Essays in Development Economics

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A thesis submitted for the degree of

Doctor of Philosophy in Economics

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Abstract

This thesis comprises three stand-alone chapters:

The first chapter is on the effect of natural disasters on labor markets. Using data from the Indonesia Family Life Survey, the Desinventar database, the US Geological Survey and district level employment indicators, we explore how a large earthquake in Indonesia affected local labor markets, in particular the evolution of wages and employment across sectors. We find that wage growth in the agriculture sector is significantly higher in earthquake affected areas. We propose two mechanisms for this result and show evidence for both mechanisms.

The second chapter investigates the intra-household allocation of leisure and consumption among siblings. Children are often treated as passive members in the household and their preferences over consumption and leisure are rarely modeled. This chapter considers children as agents with their own preferences over leisure and consumption and builds a theoretical and empirical model for children's time and consumption allocations in a household. We test the predictions of the model with data from Ethiopia, India, Peru and Vietnam. The results suggest that differences in siblings' relative time and consumption allocations are driven by their relative preferences over leisure and consumption rather than differences in parents' relative altruism.

The third chapter examines the cost of transport infrastructure in developing countries. To our knowledge, this is the first study that analyzes drivers of unit costs of construction of transport infrastructure using a large data set of 3,322 unit costs of road work activities in low and middle income countries. We find a large dispersion in unit costs for comparable work activities. Unit costs are significantly higher in conflict and corrupt countries, and these effects are robust to controlling for a country's public investment capacity and business environment. Finally, higher unit costs are significantly negatively correlated with infrastructure provision.

Word Count

The approximate number of words in this thesis is 56,445 excluding the bibliography. This is calculated using the number of words on page 2 (355) multiplied by the number of pages (159).

Declaration

I declare that this thesis represents my own work, and that none of it has already been accepted, or is currently being submitted, for any degree or diploma or certificate or other qualification in this University or elsewhere. Chapter 4 is an extended version of a jointly authored paper with Paul Collier and Måns Söderbom. I have contributed the most work on this paper.

Acknowledgments

First and foremost, I would like to express my sincere gratitude to my supervisor Stefan Dercon. He was not only critical in my decision to come to Oxford for the MSc in Economics for Development, but also to stay on for the DPhil. I feel privileged that I was able to work with him. Stefan has been a fantastic supervisor, with an incredible gift for transmitting encouragement. He made time for meetings after work and on weekends when his schedule was already very busy. Throughout, he has been a role model for the economist I aspire to become. I am also thankful for him understanding my needs to leave Oxford from time to time, either for fieldwork, or to be involved in policy work. But his support reached far beyond his supervisory responsibilities. In Austria we call the doctoral supervisor "Doktorvater", and this accurately describes the way I perceived Stefan during my DPhil.

Second, I am extremely grateful to Martin Browning, who despite not being my supervisor, was incredibly generous with his time and available to discuss my second chapter. I greatly benefited from these interactions, his advice, and thinking together through problems. I owe my appreciation of structural models to him.

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Above all, I am most grateful to my family: my proud grandparents for their support and passing on their industrious genes. I feel extremely lucky to have Elisabeth and Herbert Kirchberger as my parents. You have always made me believe that there is nothing that I cannot achieve. Your hard work enabled me to enjoy opportunities which were not available to you, and I will always be thankful for that. I am grateful that you have let me go my way, even if this meant being farther away from home than you would have preferred. Thank you for your unconditional love and support.

Preface

Chapter 2 has been presented at the 26th Annual Congress of the European Economic Association (Malaga 2012), Development Economics Conference of the German Economic Association (Bonn 2012), the North East Universities Development Consortium Annual Conference (Yale 2011), Spring Meeting of Young Economists (Groeningen 2011), Center for the Study of African Economies Annual Conference (Oxford 2011), Royal Economic Society Annual Conference (Royal Holloway 2011), World Bank/IZA Conference on Labor and Development (Mexico City 2011) and the Gorman Workshop (Oxford 2010)[1].

Chapter 3 has been presented at the Econometric Society European Meetings (Gothenburg, 2013), the Conference on Inequality in Children's Outcomes in Developing Countries (Oxford 2013), the Development Economics Conference of the German Economic Association (Munich 2013), the Royal Economic Society Annual Conference (Royal Holloway 2013), North East Universities Development Consortium Annual Conference (Dartmouth 2012), the Center for the Study of African Economies Annual Conference (Oxford 2012), Spring Meeting of Young Economists (Mannheim 2012), the Gorman Workshop (Oxford 2012), and the Center for the Study of African Economies Workshop (Oxford 2012).

Chapter 4 has been presented at the Center for the Study of African Economies Annual Conference (Oxford 2013), and the Oxford Centre for the Analysis of Resource Rich Economies brownbag seminar (Oxford 2013).

