343
AGECAME	20.23	9.65	0.08	54.25	2317
GRSSPAY	18.9	15.22	0.26	100	506
SONS	1.53	0.88	0	3	2343
EXPOSURE	66.3	63.18	1	333	2343
PROGRESSED	0.47	0.5	0	1	2343
DEGREE	0.04	0.19	0	1	2343
FE	0.03	0.17	0	1	2343
AL	0.04	0.19	0	1	2343
GCSE	0.06	0.24	0	1	2343

vant parity. First births occur at a mean age of 26.3 years, second births at 28.5 years and third births at 29.3 years.[17] Age at arrival in the UK (AGECAME) seems regular across the three subsamples, at about 20 years.

Education levels are slightly lower than UK averages (recorded in dummy variables DEGREE, FE, AL, and GCSE, corresponding to degree level, further education, A-Levels and GCSE equivalents respectively).[18] At parity 1, only 31% of women have GCSE or higher qualifications. At parity 2, the figure is 30% but this falls to 16% at parity 3. The UK average for women in this age range is 34%.[19]

When the woman's spouse is present in the household, I can match his details with the woman. Husbands' gross annual income at the time of survey is denoted as GRSSPAY, measured in thousands of pounds. As with education, women at parities 1 and 2 are similar (means of £27,000 per year — equal to the survey average), with parity 3 women having poorer husbands (£18,000). This variable is chosen over women's own income to avoid possible simultaneity issues between work and childbearing decisions. However, basic results do not depend on this selection, and husbands' income is more often reported.[20]

The number of sons a woman has already had is denoted by SONS. At parities 1, 2 and 3 the means are 0.53, 1.05 and 1.54, respectively. Sex ratios are slightly elevated at earlier parities: these figures correspond to 1.13, 1.11 and 1.05 boys per girl. The usually cited 'natural' ratio is 1.06. Little inference

Grp02	'Other Caribbean Commonwealth': Antigua and Barbuda, Bahamas, The, Dominica, Grenada, Solomon Islands, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines.
Grp04	'Other Africa': Benin, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Congo, Rep., Cote d'Ivoire, Djibouti, Equatorial Guinea, Eritrea, Gabon, Guinea, Guinea-Bissau, Liberia, Madagascar, Mali, Mauritania, Mozambique, Namibia, Niger, Rwanda, Sao Tome and Principe, Senegal, Togo.
Grp08	'Other Middle East': Bahrain, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, United Arab Emirates, West Bank and Gaza, Yemen.

[17] The differences between ages at birth understate birth spacing intervals for individual women, since those having more children are likely to have started younger. Indeed, mean ages at first and second births conditional on a third birth are 23.3 and 26.0 respectively.

[18] Educational dummies are derived from the LFS variable HIQUAL_D.

[19] Author's calculation from LFS.

[20] Though a woman's current husband may not be the father of (all) her children, this variable is nonetheless useful in proxying the woman's lifetime budget constraint.

can be made from these differences, however: aggregate level sex ratio statistics are subject to biases in both directions. See Appendix B.1.

Important variables for the survival analysis are PROGRESSED, indicating whether a woman continues to a higher birth parity, and EXPOSURE, the time at risk.[21] This latter figure measures the time the woman remains at the relevant parity before either having another child (progressing to the next parity), or the data are censored, ie, the survey occurs before a subsequent birth. PROGRESSED is one when exposure terminates in birth, and zero if exposure terminates at the survey.

3.3.3 Country differences

Table 3.2 lists the countries included in my regressions. For the first birth (parity 1), proportions of sons differ across country groups, ranging from 0.470 (Mauritius) to 0.584 (Zimbabwe). These figures represent sex ratios of 0.89 and 1.40 boys per girl respectively.

The sex of a given child does not depend on parental decisions, so the aggregate sex ratio at a *given parity* is not subject to biases due to sex preferences.[22] Thus the sex ratio at first birth is a measure of the biological sex ratio.

Despite seemingly wide disparities between countries in the first birth sex ratios, they are not statistically different, with an F-test yielding a p-value of 0.31. This result stands in contrast to Oster's assertion [2005, pp. 1170] that some country groups display higher biological sex ratios.

In later regressions, I split my sample by spouses' income, and by age at arrival. RICH indicates women above the median income, and YOUNG indicates arrival in the UK before the age of 10. POOR and OLD are respective complements. The number of women in each subgroup are given in the middle columns of Table 3.2. With the restriction that 100 observations are present from each

[21] Time at risk neglects ten months after a birth to account for post-partum amenorrhoea and a further pregnancy, following Leung [1988].

[22] Population sex ratios *are* subject to biases due to parental decision-making (see Appendix B.1 and Chapter 4).

Table 3.2: Summary statistics by country. YOUNG indicates arrival before age 10. RICH indicates above median income (spouse's) (at the relevant parity).

(a) Parity 1

			Subgroup sizes				PROGRESSED	
Country	N	SONS	POOR	RICH	YOUNG	OLD	0 Sons	1 Son
AUS	242	0.475	32	70	90	151	0.638	0.687
CAN	188	0.548			84	104	0.659	0.680
NZL	110	0.582			23	86	0.630	0.547
KEN	661	0.557	96	119	168	487	0.792	0.712
UGA	263	0.532			55	208	0.732	0.679
TZA	156	0.506			28	128	0.714	0.582
ZMB	122	0.574			40	81	0.635	0.657
ZWE	197	0.584			38	159	0.622	0.600
GHA	256	0.473			14	239	0.704	0.653
NGA	341	0.499			33	304	0.789	0.771
JAM	459	0.523			110	336	0.525	0.571
GRP02	119	0.538			37	80	0.618	0.516
BGD	980	0.557	170	31	116	854	0.818	0.837
IND	1976	0.551	366	289	280	1676	0.753	0.703
LKA	246	0.545	60	53	30	216	0.616	0.604
HKG	297	0.582			68	227	0.661	0.630
MYS	187	0.503			53	134	0.796	0.702
SGP	205	0.507			161	42	0.693	0.702
CYP	283	0.569			147	132	0.697	0.708
MLT	115	0.565			84	29	0.720	0.600
MUS	115	0.470			12	103	0.607	0.574
ZAF	345	0.513	41	106	92	252	0.655	0.616
GRP04	186	0.511			17	167	0.670	0.653
USA	402	0.483	30	122	65	335	0.702	0.624
PAK	1558	0.538	200	99	199	1342	0.849	0.807
CHN	138	0.514			5	132	0.463	0.507
JPN	111	0.532			2	109	0.577	0.525
PHL	247	0.555	57	45	1	246	0.500	0.599
IRN	147	0.578			7	140	0.661	0.612
GRP08	156	0.526			50	106	0.797	0.768
FRA	237	0.498	25	79	23	213	0.580	0.619
ITA	209	0.488			61	148	0.486	0.627
NLD	110	0.482			14	95	0.684	0.717
DEU	842	0.517	137	172	518	312	0.600	0.625
POL	149	0.550			3	145	0.507	0.402
PRT	178	0.500			8	169	0.528	0.494
ESP	120	0.525			13	107	0.561	0.492
YUG	113	0.496			1	112	0.667	0.714
TUR	236	0.564			13	222	0.631	0.677
SOM	221	0.507			0	221	0.826	0.857

(b) Parity 2

			Subgroup sizes				PROGRESSED		
Country	N	SONS	POOR	RICH	YOUNG	OLD	0 Sons	1 Son	2 Sons
AUS	147	1.014			57	89	0.278	0.329	0.368
CAN	121	1.017			55	66	0.324	0.255	0.278
KEN	478	1.059	56	98	131	342	0.551	0.242	0.267
UGA	176	0.983			41	135	0.383	0.259	0.386
ZWE	115	1.052			29	86	0.318	0.323	0.286
GHA	167	1.012			12	153	0.500	0.528	0.425
NGA	247	1.012			24	221	0.643	0.500	0.593
JAM	246	1.089			66	173	0.542	0.320	0.257
BGD	764	1.082	130	31	74	683	0.714	0.704	0.668
IND	1371	1.062	217	244	221	1132	0.529	0.335	0.353
LKA	140	1.043			19	121	0.132	0.207	0.318
HKG	179	1.140			43	135	0.432	0.262	0.306
MYS	131	1.015			42	89	0.306	0.246	0.395
SGP	137	1.073			113	23	0.188	0.317	0.238
CYP	193	1.119			102	88	0.325	0.333	0.365
ZAF	206	1.039			57	148	0.340	0.286	0.259
GRP04	116	0.940			11	103	0.679	0.448	0.476
USA	253	0.949			36	216	0.338	0.323	0.379
PAK	1221	1.039	125	94	151	1056	0.735	0.702	0.671
PHL	126	1.143			1	125	0.130	0.194	0.171
GRP08	115	1.043			34	81	0.630	0.607	0.500
FRA	129	1.023			15	114	0.353	0.259	0.243
ITA	111	1.036			40	71	0.321	0.294	0.156
DEU	494	1.036	62	123	312	174	0.390	0.283	0.355
TUR	147	1.116			11	135	0.400	0.287	0.333
SOM	174	1.011			0	174	0.739	0.725	0.750

(c) Parity 3

			Subgroup sizes				PROGRESSED			
Country	N	SONS	POOR	RICH	YOUNG	OLD	0 Sons	1 Son	2 Sons	3 Sons
KEN	148	1.331			39	105	0.483	0.177	0.167	0.190
NGA	123	1.472			8	114	0.588	0.422	0.319	0.357
BGD	490	1.602			39	448	0.628	0.556	0.615	0.487
IND	500	1.528	68	74	87	408	0.433	0.280	0.247	0.205
PAK	812	1.539	70	63	81	721	0.670	0.620	0.550	0.636
DEU	153	1.516			111	39	0.125	0.175	0.226	0.286
SOM	117	1.590			0	117	0.917	0.600	0.755	0.563

group in any regression, there are sufficiently many women for the coefficients to be identified on the interaction terms RICH*Country and POOR*Country. All subgroups are large enough for OLD*Country, though some YOUNG*Country terms will not show strong identification.

3.3.4 Son Preferences

Table 3.3 reports progression rates with respect to existing family composition. After two or three children, significant differences in the progression rates — the proportion of women having a further child — are observed between women with sons and women with daughters. At each parity, women having no sons are more likely to continue having children, though negligible differences are seen between women having more than one son.

However, looking more closely reveals great differences between country groups. The final columns of Table 3.2 list progression rates by current number of sons. Differences are not typically great at parity 1, but increase with birth order. For example, 92% of Somali women with three daughters go on to have another child, compared with 56% of those with three sons.

For clarity, statistics for India and Germany are collected in Table 3.4. For Indian women, the largest group in my sample, son preference is very strong at all parities. Conversely, for German women, there appears to be a reasonable preference for daughters at parity 3. Note that in these cases, the number of boys does indeed matter, not just the presence of a son (or daughter, for Germans). The following section seeks to assess these country differences more thoroughly.[23]

[23] After having two children, German women are less likely to have another if they have had one of each sex. This behaviour suggests a preference for a mixed family, as found by Hank and Kohler [2002] for German women. Here I focus on preferences for sons.

Table 3.3: Birth parity progression rates, whole sample.

	Number of Boys			
Children	0	1	2	3
1	0.70	0.69	–	–
2	0.52	0.43	0.44	–
3	0.57	0.46	0.47	0.45

Table 3.4: Birth parity progression rates, Indian and German women.

(a) India

	Number of Boys			
Children	0	1	2	3
1	0.75	0.70	–	–
2	0.53	0.34	0.35	–
3	0.44	0.27	0.27	0.20

(b) Germany

	Number of Boys			
Children	0	1	2	3
1	0.60	0.63	–	–
2	0.38	0.26	0.36	–
3	0.12	0.17	0.25	0.26

3.4 Results

3.4.1 Regression specification

This paper follows the example of Leung [1988] and Gangadharan and Maitra [2003], who study the son preferences of different ethnic groups in Malaysia and South Africa, respectively. I, however, group immigrants to the UK by country of origin. I test for parental sex preferences using a Proportional Hazards model of childbearing with the current number of boys included as a regressor, as discussed in detail in Appendix B.2. Reported coefficients relate proportional changes in hazard rates to unit changes in the independent variables. Negative values imply lower hazards at all points in time and hence longer transition and lower future fertility.

Specifically, the hazard rate for woman i at time t is $\theta_i(t) = \lambda_i \theta_0(t)$, where λ_i is the proportional hazard rate for woman i. My most basic regression takes the form $\log \lambda_i = \beta' X_i + \delta \mathrm{SONS}_i$.[24] Coefficients are estimated using the Cox partial likelihood method, with θ_0 left unspecified. A negative coefficient on the number of boys in the family, SONS, implies a preference for sons. This deduction follows the theoretical model presented in Section 3.2; women with boys are more likely to cease having children.

To account for life-cycle effects such as spacing of births, controls for the woman's age (AGE) and squared age (AGE2) are included in X_i. Since education is known to influence fertility, dummies for highest educational attainment (DEGREE, FE (further education), AL (A-Level) and GCSE) are also used, to account for different fecundity amongst differently educated women.

3.4.2 Initial Regressions

Table 3.5 Column (1) reports regressions without country fixed effects or SONS, so describes fertility only. The age coefficient is positive at parity 1, suggesting

[24] By including only women with the same number of children in any regression (restricting to a single parity), total family size is controlled for.

Table 3.5: Birth hazard rate regressions for immigrant women in the UK. Coefficients relate proportional changes in hazard rates to unit changes in the independent variables. Negative values imply lower hazards: $\theta_i(t) = \exp(\beta' X_i + \delta \mathrm{SONS}_i)\theta_0(t)$.

(a) Parity 1

	(1)		(2)	
AGE	0.140***	(0.0193)	0.141***	(0.0193)
AGE2	-0.00351***	(0.000360)	-0.00353***	(0.000360)
DEGREE	0.147***	(0.0387)	0.147***	(0.0387)
AL	-0.120***	(0.0441)	-0.123***	(0.0441)
FE	-0.0257	(0.0457)	-0.0308	(0.0457)
GCSE	-0.0469	(0.0356)	-0.0480	(0.0356)
SONS			-0.0847***	(0.0210)
Observations	13223		13223	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(b) Parity 2

	(1)		(2)		(3)	
AGE	-0.103***	(0.0361)	-0.104***	(0.0360)	-0.102***	(0.0360)
AGE2	-0.000120	(0.000648)	-0.000112	(0.000647)	-0.000160	(0.000647)
DEGREE	-0.0489	(0.0746)	-0.0553	(0.0745)	-0.0498	(0.0745)
AL	-0.375***	(0.0819)	-0.375***	(0.0819)	-0.380***	(0.0819)
FE	-0.304***	(0.0859)	-0.312***	(0.0859)	-0.314***	(0.0859)
GCSE	-0.351***	(0.0643)	-0.352***	(0.0643)	-0.351***	(0.0643)
SONS			-0.154***	(0.0242)		
ONEBOY					-0.350***	(0.0413)
TWOBOYS					-0.309***	(0.0462)
Observations	7704		7704		7704	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(c) Parity 3

	(1)		(2)		(3)	
AGE	-0.195***	(0.0648)	-0.196***	(0.0649)	-0.201***	(0.0648)
AGE2	0.00192*	(0.00109)	0.00191*	(0.00110)	0.00197*	(0.00109)
DEGREE	-0.993***	(0.261)	-1.014***	(0.261)	-1.036***	(0.261)
AL	-0.689***	(0.226)	-0.742***	(0.227)	-0.724***	(0.227)
FE	-0.519**	(0.222)	-0.556**	(0.222)	-0.562**	(0.222)
GCSE	-0.784***	(0.175)	-0.793***	(0.175)	-0.790***	(0.175)
SONS			-0.181***	(0.0355)		
ONEBOY					-0.437***	(0.0945)
TWOBOYS					-0.556***	(0.0950)
THREEBOYS					-0.599***	(0.115)
Observations	2343		2343		2343	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

that older women are more likely to have second children. However, this effect is diminishing, as the squared age coefficient is negative. The peak hazard is at 40 years. Feasibly younger women are in less of a hurry to have more children, whereas older women may not have more than one.

Various education effects are significant. Interestingly, the coefficient on DEGREE is positive and significant (1%) at parity 1, and the value of 0.147 (Table 3.5, Column (1)) implies a 16% increase in the hazard rate relative to women without high school qualifications.[25] The coefficient is negative at parity 2. Conversely, at parity 3 the coefficient is -0.993, suggesting a 63% reduction

[25] $\exp(0.147) = 1.16$.

(significant at 1%). The theoretical literature suggests that higher levels of human capital reduce fertility since the opportunity cost of childrearing is higher (eg, Galor and Weil [1996, 2000]). The evidence presented here accords with this: educated women are significantly less likely to have more than three children. However, they also have tighter birth spacing — they have a second child sooner — possibly to allow a quicker return to work.

When SONS is included, the coefficient is negative and significant at 1% for each parity. The higher the parity, the larger the effect *per son*. After a first child, the coefficient of -0.0847 implies a reduction in the birth hazard of 8% when women have a son instead of a daughter. After three boys, the hazard is reduced by 42% relative to a woman with three daughters.[26] This suggests a high degree of preference for sons amongst the sample overall (see Table 3.2, page 89).

A strong preference for sons is also seen when dummies for family composition (ONEBOY, TWOBOYS and THREEBOYS) are included in the model (Table 3.5, panels (a) and (b), column (3)). After two children, having one son reduces the fertility hazard by 30%, relative to a woman with no sons. Women with two sons show only a reduction of 27%, suggesting some taste for a mixed family. After three children fertility reduces with each son, from 35% to 45% compared to a woman with three daughters. The dummies are significant at 1% in each case and are not (jointly) significantly different, implying that, for the sample as a whole, having *one* son is more important than the number of sons. However, Table 3.4 suggests this taste varies considerably by country. Nonetheless, throughout this paper all results presented are robust to using presence of a son as a regressor instead of the number of sons (variable SONS).

[26] $\exp(3 * -0.181) = 0.58$.

3.4.3 Country differences

Table 3.6 reports relative birth hazard rates for women at parities 1–3 with country fixed effects.[27] The regression specification is

$$\log \lambda_i = \beta' X_i + \sum_c \gamma_c d_{ic} + \delta \mathrm{SONS}_i + \sum_c \delta_c \mathrm{SONS}_i * d_{ic}$$

d_{ic} indicates that woman i comes from country c. Column 1 in each panel includes only country dummies; since the Cox model reports hazard rates relative to an unspecified baseline hazard, one country dummy variable must be omitted. For ease of comparison, I omit the same country in each specification: India, the largest group. Country coefficients thus represent differences in fecundity between each group and India. In line with Chapter 2 and Fernández and Fogli [2005, 2006], these dummies are generally significant, indicating that women of different origins indeed have differing fertility objectives.

Including SONS and Country*SONS interaction terms (Table 3.6, Column (2)) allows son preferences to be identified for each group. The coefficient on SONS itself measures the degree of son preference of Indian women, which is significant at 1% in each regression. The effect is large: having three sons reduces the future birth hazard rate by 67% relative to having three daughters.

Of the six largest country groups,[28] Bangladeshi women show significantly less son preference at all parities (Bangladesh dummy is positive), and Pakistan, Germany and Somalia show less in two of the three regressions.[29] For every country the signs are the same at each parity. Finally, whilst Kenyan women do not show preferences significantly different to Indian women, their preferences *are* significantly different from zero at all parities (5% or better). After three sons, fecundity is just a quarter of that after three daughters.

[27] Only selected coefficients are reported in Tables 3.6–3.9. Full regressions are given in Appendix B.3, Tables B.1–B.12 (pp. 156).

[28] Kenya, Nigeria, Bangladesh, Pakistan, Germany and Somalia appear in each regression.

[29] Dubuc and Coleman [2007] suggest that son preferences amongst Indian women in the UK are stronger than those for Pakistanis since they have fewer children overall, yet still want to have a son. This hypothesis is consistent with my results, since the Pakistan coefficient is positive (significant at 1%) in each regression, as is SONS*Pakistan (10% significance for parities 2 and 3).

Table 3.6: Birth hazard rate regressions for immigrant women in the UK with country fixed effects and country son preference effects. Selected coefficients only; full results in appendix, Tables B.1–B.3 (pp. 156).

(a) Parity 1

	(1)		(2)	
AGE	0.164***	(0.0197)	0.165***	(0.0197)
AGE2	-0.00385***	(0.000366)	-0.00388***	(0.000367)
DEGREE	0.181***	(0.0396)	0.174***	(0.0397)
AL	-0.0514	(0.0449)	-0.0526	(0.0450)
FE	0.0427	(0.0470)	0.0372	(0.0471)
GCSE	0.0489	(0.0369)	0.0456	(0.0370)
Kenya	0.0309	(0.0526)	0.0445	(0.0764)
Nigeria	0.247***	(0.0674)	0.149	(0.0948)
Bangladesh	0.386***	(0.0446)	0.268***	(0.0662)
Pakistan	0.438***	(0.0386)	0.386***	(0.0562)
Germany	-0.117**	(0.0520)	-0.308***	(0.0753)
Somalia	0.628***	(0.0783)	0.333***	(0.113)
SONS			-0.261***	(0.0530)
SONS*Kenya			-0.0214	(0.105)
SONS*Nigeria			0.169	(0.134)
SONS*Bangladesh			0.209**	(0.0884)
SONS*Pakistan			0.0875	(0.0770)
SONS*Germany			0.348***	(0.103)
SONS*Somalia			0.568***	(0.156)
Observations	13223		13223	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(b) Parity 2

	(1)		(2)	
AGE	-0.0140	(0.0371)	-0.00997	(0.0372)
AGE2	-0.00141**	(0.000664)	-0.00149**	(0.000665)
DEGREE	0.0739	(0.0765)	0.0583	(0.0766)
AL	-0.198**	(0.0834)	-0.214**	(0.0836)
FE	-0.146*	(0.0883)	-0.174**	(0.0886)
GCSE	-0.188***	(0.0660)	-0.193***	(0.0662)
Kenya	-0.0527	(0.0931)	0.242	(0.149)
Nigeria	0.792***	(0.0974)	0.721***	(0.173)
Bangladesh	0.857***	(0.0629)	0.677***	(0.109)
Pakistan	0.922***	(0.0560)	0.783***	(0.0960)
Germany	0.0185	(0.0906)	-0.148	(0.155)
Somalia	1.162***	(0.0996)	1.069***	(0.176)
SONS			-0.280***	(0.0634)
SONS*Kenya			-0.303**	(0.133)
SONS*Nigeria			0.0798	(0.144)
SONS*Bangladesh			0.183**	(0.0882)
SONS*Pakistan			0.141*	(0.0796)
SONS*Germany			0.168	(0.125)
SONS*Somalia			0.0982	(0.145)
Observations	7704		7704	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(c) Parity 3

	(1)		(2)	
AGE	-0.110*	(0.0652)	-0.105	(0.0654)
AGE2	0.000569	(0.00110)	0.000473	(0.00110)
DEGREE	-0.681**	(0.265)	-0.695***	(0.266)
AL	-0.436*	(0.230)	-0.486**	(0.230)
FE	-0.304	(0.229)	-0.317	(0.230)
GCSE	-0.497***	(0.178)	-0.494***	(0.178)
Kenya	0.0755	(0.192)	0.0848	(0.302)
Nigeria	0.759***	(0.172)	0.527*	(0.312)
Bangladesh	0.907***	(0.105)	0.628***	(0.204)
Pakistan	1.021***	(0.0972)	0.742***	(0.186)
Germany	-0.0502	(0.201)	-0.817*	(0.442)
Somalia	1.453***	(0.142)	1.045***	(0.288)
SONS			-0.369***	(0.100)
SONS*Kenya			-0.0931	(0.215)
SONS*Nigeria			0.148	(0.197)
SONS*Bangladesh			0.205*	(0.122)
SONS*Pakistan			0.198*	(0.114)
SONS*Germany			0.504**	(0.238)
SONS*Somalia			0.282*	(0.169)
Observations	2343		2343	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The full tables B.1–B.3 show significant differences from India for 12, 7 and 4 countries at parities 1, 2 and 3, respectively (out of 39, 25 and 6 groups). Of the remainder at parity 1, five show preferences different to zero (including Kenya, as discussed). The SONS*Country interactions are jointly significant at 1% for the first two regressions (χ^2 test).