[1]An earlier version of this paper, circulated under the same name, investigated the effects of earthquakes using the whole sample of earthquakes in Indonesia. This was later regarded as suboptimal given the substantial within country heterogeneity so that I decided to limit the study to one large earthquake. The version contained in this thesis replaces earlier versions.

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Chapter 1

Introduction

This thesis is comprised of three stand-alone chapters. Chapters 2 and 3 are my own work. Chapter 4 is co-authored with Paul Collier and Måns Söderbom. These three chapters treat distinctive topics ranging from natural disasters to modeling children's preferences and the cost of transport infrastructure. I do not attempt to force a common argument upon these different topics in this introduction. Rather, I highlight three features they have in common, and then present a brief overview of the three chapters.

First, all three chapters treat important questions. Natural disasters are expected to increase as climate change takes place, and with increasing population density, their implications are going to be stronger. We are only at the beginning of our understanding of how these large shocks affect local economies. The second chapter responds to the fact that economics has for a long time viewed children as passive consumers of inputs produced by parents or implementers of parental orders rather than as agents. As most parents would agree, and research increasingly shows, children's preferences are formed early on and therefore deserve to be considered. Turning to the cost of roads, the argument is straightforward. The estimated global gap in infrastructure is $57 trillion (McKinsey 2013). An improved understanding of the distribution of unit costs is vital to start understanding the reasons for this gap, and to spend resources more efficiently.

Second, they present novel ideas. The main innovation of the first chapter is that it examines whether natural disasters could affect relative prices and therefore have Dutch disease-type consequences at the micro level. The main novelty of the second chapter is that it views children as agents in the family and presents a simple structural model of intra-sibling allocation which is then tested with data on children in four developing countries. The third chapter contributes to the existing knowledge by investigating differences in the cost of transport infrastructure across 99 countries with a focus on conflict and corruption as drivers of unit costs.

Third, the three chapters rely on the most recent data and methodologies available. The first chapter uses individual level panel data and presents reduced form estimates exploiting the exogenous nature of a large earthquake. Drawing on GIS technology, I link these individuals with their varying exposure to the earthquake to identify the effect of the earthquake. The second chapter estimates a structural model using detailed within sibling expenditure and time allocation data of one panel cohort in four developing countries. The third chapter uses a large and unique data set of costs per kilometer of 3,322 road construction and maintenance activities. We link these with country level characteristics and present key correlations. I subsequently give a brief introduction to each chapter.

1.1 Natural Disasters and Labor Markets

The first chapter explores the effect of natural disasters on labor markets. While it is clear that natural disasters have serious welfare consequences for affected populations, less is known with respect to how local labor markets in developing countries adjust to such large shocks, in particular the general equilibrium effects of the increase in the demand for construction as well as the inflow of resources in the aftermath of natural disasters. Combining data from the Indonesia Family Life Survey, the Desinventar database, the US Geological Survey and district level employment indicators, this chapter explores how a large earthquake in Indonesia affected local labor markets, in particular the evolution of wages and employment across sectors. We find that wage growth in the agriculture sector is significantly higher in earthquake affected areas. We propose two mechanisms for this result: a higher growth rate of the price of rice in agricultural communities which switch from being net sellers to net buyers of rice and a downward shift in the supply of workers in the agricultural sector. We show evidence for both mechanisms.

1.2 Preferences over Leisure and Consumption of Siblings and Intra-household Allocation

The second chapter investigates the intra-household allocation of leisure and consumption among siblings. Children are often treated as passive members in the household and their preferences over consumption and leisure are rarely modeled. This paper considers children as agents with their own preferences over leisure and consumption and builds a theoretical and empirical model for children's time and consumption allocations in a household. We test the predictions of the model with data from Ethiopia, India, Peru and Vietnam which contain detailed information on time use and allocations of assignable goods for sibling pairs. We find that conditioning on observable variables, the residuals of these simultaneous decisions are significantly negatively correlated. This suggests that differences in siblings' relative time and consumption allocations are driven by their relative preferences over leisure and consumption rather than differences in parents' relative altruism. Families seem to function as market economies in which children trade off leisure and consumption, select their optimal bundle, and are rewarded by their parents accordingly.

1.3 The Cost of Road Infrastructure in Developing Countries

The third chapter examines differences in unit costs of transport infrastructure. A growing literature shows that there are significant benefits of transport infrastructure for development. However, research on the cost side lags behind so that little is known about differences in the cost of infrastructure countries face. To our knowledge, this is the first study that examines drivers of unit costs of construction of transport infrastructure with a large data set of 3,322 unit costs of road work activities in low and middle income countries. We find that: (i) there is a large dispersion in unit costs for comparable road work activities; (ii) after accounting for environmental drivers of costs such as terrain ruggedness and proximity to markets, residual unit costs are significantly higher in fragile countries; (iii) there is evidence that costs are higher in countries with higher levels of corruption; (iv) these effects are robust to controlling for a country's public investment capacity and business environment; (v) higher unit costs are significantly negatively correlated with infrastructure provision.