In an alternative specification, I control for family composition with dummies indicating the number of sons (Appendix B.3, Tables B.4 and B.5, pp. 159).[30] Of countries showing significant preferences, two patterns emerge: similar magnitude coefficients on each of the dummies suggests a preference for *a* son. Conversely, differing values implies women care about the *number* of sons, or want a mix of sexes. For example, Kenya and Pakistan show preferences for having a single boy at parities 2 and 3, with significant coefficients on all dummies. Interestingly, these country groups show lowest birth hazards for women with two sons and a daughter. By contrast, at parity 3, Indian and Bangladeshi women show hazard rates declining with the number of sons, suggesting they want as many sons as possible. German woman are the opposite, with a preference for daughters, though they show a significant taste for mixed families after the second child. Australian women also show a significant taste for having a daughter; after two boys they are two-and-a-half times more likely to have another child than after two girls.[31]

The varying degrees of observed son preference amongst the groups suggests that individuals' origins — and hence, cultural values — play a definitive role in shaping preferences over family composition. In the following experiments I attempt to rule out some alternative explanations.

[30]In order to compare preferences within country groups, I omit non-interacted composition dummies. Coefficients therefore measure the hazard rates *relative to a compatriot with no sons.* (In all other specifications, coefficients measure hazards relative to an Indian woman, controlling for the number of sons. This presentation emphasises differences between countries.)

[31]$\exp(0.918) = 2.50$.

3.4.4 Income

Possibly, income could explain differences in son preference between groups. Perhaps poor women of all groups have preferences for sons, and the previous regressions are explained by differences in earnings. To exclude such stories, I construct regressions with income dummies for each country. As discussed in Section 3.3, I use husband's income. This is more often reported than women's income and raises fewer endogeneity concerns: female earnings are likely co-related with childrearing decisions. In any case, the major results do not depend on this choice of regressor.

My regression model is:

$$\begin{aligned}\log \lambda_i = \; & \beta' X_i + \sum_c \gamma_c^{\mathrm{P}} \mathrm{POOR}_i * d_{ic} + \gamma \mathrm{RICH}_i + \sum_c \gamma_c^{\mathrm{R}} \mathrm{RICH}_i * d_{ic} \\ & + \delta^{\mathrm{P}} \mathrm{SONS}_i * \mathrm{POOR}_i + \sum_c \delta_c^{\mathrm{P}} \mathrm{SONS}_i * \mathrm{POOR}_i * d_{ic} \\ & + \delta^{\mathrm{R}} \mathrm{SONS}_i * \mathrm{RICH}_i + \sum_c \delta_c^{\mathrm{R}} \mathrm{SONS}_i * \mathrm{RICH}_i * d_{ic}\end{aligned}$$

RICH indicates above-median income, and POOR is its complement; the median is taken at the *sample* level, not per country. This specification, including POOR interaction terms as well as RICH, allows son preference to be compared *at each income level.* India dummies are omitted, as before. I am less concerned with differences between the rich and poor of any country than in comparing, say, rich Germans with rich Indians. With my chosen specification, the coefficient on SONS*RICH*Germany measures exactly this.

Table 3.7 gives selected coefficients. In Column(1), only country dummies are included. The coefficient on RICH is negative and significant at Parity 1, implying that birth hazards are generally lower for richer women. This is not predicted in the literature, as fertility is usually found to increase in male earnings (see also the theoretical model of Galor and Weil [1996]). However it is very likely that assortative matching explains this finding, since educational dummies become insignificant in all of these regressions. The explanation is that

Table 3.7: Birth hazard rate regressions with country fixed effects and country son preference effects, split by income at sample median. Selected coefficients only; full results in Tables B.6–B.7 (pp. 162).

(a) Parity 1

	(1)		(2)	
AGE	0.280***	(0.0483)	0.286***	(0.0485)
AGE2	-0.00574***	(0.000887)	-0.00583***	(0.000890)
DEGREE	0.0885	(0.0848)	0.0880	(0.0854)
AL	-0.0341	(0.104)	-0.0305	(0.105)
FE	0.135	(0.115)	0.147	(0.116)
GCSE	-0.0190	(0.0840)	-0.0175	(0.0843)
POOR*Kenya	-0.177	(0.132)	-0.208	(0.204)
POOR*Bangladesh	0.663***	(0.105)	0.450***	(0.148)
POOR*Pakistan	0.397***	(0.0992)	0.226	(0.139)
POOR*Germany	-0.330***	(0.125)	-0.428**	(0.172)
RICH	-0.161*	(0.0932)	-0.388***	(0.137)
RICH*Kenya	0.0745	(0.129)	0.192	(0.185)
RICH*Bangladesh	0.184	(0.221)	0.186	(0.309)
RICH*Pakistan	0.387***	(0.132)	0.661***	(0.194)
RICH*Germany	0.0530	(0.119)	0.0330	(0.173)
SONS*POOR			-0.369***	(0.118)
SONS*POOR*Kenya			0.106	(0.267)
SONS*POOR*Bangladesh			0.416**	(0.202)
SONS*POOR*Pakistan			0.327*	(0.197)
SONS*POOR*Germany			0.167	(0.249)
SONS*RICH			0.0540	(0.143)
SONS*RICH*Kenya			-0.228	(0.258)
SONS*RICH*Bangladesh			0.00685	(0.442)
SONS*RICH*Pakistan			-0.473*	(0.264)
SONS*RICH*Germany			0.0432	(0.236)
Observations	2399		2399	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(b) Parity 2

	(1)		(2)	
AGE	-0.0789	(0.0980)	-0.0921	(0.0982)
AGE2	-0.000190	(0.00175)	0.00000580	(0.00175)
DEGREE	0.269	(0.200)	0.285	(0.202)
AL	-0.247	(0.224)	-0.287	(0.225)
FE	0.0876	(0.239)	0.0523	(0.242)
GCSE	-0.0348	(0.159)	-0.0162	(0.159)
POOR*Kenya	-0.0479	(0.260)	0.495	(0.453)
POOR*Bangladesh	0.913***	(0.161)	0.943***	(0.261)
POOR*Pakistan	1.098***	(0.156)	0.750***	(0.267)
POOR*Germany	0.251	(0.228)	0.540	(0.354)
RICH	-0.265	(0.165)	-0.0825	(0.284)
RICH*Kenya	0.0970	(0.227)	0.376	(0.367)
RICH*Bangladesh	0.913***	(0.261)	0.593	(0.457)
RICH*Pakistan	1.123***	(0.174)	0.912***	(0.290)
RICH*Germany	0.323	(0.206)	0.202	(0.354)
SONS*POOR			-0.225	(0.164)
SONS*POOR*Kenya			-0.552	(0.429)
SONS*POOR*Bangladesh			-0.0324	(0.224)
SONS*POOR*Pakistan			0.347	(0.219)
SONS*POOR*Germany			-0.334	(0.327)
SONS*RICH			-0.400**	(0.182)
SONS*RICH*Kenya			-0.295	(0.340)
SONS*RICH*Bangladesh			0.308	(0.418)
SONS*RICH*Pakistan			0.197	(0.252)
SONS*RICH*Germany			0.126	(0.303)
Observations	1180		1180	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.8: Birth hazard rate regressions with country fixed effects and country son preference effects, split by income at (1) first quartile, (2) sample median, and (3) third quartile. Selected coefficients only; full results in Tables B.8 and B.9 (pp. 164).

(a) Parity 1

	(1)		(2)		(3)	
SONS*POOR	-0.308*	(0.172)	-0.369***	(0.118)	-0.307***	(0.0990)
SONS*POOR*Kenya	0.582	(0.399)	0.106	(0.267)	-0.0367	(0.208)
SONS*POOR*Bangladesh	0.367	(0.245)	0.416**	(0.202)	0.334*	(0.185)
SONS*POOR*Pakistan	0.302	(0.265)	0.327*	(0.197)	0.261	(0.168)
SONS*POOR*Germany	0.0398	(0.394)	0.167	(0.249)	0.170	(0.193)
SONS*RICH	-0.160	(0.107)	0.0540	(0.143)	0.211	(0.230)
SONS*RICH*Kenya	-0.189	(0.208)	-0.228	(0.258)	-0.0170	(0.398)
SONS*RICH*Bangladesh	0.167	(0.335)	0.00685	(0.442)	0.598	(0.748)
SONS*RICH*Pakistan	-0.147	(0.199)	-0.473*	(0.264)	-1.247***	(0.470)
SONS*RICH*Germany	0.174	(0.189)	0.0432	(0.236)	0.0553	(0.362)
Observations	2399		2399		2399	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(b) Parity 2

	(1)		(2)		(3)	
SONS*POOR	-0.370*	(0.221)	-0.225	(0.164)	-0.292**	(0.135)
SONS*POOR*Kenya	0.501	(0.728)	-0.552	(0.429)	-0.180	(0.305)
SONS*POOR*Bangladesh	0.106	(0.271)	-0.0324	(0.224)	0.0222	(0.202)
SONS*POOR*Pakistan	0.373	(0.298)	0.347	(0.219)	0.294	(0.183)
SONS*POOR*Germany	-0.868	(0.744)	-0.334	(0.327)	-0.225	(0.283)
SONS*RICH	-0.319**	(0.145)	-0.400**	(0.182)	-0.388	(0.285)
SONS*RICH*Kenya	-0.533*	(0.291)	-0.295	(0.340)	-0.923*	(0.527)
SONS*RICH*Bangladesh	0.217	(0.344)	0.308	(0.418)	0.492	(0.566)
SONS*RICH*Pakistan	0.312	(0.197)	0.197	(0.252)	0.330	(0.386)
SONS*RICH*Germany	-0.0364	(0.242)	0.126	(0.303)	0.110	(0.389)
Observations	1180		1180		1180	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

higher skilled men are both wealthier and have higher skilled partners; while their wealth relaxes the household budget constraint allowing for more children, the increased opportunity cost of childrearing time more than offsets this. The empirical story is unclear in larger families: the RICH coefficient becomes insignificant at parity 2.[32] The educational dummies remain insignificant, and the pattern is robust to using the first and third quartiles as split points in place of median income (see Table 3.8).

Some significant differences between the country groups are seen, notably Pakistan, different from India amongst both income groups at parity 1 (10%), though not many other groups show significant coefficients. The small sample size may explain this. However, the son preference coefficients are jointly significant to zero for the poor groups at parity 1 ($p = 0.052$, χ^2 test), and for the rich group at parity 2 ($p = 0.066$).[33]

Whilst this analysis is not conclusive, the evidence suggests that sex preference behaviour is significantly different across country groups, regardless of income. That is, at a given income, behaviours are comparatively similar within groups relative to other groups, and this is robust to the choice of the income group split, indicating that cultural values shared by the group may dominate price-side (ie, environmental) factors when it comes to parental sex preferences.

3.4.5 Time of arrival

The literature on cultural transmission (reviewed in Chapter 1) suggests that, if cultural values *are* a dominant cause of son-preferring behaviour, then these values must have been picked up — learnt — early in life. My identification strategy depends on the assumption that women from different countries have picked up different values before coming to the UK. Feasibly, a longer exposure to the prevailing culture in a woman's country of origin would lead her to hold

[32]Only Indian and Pakistani women would be included at parity 3 so I restrict attention to parities 1 and 2.

[33]Only the Pakistani dummy appears at parity 3; this coefficient is significant at 5% as described ($p = 0.043$).

those values more strongly. Here, I test whether arrival in Britain at a young age results in weaker son preferences.

The LFS contains data the years of arrival in the UK for immigrants. This allows me to perform an analogue of the previous exercise, splitting the sample by age at arrival (AGECAME). I use this to define an indicator variable YOUNG, equal to one for women arriving before a certain age, zero otherwise, with OLD being the complement. YOUNG*Country and OLD*Country interactions are included to capture fecundity effects associated with arriving young/arriving later for each country group, along with SONS interactions to capture sex preferences. These regressions are found in Table 3.9.[34]

In each panel, Column (1) reports regressions with the split point at ten years. Women arriving before their tenth birthday show insignificant son preference. Of the largest five country groups,[35] no SONS*YOUNG*Country coefficient is significant except for Nigeria at parity 2, implying that son preferring behaviour is not particularly different across these groups. The YOUNG interaction terms show significance jointly for only parity 2, at 10%.

Conversely, women arriving after the age of ten *do* show significant son preference at each parity. Moreover, differences between groups are significant. Bangladeshi women show less son preference at all three parities, and Pakistani and German women less for two of the three. For each country all signs match except for Nigeria at parity 2, and the coefficients are jointly significant at at least 5% in each regression.

For SONS*OLD*Country coefficients, the signs are usually positive except for Kenya (usually negative), suggesting that some countries consistently exhibit son preference. Conversely, the signs for SONS*YOUNG*Country coefficients

[34]The regression equation is

$$\begin{aligned}\log \lambda_i = \; & \beta' X_i + \sum_c \gamma_c^{\mathrm{O}} \mathrm{OLD}_i * d_{ic} + \gamma \mathrm{YOUNG}_i + \sum_c \gamma_c^{\mathrm{Y}} \mathrm{YOUNG}_i * d_{ic} \\ & + \delta^{\mathrm{O}} \mathrm{SONS}_i * \mathrm{OLD}_i + \sum_c \delta_c^{\mathrm{O}} \mathrm{SONS}_i * \mathrm{OLD}_i * d_{ic} \\ & + \delta^{\mathrm{Y}} \mathrm{SONS}_i * \mathrm{YOUNG}_i + \sum_c \delta_c^{\mathrm{Y}} \mathrm{SONS}_i * \mathrm{YOUNG}_i * d_{ic}\end{aligned}$$

[35]Kenya, Nigeria, Bangladesh, Pakistan and Germany appear in each regression.

Table 3.9: Birth hazard rate regressions with country fixed effects and country son preference effects, split by age on immigration to the UK. Column (1) split at age 10, Column (2) at age 15. Selected coefficients only; full results in Tables B.10–B.12 (pp. 162).

(a) Parity 1

	(1)		(2)	
SONS*OLD	-0.285***	(0.0583)	-0.250***	(0.0609)
SONS*OLD*Kenya	-0.0168	(0.121)	-0.0379	(0.140)
SONS*OLD*Nigeria	0.174	(0.142)	0.141	(0.145)
SONS*OLD*Bangladesh	0.233**	(0.0952)	0.167*	(0.101)
SONS*OLD*Pakistan	0.132	(0.0838)	0.0784	(0.0874)
SONS*OLD*Germany	0.372**	(0.159)	0.348**	(0.174)
SONS*YOUNG	-0.101	(0.133)	-0.294***	(0.110)
SONS*YOUNG*Kenya	-0.0794	(0.218)	0.0735	(0.171)
SONS*YOUNG*Nigeria	-0.0870	(0.424)	0.123	(0.361)
SONS*YOUNG*Bangladesh	0.0493	(0.254)	0.360*	(0.189)
SONS*YOUNG*Pakistan	-0.180	(0.205)	0.134	(0.168)
SONS*YOUNG*Germany	0.171	(0.173)	0.360**	(0.153)
Observations	13112		13112	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(b) Parity 2

	(1)		(2)	
SONS*OLD	-0.273***	(0.0704)	-0.253***	(0.0733)
SONS*OLD*Kenya	-0.282*	(0.154)	-0.476**	(0.189)
SONS*OLD*Nigeria	-0.0183	(0.152)	-0.0110	(0.155)
SONS*OLD*Bangladesh	0.171*	(0.0962)	0.129	(0.100)
SONS*OLD*Pakistan	0.147*	(0.0872)	0.146	(0.0906)
SONS*OLD*Germany	0.0613	(0.218)	0.0150	(0.238)
SONS*YOUNG	-0.217	(0.149)	-0.305**	(0.130)
SONS*YOUNG*Kenya	-0.367	(0.284)	-0.0876	(0.209)
SONS*YOUNG*Nigeria	1.153**	(0.587)	0.594	(0.457)
SONS*YOUNG*Bangladesh	0.127	(0.235)	0.298	(0.190)
SONS*YOUNG*Pakistan	-0.0392	(0.210)	0.00775	(0.176)
SONS*YOUNG*Germany	0.146	(0.197)	0.237	(0.180)
Observations	7630		7630	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(c) Parity 3

	(1)		(2)	
SONS*OLD	-0.411***	(0.110)	-0.368***	(0.115)
SONS*OLD*Kenya	-0.120	(0.248)	-0.263	(0.295)
SONS*OLD*Nigeria	0.194	(0.200)	0.140	(0.203)
SONS*OLD*Bangladesh	0.243*	(0.132)	0.207	(0.139)
SONS*OLD*Pakistan	0.267**	(0.125)	0.218*	(0.131)
SONS*OLD*Germany	1.219***	(0.415)	1.071**	(0.464)
SONS*YOUNG	-0.130	(0.255)	-0.383*	(0.209)
SONS*YOUNG*Kenya	-0.172	(0.500)	0.0762	(0.353)
SONS*YOUNG*Nigeria	-0.656	.	2.277	(1.839)
SONS*YOUNG*Bangladesh	-0.00885	(0.395)	0.189	(0.270)
SONS*YOUNG*Pakistan	-0.169	(0.297)	0.181	(0.242)
SONS*YOUNG*Germany	-0.00803	(0.384)	0.357	(0.337)
Observations	2317		2317	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

are mixed. Therefore, though these lower significance levels may result from reduced power due to small group sizes, the data is consistent with less variation in son preference for younger arrivals.

Column (2) in each panel moves the age split point to fifteen. Son preference becomes significant for young arrivals in all three regressions. Since the number of these young arrivals is only increased by 35% (parities 1 and 2), the extra power of the tests does not solely explain the higher significance. The OLD*SONS coefficients remain significant at 1%, but are reduced in each case. Also, the SONS*YOUNG coefficients are larger in magnitude for all parities. At parity one, the number of significant SONS*YOUNG*Country coefficients rises from three to six (see Table B.10). Some of the OLD interactions become insignificant, and the joint p-value of the SONS*OLD*County coefficients at parity 3 increases to 0.11. These findings suggest that women arriving when younger display less son preference, and that the 10–15 age range may be a cut-off point. This range coincides roughly with high school education in the UK. Girls arriving before ten could be expected to receive at least six years of education in Britain and hence receive considerable exposure to prevailing values.

Overall, the results presented here can be taken as marginal evidence that immersion in another country diminishes the cultural influence of individuals' countries of origin. It is likely that arriving in a foreign environment at a young age in fact exposes individuals more strongly to the prevailing culture, particularly though education. The evidence is consistent with this story.

3.5 Conclusion

Previous work has not provided clear explanation for the causes of son preference in many countries worldwide. The evidence presented in here is supportive of a cultural explanation for cross-country differences in sex preferences. Conversely, the theoretical results derived from my model imply that price-side effects are an unlikely explanation for the variation in parental behaviour observed in my sample. In any case, this paper provides the first estimates of underlying son preferences that can be compared across countries. Aggregate sex ratios are not suitable for this purpose.

Sample selection biases may be of some concern. Aside from selection into the survey itself, the decision to emigrate to the UK may differ between groups studies. For example, a Dutch woman may have very different reasons than an Iranian. However, selection effects could conceivably reinforce the results: if women are more likely to emigrate to Britain if they are 'culturally similar', then migrants might display less variation than a representative sample of foreign women.

Whilst son preference has the attention of policy-makers, there is currently no consensus about potential policy interventions. That will remain the case until a coherent theory of parental sex preferences is established. The present work seeks to advance the debate by highlighting the importance of cultural factors.

Chapter 4

Son preference and sex ratios: How many 'missing women' are missing?

When parents prefer sons, heterogeneity in the probability of having sons can lead to excess girls. I argue that this may lead to under-counting the number of 'missing women'. First, I prove that relaxing assumptions on population homogeneity means that son preference can lead to skewed sex ratios. Second, I measure significant heterogeneity in the sex ratio at birth: ten percent of women have probabilities of having boys that are less than 42% or more than 61%. Third, existing work measures significant differences in parents' son preferences between countries. I exploit these differences in parental behaviour to simulate sex ratios in the presence of heterogeneity. I measure that parents' son preferences account for 1.5% of differences between sex ratios worldwide (significant at 10%). The presence of this effect may imply that sex ratios are more biased than previously estimated, since previous comparisons use benchmarks that already contain too few girls. Therefore there may be more women missing due to discrimination than we thought.

4.1 Introduction

Since recognition of the 'missing women' problem by Sen [1989], several explanations have been made for the high proportion of boys in a number of countries.

Recent work has highlighted biological factors as a possible cause of differences in sex ratios (the number of boys per girl), notably the Hepatitis-B virus [Oster, 2005]. Conversely, a majority of authors conclude that social norms are the proximate cause, as these lead to lower survival rates for girls.[1] To date, however, the effect of son preference in fertility decisions has been neglected, despite evidence that parents' sex preferences are mainly determined by cultural background (see Chapter 3).

This paper estimates the effect of parental fertility decisions on sex ratios worldwide when women are heterogeneous in the probability of bearing sons. If women in a population have boys with differing probabilities, then son-preferring fertility behaviour will lead to excess girls. The extra girls borne by women that are more likely to have girls outnumber the reduction of girls borne to women likely to have boys. Previous theoretical work [Weiler, 1959; Goodman, 1961; Yamaguchi, 1989] has recognised this phenomenon in principle; I know of no attempt to quantify the effect in practice.

A growing body of biological research suggests that women are indeed heterogeneous in the probability with which they have sons.[2,3] The majority of demographic work has considered the first-order implications of such phenomena in affecting the aggregate sex ratio.[4] However, many of these mechanisms also imply that populations will be heterogeneous; they have a second-order effect. This paper focusses on the implications of that heterogeneity on the sex

[1]Proponents of cultural explanations include Sen [1992]; Das Gupta et al. [2002]; Arokiasamy [2004]; Das Gupta [2005]; Qian [2006]; Chamarbagwala and Ranger [2006] and Lin et al. [2008].

[2]Graffelman and Hoekstra [2000] outline some of the possible causes:

> [M]ore than 30 factors ... could affect the sex ratio. Among these are family size, age of the parents, age difference of the parents, birth order of the child, race, incest, blood groups, season, frequency of sexual intercourse, socioeconomic status of the parents, legality of the child, climatological conditions, profession of the parents, pollution, use of the contraceptive pill, nutrition, hormonal treatments, type and timing of fertilization, urbanity, several diseases, handedness of the parents, stress.

[3]The existence of many of these phenomena can be explained in an evolutionary context: the aim is to maximise the reproductive fitness of one's offspring. For example, beautiful people are relatively more likely to have daughters since good looks confer a greater advantage to girls than to boys [Miller and Kanazawa, 2007].

[4]Eg, Graffelman and Hoekstra [2000]; Oster [2005].

ratio in the presence of a cultural preference for boys.

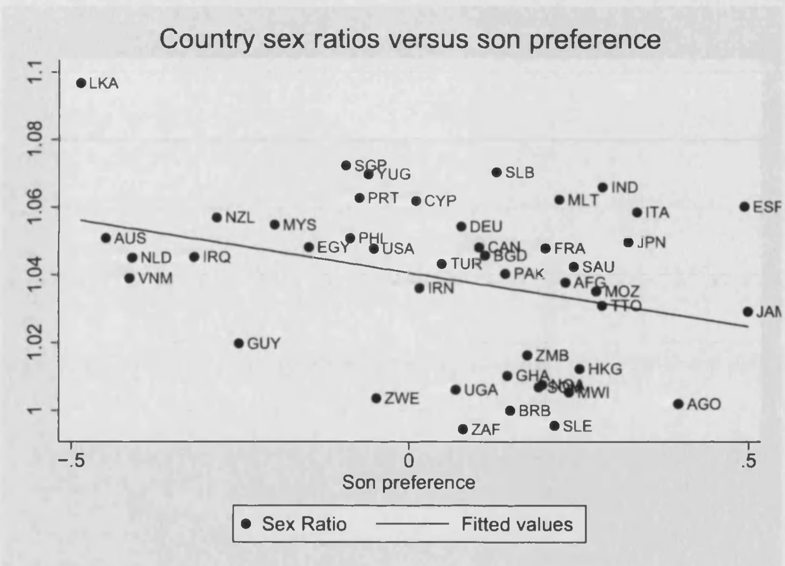
Like previous authors [reviewed in James, 2000], I find significant heterogeneity in the probability of having a son, suggesting that ten percent of women have boys with probabilities outside the interval [0.42, 0.61]. Accounting for parental behaviour, this heterogeneity leads to sex ratios in the range 1.043–1.051, explaining 1.5% of differences worldwide (significant at the 10% level). As the theory suggests, son preference is associated with excess girls. Thus, since previous estimates of missing women have used comparisons without accounting for these excess girls at birth, the number of women missing due to explicit discrimination may have been under-counted.

Chapter 3 provides theoretical and empirical evidence that parents' preference for sons is mainly driven by cultural factors. I provide uniquely comparable estimates of son preference between countries, based on the behaviour of foreign-born women in the UK. Figure 4.1 plots son preference after two children versus sex ratios in those women's countries of origin. The correlation is significant and negative (and robust to omission of outliers). This suggests that culturally-driven son preference may lead to a reduction in the sex ratio.

Consider an extreme example: women continue to have children until they have a son. If boys and girls are equally likely for every women, the sex ratio in aggregate will be 1 [Weiler, 1959; Goodman, 1961; Sheps, 1963]. However, if half of women only ever have boys and half only girls, the former will obtain their son at the first birth. The latter will continue to have girls until some maximum family size is reached, and *girls will outnumber boys.* I prove a more general form of this result in Section 4.2. The phenomenon relies on the existence of heterogeneity in the probability of a son.

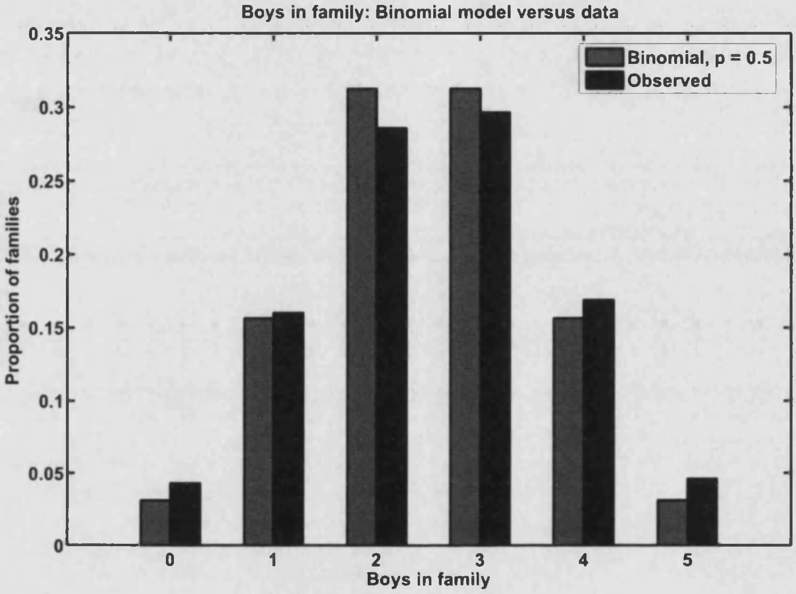
Figure 4.2 suggests that within-population heterogeneity of probability of having a son is indeed a possibility. In Section 4.3, I provide estimates of such heterogeneity, and find homogeneity is rejected at the 0.01% level. I derive an estimator based on modelling childbirth as a limited dependent variable problem with random effects. A woman i has an unobserved factor X_i, and child j is a

Figure 4.1: Son preference of immigrant women versus sex ratios in their countries of origin. Son preference (after two children) is estimated from a birth-hazard regression for foreign-born women in the UK grouped by country of origin. Child sex ratio is derived from World Development Indicators (1997), under-15 male population divided by under-15 female population. Correlation is significant at 5% (robust to inclusion/exclusion of outliers).[a]



[a]Son preference is $-\delta_c$ from the Cox Proportional Hazards regression $\log \lambda_i = \beta' X_i + \sum_c \gamma_c d_{ic} + \sum_c \delta_c \mathrm{SONS}_i * d_{ic}$, where woman i from country c has birth hazard $\theta_{ic}(t) = \lambda_{ic}\theta_0(t)$ relative to the (unspecified) baseline $\theta_0(t)$. See Section 3.4, page 92. Countries with son preference coefficients absolutely greater than 0.5 are omitted here for clarity.

Figure 4.2: Family composition (5 children) under a binomial model ($B \sim$ Bernoulli(0.5)), versus actual data (see Table 4.1). The data show more dispersion than predicted by the model with homogeneous probabilities of having sons.



boy if $X_i + \epsilon_{ij} > 0$, with ϵ_{ij} being drawn from an independent standard normal distribution. Thus, woman i gives birth to boys with probability $\Phi(X_i)$.[5] By assuming a distributional form for X, parameters may be obtained by maximum likelihood estimation. I find significant heterogeneity amongst a sample of 116,513 British-born women: 10% of women have boys with probabilities outside [0.42, 0.61]. My measurements are closely in line with previous work, despite the difference in estimation technique.

In Section 4.4, I simulate the effect of son preferences on aggregate sex ratios, using the estimates for heterogeneity derived in Section 4.3. To obtain preferences for sons, I estimate the son preferences of immigrant women in the UK. By grouping the women by country of origin, I measure the fertility behaviour in response to their existing family compositions. I can then calculate the sex ratio that would emerge in a population of women behaving this way.

[5] Φ is the standard normal cumulative distribution function (CDF).

This simulated sex ratio is then compared with the sex ratio in the women's countries of origin.

The contribution of this paper is to establish that fertility behaviour does feasibly affect sex ratios in practice. Moreover, the bias is towards the less-favoured sex. Therefore, even though the effect I find is likely outweighed by discriminatory behaviour (such as selective abortion, infanticide or neglect), it is important because missing women cannot be measured correctly unless sex ratios at birth are properly accounted for. This reinforces the arguments made by Mayer [1999] and Griffiths et al. [2000], that sex ratios alone should be treated with caution as a measure of women's position in society: I maintain sex ratios must be treated with care when measuring the number of missing women.

Related Literature

There have been numerous attempts to quantify the number of missing women worldwide, notably Drèze and Sen [1989], who arrive at a figure of 100 million, and Coale [1991] finding a reduced figure of 60 million. Oster [2005] takes account of Hepatitis-B and its effect on the probabilities of having sons, coming to a still lower figure of 32 million. All three works take probabilities of sons to be homogeneous within countries.[6]

Meanwhile, there is a growing literature that implies within-population heterogeneity in the probability of having boys. Factors thought to affect the 'parental' sex ratio include status and personal traits such as dominance [Kemper, 1994; James, 1994; Grant, 1996, cited in Edlund, 1999], parental perception of the adult sex ratio [James, 1995], times of war [Graffelman and Hoekstra, 2000], Hepatitis B [Oster, 2005, 2006], maternal partnership status [Norberg, 2004] and maternal diet [Matthews et al., 2008]. Further, Lindsey and Altham [1998] find that a binomial model, as implied by homogeneity in son-probabilities, has a poor fit to family composition data. They find the number of

[6]Nonetheless, Oster's work does in fact imply heterogeneity with at least two types: virus carriers and non-carriers.

sons in families is 'overdispersed', suggesting heterogeneity. The demographic literature on probability heterogeneity is comprehensively surveyed by James [2000]. The theoretical result that population heterogeneity creates a link between son preference and aggregate sex ratios is not new, going back to Weiler [1959] and Goodman [1961], but the finding is not recognised in the economic literature.

There is wide acknowledgement that cultural factors such as son preferences and the status of women drive mortality-rate differentials and incentivise female infanticide and selective abortion [Sen, 1992; Das Gupta et al., 2002, for example]. Despite this recognition, no one has yet attempted to measure the effect of parents' fertility decisions on sex ratios. This omission surely results from an awareness of the fact that with *homogeneous* probabilities of having boys, son preference will have no effect on the sex ratio in large populations [Sheps, 1963; Leung, 1988].

The present paper sits at the juncture of two strands of literature. The first strand considers sex ratios and the biological factors affecting an individual woman's probability of having boys. However, instead of accounting for biological differences amongst women from different countries (as in Oster [2005]), I treat biological differences as unobserved but existing within every population. In this paper, differences between countries are *cultural*. Here, I follow the new literature on cultural differences between countries, such as [Fernández and Fogli, 2005, 2006], which determine that cultural background is a significant predictor of fertility outcomes. Of particular relevance to the present work is Chapter 3, which finds strong evidence that son preferences amongst immigrant women in the UK is driven by cultural factors, rather than economic mechanisms. This accords with Chamarbagwala and Ranger [2006], who argue that several cultural aspects such as religious composition and caste structure explain in part the high sex ratios found in some parts of India. Their suggested mechanism relies on selective abortion, infanticide and neglect of girls leading to an increase in the sex ratio (an excess of boys).

The results of this paper imply that son preferences lead to an excess of girls. This finding is of compatible with the results of Coale [1991]; Chamarbagwala and Ranger [2006] and others if discrimination outweighs the contribution of fertility decisions. In fact, the work here reinforces previous studies. I demonstrate the existence of a mechanism that opposes the effect of discrimination on the sex ratio. Thus, previous estimates may understate the importance of discrimination, and the number of missing women may be under-measured.

4.2 Theory

In this section I prove that parents' fertility decisions can affect population sex ratios, with a bias *against* the favoured sex. A necessary and sufficient condition is that the probability of a son is heterogeneous within the population.[7] This finding dates back to Weiler [1959] and Goodman [1961, both papers cited in Yamaguchi, 1989]; my proof is presented here for clarity and to support the intuition. In this paper, I focus on *lexis variation*, whereby women differ in their probabilities of having sons, but each woman's probability does not change over time.[8]

4.2.1 Background

Much existing research has focussed on homogeneous populations. In large samples, homogeneity entails that the population sex ratio matches the 'natural' ratio of boys to girls — the ratio which would prevail if parents only cared about the *size* of their families, not their sexes [Sheps, 1963; Leung, 1988]. With homogeneity, the probability that a further child is a boy is independent of the current family composition. *Why you choose to have a child* doesn't affect the probability you'll have a son. (This argument establishes that heterogeneity is

[7]Throughout this paper, the 'probability of having a son' refers only to the biological chance of conceiving and bearing a boy. I assume that selective abortion never occurs. In the empirical sections, child mortality is also ignored (following Gangadharan and Maitra [2003]). Neither of these factors are likely to affect my results, since these phenomena are uncommon in the UK. (However, see Dubuc and Coleman [2007].)

[8]James [2000] discusses in detail the implications of different types of variation.

necessary for son preference to affect sex ratios.)

Heterogeneity implies that the composition of a family *is not* independent of its size. When one sex is preferred, a woman's childbearing decisions are co-related to the probability she has boys.

Without loss of generality, let parents prefer sons. Then, those having boys are more likely to cease having children than those having girls. So those likely to have sons will, on average, have smaller families than those likely to have daughters. The difference in family sizes gives an excess of girls relative to the case without sex preferences.

4.2.1.1 Progression Rates

Of women with a certain number of children, the proportion going on to have further children is known as the *progression rate.* Rates can be compared between women who have different family compositions. Usually, women having boys are found to have lower progression rates, indicating a preference for sons[9] and this is rationalised by the microeconomic models of Leung [1991] and Chapter 3. For the model here, I choose the most extreme form of this behaviour: women have children until they bear a son (this may be called a *1-boy stopping rule*). This formulation simplifies the algebra considerably, but is not necessary for the intuition.[10]

4.2.2 Model

4.2.2.1 Homogeneity

First, consider the case of homogeneous probabilities. Let there be N women, each with natural probability p of having a boy at any birth. Since each woman i continues bearing children until a son is born, the number of boys in each family (b_i) will be one. Thus, the number of boys in the population will be

[9] See, for example, Leung [1988]; Gangadharan and Maitra [2003]; Das Gupta [2005].

[10] Any n-boy stopping rule would yield exactly the same bias in the sex ratio (proof omitted). The effect of mixed-family stopping rule (eg, n boys, m girls) would be smaller but qualitatively similar (as long as $n > m$). The intuition is unchanged provided that after a son a woman is less likely to continue having children than after a daughter.

$$B \stackrel{def}{=} \sum_{i=1}^{N} b_i = N$$

The number of girls in each family takes a geometric distribution.[11] $g_i \sim \text{Geom}(p)$. The total number of girls, $G \stackrel{def}{=} \sum_{i=1}^{N} g_i$, tends to $N\frac{(1-p)}{p}$ as $N \to \infty$, because the expected number of girls in each family is $\frac{1-p}{p}$. Therefore the sex ratio $\frac{B}{G}$ converges to $\frac{p}{1-p}$, as when parents have no son preference. Equivalently, $\frac{B}{B+G} \to p$.

4.2.2.2 Heterogeneity

Now, consider a mean preserving spread in the probabilities, with a fraction α having boys with probability p_1, and the remainder with probability $p_2 = \frac{p-\alpha p_1}{1-\alpha}$. With no son preference, childbearing ends independently of the composition of each family and (hence) independently of the woman's type. The population sex ratio will again be $\frac{p}{1-p}$.

With son preference, each woman still has one son, so $\tilde{B} = N$. However the distribution of girls is not the same for all women, since $g_i \sim \text{Geom}(p_i)$, and $\text{E}[g_i] = \frac{1-p_i}{p_i}$. Thus, as $N \to \infty$,

$$\tilde{G} \stackrel{def}{=} \sum_{i=1}^{N} g_i \to N\alpha\frac{1-p_1}{p_1} + N(1-\alpha)\frac{1-p_2}{p_2}$$

Hence the population sex ratio is:

$$\begin{aligned}
\frac{\tilde{B}}{\tilde{G}} &\to \left(\alpha\frac{1-p_1}{p_1} + (1-\alpha)\frac{1-p_2}{p_2}\right)^{-1} \\
&= \frac{p_1 p_2}{\alpha(1-p_1)p_2 + (1-\alpha)p_1(1-p_2)} \\
&= \frac{p_1 p_2}{(1-\alpha)p_1 + \alpha p_2 - p_1 p_2}
\end{aligned}$$

$\frac{\tilde{B}}{\tilde{G}}$ is necessarily *smaller* than the sex ratio with no preference, as the following theorem shows.

[11] I take the geometric defined as the number of *failures* before a success, not the number of *attempts*. $f_{\text{Geom}(p)}(g) = (1-p)^g p$.

Theorem 1. *In a large population of women, let a proportion α have boys with probability p_1, and the remainder have boys with probability p_2. Then $\tilde{B}/\tilde{G} < B/G$ if and only if $p_1 \neq p_2$. Heterogeneity is a necessary and sufficient condition for son preference to bias in the population sex ratio.*

Proof. I begin with the following inequality, due to Cauchy (it is also implied by Jensen's inequality). $2p_1p - 2 \leq p_1^2 + p_2^2$ holds with equality only when $p_1 = p_2$, ie, the case of homogeneity. Otherwise, the inequality is strict:

$$
\begin{aligned}
2p_1p_2 &< p_1^2 + p_2^2 \\
(2\alpha - 2\alpha^2)p_1p_2 &< \alpha(1-\alpha)(p_1^2 + p_2^2) \\
(1 - (1-\alpha)^2 - \alpha^2)p_1p_2 &< \alpha(1-\alpha)(p_1^2 + p_2^2) \\
p_1p_2 &< \alpha(1-\alpha)p_1^2 + (1-\alpha)^2 p_1p_2 \\
&\quad + \alpha^2 p_1p_2 + \alpha(1-\alpha)p_2^2 \\
p_1p_2 - \alpha p_1^2 p_2 - (1-\alpha)p_1p_2^2 &< \alpha(1-\alpha)p_1^2 + (1-\alpha)^2 p_1p_2 \\
&\quad + \alpha^2 p_1p_2 + \alpha(1-\alpha)p_2^2 \\
&\quad - \alpha p_2^2 p_2 - (1-\alpha)p_1p_2^2 \\
p_1p_2(1 - \alpha p_1 - (1-\alpha)p_2) &< (\alpha p_1 + (1-\alpha)p_2)((1-\alpha)p_1 + \alpha p_2 - p_1p_2) \\
\frac{p_1p_2}{(1-\alpha)p_1 + \alpha p_2 - p_1p_2} &< \frac{\alpha p_1 + (1-\alpha)p_2}{1 - \alpha p_1 - (1-\alpha)p_2} \\
\therefore \frac{\tilde{B}}{\tilde{G}} &< \frac{B}{G}
\end{aligned}
$$

Therefore the sex ratio is biased in favour of girls. Note that, under homogeneity of probabilities, each of the inequalities becomes an equality. The parental decisions only affect the sex ratio under heterogeneity. □

We see that a mean preserving spread in the probability of having sons skews the sex ratio in favour of girls when parents prefer boys. In the next sections, I take this theoretical result and estimate the magnitude of the effect in reality.

One caveat must be noted. Here, I treat women as biologically heterogeneous but socially identical: they share the same preferences and behave the same. This is unlikely to be the case in practice. No work to date has considered heterogeneity in son preference within groups, despite evidence of variations between groups (see Chapter 3). However, heterogeneity in behaviour would likely result in a averaged outcome; the effects modelled here would apply for any subgroups behaving similarly. The overall effect would be an aggregate of the subgroup effects.

4.3 Estimating Heterogeneity

In this section, I attempt to estimate within-population heterogeneity in the probability of having a son. Previous work by economists has considered child-bearing as a Bernoulli trial with a probability p of bearing a son, and $1 - p$ of bearing a daughter; authors have allowed p to differ between populations but not within them. Here, this restriction is reversed: p varies within populations, but the distribution is the same across countries.

I assume that, throughout their life, each woman has the same probability of having sons. In other words, I assume only *lexis variation.* Therefore, since I observe multiple outcomes (children) for some women, I am able to estimate the underlying distribution of probabilities, given some functional assumptions.

4.3.1 Empirical model

Consider a population of women, with each woman i having some underlying factor X_i which affects the likelihood that she bears a son when she has a child. For simplicity, let X be distributed as a normal random variable with mean μ and variance σ^2:

$$X_i \sim \mathrm{N}(\mu, \sigma^2)$$

When woman i bears a child j, an independent, identically distributed draw is made. I take this ϵ_{ij} also to be Gaussian, and without loss of generality, normalise the mean and variance to 0 and 1 respectively:

$$\epsilon_{ij} \sim \mathrm{N}(0, 1)$$

A boy is born if the sum of X and ϵ is greater than zero. That is, if B_{ij} is a random variable indicating birth of a boy,

$$B_{ij} \stackrel{def}{=} \begin{cases} 0 \text{ if } X_i + \epsilon_{ij} \leq 0 \\ 1 \text{ if } X_i + \epsilon_{ij} > 0 \end{cases}$$

Let Φ and ϕ be the cumulative distribution and probability density functions of the standard normal distribution.[12] The probability of woman i having a boy at any birth is

$$\begin{aligned} p_i &= \mathrm{P}[X_i + \epsilon_{ij} > 0] \\ &= \mathrm{P}[\epsilon_{ij} < -X_i] \\ &= 1 - \Phi(-X_i) \\ &= \Phi(X_i) \end{aligned}$$

Thus, B_{ij} may be treated as a Bernoulli trial with probability of success $p_i = \Phi(X_i)$.[13]

4.3.2 Likelihood functions

If X_i were known, the likelihood of observing a certain family composition for woman i can be easily computed. Suppose observed sons are indicated by

[12] When necessary, the CDF and PDF of X will be denoted Φ_X and ϕ_X.

[13] This 'Probit' derivation is inherently isomorphic to the formulation $B_{ij} \sim \text{Bernoulli}(p_i)$ with p having CDF $\Phi_X(\Phi^{-1}(p))$. Whilst somewhat arbitrary, the approach taken here is easily comprehensible, treating X as an unobserved variable in an LDV problem. An alternative method would be to estimate a distribution for p directly: possible distributions include the Beta, Kumaraswamy, Raised Cosine, Triangular, Truncated Normal, and Uniform (the support must be inside [0,1]). As well as being analytically simple, my chosen functional form gives p to be distributed on the *whole* of [0,1] with extreme values being unlikely, regardless of parametrisation. None of these other distributions display this property.