Chapter 2

Natural Disasters and Labor Markets

2.1 Introduction

The objective of this chapter is to understand the effects of large scale destructive shocks on labor markets in lower and middle income countries. Such shocks have two distinct features: first, a large proportion of the damage occurs in the housing sector; for example, 40% of the damage and losses from the 2010 earthquake in Haiti are due to destroyed and damaged housing and this share is even higher for other earthquakes (Government of Haiti et al 2010; BNPB et al 2009; BAPPENAS 2006). Second, once the emergency phase is over, aid flows earmarked for reconstruction often last for several years following the disaster. Fund allocations following the 2004 tsunami to the housing sector in Aceh in Indonesia amounted to $US 1.6 billion, which is equivalent to 25% of total reconstruction funding and 30% of Aceh's regional GDP, and were rising for several years after the tsunami. Little is known about how labor markets are affected by the interaction of the initial human and physical destruction and the inflow of resources in the aftermath which are largely spent in non-tradable sectors of the local economy.

We use a large earthquake hitting Yogyakarta in Indonesia on 27 May 2006 at 05:53:58 am to study the labor market effects of large destructive shocks. The Yogyakarta earthquake was one of the costliest disasters in the past 10 years and disaster response was coordinated and swift. It is therefore a useful example to study the interplay between destruction and large inflows of resources. To measure the effect of the earthquake, we use a shake map indicating the estimated instrumental intensity of the earthquake which takes into account recorded ground motions (peak ground velocity and peak ground acceleration). As a different measure, we obtain data of the number of houses destroyed and damaged per district. We link these with data from the Indonesia Family Life Survey, which contains detailed labor market information and is the only large scale panel survey in Indonesia. Since sectoral choice of individuals is likely to be correlated with time invariant and time varying unobservables, it is vital to have information on the sector of employment before the earthquake took place. To unpack the mechanisms and measure general equilibrium effects, we use community level price data and district level employment indicators from the Socio-Economic Surveys in 2004 and 2007.

The central contribution of this chapter is to understand how resilient labor markets are when hit by a large scale shock and how the effects of the shock work through labor markets in the context of a lower middle income country with a high level of informality. We ask two related but different questions; first, whether aid inflows following natural disasters have Dutch-disease style implications thereby raising wages in nontradable sectors of the local economy; and second, what the effects of disasters blocking off communities and trade routes are on local labor markets. We exploit the exogenous nature of the earthquake and differences in exposure to the earthquake to identify the effect on the evolution of wages and heterogeneity across sectors and employment categories.

This is important as the damage from natural disasters has been rising in the past two decades (United Nations and World Bank 2010). Labor markets are regarded to be playing a vital role in determining individual's and household's welfare. For example, the entire World Development Report 2013 is devoted to jobs and argues that "jobs are instrumental to achieving economic and social development. Beyond their critical importance for individual well-being, they lie at the heart of many broader societal objectives, such as poverty reduction, economy-wide productivity growth and social cohesion" (World Bank 2013). In order to optimally design responses to large disasters, it is therefore crucial to understand the labor market consequences of such shocks[1].

We find that labor markets are remarkably resilient against such large shocks and on average wage growth was even higher in earthquake affected regions. We do not find robust evidence for differences in the effect of the earthquake according to whether individuals are self-employed, firm owners, government workers or employed in the private sector. Given that these employment categories have different levels of job protection and regulations, this result is rather surprising. However, we do find substantial heterogeneity with respect to the sectoral evolution of wages. Individuals working in the agricultural sector in areas that were strongly affected by the earthquake enjoyed a substantially higher earnings growth compared to individuals working in the commercial services sector; nevertheless, individuals working in the commercial services sector did not have negative earnings growth effects. This suggests that local labor markets are fairly segmented and mobility is limited. In the agriculture sector this is likely to be the case since land as a factor of production is immobile, many farms are family farms, and monitoring of labor is fairly difficult in this sector. The result is robust to a range of specifications relying on alternative identifying assumptions compared to our preferred specification, including a differences-in-differences specification, fixed effects, a dynamic specification and a dynamic instrumental variables specification. A range of measures of the intensity of the earthquake shock and varying control groups also produce very consistent results.