$b_{i1} \ldots b_{ik_i}$. Then, since individual births are independent,

$$\begin{aligned}
\mathcal{L}(b_{ij}|X_i) &\stackrel{def}{=} \mathrm{P}[B_{ij} = b_{ij} \text{ for } j = 1 \ldots k_i] \\
&= \prod_{j=1}^{k_i} \mathrm{P}[B_{ij} = b_{ij}] \\
&= \prod_{j=1}^{k_i} \Phi(X_i)^{b_{ij}} (1 - \Phi(X_i))^{(1-b_{ij})} \\
&= \Phi(X_i)^{k_i^{\mathrm{B}}} (1 - \Phi(X_i))^{k_i^{\mathrm{G}}}
\end{aligned}$$

k_i^{B} and k_i^{G} are the numbers of boys and girls borne by women i. ($k_i^{\mathrm{B}} + k_i^{\mathrm{G}} = k_i$.) Since only the numbers of boys and girls matter, the likelihood may be rewritten $\mathcal{L}(k_i^{\mathrm{B}}, k_i^{\mathrm{G}}|X_i) = \binom{k_i^{\mathrm{B}}+k_i^{\mathrm{G}}}{k_i^{\mathrm{B}}} \Phi(X_i)^{k_i^{\mathrm{B}}} (1 - \Phi(X_i))^{k_i^{\mathrm{G}}}$, with the combination factor accounting for the number of different ways that composition can occur.[14]

The unconditional likelihood is obtained by integrating over X, given its distribution:

$$\mathcal{L}_i = \mathcal{L}(k_i^{\mathrm{B}}, k_i^{\mathrm{G}}; \mu, \sigma) = \binom{k_i^{\mathrm{B}} + k_i^{\mathrm{G}}}{k_i^{\mathrm{B}}} \int_{\mathbb{R}} \Phi(x)^{k_i^{\mathrm{B}}} (1 - \Phi(x))^{k_i^{\mathrm{G}}} d\Phi_X(x) \qquad (4.1)$$

The sample likelihood is the product of the women's individual likelihoods, $\mathcal{L}(\mu, \sigma) = \prod_i \mathcal{L}_i$, because the X_i are independent. Estimates of the parameters of the distribution of X may be made by maximising this likelihood: $(\hat{\mu}, \hat{\sigma}) = \arg\max_{\mu} \mathcal{L}(\mu, \sigma)$.[15]

4.3.3 Data and Estimations

Using data from the UK Labour Force Survey 1996–2005, I construct fertility histories for 116,513 British-born women aged 16–55. When a household enters the survey, a matrix of household relationships is recorded, so I match women with their natural children under the age of 16.[16] Table 4.1 records the compo-

[14]Under the assumption of only lexis variation (constant probabilities for each woman), including uncompleted families does not affect the estimator.

[15]Recall that μ and σ parameterise the distribution of X. They appear in Equation 4.1 via the integrating density, $d\Phi_X(x)$.

[16]The survey is conducted as a rolling panel with households appearing in the survey for five quarters. I use only the households' first-quarter responses. Birth histories ignore mortality

	Number of Boys										
Children	0	1	2	3	4	5	6	7	8	9	10
1	24526	25710	–	–	–	–	–	–	–	–	–
2	11205	24283	12014	–	–	–	–	–	–	–	–
3	1812	5100	5394	2182	–	–	–	–	–	–	–
4	233	744	1188	904	328	–	–	–	–	–	–
5	29	108	193	200	114	31	–	–	–	–	–
6	2	14	30	56	32	14	7	–	–	–	–
7	0	1	9	7	10	9	4	1	–	–	–
8	0	0	4	2	4	3	2	0	0	–	–
9	0	0	0	1	0	0	0	0	1	0	–
10	0	0	0	0	0	1	1	0	0	0	0

Table 4.1: Family composition data from the UK Labour Force Survey 1996–2005. British-born women aged 16–55.

Table 4.2: Maximum likelihood estimates of distribution of $X \sim \mathrm{N}(\mu, \sigma^2)$ from family composition data. The underlying probability that a woman has sons is $p = \Phi(X)$. Bootstrap standard errors in parenthesis (200 samples).

	Estimate	Std. Dev.	90% CI
$\hat{\mu}$	0.0305	(0.00285)	[0.0258, 0.0351]
$\hat{\sigma}$	0.145	(0.0165)	[0.118, 0.172]

sitions of these families. As can be seen in Equation 4.1, my estimator requires only the number of boys and girls in each household.

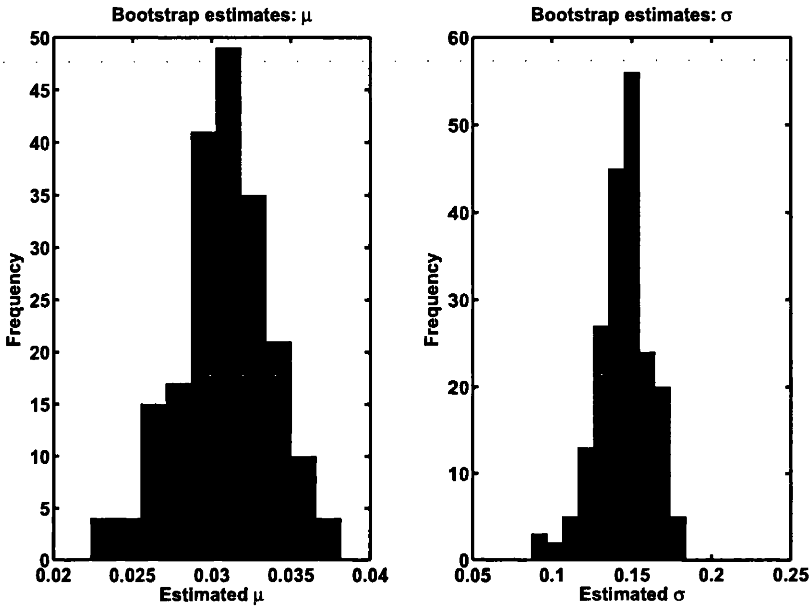
My estimates of the parameters underlying X are derived by Maximum Likelihood Estimation, as outlined in the previous section, and standard errors by the bootstrap method (200 bootstrap samples). Baseline estimates are shown in Table 4.2, with Figure 4.3 giving estimated values for the bootstrap samples.

Two implications are immediate: first, the median woman has natural probability of $\Phi(\mu) = 0.512$ of giving birth to a boy, yielding a 'natural' sex ratio of 1.050 boys per girl. This figure is lower than the usually cited ratio of 1.06 and the difference is statistically different at the 5% level.[17] However, my estimate lies within the range 1.03–1.06 given by Edlund [1999] as 'biologically normal'. The coherence of my estimate $\hat{\mu}$ with existing studies acts as a 'sanity check' on

and the possibility some children are absent from the household. I expect these omissions to have only minor effects on my results. I take the oldest child under the age of 16 to be the woman's first, following the example of Gangadharan and Maitra [2003]. The same caveats apply to the birth histories used in Section 4.4.2.

[17]The median probability will be different from the mean, $\mathrm{E}_X\,\Phi(X)$. However, in this case they are identical to three significant figures.

Figure 4.3: Bootstrap estimates for parameters μ and σ of $X \sim \mathrm{N}(\mu, \sigma^2)$ (200 samples from family composition data, Table 4.1). Probability of a son is $p = \Phi(X)$.



my methodology.

The second implication is more important: the variation in X, and hence p, is large. The baseline estimate gives a standard deviation for X of 0.145. This implies a 90% confidence interval (CI) of [0.42 , 0.61] for p. *Five percent of women are likely to have a boy with a greater than 61% chance, and five percent of women are likely to have a boy with a less than 42% chance.* Even taking a minimal value of σ (at the lower end of the 90% CI interval, $\sigma = 0.118$) yields a 90% confidence interval of [0.44, 0.59] for p.

I test for the significance of this heterogeneity with a likelihood ratio test. Homogeneity entails that X takes a degenerate distribution with value μ. Then all women would have boys with probability $\Phi(\mu)$. This case is equivalent to $\sigma = 0$, though now the likelihood function in Equation 4.1 is not well defined. However, the likelihood of a family comprising k_i^{B} boys and k_i^{G} girls nonetheless exists:

$$\mathcal{L}(k_i^{\mathrm{B}}, k_i^{\mathrm{G}}; \mu) = \binom{k_i^{\mathrm{B}} + k_i^{\mathrm{G}}}{k_i^{\mathrm{B}}} \Phi(\mu)^{k_i^{\mathrm{B}}} (1 - \Phi(\mu))^{k_i^{\mathrm{G}}}$$

The restricted sample likelihood is analogous to the sample likelihood, being $\mathcal{L}(\mu) = \prod_i \mathcal{L}(k_i^{\mathrm{B}}, k_i^{\mathrm{G}}; \mu)$. MLE on this restricted model yields an estimate of $\check{\mu} = 0.0303$. Thus, the likelihood ratio statistic can be computed:

$$\Lambda = \frac{\max\limits_{\mu} \mathcal{L}(\mu)}{\max\limits_{\mu,\sigma} \mathcal{L}(\mu, \sigma)}$$

The restricted likelihood reduces the dimension of the problem by one, so the we have (asymptotically) $-2\log\Lambda \sim \chi_1^2$. I am able to reject the null hypothesis that there is no heterogeneity at the 0.01% significance level ($-2\log\Lambda = 16.8$). This result suggests that my model does indeed perform better than one in which all women have the same probability of having sons, as can be seen in Figure 4.4.

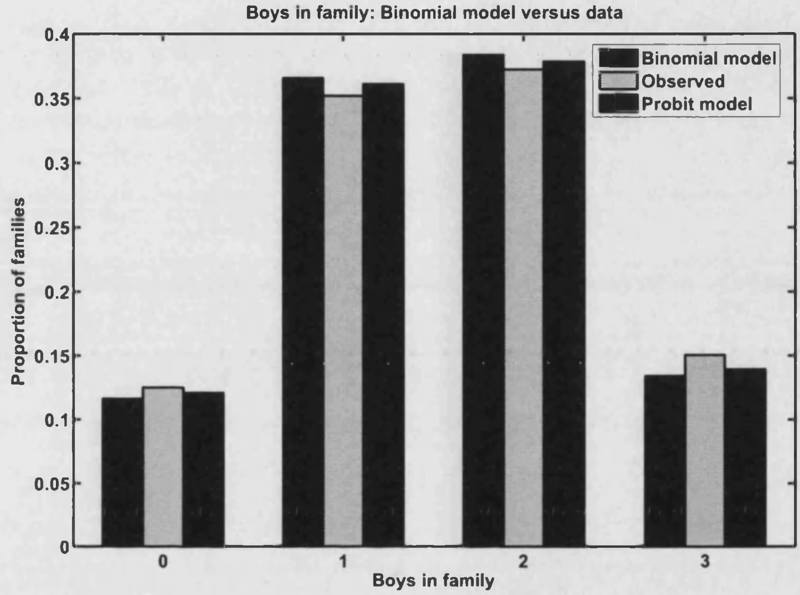
Lindsey and Altham [1998] find significant 'overdispersion' in family composition relative to a binomial model, as I do. Using their data, I am able to make a second estimate of heterogeneity in the probability of having sons.[18] Their data gives $\hat{\mu}' = 0.0367$ and $\hat{\sigma}' = 0.127$. The mean is significantly different from my original estimate at the 1% significance level, but the standard deviation estimate is not significantly different. Predicted son-probabilities are not practically dissimilar, with a 90% CI for p of [0.43, 0.60].

James [2000] surveys a variety of estimates of the standard deviation of p, centred on 0.05. My original estimates ($\hat{\mu} = 0.0305$,$\hat{\sigma} = 0.145$) give a standard deviation of 0.0572, and my estimates with the Lindsey and Altham data give 0.0502.

I can also compare Lindsey and Altham's model with my own. Under a fixed parametrisation with respect to family size, their Beta-Binomial model performs very similarly using Pearson's χ^2 test. However, as they note, they

[18]Theirs is a sample of almost one million families from Saxony in the period 1876–1885, collected by Arthur Geissler.

Figure 4.4: Family composition (3 children): under (a) binomial model, $B \sim \text{Bernoulli}(\Phi(0.0303))$; (b) under 'probit' form heterogeneity, $B \sim \text{Bernoulli}(\Phi(X))$, $X \sim \text{N}(0.0305, 0.145^2)$; and (c) actual data (Table 4.1).



merely perform a data-fitting exercise and they highlight the lack of biological explanation behind their results. My model is perhaps more amenable to a biological explanation, since it is based on individual effects for each woman. Lindsey and Altham's model performs better than mine when parameters are allowed to vary with family size. They suggest that sex preferences are not the cause, since final children are omitted from their sample, though it is impossible to test this assertion with their data. In Appendix C.1, I propose a robustness check to deal with this concern.

Since Lindsey and Altham find family-size effects, women may not have constant probabilities of bearing sons over throughout their lives. This implies some Markov variation in the probabilities of birth [James, 2000], with p changing (monotonically) with birth order. My estimation technique does not account for such effects.

In sum, I conclude [after James, 2000] that lexis variation does exist in women's probability of having sons. In the next section I use my estimates to calculate the effect of parents' son preferences on the aggregate sex ratio in practice.

4.4 Sex ratio simulation

If parents have preferences for sons, heterogeneity in the chance that individual women have boys will lead to a skew in the sex ratio, as proved in Section 4.2. Here I attempt to calibrate the size of this effect using a simulation.

4.4.1 Procedure

I construct predictions of the sex ratio in countries worldwide based on two pieces of data: first, the underlying distribution of probabilities of having sons (estimated in the previous section), and the observed sex preferences of women from a variety countries (following Chapter 3).

Two assumptions underlie this calibration. First, I take as given that my heterogeneity estimates apply to women from all countries. My justification is that estimates from recent UK data (1996–2005) are similar to estimates based on data from Saxony in the late 19$^{\text{th}}$ century [Lindsey and Altham, 1998]. Both sets of estimates fall in line with previous estimations of lexis variation in the probability of having sons James [2000].

Second, and more problematically, it is necessary to assume that the fertility behaviour of immigrants to the UK is the same as that of women in their countries of origin. This assertion somewhat stretches the external validity of Chapter 3. Problems include: (1) emigrants being unrepresentative, (2) cost differences between childrearing in the UK and elsewhere, and (3) cultural assimilation within the UK. However, the first and third of these concerns are likely to bias measures of son preference down, relative to what they would be in the countries of origin. Women moving to the UK may be more likely to have preferences similar to British women, and absorption of local norms will reduce son preference (British women appear to show little son preference — see Appendix C.1).

The second concern — price differentials — may bias the measure up if girls cost more to raise than boys (see Section 3.2, page 76). Women already having girls may reduce their fertility due to a wealth effect. However, in light of the large cultural effects found in that paper, it is likely that son preferences of immigrant women in the UK are less extreme than those of their compatriots. Therefore the effects predicted in this section may give a lower bound for the effect of parents' preferences on sex ratios worldwide.

Initially I generate a population of women ($i = 1 \ldots N$) and assign them probabilities of having sons (p_i) using the distribution derived in Section 4.3. Then, for each woman, I construct a latent family composition ($\bar{B}_{ij}$ for $j = 1 \ldots k$; $\bar{B}_{ij}$ indicates woman i's j^{th} child would be a son). This gives the sexes of the women's (first) k children. This is the 'biological' population, which stays the same throughout the simulation.

$$
\begin{aligned}
p_i &= \Phi(X_i) \text{ with } X_i \sim \mathrm{N}(\hat{\mu}, \hat{\sigma}) \\
\bar{B}_{ij} &\sim \text{Bernoulli}(p_i)
\end{aligned}
$$

I then allow the fertility behaviour to vary by country. Let q_{bj} be the proportion of women from a given country who continue to have children, after having b boys amongst j children. (I measure these q_{bj} in Section 4.4.2, below.) For example, I take Indian women who have a boy and two girls and measure the proportion who go on to have a fourth child. This measurement is q_{13}^{INDIA}.

Finally, I simulate each woman's fertility decisions according to the observed patterns the data. I simulate the sex ratios for each country separately. I use the q probabilities to generate 'actual' birth histories for each woman in the simulation. If woman already has j children and b boys, child $j+1$ is born with probability q_{bj}. This continues until the woman fails to have a child. I denote a birth of a j^{th} child to woman i by C_{ij}.

$$C_{ij+1} \sim \begin{cases} \text{Bernoulli}(q_{b_i j_i}) \text{ if } C_{ij'} = 1 \text{ for all } j' \leq j \\ 0 \text{ otherwise} \end{cases}$$

$$B_{ij+1} = \begin{cases} \bar{B}_{ij+1} \text{ if } C_{ij+1} = 1 \\ \text{[missing] otherwise} \end{cases}$$

This procedure provides me with a simulated sample of birth histories based on the sex preferences of women from each country. The ratio of boys to girls in this sample is easy to compute, and I compare this with the child sex ratios found in reality. Country data is taken from the World Development Indicators (1997), with the sex ratio being the under-15 male population divided by the under-15 female population.

4.4.2 Fertility Behaviour

4.4.2.1 Estimation method

Estimates of parental behaviour are derived from the birth histories of foreign-born women, grouping women by country of origin. For each possible family composition (up to three children), I calculate the asymptote of the Kaplan-Meier failure rate (KMFR). The KMFR is a non-parametric measure of the proportion of women who go on to have another child. The naïve progression rate, defined as the number of women *observed* to have a further child, does not account for the time women remain under observation (ie, censoring when the survey happens shortly after a birth). Thus, the KMFR is a more robust measure of true continuation rates.

Here, I consider childbirth as an absorbing transition from one state to another. Women either 'survive' with the number of children they have, or 'fail', and have another at some time. Alternatively, they may exit the dataset before failure (censoring). The asymptotic Kaplan-Meier failure rate is defined as follows [Jenkins, 2005b, p. 55]. Let $t_1 < \ldots < t_m < \ldots < t_M$ be the observed transition times for women from a given country with a given family composition. For simplicity, assume transitions are never contemporary. Let n_m be the number of women at risk of making a transition immediately prior to t_m. This does not include women no longer under observation. The Kaplan-Meier estimate of the proportion surviving to time t is then:

$$\hat{S}(t) \stackrel{def}{=} \prod_{m|t_m<t} \left(1 - \frac{1}{n_m}\right)$$

The proportion of women surviving by t_1 is simply one minus proportion who have made a transition, which is estimated by the number of exits (one) divided by the number at risk, n_1. So $\hat{S}(t_1) = 1 - \frac{1}{n_1}$. Similarly, the proportion surviving from t_1 to t_2 is $1 - \frac{1}{n_2}$, so the overall proportion surviving to t_2 is thus the product of these: $\hat{S}(t_1) = 1 - (\frac{1}{n_1})(\frac{1}{n_1})$.

I am interested in the proportion of women, q, who have a child at any point in the future, ie, the asymptote of $1 - S(t)$ as $t \to \infty$. Therefore I have:

$$q \stackrel{def}{=} 1 - \hat{S}(\infty) = 1 - \prod_{m} \left(1 - \frac{1}{n_m}\right)$$

4.4.2.2 Data

Data is taken from the UK Labour Force Survey 1996–2005. Household composition records are available, so parents can be matched with their natural children and birth histories compiled. Table 4.3 gives estimated continuation rates for women from 55 countries for which more than 30 records are present at the second birth.[19]

As demonstrated in Chapter 3, considerable variation in behaviour is seen amongst the women from different countries. For example, Australian women show some preference for daughters: 50% of those having two sons have a third child, compared with 37% of those with two daughters. Those with mixed

[19] Not all countries of origin in the LFS are identified uniquely. Five groups of countries appear in my regressions; I define the sex ratio for these to be total boys over total girls. The groups are:

families are more likely to stop. On the other hand, Singapore shows a different pattern: 33% of those with three daughters have a fourth child compared with none of those with three sons.

4.4.3 Simulation results

Using the fertility behaviour for women from different countries, I compute expected sex ratios for those countries. I use three sets of estimates for the underlying likelihoods of having sons: my benchmark derived in Section 4.3 ($\mu = 0.0305, \sigma = 0.145$), my estimate using data from Lindsey and Altham [1998] ($\mu = 0.0367, \sigma = 0.127$), and a conservative estimate of the heterogeneity in my sample, at the bottom of the 90% CI ($\mu = 0.0305, \sigma = 0.118$). I simulate births for one million women (the same latent birth histories are used for each country estimate). Results are presented in Table 4.4, alongside the child sex ratio from the World Development Indicators (under-15 male population divided by under-15 female population).

Simulated sex ratios range from 1.043 (Colombia) to 1.051 (Australia) in my benchmark model. The ranges are similar for all three sets of estimates, though they are higher overall for the estimates with Lindsey and Altham's data. The larger estimate for μ shifts the whole distribution in favour of having sons.

Figure 4.5 plots my simulated sex ratios against the data and fitted values from the regression $SR_{\text{PREDICTED}} = \alpha + \beta SR_{\text{DATA}}$. R^2 is 0.053, and the estimate $\hat{\beta} = 0.015$ is significantly different to zero at the 10% level, suggesting that parents' preferences do indeed have an effect on country sex ratios due to heterogeneity in the probability of having a son. However, the intercept, $\hat{\alpha}$ is

Grp02 'Other Caribbean Commonwealth': Antigua and Barbuda, Bahamas, Dominica, Grenada, Solomon Islands, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines.

Grp04 'Other Africa': Benin, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Congo, Rep., Cote d'Ivoire, Djibouti, Equatorial Guinea, Eritrea, Gabon, Guinea, Guinea-Bissau, Liberia, Madagascar, Mali, Mauritania, Mozambique, Namibia, Niger, Rwanda, Sao Tome and Principe, Senegal, Togo.

Grp07 'Other South America': Bolivia, Ecuador, Paraguay, Peru, Suriname

Grp08 'Other Middle East': Bahrain, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, United Arab Emirates, West Bank and Gaza, Yemen.

Grp12 Afghanistan, Bhutan, Maldives, Nepal.

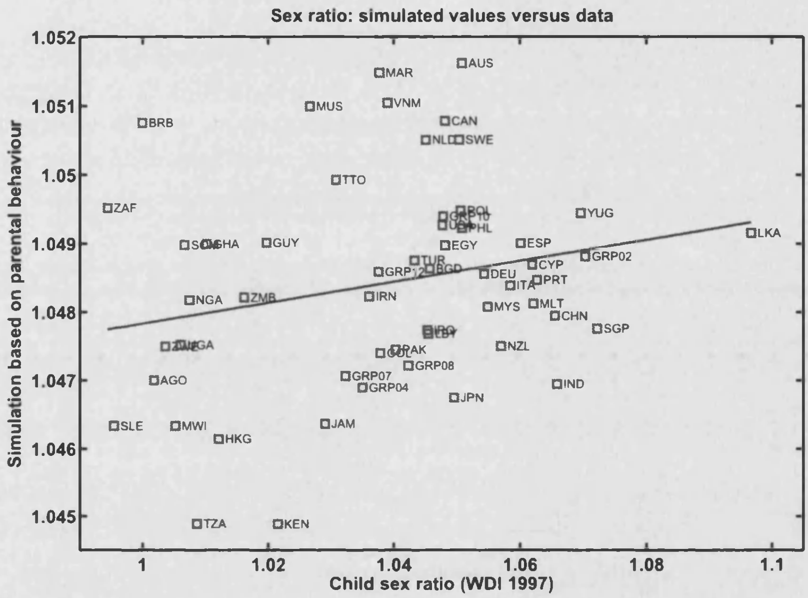
Table 4.3: Kaplan-Meier birth continuation rates by family composition. Foreign-born women in the UK LFS are grouped by country of origin. Statistics give the proportion of women having a further child given they already have b boys of j children.

	1 child		2 children			3 children			
Country	0 boys	1 boy	0 boys	1 boy	2 boys	0 boys	1 boy	2 boys	3 boys
AGO	0.93	0.88	0.67	0.33	0.33	–	–	–	–
AUS	0.76	0.78	0.37	0.44	0.50	0.40	0.13	0.34	1.00
BGD	0.91	0.93	0.84	0.82	0.81	0.74	0.73	0.71	0.61
BRB	0.62	0.70	0.43	0.22	0.55	–	–	–	–
CAN	0.76	0.75	0.37	0.34	0.34	0.00	0.13	0.17	0.60
CHN	0.58	0.60	0.40	0.34	0.07	–	–	–	–
COL	0.65	0.66	0.37	0.77	0.00	–	–	–	–
CYP	0.76	0.76	0.36	0.40	0.43	0.50	0.27	0.24	0.40
DEU	0.71	0.73	0.44	0.41	0.46	0.12	0.29	0.35	0.30
EGY	0.66	0.71	0.35	0.52	0.46	–	–	–	–
ESP	0.64	0.63	0.37	0.48	0.27	–	–	–	–
FRA	0.71	0.74	0.41	0.31	0.28	0.29	0.11	0.21	0.50
GHA	0.81	0.74	0.61	0.62	0.57	0.43	0.28	0.61	0.50
GRP02	0.68	0.59	0.15	0.38	0.28	–	–	–	–
GRP04	0.81	0.80	0.76	0.64	0.49	0.40	0.28	0.45	0.50
GRP07	0.78	0.82	0.43	0.37	0.27	–	–	–	–
GRP08	0.86	0.85	0.80	0.73	0.58	0.75	0.45	0.55	0.55
GRP12	0.90	0.93	1.00	0.69	0.63	–	–	–	–
GUY	0.67	0.64	0.25	0.38	0.54	–	–	–	–
HKG	0.76	0.67	0.47	0.32	0.35	0.53	0.20	0.19	0.30
IND	0.81	0.75	0.59	0.39	0.39	0.53	0.31	0.27	0.22
IRN	0.80	0.69	0.14	0.28	0.12	–	–	–	–
IRQ	1.00	0.81	0.73	0.56	0.75	–	–	–	–
ITA	0.56	0.72	0.45	0.33	0.20	–	–	–	–
JAM	0.57	0.65	0.71	0.43	0.30	0.70	0.41	0.28	0.53
JPN	0.67	0.64	0.44	0.22	0.13	–	–	–	–
KEN	0.83	0.75	0.64	0.29	0.31	0.53	0.19	0.20	0.21
LBY	0.85	0.71	0.55	0.69	0.72	–	–	–	–
LKA	0.73	0.70	0.16	0.29	0.41	–	–	–	–
MAR	0.91	0.81	0.34	0.53	0.75	–	–	–	–
MLT	0.76	0.62	0.52	0.38	0.41	–	–	–	–
MUS	0.68	0.65	0.30	0.33	0.61	–	–	–	–
MWI	0.91	0.76	0.64	0.59	0.42	–	–	–	–
MYS	0.86	0.75	0.42	0.32	0.46	0.00	0.42	0.27	0.38
NGA	0.89	0.86	0.79	0.60	0.68	0.73	0.47	0.53	0.55
NLD	0.76	0.77	0.40	0.39	0.74	–	–	–	–
NZL	0.71	0.62	0.52	0.37	0.46	–	–	–	–
PAK	0.92	0.87	0.84	0.78	0.74	0.80	0.68	0.65	0.76
PHL	0.54	0.71	0.21	0.25	0.21	–	–	–	–
POL	0.58	0.49	0.05	0.29	0.47	–	–	–	–
PRT	0.71	0.63	0.55	0.26	0.53	–	–	–	–
SGP	0.76	0.76	0.38	0.39	0.30	0.33	0.29	0.25	0.00
SLE	0.75	0.56	0.54	0.42	0.40	–	–	–	–
SOM	0.91	0.92	0.85	0.86	0.86	0.92	0.79	0.81	0.90
SWE	0.82	0.82	0.00	0.33	0.24	–	–	–	–
TTO	0.66	0.67	0.55	0.21	0.61	–	–	–	–
TUR	0.82	0.83	0.57	0.46	0.50	0.25	0.35	0.44	0.38
TZA	0.79	0.63	0.54	0.30	0.24	0.40	0.15	0.14	0.33
UGA	0.78	0.74	0.52	0.32	0.41	0.36	0.45	0.37	0.38
USA	0.78	0.71	0.43	0.39	0.49	0.25	0.41	0.44	0.20
VNM	0.79	0.88	0.41	0.40	0.56	–	–	–	–
YUG	0.84	0.77	0.49	0.43	0.58	–	–	–	–
ZAF	0.76	0.73	0.44	0.36	0.34	0.25	0.00	0.32	0.25
ZMB	0.77	0.77	0.71	0.48	0.53	0.25	0.52	0.18	1.00
ZWE	0.71	0.69	0.42	0.43	0.40	0.33	0.37	0.19	0.25

Table 4.4: Simulation of sex ratios worldwide, accounting for son preference and heterogeneity in the probability of having sons. Three different estimates of the underlying distribution of sexes are used: my benchmark, estimates from Lindsey and Altham's 1998 data, and a conservative estimate from my data. Parental behaviour is taken from UK LFS data (Table 4.3). Actual country sex ratios (under-15 male population divided by the under-15 female population) are taken from the World Development Indicators (1997).

		Predicted Values		
Country	Data	$\mu = 0.0305$ $\sigma = 0.145$	$\mu = 0.0376$ $\sigma = 0.127$	$\mu = 0.0305$ $\sigma = 0.118$
AGO	1.002	1.047	1.060	1.048
AUS	1.051	1.052	1.063	1.051
BGD	1.046	1.049	1.061	1.049
BRB	1.000	1.051	1.062	1.050
CAN	1.048	1.051	1.063	1.051
CHN	1.066	1.048	1.060	1.049
COL	1.038	1.047	1.060	1.048
CYP	1.062	1.049	1.061	1.049
DEU	1.054	1.049	1.060	1.049
EGY	1.048	1.049	1.061	1.049
ESP	1.060	1.049	1.061	1.050
FRA	1.048	1.049	1.061	1.050
GHA	1.010	1.049	1.061	1.049
GRP02	1.070	1.049	1.061	1.049
GRP04	1.035	1.047	1.059	1.048
GRP07	1.032	1.047	1.059	1.048
GRP08	1.042	1.047	1.060	1.048
GRP12	1.038	1.049	1.061	1.049
GUY	1.020	1.049	1.061	1.049
HKG	1.012	1.046	1.059	1.047
IND	1.066	1.047	1.059	1.048
IRN	1.036	1.048	1.061	1.049
IRQ	1.045	1.048	1.060	1.049
ITA	1.058	1.048	1.060	1.049
JAM	1.029	1.046	1.059	1.048
JPN	1.050	1.047	1.059	1.048
KEN	1.022	1.045	1.058	1.047
LBY	1.045	1.048	1.060	1.048
LKA	1.097	1.049	1.061	1.049
MAR	1.038	1.051	1.063	1.051
MLT	1.062	1.048	1.061	1.049
MUS	1.027	1.051	1.063	1.051
MWI	1.005	1.046	1.059	1.047
MYS	1.055	1.048	1.060	1.049
NGA	1.007	1.048	1.060	1.049
NLD	1.045	1.051	1.062	1.050
NZL	1.057	1.047	1.060	1.048
PAK	1.040	1.047	1.060	1.048
PHL	1.051	1.049	1.061	1.049
POL	1.051	1.049	1.061	1.049
PRT	1.063	1.048	1.061	1.049
SGP	1.072	1.048	1.060	1.048
SLE	0.995	1.046	1.059	1.048
SOM	1.007	1.049	1.061	1.049
SWE	1.050	1.051	1.062	1.050
TTO	1.031	1.050	1.062	1.050
TUR	1.043	1.049	1.061	1.049
TZA	1.009	1.045	1.058	1.046
UGA	1.006	1.048	1.060	1.048
USA	1.048	1.049	1.062	1.050
VNM	1.039	1.051	1.063	1.051
YUG	1.070	1.049	1.062	1.050
ZAF	0.994	1.050	1.062	1.050
ZMB	1.016	1.048	1.060	1.048
ZWE	1.004	1.047	1.060	1.048

Figure 4.5: Simulated sex ratios and country data. Simulation is based on heterogeneity in the probability of a son as derived in Section 4.3 ($\mu = 0.0305, \sigma = 0.145$). Parental behaviour is given in Table 4.3.



1.033, and is significantly different from one at 0.1%, implying that my model does not capture the whole story. Regressions with the other distributional estimates produce similar results.

The estimated slope, 0.015, is shallow. It suggests that parental behaviour and underlying heterogeneity accounts for 1.5% of the difference in sex ratios between countries. There are several possible reasons for this small figure. First is data quality. Aside from the usual noise issues, I have used child sex ratios, not birth sex ratios. If son-preferring fertility behaviour is correlated with discriminatory behaviour (as is likely), countries that are expected to have excess girls at birth will also have high female mortality, reducing the number of girls as I measure them. Under this assumption, my estimate of 1.5% will be biased *downwards*, since mortality due to discrimination lowers the excess of girls I am looking for. Data quality would be one area in which this study could be improved.

My two identifying assumptions may be incorrect: behaviour of immigrants to the UK may not represent countries of origin in terms of preferences, or the underlying distribution of 'natural' probabilities of sons is not identical across countries for biological or social reasons [cf. Oster, 2005; Matthews et al., 2008]. However, as discussed in Section 4.4.1, the former of these caveats may work against finding a positive result, if immigrants in the UK prefer sons less than their compatriots. The second concern is allayed by James [2000] and others who find similar levels of heterogeneity.

Finally, in a model simulating at most four children, the theoretical minimum and maximum sex ratios are 1.030 and 1.068 respectively (under my benchmark son-probability estimates). These ratios occur when parents practice extremely selective behaviour: stopping only after one son or daughter. The range seen in the data is [0.994, 1.097], so child mortality plainly plays a larger role in affecting sex ratios than parental preferences do.

Nonetheless, 1.5% very probably represents a lower bound on the effect of parental preferences on aggregate sex ratios. Most importantly, mortality differences between girls and boys in the countries of origin will likely bias my estimate downwards. Moreover, parental behaviour of immigrants to the UK is likely to be less extreme than women in their originating countries.

4.5 Discussion

For almost fifty years, it has been recognised that parental preferences can influence aggregate sex ratios when women have heterogeneous 'natural' probabilities of having boys [Yamaguchi, 1989]. However, the literature on 'missing women' has, to date, failed to account for such effects. In the present paper I attempt to calibrate the size of this effect.

My simulation gives that 1.5% of differences in country sex ratios are explained by parental preferences. However, as I discuss in Section 4.4.3, this figure is likely to be a lower bound on the potential effect. The major causes are attenuated preferences amongst immigrants to the UK and the limitation of using child sex ratios rather than birth sex ratios. My estimates of heterogeneity in son-probability are broadly in line with previous work by Lindsey and Altham [1998] and authors surveyed by James [2000], suggesting that misspecifiction of that distribution is not a concern.

Due to limited data and the caveats given above, I do not compute any adjusted estimates of the number of missing women worldwide. Nonetheless, the implications of my findings are not heartening: there may be more missing women than previously thought. My model predicts that a country with strong son preferences will have a *low* sex ratio at birth, because heterogeneity in the probability of having a son leads to excess girls, relative to homogeneity. Previous comparisons have used a baseline that is *not* biased towards girls. Thus, countries such as China or India which are known to favour boys [Das Gupta et al., 2002] are missing *more* girls than we had believed. At the very least, the results presented here should caution the use of aggregate sex ratios as a measure of attitudes, particularly in light of the negative correlation with parental preferences (Figure 4.1).

As Das Gupta [2005] notes, social and cultural preferences for sons play a prime role in skewing sex ratios in several developing countries, whether due to selective abortion, infanticide, or higher mortality rates for girls. I present evidence that fertility decisions guided by the same parental preferences can also lead to biased sex ratios in aggregate. Since son preferences bias the ratio downward, previous estimates of the number of missing women may be too low. Future work should aim to better account for the effect of parents' preferences.

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Appendix A

Appendix to Chapter 2

A.1 Country Groupings

Due to the agglomeration in the Labour Force Survey of several countries under some country codes, I do not have perfect resolution for the country of origin variable. I hence take population-weighted means for my proxy data, as listed in Table 2.2. The members of these groups are given below.

GRP01	Botswana, Lesotho, Swaziland
GRP02	'Other Caribbean Commonwealth': Antigua and Barbuda, Bahamas, The, Dominica, Grenada, Solomon Islands, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines
GRP03	'Other New Commonwealth': Fiji, Tonga
GRP04	'Other Africa': Benin, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Congo, Rep., Cote d'Ivoire, Djibouti, Equatorial Guinea, Eritrea, Gabon, Guinea, Guinea-Bissau, Liberia, Madagascar, Mali, Mauritania, Mozambique, Namibia, Niger, Rwanda, Sao Tome and Principe, Senegal, Togo

GRP05	'Other Caribbean': Aruba, Dominican Republic, Haiti, Netherlands Antilles, Puerto Rico
GRP06	'Other Central America': Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, Panama
GRP07	'Other South America': Bolivia, Ecuador, Paraguay, Peru, Suriname
GRP08	'Other Middle East': Bahrain, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, United Arab Emirates, West Bank and Gaza, Yemen, Rep.
GRP09	'Other Asia': Brunei, Comoros, Mongolia, Papua New Guinea
GRP10	France and Monaco
GRP11	French Polynesia, Kiribati, New Caledonia, Samoa, Vanuatu, American Samoa, Cayman Islands, Faeroe Islands, Guam, Korea, Dem. Rep., Marshall Islands, Mayotte, Northern Mariana Islands, Palau, Virgin Islands (U.S.), Timor-Leste
GRP12	Afghanistan, Bhutan, Maldives, Nepal
GRP13	Georgia, Armenia, Azerbaijan
GRP14	Kazakhstan, Kyrgyz Republic, Tajikistan, Turkmenistan, Uzbekistan

Appendix B

Appendix to Chapter 3

B.1 Sex Ratio Comparisons

A reasonable amount of research into fertility determinants has used country-level or regional fertility rates. This appendix argues that aggregate sex ratio statistics are not an appropriate analogue to fertility rates when studying son preferences.

The concept underlying sex ratio comparisons is that, if parents have a preference for children of a given sex, that sex will be more prevalent, due to a combination of fertility decisions and mortality due to discrimination.[1] However, whilst differential mortality due to discrimination has an unambiguous effect on population sex ratios, the major obstacle for this type of analysis is the ambiguity of the effect of individuals' fecundity decisions.

A natural (ie, physiological) sex ratio of 1.06 (106 boys for every 100 girls) is given by many authors. However, various other factors are believed to affect this ratio, notably times of war [Graffelman and Hoekstra, 2000], Hepatitis B [Oster, 2005, 2006], maternal partnership status [Norberg, 2004] and maternal diet [Matthews et al., 2008]. Though Oster's work is not conclusive, a secondary

[1]This discrimination may be either pre- or post-natal, possibly taking the form of selective abortions [Goodkind, 1999], infanticide, or neglect — either explicit or implicit. Lin et al. [2008] find that the trade-off between abortion rates and female neonatal mortality to be high in Taiwan.

argument gives that the figure of 1.06 may not be common to all ethnic groups, notably the Chinese.

B.1.1 Parental decisions

The simplest means of controlling the sex composition of one's family is what might be called a *stopping rule*. This sets some criterion for ceasing childbearing, such as having a boy, or having children of both sexes.

Under a stopping rule or some similar mechanism (including that resulting from the model presented in Section 3.2), the sex ratio is likely to converge to its natural rate when surveying a large number of homogeneous families. This result is demonstrated by Leung [1988], and is proved for a general class of stopping rules by Sheps [1963, cited in Leung, 1988]. However, the homogeneity condition is necessary: if women have differing probabilities of having boys, a stopping rule favouring boys leads to an excess of girls. This is because the sex ratio converges in large samples to the harmonic mean of the individuals' natural sex ratios, since the mean number of girls is inversely proportional to the probability of having a girl. Finally, the harmonic mean is less than the arithmetic mean. Chapter 4 provides an explicit proof and provides an estimate of the size of the effect in reality. I find that the preferences of immigrants to the UK do significantly predict sex ratios in their countries of origin.

Finally, Leung suggests that the presence of incomplete families will likely bias downward the observed number of boys [p. 100]. His logic is that, if parents favour boys, incomplete families will contain fewer boys than complete ones, since parents are more likely to cease having children after having boys. However, this argument is fallacious: if any given birth is a boy with homogeneous probability p, then the sex ratio for any given birth parity is $\frac{p}{1-p}$. Thus the overall sex ratio must equal $\frac{p}{1-p}$. The flaw in Leung's argument stems from an incorrect partition of families in to 'complete' and 'incomplete' — these categories are not independent of the sex composition of the family. Below, I prove that the sex ratio in a population containing incomplete families must converge to $\frac{p}{1-p}$.

Theorem 2. *In a large homogeneous population having boys with probability p and practising a one-boy stopping rule, the ratio of girls to boys converges to $\frac{p}{1-p}$, even when incomplete families are counted.*

Proof. Consider a population of families who practice a one-boy stopping rule. Boys are born with common probability p. At the time of survey, not all families have had the opportunity to complete their fertility. Family i has had the opportunity to have k_i children at most ($k_i \in \mathbb{N}$).

Let $B_k = \sum_{k_i=k} b_i$ be the number of boys in families limited to size k, and similarly $G_k = \sum_{k_i=k} g_i$ be the number of girls. If N_k is the number of such families, then:

$$\begin{aligned} B_k &\rightarrow N_k \left[1-(1-p)^k\right] \\ G_k &\rightarrow N_k \left[k(1-p)^k + \sum_{j=1}^{k-1} j(1-p)^j p\right] \end{aligned}$$

The first expression follows from the fact that families continue having children until they have a boy; the number of boys is N_k times the expected chance of having a boy within k attempts.

To derive the second expression, note that a given family has probability $(1-p)^j p$ of having $j < k$ girls, and a probability $(1-p)^k$ of k girls.

Manipulation of the second term yields:

$$\begin{aligned} G_k &\rightarrow N_k \left[k(1-p)^k + \frac{1-p}{p} - \frac{(1-p)^k(kp+(1-p))}{p}\right] \\ &\rightarrow N_k \frac{1-p}{p}\left[1-(1-p)^k\right] \end{aligned}$$

Thus we have $G_k \rightarrow \frac{1-p}{p} B_k$ for each k. Therefore in large populations, the sex ratio $\frac{B}{G}$ will approach the natural ratio $\frac{p}{1-p}$. Leung's assertion [1988, p. 100] is incorrect. □

B.1.2 Implications

Due to the reasons outlined above, macro-level measures of sex bias should come under tough scrutiny. Though, as Leung admits, severely skewed sex ratios may indicate sex preferences amongst parents, the magnitude — and even the direction — of these preferences will remains unclear. With parental decisions being impossible to control for, even measurement of the 'biologically normal population sex ratio' [Edlund, 1999, p. 1275] is tenuous.

These arguments present a bar on the feasibility of cross-sectional comparison of aggregate sex ratios, such as Oster [2005].[2] However, to date no study has sought to perform any micro-level investigation of son preferences between country groups. This partly stems from a lack of appropriate data: the focus on aggregate sex ratios results from the easily access to these statistics. I intend this paper to close this gap in the literature, using a survey of immigrant women in the United Kingdom with different countries of origin.

B.2 Empirical Methodology

B.2.1 Hazard rate estimation

This paper uses hazard rate estimation to measure the dependence of childbearing on existing family composition. These techniques sidestep the problems of measuring tastes for sons with aggregate statistics and allow this unique cross-country comparison of parental sex preferences.

In essence, a birth is considered to be an absorbing transition from one state (eg, birth parity k) to another (parity $k+1$). This transition is probabilistic, and survival analysis presents a set of tools for assessing how various factors affect the likelihood of this transition at any given time. Jenkins [2005b,a] provides a complete theoretical exposition, along with full notes on implementation of

[2]Possible exceptions to this critique include Dubuc and Coleman [2007] and Lin et al. [2008], which use sex ratios at birth in time-series. While the issues discussed here are still pertinent when considering sex ratios absolutely, analyses of *changes* in sex ratios should be more robust to these concerns. Moreover, the focus of these papers — sex-selective abortion — has unambiguous effects on the sex ratio.

these techniques in the statistical package Stata.

Consider that the time to transition (next birth) for a woman is T, distributed with cumulative distribution function (CDF) $F(\cdot)$. $P(T \leq t) = F(t)$. $F(\cdot)$ is named the *failure function*; conversely, $S(t) = 1 - F(t)$ is the *survivor function*, denoting the probability of surviving in the current state until time t.[3]

Denoting the probability density function (PDF) by $f = F'$, the *hazard rate* $\theta(\cdot)$ is given by

$$\theta(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)}$$

Loosely, θ describes the transition intensity at any time Jenkins [2005b, p. 15]. As opposed to unconditional probability of transition at time t, it reflects the probability of transition at time t *given survival to time* t. Recall that $S(t)$ is the probability of surviving to time t; the derivation of the hazard rate follows from Bayes' rule.

With data on transition times and the time to survey, parametric estimation of θ can be performed by the maximum likelihood method (MLE). Let C_i indicate that transition is observed, otherwise the record is *censored* at the time of survey.

$$C_i = \begin{cases} 1 & \text{if the spell is complete} \\ 0 & \text{if the spell is censored} \end{cases}$$

T_i denotes the time at risk for woman i. This is the total time for which the woman is observed, until she exits the sample through transition or is censored at the time of survey. If transition is observed, the likelihood is given by $\mathcal{L}_i = f(T_i)$, since this is the instantaneous probability of transition. Otherwise, in the case of censoring, the likelihood function for woman i is given by $\mathcal{L}_i = S(T_i)$; this is

[3] I treat transition time as a continuous variable. In the data, time is measured in months (records are anonymised by removing day of birth information). Whilst a discrete model might be appropriate, with months corresponding to menstrual cycles, fertility spacing is sufficient that continuous time models are a valid approximation. I therefore follow the existing literature.

the probability that she survives to the time of survey. Therefore the likelihood functions may be written as follows.

$$\begin{aligned}
\mathcal{L}_i &= C_i f(T_i) + (1 - C_i)S(T_i) \\
&= C_i \theta(T_i) S(T_i) + (1 - C_i)S(T_i) \\
\log \mathcal{L}_i &= C_i \log \theta(T_i) + \log S(T_i) \\
\log \mathcal{L} &= \sum_i [C_i \log \theta(T_i) + \log S(T_i)]
\end{aligned}$$

B.2.2 Estimation specifications

In order to conduct estimation of hazard functions, some parametric assumptions must be made. Under the Proportional Hazards (PH) assumption, the hazard function θ takes the form

$$\theta_i(t) = \theta_0(t) \exp(\beta' X_i)$$

As its name suggests, the hazard rate is proportionally higher for some individuals at all points in time. $\lambda_i \stackrel{def}{=} \exp(\beta' X_i)$ denotes the proportion for individual i. β captures the effects of the factors in X on the hazard rate, with a unit change in $X_{(k)}$ representing a proportional change in θ of $\exp(\beta_{(k)})$. The conventional method for estimating β is to specify a distribution for θ_0 and estimate its parameters, as in Leung [1988] and Gangadharan and Maitra [2003]. They use the Weibull distribution, which is parameterised (following Jenkins [2005b, §3, p. 26]) as $\theta_0 = \alpha t^{\alpha-1}$, where $\alpha > 0$ gives the shape of the distribution, and is estimated as a free parameter.[4]

[4] Gangadharan and Maitra [2003] in fact use a Gamma distribution in some sections of their work; this is a generalisation of the Weibull distribution, additionally using a second parameter to define the shape of the hazard function. However, identifying this second parameter empirically requires a large data set, making this approach infeasible for some subgroups in my sample.

B.2.3 The Cox PH model

However, an alternative method is the Cox Proportional Hazards model due to Cox [1972].[5] This leaves the underlying hazard function θ_0 undetermined and uses the ratio of hazard rates of different individuals to estimate parameters [Jenkins, 2005b]. This is a more general approach and is thus preferable in theory. For the regressions in this paper, analogous estimations with the Weibull model give near-identical results for $\hat{\beta}$ and are therefore not reported.

The Cox model is estimated using a Partial Likelihood (PL) method, rather than maximum likelihood estimation. The sample partial likelihood is

$$\mathcal{L}_P = \prod_{k=1}^{K} \mathcal{L}_k$$

Here, k indexes *transition events*, not individuals. I use index $i = 1 \ldots N$ to index individuals, ordered by time at risk T_i. Thus, when individual i_k experiences event k at time T_{i_k}, individuals $i_k + 1 \ldots N$ remain at risk (the rest have exited either through transition or censoring).

$\mathcal{L}_k$ is defined as the probability that i_k undergoes transition at time T_{i_k}, conditional on being in the risk set at that time. That is,

$$\mathcal{L}_k = \mathrm{P}[i_k \text{ experiences event } k | i_k \text{ remains at risk}]$$

From the derivation of the hazard rate, recall that the probability of a transition occurring in the time period $[t, t + dt)$ is $f(t)dt = \theta(t)S(t)dt$. So define

$$P_{\tilde{i}} \stackrel{def}{=} \mathrm{P}\left[\begin{array}{l} \text{event } k \text{ is experienced by } \tilde{i} \\ \quad \text{and not by } i = i_k \ldots \tilde{i} - 1, \tilde{i} + 1 \ldots N \end{array}\right]$$

In particular, $P_{i_k} = \mathrm{P}[\text{event } k \text{ is experienced by } i_k \text{ and not by } i = i_k + 1 \ldots N]$.

[5]This exposition follows that of Jenkins [2005b].

We have then that, since transitions are independent,

$$\begin{aligned} P_{\bar{i}} &= f_{\bar{i}} \prod_{i \neq \bar{i}} S_i(T_{i_k}) \\ &= [\theta_{\bar{i}}(T_{i_k}) S_{i_k}(T_{i_k})] \prod_{i \neq \bar{i}} S_i(T_{i_k}) \end{aligned}$$

Now $\mathcal{L}_k$ can be computed:

$$\begin{aligned} \mathcal{L}_k &= \frac{P_{i_k}}{P_{i_k} + P_{i_k+1} + \cdots + P_N} \\ &= \frac{\theta_{i_k}(T_{i_k})}{\theta_{i_k}(T_{i_k}) + \theta_{i_k+1}(T_{i_k}) + \cdots + \theta_N(T_{i_k})} \end{aligned}$$

The first line follows naturally from the definition of $\mathcal{L}_k$ as a conditional probability, and the second from the evaluation of the P_is; the survivor functions cancel. Applying the proportional hazards assumption, $\theta_i(t) = \theta_0(t)\lambda_i$, yields

$$\begin{aligned} \mathcal{L}_k &= \frac{\theta_0(T_{i_k})\lambda_{i_k}}{\left(\sum_{i=i_k}^{N} \theta_0(T_{i_k})\lambda_i\right)} \\ &= \frac{\lambda_{i_k}}{\left(\sum_{i=i_k}^{N} \lambda_i\right)} \end{aligned}$$

For any estimate $\hat{\beta}$, this derivation provides a computation of the partial likelihood $\mathcal{L}_P$. (Recall that $\lambda_i = \exp(\beta' X_i)$.) The Cox estimator maximises this partial likelihood:

$$\begin{aligned} \hat{\beta}_{\text{Cox}} &= \arg\max_{\beta} \left\{ \prod_{k=1}^{K} \mathcal{L}_k \right\} \\ &= \arg\max_{\beta} \left\{ \prod_{k=1}^{K} \frac{\lambda_{i_k}}{\left(\sum_{i=i_k}^{N} \lambda_i\right)} \right\} \end{aligned}$$

B.2.4 Interpretation of coefficients

Coefficients arising from the Cox PH estimator have exactly the same interpretation as those derived from fully parametric estimators under the PH assumption, save for the exclusion of any constant term, reflecting the fact that the baseline hazard is undefined. In a fully parametric model the shape of the baseline hazard must be estimated. However, since the shape parameters define the baseline hazard at a normalised level, an intercept term is needed.

The lack of a need for an intercept term with the Cox model becomes clear on consideration that only the *order* of the transitions $k = 1 \dots K$ matters; all exposure times could be scaled up linearly without affecting the estimated coefficients.

The PH specification is also known as the 'multiplicative hazards' or 'log relative hazard' model. Recall, the PH imposition is $\theta(t, X_i) = \theta_0(t)\exp(\beta' X_i) = \theta_0(t)\lambda_i$. This implies that absolute differences in X give proportionate differences in the hazard rate at all times:

$$\frac{\theta(t, X_i)}{\theta(t, X_j)} = \exp(\beta' X_i - \beta' X_j) = \exp(\beta'(X_i - X_j))$$

Alternately:

$$\log \frac{\theta(t, X_i)}{\theta(t, X_j)} = \beta'(X_i - X_j)$$

Supposing that X_i and X_j differ only on dimension q (ie, $X_{ip} = X_{jp}$ for all $p \neq q$), then it can be seen that

$$\log \frac{\theta(t, X_i)}{\theta(t, X_j)} = \beta_q'(X_{iq} - X_{jq})$$

Hence

$$\beta_q = \frac{\partial \log \theta(t, X)}{\partial X_q}$$

In vector terms, $\beta = \nabla_X \log \theta(t, X)$.

B.2.5 Son preference

It is estimates of these β terms that are reported in Section 3.4. Positive terms correspond to higher hazard rates and, in this application, higher onward fertility.

I shall use the term 'observed son preference' to label the phenomenon where women reduce their onward fertility in response to having sons.[6] This is measured as a negative coefficient on the variable SONS, denoting the number of male children a woman has had at the parity in question. The proportional effect on the hazard rate is $\exp \beta_{\mathrm{SONS}}$, so coefficients of -0.5, -0.1 and -0.05 reflect reductions in the hazard rate by factors of 0.61, 0.9 and 0.95 respectively per son.

B.3 Full Regression Tables

Table B.1: Birth hazard rate regressions at parity 1 for immigrant women in the UK. Country fixed effects and country son preference effects.

	(1)		(2)	
AGE	0.164***	(0.0197)	0.165***	(0.0197)
AGE2	-0.00385***	(0.000366)	-0.00388***	(0.000367)
DEGREE	0.181***	(0.0396)	0.174***	(0.0397)
AL	-0.0514	(0.0449)	-0.0526	(0.0450)
FE	0.0427	(0.0470)	0.0372	(0.0471)
GCSE	0.0489	(0.0369)	0.0456	(0.0370)
Australia	0.155*	(0.0838)	-0.0688	(0.118)
Canada	0.0677	(0.0934)	-0.112	(0.139)
New Zealand	0.0302	(0.128)	-0.112	(0.190)
Kenya	0.0309	(0.0526)	0.0445	(0.0764)
Uganda	-0.0455	(0.0785)	-0.150	(0.112)
Tanzania	-0.107	(0.103)	0.0101	(0.140)
Zambia	0.0684	(0.116)	-0.152	(0.179)
Zimbabwe	-0.186*	(0.0952)	-0.359**	(0.145)
Ghana	-0.0510	(0.0806)	-0.100	(0.110)
Nigeria	0.247***	(0.0674)	0.149	(0.0948)
Jamaica	-0.559***	(0.0688)	-0.787***	(0.101)
Grp02	-0.498***	(0.125)	-0.560***	(0.176)
Bangladesh	0.386***	(0.0446)	0.268***	(0.0662)
Sri Lanka	-0.0667	(0.0862)	-0.0916	(0.127)
HK & China	-0.168**	(0.0771)	-0.254**	(0.117)
Malaysia	0.202**	(0.0894)	0.210*	(0.123)
Singapore	0.0123	(0.0884)	-0.148	(0.126)
Cyprus	-0.130*	(0.0758)	-0.252**	(0.115)
Malta	-0.210*	(0.119)	-0.190	(0.171)
Mauritius	-0.345***	(0.124)	-0.440***	(0.169)
SA	0.0156	(0.0727)	-0.0954	(0.103)
Grp04	-0.0168	(0.0940)	-0.203	(0.134)
US	0.176***	(0.0672)	0.0812	(0.0915)
Pakistan	0.438***	(0.0386)	0.386***	(0.0562)
China	-0.491***	(0.125)	-0.676***	(0.184)
Japan	-0.0162	(0.131)	-0.189	(0.187)
Philippines	-0.281***	(0.0898)	-0.641***	(0.141)
Iran	-0.160	(0.107)	-0.0831	(0.161)
Grp08	0.395***	(0.0945)	0.270**	(0.136)
France	0.00998	(0.0885)	-0.123	(0.127)
Italy	-0.275***	(0.0967)	-0.581***	(0.144)
Netherlands	0.270**	(0.118)	0.0188	(0.165)
Germany	-0.117**	(0.0520)	-0.308***	(0.0753)
Poland	-0.701***	(0.125)	-0.688***	(0.176)
Portugal	-0.434***	(0.108)	-0.582***	(0.151)
Spain	-0.261**	(0.129)	-0.404**	(0.181)
Serbia & Montenegro	0.0487	(0.116)	-0.0931	(0.167)
Turkey	-0.158*	(0.0848)	-0.311**	(0.130)
Somalia	0.628***	(0.0783)	0.333***	(0.113)
	ctd.		ctd.	

[6] The theory set out in Section 3.2 suggests that, providing boys are no more expensive than girls, observed son preference does indeed imply an *underlying* preference for sons in a neoclassical consumption-fertility model.

	(1) ctd.	(2) ctd.	
SONS		-0.261***	(0.0530)
SONS*Australia		0.428**	(0.167)
SONS*Canada		0.325*	(0.187)
SONS*New Zealand		0.256	(0.257)
SONS*Kenya		-0.0214	(0.105)
SONS*Uganda		0.181	(0.156)
SONS*Tanzania		-0.247	(0.207)
SONS*Zambia		0.394*	(0.234)
SONS*Zimbabwe		0.308	(0.192)
SONS*Ghana		0.0589	(0.161)
SONS*Nigeria		0.169	(0.134)
SONS*Jamaica		0.415***	(0.137)
SONS*Grp02		0.0955	(0.250)
SONS*Bangladesh		0.209**	(0.0884)
SONS*Sri Lanka		0.0487	(0.172)
SONS*HK & China		0.157	(0.156)
SONS*Malaysia		-0.0373	(0.177)
SONS*Singapore		0.290*	(0.176)
SONS*Cyprus		0.215	(0.153)
SONS*Malta		-0.0382	(0.237)
SONS*Mauritius		0.151	(0.249)
SONS*SA		0.192	(0.145)
SONS*Grp04		0.339*	(0.188)
SONS*US		0.155	(0.134)
SONS*Pakistan		0.0875	(0.0770)
SONS*China		0.333	(0.251)
SONS*Japan		0.316	(0.262)
SONS*Philippines		0.649***	(0.182)
SONS*Iran		-0.107	(0.216)
SONS*Grp08		0.223	(0.189)
SONS*France		0.239	(0.176)
SONS*Italy		0.573***	(0.194)
SONS*Netherlands		0.493**	(0.234)
SONS*Germany		0.348***	(0.103)
SONS*Poland		-0.0430	(0.250)
SONS*Portugal		0.259	(0.216)
SONS*Spain		0.254	(0.258)
SONS*Serbia & Montenegro		0.250	(0.233)
SONS*Turkey		0.269	(0.171)
SONS*Somalia		0.568***	(0.156)
Observations	13223	13223	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Birth hazard rate regressions at parity 2 for immigrant women in the UK. Country fixed effects and country son preference effects.

	(1)		(2)	
AGE	-0.0140	(0.0371)	-0.00997	(0.0372)
AGE2	-0.00141**	(0.000664)	-0.00149**	(0.000665)
DEGREE	0.0739	(0.0765)	0.0583	(0.0766)
AL	-0.198**	(0.0834)	-0.214**	(0.0836)
FE	-0.146*	(0.0883)	-0.174**	(0.0886)
GCSE	-0.188***	(0.0660)	-0.193***	(0.0662)
Australia	0.243	(0.151)	-0.501*	(0.284)
Canada	-0.0594	(0.178)	-0.198	(0.288)
Kenya	-0.0527	(0.0931)	0.242	(0.149)
Uganda	0.00941	(0.140)	-0.228	(0.244)
Zimbabwe	0.00204	(0.173)	-0.322	(0.329)
Ghana	0.699***	(0.119)	0.556***	(0.205)
Nigeria	0.792***	(0.0974)	0.721***	(0.173)
Jamaica	0.0607	(0.118)	0.261	(0.200)
Bangladesh	0.857***	(0.0629)	0.677***	(0.109)
Sri Lanka	-0.112	(0.186)	-0.925**	(0.369)
HK & China	-0.117	(0.141)	-0.143	(0.248)
Malaysia	0.113	(0.166)	-0.375	(0.296)
Singapore	-0.264	(0.173)	-0.617*	(0.316)
Cyprus	-0.00306	(0.131)	-0.261	(0.251)
SA	0.00418	(0.137)	-0.120	(0.233)
Grp04	0.543***	(0.137)	0.473**	(0.234)
US	0.256**	(0.117)	-0.0418	(0.197)
Pakistan	0.922***	(0.0560)	0.783***	(0.0960)
Philippines	-0.314	(0.219)	-0.694*	(0.417)
Grp08	0.781***	(0.130)	0.731***	(0.223)
France	0.153	(0.173)	-0.00482	(0.284)
Italy	-0.188	(0.191)	-0.183	(0.295)
Germany	0.0185	(0.0906)	-0.148	(0.155)
Turkey	-0.203	(0.153)	-0.471	(0.295)
Somalia	1.162***	(0.0996)	1.069***	(0.176)
SONS			-0.280***	(0.0634)
SONS*Australia			0.753***	(0.224)
SONS*Canada			0.139	(0.234)
SONS*Kenya			-0.303**	(0.133)
SONS*Uganda			0.234	(0.203)
SONS*Zimbabwe			0.322	(0.273)
SONS*Ghana			0.143	(0.172)
SONS*Nigeria			0.0798	(0.144)
SONS*Jamaica			-0.197	(0.177)
SONS*Bangladesh			0.183**	(0.0882)
SONS*Sri Lanka			0.736***	(0.251)
SONS*HK & China			0.0464	(0.196)
SONS*Malaysia			0.481**	(0.226)
SONS*Singapore			0.345	(0.240)
SONS*Cyprus			0.257	(0.189)
SONS*SA			0.122	(0.196)
SONS*Grp04			0.0403	(0.222)
SONS*US			0.297*	(0.163)
SONS*Pakistan			0.141*	(0.0796)
SONS*Philippines			0.363	(0.303)
SONS*Grp08			0.0572	(0.184)
SONS*France			0.151	(0.245)
SONS*Italy			-0.0266	(0.259)
SONS*Germany			0.168	(0.125)
SONS*Turkey			0.262	(0.234)
SONS*Somalia			0.0982	(0.145)
Observations	7704		7704	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Birth hazard rate regressions at parity 3 for immigrant women in the UK. Country fixed effects and country son preference effects.

	(1)		(2)	
AGE	-0.110*	(0.0652)	-0.105	(0.0654)
AGE2	0.000569	(0.00110)	0.000473	(0.00110)
DEGREE	-0.681**	(0.265)	-0.695***	(0.266)
AL	-0.436*	(0.230)	-0.486**	(0.230)
FE	-0.304	(0.229)	-0.317	(0.230)
GCSE	-0.497***	(0.178)	-0.494***	(0.178)
Kenya	0.0755	(0.192)	0.0848	(0.302)
Nigeria	0.759***	(0.172)	0.527*	(0.312)
Bangladesh	0.907***	(0.105)	0.628***	(0.204)
Pakistan	1.021***	(0.0972)	0.742***	(0.186)
Germany	-0.0502	(0.201)	-0.817*	(0.442)
Somalia	1.453***	(0.142)	1.045***	(0.288)
SONS			-0.369***	(0.100)
SONS*Kenya			-0.0931	(0.215)
SONS*Nigeria			0.148	(0.197)
SONS*Bangladesh			0.205*	(0.122)
SONS*Pakistan			0.198*	(0.114)
SONS*Germany			0.504**	(0.238)
SONS*Somalia			0.282*	(0.169)
Observations	2343		2343	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Birth hazard rate regressions at parity 2 for immigrant women in the UK. Country fixed effects and family composition interactions. Note that non-interacted family composition dummies are *not* included, to allow easy comparison of coefficients for each country. Each interaction coefficient measures the hazard relative to a compatriot with no sons.

	(1)	
AGE	-0.0136	(0.0373)
AGE2	-0.00144**	(0.000668)
DEGREE	0.0583	(0.0770)
AL	-0.219***	(0.0838)
FE	-0.173*	(0.0889)
GCSE	-0.190***	(0.0663)
Australia	-0.541*	(0.326)
Bangladesh	0.596***	(0.120)
Canada	-0.283	(0.312)
Cyprus	-0.278	(0.289)
France	-0.0191	(0.300)
Germany	-0.150	(0.166)
Ghana	0.331	(0.243)
Grp04	0.484**	(0.243)
Grp08	0.577**	(0.256)
HK & China	-0.0877	(0.263)
Italy	-0.451	(0.343)
Jamaica	0.252	(0.212)
Kenya	0.275*	(0.153)
Malaysia	-0.296	(0.312)
Nigeria	0.751***	(0.186)
Pakistan	0.686***	(0.105)
Philippines	-1.131*	(0.583)
SA	-0.181	(0.255)
Singapore	-0.989**	(0.416)
Somalia	1.106***	(0.190)
Sri Lanka	-1.126**	(0.455)
Turkey	-0.391	(0.326)
Uganda	-0.110	(0.249)
US	-0.150	(0.220)
Zimbabwe	-0.402	(0.387)
ONEBOY*Australia	0.294	(0.377)
TWOBOYS*Australia	0.918**	(0.415)
ONEBOY*Bangladesh	-0.218**	(0.110)
TWOBOYS*Bangladesh	-0.208*	(0.120)
ONEBOY*Canada	-0.285	(0.410)
TWOBOYS*Canada	-0.277	(0.437)
ONEBOY*Cyprus	-0.247	(0.332)
TWOBOYS*Cyprus	-0.105	(0.347)
ONEBOY*France	-0.426	(0.388)
TWOBOYS*France	-0.211	(0.441)

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	(1) ctd.	
ONEBOY*Germany	-0.428**	(0.190)
TWOBOYS*Germany	-0.231	(0.202)
ONEBOY*Ghana	0.0218	(0.272)
TWOBOYS*Ghana	-0.286	(0.334)
ONEBOY*Grp04	-0.560*	(0.293)
TWOBOYS*Grp04	-0.316	(0.391)
ONEBOY*Grp08	-0.197	(0.298)
TWOBOYS*Grp8	-0.446	(0.349)
ONEBOY*HK & China	-0.671**	(0.332)
TWOBOYS*HK & China	-0.503	(0.339)
ONEBOY*India	-0.588***	(0.103)
TWOBOYS*India	-0.535***	(0.117)
ONEBOY*Italy	-0.00131	(0.422)
TWOBOYS*Italy	-0.704	(0.558)
ONEBOY*Jamaica	-0.761***	(0.251)
TWOBOYS*Jamaica	-0.888***	(0.307)
ONEBOY*Kenya	-1.043***	(0.186)
TWOBOYS*Kenya	-1.040***	(0.212)
ONEBOY*Malaysia	-0.289	(0.403)
TWOBOYS*Malaysia	0.338	(0.397)
ONEBOY*Nigeria	-0.529**	(0.208)
TWOBOYS*Nigeria	-0.396*	(0.238)
ONEBOY*Pakistan	-0.233***	(0.0839)
TWOBOYS*Pakistan	-0.282***	(0.0943)
ONEBOY*Philippines	0.573	(0.646)
TWOBOYS*Philippines	0.326	(0.690)
ONEBOY*SA	-0.329	(0.308)
TWOBOYS*SA	-0.305	(0.355)
ONEBOY*Singapore	0.463	(0.466)
TWOBOYS*Singapore	0.215	(0.517)
ONEBOY*Somalia	-0.538**	(0.217)
TWOBOYS*Somalia	-0.376	(0.239)
ONEBOY*Sri Lanka	0.573	(0.532)
TWOBOYS*Sri Lanka	0.950*	(0.521)
ONEBOY*Turkey	-0.404	(0.379)
TWOBOYS*Turkey	-0.106	(0.414)
ONEBOY*Uganda	-0.622*	(0.318)
TWOBOYS*Uganda	-0.0751	(0.338)
ONEBOY*US	-0.0517	(0.259)
TWOBOYS*US	0.0357	(0.295)
ONEBOY*Zimbabwe	-0.0587	(0.437)
TWOBOYS*Zimbabwe	0.0774	(0.518)
Observations	7704	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: Birth hazard rate regressions at parity 3 for immigrant women in the UK. Country fixed effects and family composition interactions. Note that non-interacted family composition dummies are *not* included, to allow easy comparison of coefficients for each country. Each interaction coefficient measures the hazard relative to a compatriot with no sons.

	(1)	
AGE	-0.109*	(0.0659)
AGE2	0.000515	(0.00111)
DEGREE	-0.707***	(0.266)
AL	-0.459**	(0.231)
FE	-0.320	(0.230)
GCSE	-0.506***	(0.178)
Bangladesh	0.489*	(0.276)
Germany	-0.886	(0.735)
Kenya	0.0554	(0.332)
Nigeria	0.470	(0.374)
Pakistan	0.710***	(0.232)
Somalia	1.141***	(0.362)
ONEBOY*Bangladesh	-0.308	(0.216)
TWOBOYS*Bangladesh	-0.308	(0.215)
THREEBOYS*Bangladesh	-0.662***	(0.252)
ONEBOY*Germany	-0.0402	(0.770)
TWOBOYS*Germany	0.121	(0.765)
THREEBOYS*Germany	0.289	(0.818)
ONEBOY*India	-0.724***	(0.240)
TWOBOYS*India	-0.911***	(0.248)
THREEBOYS*India	-1.204***	(0.325)
ONEBOY*Kenya	-0.871**	(0.404)
TWOBOYS*Kenya	-1.294***	(0.489)
THREEBOYS*Kenya	-0.970*	(0.567)
ONEBOY*Nigeria	-0.439	(0.392)
TWOBOYS*Nigeria	-0.686*	(0.409)
THREEBOYS*Nigeria	-0.476	(0.549)
ONEBOY*Pakistan	-0.362**	(0.144)
TWOBOYS*Pakistan	-0.670***	(0.144)
THREEBOYS*Pakistan	-0.362**	(0.171)
ONEBOY*Somalia	-0.597	(0.365)
TWOBOYS*Somalia	-0.418	(0.344)
THREEBOYS*Somalia	-0.526	(0.451)
Observations	2343	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: Birth hazard rate regressions at parity 1. Country fixed effects and country son preference effects, split by income at sample median.

	(1)		(2)	
AGE	0.280***	(0.0483)	0.286***	(0.0485)
AGE2	-0.00574***	(0.000887)	-0.00583***	(0.000890)
DEGREE	0.0885	(0.0848)	0.0880	(0.0854)
AL	-0.0341	(0.104)	-0.0305	(0.105)
FE	0.135	(0.115)	0.147	(0.116)
GCSE	-0.0190	(0.0840)	-0.0175	(0.0843)
POOR*Australia	0.0532	(0.213)	-0.251	(0.281)
POOR*Kenya	-0.177	(0.132)	-0.208	(0.204)
POOR*Bangladesh	0.663***	(0.105)	0.450***	(0.148)
POOR*Sri Lanka	-0.0525	(0.173)	-0.577*	(0.314)
POOR*SA	0.0277	(0.202)	-0.587*	(0.344)
POOR*US	-0.149	(0.244)	0.220	(0.364)
POOR*Pakistan	0.397***	(0.0992)	0.226	(0.139)
POOR*Philippines	-0.539***	(0.187)	-0.856***	(0.301)
POOR*France	-0.220	(0.285)	-0.609	(0.457)
POOR*Germany	-0.330***	(0.125)	-0.428**	(0.172)
RICH	-0.161*	(0.0932)	-0.388***	(0.137)
RICH*Australia	0.228	(0.163)	0.163	(0.224)
RICH*Kenya	0.0745	(0.129)	0.192	(0.185)
RICH*Bangladesh	0.184	(0.221)	0.186	(0.309)
RICH*Sri Lanka	-0.237	(0.208)	0.0130	(0.298)
RICH*SA	0.299**	(0.136)	0.460**	(0.193)
RICH*US	0.308**	(0.129)	0.342*	(0.187)
RICH*Pakistan	0.387***	(0.132)	0.661***	(0.194)
RICH*Philippines	-0.255	(0.203)	-0.446	(0.321)
RICH*France	-0.0318	(0.159)	0.113	(0.235)
RICH*Germany	0.0530	(0.119)	0.0330	(0.173)
SONS*POOR			-0.369***	(0.118)
SONS*POOR*Australia			0.652	(0.432)
SONS*POOR*Kenya			0.106	(0.267)
SONS*POOR*Bangladesh			0.416**	(0.202)
SONS*POOR*Sri Lanka			0.861**	(0.375)
SONS*POOR*SA			1.092**	(0.425)
SONS*POOR*US			-0.495	(0.490)
SONS*POOR*Pakistan			0.327*	(0.197)
SONS*POOR*Philippines			0.566	(0.384)
SONS*POOR*France			0.700	(0.583)
SONS*POOR*Germany			0.167	(0.249)
SONS*RICH			0.0540	(0.143)
SONS*RICH*Australia			0.173	(0.327)
SONS*RICH*Kenya			-0.228	(0.258)
SONS*RICH*Bangladesh			0.00685	(0.442)
SONS*RICH*Sri Lanka			-0.446	(0.413)
SONS*RICH*SA			-0.309	(0.272)
SONS*RICH*US			-0.0613	(0.258)
SONS*RICH*Pakistan			-0.473*	(0.264)
SONS*RICH*Philippines			0.339	(0.413)
SONS*RICH*France			-0.258	(0.318)
SONS*RICH*Germany			0.0432	(0.236)
Observations	2399		2399	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7: Birth hazard rate regressions at parity 2. Country fixed effects and country son preference effects, split by income at sample median.

	(1)		(2)	
AGE	-0.0789	(0.0980)	-0.0921	(0.0982)
AGE2	-0.000190	(0.00175)	0.00000580	(0.00175)
DEGREE	0.269	(0.200)	0.285	(0.202)
AL	-0.247	(0.224)	-0.287	(0.225)
FE	0.0876	(0.239)	0.0523	(0.242)
GCSE	-0.0348	(0.159)	-0.0162	(0.159)
POOR*Kenya	-0.0479	(0.260)	0.495	(0.453)
POOR*Bangladesh	0.913***	(0.161)	0.943***	(0.261)
POOR*Pakistan	1.098***	(0.156)	0.750***	(0.267)
POOR*Germany	0.251	(0.228)	0.540	(0.354)
RICH	-0.265	(0.165)	-0.0825	(0.284)
RICH*Kenya	0.0970	(0.227)	0.376	(0.367)
RICH*Bangladesh	0.913***	(0.261)	0.593	(0.457)
RICH*Pakistan	1.123***	(0.174)	0.912***	(0.290)
RICH*Germany	0.323	(0.206)	0.202	(0.354)
SONS*POOR			-0.225	(0.164)
SONS*POOR*Kenya			-0.552	(0.429)
SONS*POOR*Bangladesh			-0.0324	(0.224)
SONS*POOR*Pakistan			0.347	(0.219)
SONS*POOR*Germany			-0.334	(0.327)
SONS*RICH			-0.400**	(0.182)
SONS*RICH*Kenya			-0.295	(0.340)
SONS*RICH*Bangladesh			0.308	(0.418)
SONS*RICH*Pakistan			0.197	(0.252)
SONS*RICH*Germany			0.126	(0.303)
Observations	1180		1180	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: Birth hazard rate regressions at parity 1 with country fixed effects and country son preference effects, split by income at (1) first quartile, (2) sample median, and (3) third quartile.

	(1)		(2)		(3)	
AGE	0.286***	(0.0484)	0.286***	(0.0485)	0.273***	(0.0481)
AGE2	-0.00583***	(0.000889)	-0.00583***	(0.000890)	-0.00563***	(0.000882)
DEGREE	0.0537	(0.0843)	0.0880	(0.0854)	0.0605	(0.0848)
AL	-0.0630	(0.105)	-0.0305	(0.105)	-0.0288	(0.105)
FE	0.124	(0.116)	0.147	(0.116)	0.152	(0.117)
GCSE	-0.0533	(0.0842)	-0.0175	(0.0843)	0.00259	(0.0847)
POOR*Australia	-1.580	(1.008)	-0.251	(0.281)	-0.340	(0.221)
POOR*Kenya	-0.552*	(0.316)	-0.208	(0.204)	-0.128	(0.152)
POOR*Bangladesh	0.451**	(0.182)	0.450***	(0.148)	0.379***	(0.136)
POOR*Sri Lanka	-0.796*	(0.465)	-0.577*	(0.314)	-0.437*	(0.254)
POOR*SA	-0.255	(0.719)	-0.587*	(0.344)	-0.222	(0.216)
POOR*US	0.313	(1.008)	0.220	(0.364)	-0.313	(0.230)
POOR*Pakistan	0.127	(0.188)	0.226	(0.139)	0.253**	(0.120)
POOR*Philippines	-0.546	(0.465)	-0.856***	(0.301)	-0.640***	(0.235)
POOR*France	-0.749	(0.593)	-0.609	(0.457)	-0.271	(0.280)
POOR*Germany	-0.493*	(0.274)	-0.428**	(0.172)	-0.334**	(0.136)
RICH	-0.264*	(0.148)	-0.388***	(0.137)	-0.577***	(0.177)
RICH*Australia	0.0671	(0.178)	0.163	(0.224)	0.628**	(0.292)
RICH*Kenya	0.107	(0.149)	0.192	(0.185)	0.323	(0.291)
RICH*Bangladesh	0.181	(0.232)	0.186	(0.309)	0.562	(0.530)
RICH*Sri Lanka	-0.154	(0.243)	0.0130	(0.298)	0.175	(0.411)
RICH*SA	0.143	(0.166)	0.460**	(0.193)	0.738***	(0.260)
RICH*US	0.215	(0.162)	0.342*	(0.187)	0.971***	(0.244)
RICH*Pakistan	0.529***	(0.145)	0.661***	(0.194)	1.134***	(0.356)
RICH*Philippines	-0.704***	(0.249)	-0.446	(0.321)	-0.924	(0.600)
RICH*France	-0.0513	(0.215)	0.113	(0.235)	0.266	(0.312)
RICH*Germany	-0.139	(0.135)	0.0330	(0.173)	0.167	(0.264)
SONS*POOR	-0.308*	(0.172)	-0.369***	(0.118)	-0.307***	(0.0990)
SONS*POOR*Australia	1.546	(1.239)	0.652	(0.432)	0.622*	(0.335)
SONS*POOR*Kenya	0.582	(0.399)	0.106	(0.267)	-0.0367	(0.208)
SONS*POOR*Bangladesh	0.367	(0.245)	0.416**	(0.202)	0.334*	(0.185)
SONS*POOR*Sri Lanka	1.290**	(0.575)	0.861**	(0.375)	0.588*	(0.311)
SONS*POOR*SA	1.496*	(0.802)	1.092**	(0.425)	0.531*	(0.290)
SONS*POOR*US	-0.504	(1.168)	-0.495	(0.490)	0.156	(0.315)
SONS*POOR*Pakistan	0.302	(0.265)	0.327*	(0.197)	0.261	(0.168)
SONS*POOR*Philippines	0.176	(0.597)	0.566	(0.384)	0.296	(0.307)
SONS*POOR*France	-0.180	(1.169)	0.700	(0.583)	0.231	(0.352)
SONS*POOR*Germany	0.0398	(0.394)	0.167	(0.249)	0.170	(0.193)
SONS*RICH	-0.160	(0.107)	0.0540	(0.143)	0.211	(0.230)
SONS*RICH*Australia	0.361	(0.268)	0.173	(0.327)	-0.0983	(0.428)
SONS*RICH*Kenya	-0.189	(0.208)	-0.228	(0.258)	-0.0170	(0.398)
SONS*RICH*Bangladesh	0.167	(0.335)	0.00685	(0.442)	0.598	(0.748)
SONS*RICH*Sri Lanka	0.0531	(0.310)	-0.446	(0.413)	-0.772	(0.603)
SONS*RICH*SA	0.0323	(0.236)	-0.309	(0.272)	-0.480	(0.372)
SONS*RICH*US	-0.00183	(0.226)	-0.0613	(0.258)	-0.414	(0.345)
SONS*RICH*Pakistan	-0.147	(0.199)	-0.473*	(0.264)	-1.247***	(0.470)
SONS*RICH*Philippines	0.542*	(0.319)	0.339	(0.413)	1.496**	(0.716)
SONS*RICH*France	0.0393	(0.285)	-0.258	(0.318)	-0.379	(0.464)
SONS*RICH*Germany	0.174	(0.189)	0.0432	(0.236)	0.0553	(0.362)
Observations	2399		2399		2399	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.9: Birth hazard rate regressions at parity 2 with country fixed effects and country son preference effects, split by income at (1) first quartile, (2) sample median, and (3) third quartile.

	(1)		(2)		(3)	
AGE	-0.100	(0.0988)	-0.0921	(0.0982)	-0.109	(0.0984)
AGE2	0.000103	(0.00176)	0.00000580	(0.00175)	0.000208	(0.00176)
DEGREE	0.291	(0.201)	0.285	(0.202)	0.287	(0.206)
AL	-0.272	(0.226)	-0.287	(0.225)	-0.289	(0.226)
FE	0.0423	(0.243)	0.0523	(0.242)	0.0415	(0.240)
GCSE	-0.00791	(0.160)	-0.0162	(0.159)	0.00774	(0.159)
POOR*Kenya	-0.157	(0.900)	0.495	(0.453)	0.190	(0.345)
POOR*Bangladesh	0.571*	(0.333)	0.943***	(0.261)	0.895***	(0.235)
POOR*Pakistan	0.597	(0.365)	0.750***	(0.267)	0.808***	(0.217)
POOR*Germany	1.038	(0.855)	0.540	(0.354)	0.293	(0.309)
RICH	-0.499	(0.323)	-0.0825	(0.284)	-0.152	(0.357)
RICH*Kenya	0.508*	(0.302)	0.376	(0.367)	0.955*	(0.504)
RICH*Bangladesh	0.728*	(0.390)	0.593	(0.457)	0.738	(0.565)
RICH*Pakistan	0.826***	(0.234)	0.912***	(0.290)	0.819*	(0.464)
RICH*Germany	0.381	(0.273)	0.202	(0.354)	0.613	(0.457)
SONS*POOR	-0.370*	(0.221)	-0.225	(0.164)	-0.292**	(0.135)
SONS*POOR*Kenya	0.501	(0.728)	-0.552	(0.429)	-0.180	(0.305)
SONS*POOR*Bangladesh	0.106	(0.271)	-0.0324	(0.224)	0.0222	(0.202)
SONS*POOR*Pakistan	0.373	(0.298)	0.347	(0.219)	0.294	(0.183)
SONS*POOR*Germany	-0.868	(0.744)	-0.334	(0.327)	-0.225	(0.283)
SONS*RICH	-0.319**	(0.145)	-0.400**	(0.182)	-0.388	(0.285)
SONS*RICH*Kenya	-0.533*	(0.291)	-0.295	(0.340)	-0.923*	(0.527)
SONS*RICH*Bangladesh	0.217	(0.344)	0.308	(0.418)	0.492	(0.566)
SONS*RICH*Pakistan	0.312	(0.197)	0.197	(0.252)	0.330	(0.386)
SONS*RICH*Germany	-0.0364	(0.242)	0.126	(0.303)	0.110	(0.389)
Observations	1180		1180		1180	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.10: Birth hazard rate regressions at parity 1. Country fixed effects and country son preference effects, split by age on immigration to the UK. Column (1) split at age 10, Column (2) at age 15.

	(1)		(2)	
AGE	0.162***	(0.0199)	0.162***	(0.0199)
AGE2	-0.00382***	(0.000369)	-0.00382***	(0.000370)
DEGREE	0.151***	(0.0404)	0.149***	(0.0403)
AL	-0.0821*	(0.0460)	-0.0870*	(0.0460)
FE	0.00541	(0.0482)	0.00408	(0.0482)
GCSE	0.00901	(0.0385)	0.00363	(0.0388)
OLD*Australia	-0.0729	(0.148)	-0.0381	(0.156)
OLD*Canada	-0.0995	(0.191)	0.0538	(0.213)
OLD*New Zealand	-0.141	(0.234)	-0.161	(0.240)
OLD*Kenya	0.0110	(0.0889)	-0.0624	(0.104)
OLD*Uganda	-0.244*	(0.129)	-0.317**	(0.154)
OLD*Tanzania	-0.0222	(0.157)	-0.211	(0.182)
OLD*Zambia	-0.181	(0.213)	-0.227	(0.228)
OLD*Zimbabwe	-0.414**	(0.164)	-0.391**	(0.168)
OLD*Ghana	-0.0957	(0.115)	-0.0597	(0.117)
OLD*Nigeria	0.211**	(0.101)	0.227**	(0.103)
OLD*Jamaica	-0.831***	(0.119)	-0.764***	(0.149)
OLD*Grp02	-0.394*	(0.218)	-0.0270	(0.240)
OLD*Bangladesh	0.298***	(0.0712)	0.319***	(0.0757)
OLD*Sri Lanka	-0.0726	(0.135)	-0.0567	(0.136)
OLD*HK & China	-0.229*	(0.130)	-0.196	(0.136)
OLD*Malaysia	0.301**	(0.140)	0.339**	(0.145)
OLD*Singapore	-0.616*	(0.319)	-0.393	(0.337)
OLD*Cyprus	-0.350**	(0.164)	-0.333*	(0.173)
OLD*Malta	-0.423	(0.336)	-0.766*	(0.411)
OLD*Mauritius	-0.449**	(0.182)	-0.438**	(0.185)
OLD*SA	-0.0369	(0.117)	-0.0140	(0.122)
OLD*Grp04	-0.193	(0.140)	-0.204	(0.144)
OLD*US	0.138	(0.0992)	0.195*	(0.103)
OLD*Pakistan	0.386***	(0.0614)	0.411***	(0.0645)
OLD*China	-0.595***	(0.188)	-0.609***	(0.194)
OLD*Japan	-0.203	(0.191)	-0.206	(0.194)
OLD*Philippines	-0.622***	(0.142)	-0.612***	(0.143)
OLD*Iran	-0.127	(0.170)	-0.121	(0.173)
OLD*Grp8	0.406**	(0.162)	0.415**	(0.168)
OLD*France	-0.0639	(0.138)	-0.0622	(0.140)
OLD*Italy	-0.756***	(0.182)	-0.690***	(0.185)
OLD*Netherlands	0.0816	(0.177)	0.0804	(0.180)
OLD*Germany	-0.298***	(0.115)	-0.289**	(0.126)
OLD*Poland	-0.697***	(0.179)	-0.707***	(0.185)
OLD*Portugal	-0.573***	(0.157)	-0.573***	(0.161)
OLD*Spain	-0.425**	(0.194)	-0.437**	(0.198)
OLD*Serbia & Montenegro	-0.0782	(0.168)	-0.0631	(0.168)
OLD*Turkey	-0.313**	(0.134)	-0.303**	(0.136)
OLD*Somalia	0.344***	(0.114)	0.359***	(0.115)
YOUNG	0.110	(0.104)	0.141	(0.0896)
YOUNG*Australia	-0.107	(0.203)	-0.157	(0.184)
YOUNG*Canada	-0.181	(0.215)	-0.289	(0.191)
YOUNG*New Zealand	-0.161	(0.347)	-0.113	(0.326)
YOUNG*Kenya	0.0984	(0.157)	0.0978	(0.121)
YOUNG*Uganda	0.231	(0.229)	0.0324	(0.170)
YOUNG*Tanzania	0.182	(0.317)	0.440**	(0.223)
YOUNG*Zambia	-0.0880	(0.330)	-0.0294	(0.288)
YOUNG*Zimbabwe	-0.0886	(0.316)	-0.213	(0.288)
YOUNG*Ghana	0.400	(0.458)	-0.146	(0.362)
YOUNG*Nigeria	-0.00724	(0.284)	0.00636	(0.249)
YOUNG*Jamaica	-0.610***	(0.203)	-0.850***	(0.148)
YOUNG*Grp02	-0.812***	(0.304)	-0.990***	(0.262)
YOUNG*Bangladesh	0.0911	(0.186)	0.108	(0.137)
YOUNG*Sri Lanka	-0.140	(0.366)	-0.156	(0.362)
YOUNG*HK & China	-0.364	(0.267)	-0.423*	(0.232)
YOUNG*Malaysia	-0.0560	(0.260)	-0.0706	(0.232)
YOUNG*Singapore	-0.114	(0.161)	-0.191	(0.151)
YOUNG*Cyprus	-0.187	(0.179)	-0.228	(0.165)
YOUNG*Malta	-0.170	(0.214)	-0.0997	(0.198)
YOUNG*Mauritius	-0.302	(0.457)	-0.332	(0.416)
YOUNG*SA	-0.285	(0.218)	-0.290	(0.193)
YOUNG*Grp04	-0.335	(0.509)	-0.0746	(0.416)
YOUNG*US	-0.153	(0.243)	-0.266	(0.208)
YOUNG*Pakistan	0.418***	(0.143)	0.313***	(0.117)
YOUNG*China	-1.776*	(1.005)	-1.032*	(0.583)
YOUNG*Japan	2.185**	(1.005)	0.954	(0.712)
YOUNG*Philippines	1.015	(1.005)	-0.425	(1.004)
YOUNG*Iran	0.876*	(0.509)	0.696	(0.454)
YOUNG*Grp8	-0.0316	(0.254)	0.00425	(0.232)
YOUNG*France	-0.239	(0.317)	-0.184	(0.300)
YOUNG*Italy	-0.246	(0.243)	-0.423*	(0.232)
YOUNG*Netherlands	-0.459	(0.509)	-0.319	(0.454)
YOUNG*Germany	-0.372***	(0.124)	-0.385***	(0.109)
YOUNG*Poland	1.237	(1.005)	-0.0192	(0.583)
YOUNG*Portugal	-0.386	(0.585)	-0.368	(0.454)
YOUNG*Spain	-0.113	(0.509)	0.00685	(0.454)
YOUNG*Serbia & Montenegro	1.067	(1.005)	0.727	(0.712)
YOUNG*Turkey	-0.133	(0.713)	-0.134	(0.583)
YOUNG*Somalia			3.300***	(1.005)
	ctd.		ctd.	

	(1) ctd.		(2) ctd.	
SONS*OLD	-0.285***	(0.0583)	-0.250***	(0.0609)
SONS*OLD*Australia	0.615***	(0.212)	0.639***	(0.221)
SONS*OLD*Canada	0.361	(0.251)	0.414	(0.275)
SONS*OLD*New Zealand	0.130	(0.307)	0.242	(0.315)
SONS*OLD*Kenya	-0.0168	(0.121)	-0.0379	(0.140)
SONS*OLD*Uganda	0.254	(0.179)	0.322	(0.206)
SONS*OLD*Tanzania	-0.249	(0.232)	-0.151	(0.268)
SONS*OLD*Zambia	0.606**	(0.278)	0.545*	(0.312)
SONS*OLD*Zimbabwe	0.241	(0.219)	0.185	(0.228)
SONS*OLD*Ghana	0.0490	(0.170)	-0.0244	(0.174)
SONS*OLD*Nigeria	0.174	(0.142)	0.141	(0.145)
SONS*OLD*Jamaica	0.528***	(0.161)	0.523***	(0.200)
SONS*OLD*Grp02	0.0523	(0.298)	-0.461	(0.369)
SONS*OLD*Bangladesh	0.233**	(0.0952)	0.167*	(0.101)
SONS*OLD*Sri Lanka	0.0929	(0.185)	0.0622	(0.186)
SONS*OLD*HK & China	0.116	(0.177)	-0.0411	(0.188)
SONS*OLD*Malaysia	-0.314	(0.216)	-0.361	(0.223)
SONS*OLD*Singapore	1.029**	(0.418)	0.916**	(0.445)
SONS*OLD*Cyprus	0.317	(0.220)	0.210	(0.239)
SONS*OLD*Malta	-0.0964	(0.489)	0.224	(0.560)
SONS*OLD*Mauritius	0.0718	(0.273)	0.0348	(0.285)
SONS*OLD*SA	0.143	(0.169)	0.132	(0.176)
SONS*OLD*Grp04	0.276	(0.201)	0.282	(0.205)
SONS*OLD*US	0.209	(0.146)	0.161	(0.150)
SONS*OLD*Pakistan	0.132	(0.0838)	0.0784	(0.0874)
SONS*OLD*China	0.272	(0.257)	0.220	(0.266)
SONS*OLD*Japan	0.419	(0.265)	0.402	(0.268)
SONS*OLD*Philippines	0.664***	(0.184)	0.624***	(0.186)
SONS*OLD*Iran	-0.00827	(0.225)	-0.0396	(0.229)
SONS*OLD*Grp8	0.272	(0.223)	0.232	(0.235)
SONS*OLD*France	0.227	(0.189)	0.176	(0.192)
SONS*OLD*Italy	0.920***	(0.241)	0.836***	(0.247)
SONS*OLD*Netherlands	0.511**	(0.251)	0.490*	(0.256)
SONS*OLD*Germany	0.372**	(0.159)	0.348**	(0.174)
SONS*OLD*Poland	-0.0536	(0.259)	-0.0423	(0.263)
SONS*OLD*Portugal	0.248	(0.225)	0.204	(0.229)
SONS*OLD*Spain	0.294	(0.279)	0.285	(0.284)
SONS*OLD*Serbia & Montenegro	0.259	(0.235)	0.216	(0.237)
SONS*OLD*Turkey	0.284	(0.179)	0.250	(0.181)
SONS*OLD*Somalia	0.595***	(0.158)	0.551***	(0.159)
SONS*YOUNG	-0.101	(0.133)	-0.294***	(0.110)
SONS*YOUNG*Australia	0.0746	(0.287)	0.253	(0.264)
SONS*YOUNG*Canada	0.163	(0.297)	0.262	(0.267)
SONS*YOUNG*New Zealand	1.148**	(0.491)	0.474	(0.461)
SONS*YOUNG*Kenya	-0.0794	(0.218)	0.0735	(0.171)
SONS*YOUNG*Uganda	-0.147	(0.326)	0.0446	(0.251)
SONS*YOUNG*Tanzania	-0.260	(0.457)	-0.457	(0.330)
SONS*YOUNG*Zambia	-0.0558	(0.441)	0.257	(0.364)
SONS*YOUNG*Zimbabwe	0.540	(0.405)	0.609*	(0.364)
SONS*YOUNG*Ghana	0.0151	(0.586)	0.592	(0.470)
SONS*YOUNG*Nigeria	-0.0870	(0.424)	0.123	(0.361)
SONS*YOUNG*Jamaica	-0.0726	(0.279)	0.324	(0.206)
SONS*YOUNG*Grp02	-0.0308	(0.475)	0.530	(0.353)
SONS*YOUNG*Bangladesh	0.0493	(0.254)	0.360*	(0.189)
SONS*YOUNG*Sri Lanka	-0.226	(0.483)	-0.0466	(0.470)
SONS*YOUNG*HK & China	0.181	(0.337)	0.557*	(0.288)
SONS*YOUNG*Malaysia	0.484	(0.337)	0.580*	(0.307)
SONS*YOUNG*Singapore	-0.00264	(0.227)	0.241	(0.213)
SONS*YOUNG*Cyprus	-0.0790	(0.238)	0.173	(0.217)
SONS*YOUNG*Malta	-0.187	(0.297)	-0.0958	(0.279)
SONS*YOUNG*Mauritius	0.712	(0.620)	0.449	(0.539)
SONS*YOUNG*SA	0.222	(0.294)	0.325	(0.263)
SONS*YOUNG*Grp04	0.967	(0.616)	0.609	(0.528)
SONS*YOUNG*US	-0.159	(0.347)	0.105	(0.305)
SONS*YOUNG*Pakistan	-0.180	(0.205)	0.134	(0.168)
SONS*YOUNG*Philippines			1.748	(1.230)
SONS*YOUNG*China	2.201*	(1.232)	1.776**	(0.772)
SONS*YOUNG*Japan	-37.47	(35511541.9)	-45.24	.
SONS*YOUNG*Iran	-1.535*	(0.877)	-0.999	(0.680)
SONS*YOUNG*Grp8	-0.0187	(0.363)	0.235	(0.321)
SONS*YOUNG*France	0.128	(0.502)	0.488	(0.455)
SONS*YOUNG*Italy	-0.223	(0.340)	0.168	(0.319)
SONS*YOUNG*Netherlands	0.556	(0.684)	0.636	(0.616)
SONS*YOUNG*Germany	0.171	(0.173)	0.360**	(0.153)
SONS*YOUNG*Poland	-0.669	(1.232)	-0.187	(0.920)
SONS*YOUNG*Portugal	0.705	(0.827)	1.104	(0.680)
SONS*YOUNG*Spain	-0.141	(0.684)	-0.104	(0.616)
SONS*YOUNG*Turkey	0.0851	(0.793)	0.241	(0.661)
Observations	13112		13112	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.11: Birth hazard rate regressions at parity 2. Country fixed effects and country son preference effects, split by age on immigration to the UK. Column (1) split at age 10, Column (2) at age 15.

	(1)		(2)	
AGE	-0.00852	(0.0373)	-0.00951	(0.0373)
AGE2	-0.00153**	(0.000668)	-0.00151**	(0.000668)
DEGREE	0.0657	(0.0782)	0.0636	(0.0780)
AL	-0.195**	(0.0852)	-0.203**	(0.0853)
FE	-0.183**	(0.0916)	-0.189**	(0.0914)
GCSE	-0.186***	(0.0691)	-0.185***	(0.0691)
OLD*Australia	-0.712*	(0.408)	-0.605	(0.418)
OLD*Canada	-0.299	(0.421)	0.128	(0.429)
OLD*Kenya	0.225	(0.174)	0.279	(0.208)
OLD*Uganda	-0.248	(0.272)	-0.291	(0.327)
OLD*Zimbabwe	-0.453	(0.374)	-0.542	(0.394)
OLD*Ghana	0.632***	(0.216)	0.644***	(0.219)
OLD*Nigeria	0.893***	(0.180)	0.866***	(0.185)
OLD*Jamaica	0.426*	(0.233)	0.426	(0.267)
OLD*Bangladesh	0.745***	(0.118)	0.787***	(0.124)
OLD*Sri Lanka	-0.903**	(0.405)	-0.903**	(0.407)
OLD*HK & China	-0.120	(0.283)	-0.102	(0.290)
OLD*Malaysia	-0.371	(0.386)	-0.199	(0.383)
OLD*Singapore	1.145**	(0.506)	1.137**	(0.515)
OLD*Cyprus	-0.387	(0.391)	-0.368	(0.417)
OLD*SA	-0.150	(0.264)	-0.188	(0.277)
OLD*Grp04	0.512**	(0.241)	0.460*	(0.251)
OLD*US	-0.0392	(0.211)	-0.0559	(0.219)
OLD*Pakistan	0.822***	(0.106)	0.800***	(0.111)
OLD*Philippines	-0.715*	(0.431)	-0.718*	(0.433)
OLD*Grp8	0.884***	(0.267)	0.914***	(0.271)
OLD*France	0.0122	(0.305)	0.0761	(0.305)
OLD*Italy	-0.219	(0.351)	-0.226	(0.353)
OLD*Germany	-0.212	(0.259)	-0.108	(0.286)
OLD*Turkey	-0.309	(0.299)	-0.378	(0.309)
OLD*Somalia	1.108***	(0.180)	1.111***	(0.182)
YOUNG	0.168	(0.192)	0.132	(0.169)
YOUNG*Australia	-0.414	(0.422)	-0.487	(0.399)
YOUNG*Canada	-0.204	(0.413)	-0.486	(0.399)
YOUNG*Kenya	0.129	(0.315)	0.0804	(0.235)
YOUNG*Uganda	-0.000275	(0.547)	-0.170	(0.369)
YOUNG*Zimbabwe	0.347	(0.717)	0.585	(0.638)
YOUNG*Ghana	-0.371	(0.996)	-0.0843	(0.792)
YOUNG*Nigeria	-1.130	(0.811)	-0.204	(0.574)
YOUNG*Jamaica	-0.103	(0.395)	0.0733	(0.307)
YOUNG*Bangladesh	0.389	(0.294)	0.364	(0.234)
YOUNG*Sri Lanka	-1.198	(0.932)	-1.014	(0.901)
YOUNG*HK & China	-0.266	(0.527)	-0.307	(0.497)
YOUNG*Malaysia	-0.441	(0.476)	-0.636	(0.474)
YOUNG*Singapore	-1.241***	(0.424)	-1.175***	(0.407)
YOUNG*Cyprus	-0.212	(0.349)	-0.201	(0.327)
YOUNG*SA	0.0437	(0.516)	0.106	(0.448)
YOUNG*Grp04	1.202	(0.998)	1.242*	(0.689)
YOUNG*US	0.00846	(0.586)	0.188	(0.464)
YOUNG*Pakistan	0.627***	(0.241)	0.788***	(0.198)
YOUNG*Philippines	2.478**	(1.008)	2.293	(1.546)
YOUNG*Grp8	0.320	(0.430)	0.392	(0.400)
YOUNG*France	-0.0636	(0.827)	-0.416	(0.810)
YOUNG*Italy	-0.140	(0.553)	-0.0930	(0.544)
YOUNG*Germany	-0.234	(0.236)	-0.242	(0.212)
YOUNG*Turkey	-2.446	(2.090)	-0.305	(1.212)
SONS*OLD	-0.273***	(0.0704)	-0.253***	(0.0733)
SONS*OLD*Australia	0.753**	(0.318)	0.779**	(0.328)
SONS*OLD*Canada	0.0943	(0.336)	-0.373	(0.379)
SONS*OLD*Kenya	-0.282*	(0.154)	-0.476**	(0.189)
SONS*OLD*Uganda	0.190	(0.235)	0.221	(0.272)
SONS*OLD*Zimbabwe	0.444	(0.309)	0.452	(0.323)
SONS*OLD*Ghana	0.0991	(0.183)	0.0550	(0.187)
SONS*OLD*Nigeria	-0.0183	(0.152)	-0.0110	(0.155)
SONS*OLD*Jamaica	-0.342	(0.209)	-0.450*	(0.254)
SONS*OLD*Bangladesh	0.171*	(0.0962)	0.129	(0.100)
SONS*OLD*Sri Lanka	0.651**	(0.276)	0.642**	(0.277)
SONS*OLD*HK & China	0.0595	(0.230)	0.0712	(0.242)
SONS*OLD*Malaysia	0.473	(0.308)	0.385	(0.304)
SONS*OLD*Singapore	-1.216**	(0.572)	-1.263**	(0.605)
SONS*OLD*Cyprus	0.271	(0.293)	0.226	(0.322)
SONS*OLD*SA	0.143	(0.222)	0.115	(0.234)
SONS*OLD*Grp04	0.0816	(0.224)	0.127	(0.231)
SONS*OLD*US	0.422**	(0.174)	0.388**	(0.179)
SONS*OLD*Pakistan	0.147*	(0.0872)	0.146	(0.0906)
SONS*OLD*Philippines	0.371	(0.312)	0.370	(0.314)
SONS*OLD*Grp8	0.100	(0.217)	0.0804	(0.220)
SONS*OLD*France	0.109	(0.264)	0.00987	(0.271)
SONS*OLD*Italy	0.0984	(0.311)	0.146	(0.313)
SONS*OLD*Germany	0.0613	(0.218)	0.0150	(0.238)
SONS*OLD*Turkey	0.128	(0.248)	0.171	(0.252)
SONS*OLD*Somalia	0.0906	(0.148)	0.0702	(0.150)
SONS*YOUNG	-0.217	(0.149)	-0.305**	(0.130)
SONS*YOUNG*Australia	0.762**	(0.343)	0.782**	(0.321)
	ctd.		ctd.	

	(1) ctd.		(2) ctd.	
SONS*YOUNG*Canada	0.142	(0.344)	0.524*	(0.316)
SONS*YOUNG*Kenya	-0.367	(0.284)	-0.0876	(0.209)
SONS*YOUNG*Uganda	0.159	(0.417)	0.250	(0.312)
SONS*YOUNG*Zimbabwe	-0.339	(0.617)	-0.301	(0.558)
SONS*YOUNG*Ghana	0.649	(0.641)	0.687	(0.521)
SONS*YOUNG*Nigeria	1.153**	(0.587)	0.594	(0.457)
SONS*YOUNG*Jamaica	-0.0202	(0.363)	-0.0260	(0.271)
SONS*YOUNG*Bangladesh	0.127	(0.235)	0.298	(0.190)
SONS*YOUNG*Sri Lanka	1.429**	(0.633)	1.299**	(0.607)
SONS*YOUNG*HK & China	0.0101	(0.388)	0.0792	(0.356)
SONS*YOUNG*Malaysia	0.407	(0.349)	0.594*	(0.349)
SONS*YOUNG*Singapore	0.647**	(0.309)	0.725**	(0.298)
SONS*YOUNG*Cyprus	0.168	(0.270)	0.259	(0.250)
SONS*YOUNG*SA	-0.112	(0.435)	0.00767	(0.380)
SONS*YOUNG*Grp04	-1.807	(1.199)	-1.489*	(0.847)
SONS*YOUNG*US	-0.500	(0.516)	-0.188	(0.403)
SONS*YOUNG*Pakistan	-0.0392	(0.210)	0.00775	(0.176)
SONS*YOUNG*Philippines			-1.009	(1.176)
SONS*YOUNG*Grp8	-0.262	(0.394)	-0.0709	(0.351)
SONS*YOUNG*France	0.352	(0.713)	0.817	(0.627)
SONS*YOUNG*Italy	-0.346	(0.480)	-0.335	(0.474)
SONS*YOUNG*Germany	0.146	(0.197)	0.237	(0.180)
SONS*YOUNG*Turkey	1.525	(1.165)	0.314	(0.808)
Observations	7630		7630	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.12: Birth hazard rate regressions at parity 3. Country fixed effects and country son preference effects, split by age on immigration to the UK. Column (1) split at age 10, Column (2) at age 15.

	(1)		(2)	
AGE	-0.0995	(0.0658)	-0.103	(0.0656)
AGE2	0.000373	(0.00111)	0.000435	(0.00111)
DEGREE	-0.748***	(0.275)	-0.780***	(0.277)
AL	-0.516**	(0.233)	-0.543**	(0.232)
FE	-0.301	(0.233)	-0.310	(0.232)
GCSE	-0.521***	(0.183)	-0.535***	(0.182)
OLD*Kenya	0.109	(0.347)	0.347	(0.410)
OLD*Nigeria	0.584*	(0.317)	0.703**	(0.323)
OLD*Bangladesh	0.662***	(0.217)	0.756***	(0.231)
OLD*Pakistan	0.702***	(0.202)	0.790***	(0.214)
OLD*Germany	-1.560*	(0.886)	-1.370	(0.995)
OLD*Somalia	1.041***	(0.296)	1.132***	(0.302)
YOUNG	0.00543	(0.458)	0.438	(0.377)
YOUNG*Kenya	0.189	(0.719)	-0.329	(0.506)
YOUNG*Nigeria	-44.08	.	-4.695	(3.798)
YOUNG*Bangladesh	0.289	(0.680)	0.165	(0.446)
YOUNG*Pakistan	0.852*	(0.483)	0.482	(0.380)
YOUNG*Germany	-0.573	(0.662)	-1.038*	(0.581)
SONS*OLD	-0.411***	(0.110)	-0.368***	(0.115)
SONS*OLD*Kenya	-0.120	(0.248)	-0.263	(0.295)
SONS*OLD*Nigeria	0.194	(0.200)	0.140	(0.203)
SONS*OLD*Bangladesh	0.243*	(0.132)	0.207	(0.139)
SONS*OLD*Pakistan	0.267**	(0.125)	0.218*	(0.131)
SONS*OLD*Germany	1.219***	(0.415)	1.071**	(0.464)
SONS*OLD*Somalia	0.325*	(0.175)	0.283	(0.179)
SONS*YOUNG	-0.130	(0.255)	-0.383*	(0.209)
SONS*YOUNG*Kenya	-0.172	(0.500)	0.0762	(0.353)
SONS*YOUNG*Nigeria	-0.656	.	2.277	(1.839)
SONS*YOUNG*Bangladesh	-0.00885	(0.395)	0.189	(0.270)
SONS*YOUNG*Pakistan	-0.169	(0.297)	0.181	(0.242)
SONS*YOUNG*Germany	-0.00803	(0.384)	0.357	(0.337)
Observations	2317		2317	

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C

Appendix to Chapter 4

C.1 Robustness of heterogeneity estimates

If parents base their fertility decisions on their current family composition, there may be concerns that my estimates of heterogeneity in son-probability are biased. In particular, the measured heterogeneity might be a result of differences in behaviour due to preferences over family composition. Here, I test for the effect of observed parental behaviour in a simulation. The exercise is very similar to that of Section 4.4, however the outcome of interest if not the final sex ratio, but the estimates of underlying heterogeneity.

Figure C.1 suggests there may be cause for concern when estimating heterogeneity. The homogeneous model without son preference performs relatively badly, and is rejected at the 10% level using Pearson's χ^2 test. Including son preference improves the fit slightly, and the difference from the data becomes insignificant. However, once heterogeneity is introduced, the fit improves further and the p-value increases to 0.97. This suggests that, although parents' preferences can affect the overall ratios of families with given compositions, variation in the probability of having sons is present nonetheless. The remainder of this section formally tests the robustness of my heterogeneity estimates to the preferences of women in my sample.

Figure C.1: Family composition, data versus simulations accounting for son preferences. Where applied, son preferences are as reported in Table C.1. Heterogeneity model uses my benchmark estimates from Section 4.3.3 ($\hat{\mu} = 0.303$, $\hat{\sigma} = 0.145$). Homogeneity uses the restricted model, with a fixed probability of 0.512 of having boys (equivalent to $\tilde{\mu} = 0.0303$).

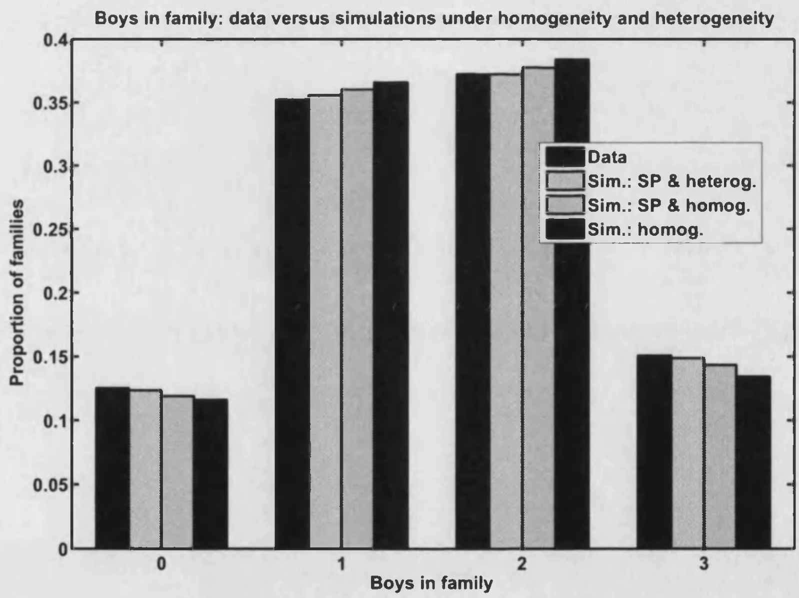


Table C.1: Kaplan-Meier birth continuation rates by family composition for UK-born women. Sample selection is that in Section 4.3.3. Statistics give the proportion of women having a further child given they already have b boys of j children.

Children	0 boys	1 boy	2 boys	3 boys	4 boys	5 boys
1	0.70	0.69	–	–	–	–
2	0.40	0.33	0.42	–	–	–
3	0.35	0.30	0.30	0.34	–	–
4	0.38	0.35	0.30	0.28	0.31	–
5	0.58	0.46	0.44	0.40	0.34	0.34

Following the model of Section 4.2, suppose that the true distribution of the underlying factor X were $\mathrm{N}(\tilde{\mu}, \tilde{\sigma}^2)$. I generate a population of such women and also a latent family composition for each woman. Next, I simulate each woman's fertility decisions according to the observed patterns amongst the women in my sample. If some woman has two boys and a girl, I set the probability of her having a fourth child to be that observed amongst actual women with those children, giving simulated birth histories for each of the women. See Section 4.4.1 for details.

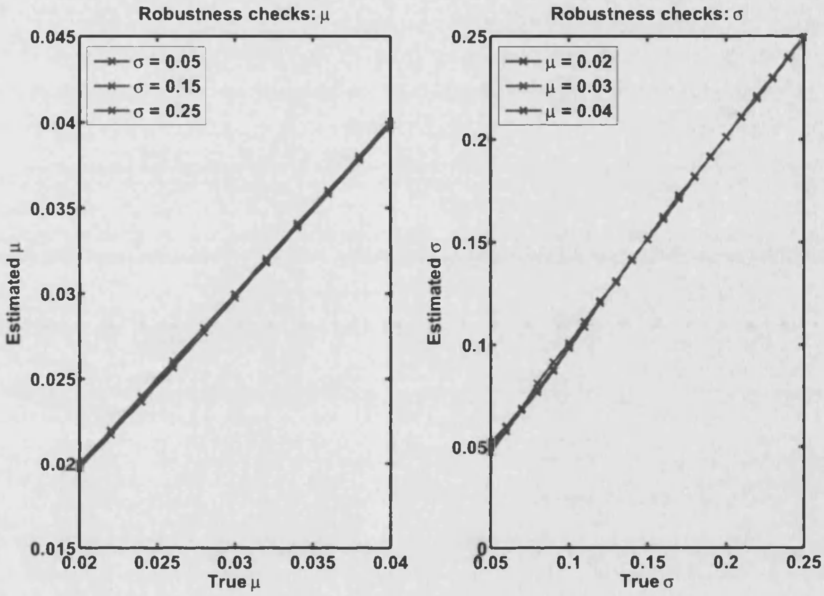
The key step is to compute estimates $\hat{\mu}$ and $\hat{\sigma}$ based on these simulated birth histories by the MLE method of Section 4.3. By comparing $\hat{\mu}$ and $\hat{\sigma}$ to $\tilde{\mu}$ and $\tilde{\sigma}$, the robustness of the estimator to parental fertility decisions can be assessed. In the case where $\hat{\mu} \approx \tilde{\mu}$ and $\hat{\sigma} \approx \tilde{\sigma}$ for measured values, these estimates can be considered robust to son and daughter preferences.

Table C.1 records birth progression rates for the UK-born women in my sample, grouped by existing family composition. These estimates are computed exactly as in Section 4.4.2. This data gives the proportion q_{bj} of women who go on to have another child if they already have b boys amongst j children.[1]

Figure C.2 gives estimated $\hat{\mu}$ and $\hat{\sigma}$ based on various values of $\tilde{\mu}$ and $\tilde{\sigma}$ in a simulation with one million women. Tested values are encompass the parameter

[1]These British-born women appear to have preferences for mixed families: after two or three children, progression rates are lowest with children of each sex. Conversely, after four and five children some son preference is seen. It is feasible that these women having more children are not representative, and both the larger family and son preference is driven by some unobserved factor, such as being a second generation migrant.

Figure C.2: Robustness check on heterogeneity estimates under observed parental decisions. Estimated $\hat{\mu}$ and $\hat{\sigma}$ based on different possible 'true' values $\tilde{\mu}$ and $\tilde{\sigma}$. 1,000,000 women simulated, following the fertility behaviour given in Table C.1.



confidence intervals derived by the bootstrap procedure of Section 4.3.3. For each parameter, estimates are very close to the posited values. Correlation in either case is 1.00 (three significant figures), and the slopes are also very close to one. I conclude that the preferences held by British-born women are very unlikely to bias my estimates of heterogeneity in the probability of having sons.