We propose two mechanisms for this result. First, the destruction of infrastructure led to increases in the price of food, particularly in areas which are net consumers of food. Second, a downward shift in the supply of labor due to fatalities and injuries and an increase in the demand for labor in sectors producing non-tradables in the aftermath of the disaster drew workers out of the agricultural sector (the low-wage sector) into higher-wage non-tradable

[1]While studying the effects of earthquakes on labor markets is important by itself, the earthquake shock can also be viewed as a rare occasion to study the structural transformation of local economies. Alvarez-Cuadrado and Poschke (2011) examine the importance of 'push factors' due to increased agricultural productivity and 'pull factors' due to increased technological progress in manufacturing in driving the structural transformation of 12 industrialized countries. The sharp exogenous rise in inflows of resources and demand for reconstruction allows isolating the increase in demand for labor outside the agricultural sector from increases in agricultural productivity and analyze their effects in a general equilibrium context.

sectors, leading to a rise in the marginal product of labor and wages in the agriculture sector. We find evidence for both mechanisms. The earthquake led to higher growth in the price of rice. We also show that the growth in rice prices was higher in communities which switched from being net producers to being net consumers. Employment in the agricultural sector contracted and expanded in the construction sector in the aftermath of the earthquake. The evidence suggests that both these effects resulted in higher wage growth for agricultural workers.

The chapter contributes to an emerging literature on the effects of natural disasters on various outcomes, such as consumption, income, and migration. Studies of two earthquakes that struck El Salvador in 2001 find that the earthquake shock led to lower migration and a reduction in household income (Baez and Santos 2008; Halliday 2006; Yang 2008). Premand (2008) finds moderate short term effects of hurricane Mitch on consumption growth but no evidence for persistence. In contrast to these papers, we focus on labor markets, in particular heterogeneity across sectors and levels of formality. De Mel et al. (2012) study the effects of cash grants on the recovery of Sri Lankan entreprises after the tsunami and find significant effects of grants on retailers, but little effect on firms in the manufacturing or services sector. Their main interest is in studying profits and the capital stock of firms. The research most closely linked to this chapter is by Belasen and Polachek (2008) and Belasen and Polachek (2009) who investigate the labor market consequences of hurricanes in Florida, exploiting differences in county-level earnings and employment rates calculated from quarterly data[2]. This chapter differs from their study in that we use panel data of individuals, and investigate the effects of an entirely exogenous shock in the context of a lower middle income country.

This chapter also relates to a substantial body of literature in development economics exploring how shocks impact households along a number of dimensions, including households' ability to smooth consumption, ex-ante and ex-post coping strategies as well as short and long-term effects of shocks on a range of outcomes such as consumption, schooling, health and child work (Townsend 1994; Paxson 1992; Udry 1995; Dercon 2004). Employment in the non-agricultural sector has been found to be an important strategy for agricultural households

[2]Some studies use hurricanes as natural experiments to investigate the impact of migration on receiving labor markets, for example see McIntosh (2008) and Silva et al. (2010).

to diversify their portfolio ex-ante as well as ex-post (Rose 2001; Kochar 1999). Jayachandran (2006) finds that agricultural productivity shocks have stronger negative effects on wages when workers are poorer, less mobile and more credit constrained. Mueller and Quisumbing (2010) find long term negative effects of floods on agricultural wages in Bangladesh. This chapter focuses on the labor market consequences of a non-weather related large exogenous shock in a developing country.

A growing number of macroeconomic studies contribute to the ongoing debate in macroeconomics on whether natural disasters harm economic growth, foster it, have impacts only under certain conditions, or no impact at all (Hochrainer 2009; Loayza et al. 2012; Strobl 2011; Noy 2009; Fomby et al. 2013)[3]. These papers (apart from Strobl (2011)) use data on natural disasters from the Emergency Disasters Database (EM-DAT), maintained by the Centre for Research on the Epidemiology of Disasters (CRED), and estimate cross country panel models to understand macroeconomic effects of natural disasters. Strobl (2011) computes a proxy of local destruction to estimate the effects of hurricanes on economic growth. Studying the labor market in a micro setting as done in this chapter is a step towards providing evidence on the underlying mechanisms at play. Finally, the chapter relates to research on the multiplier effect of job creation in the tradable sector (Moretti 2010), the employment effects of construction projects (Carrington 1996), and labor market effects of oil price changes (Keane and Prasad 1996; Kline 2008).

Our findings imply that large-scale destruction coupled with a substantial inflow of financial resources has not significantly negatively affected wage growth. We do not find evidence that local economies experience a dutch disease effect which harms their competitiveness through the increase in relative prices of nontradable and tradable goods. Due to data constraints we are not able to separately identify the effects of destruction and reconstruction, a topic important for further research.

The chapter is structured as follows. Sections 2.2 describes the Indonesian context and

[3] For a recent survey see Kellenberg and Mobarak (2011).

the data; section 2.3 provides a conceptual framework to outline the channels through which natural disasters might impact on local labor markets; section 2.4 discusses identification and estimation; section 2.5 presents the results and explores mechanisms. Section 2.6 concludes.

2.2 Context and Data

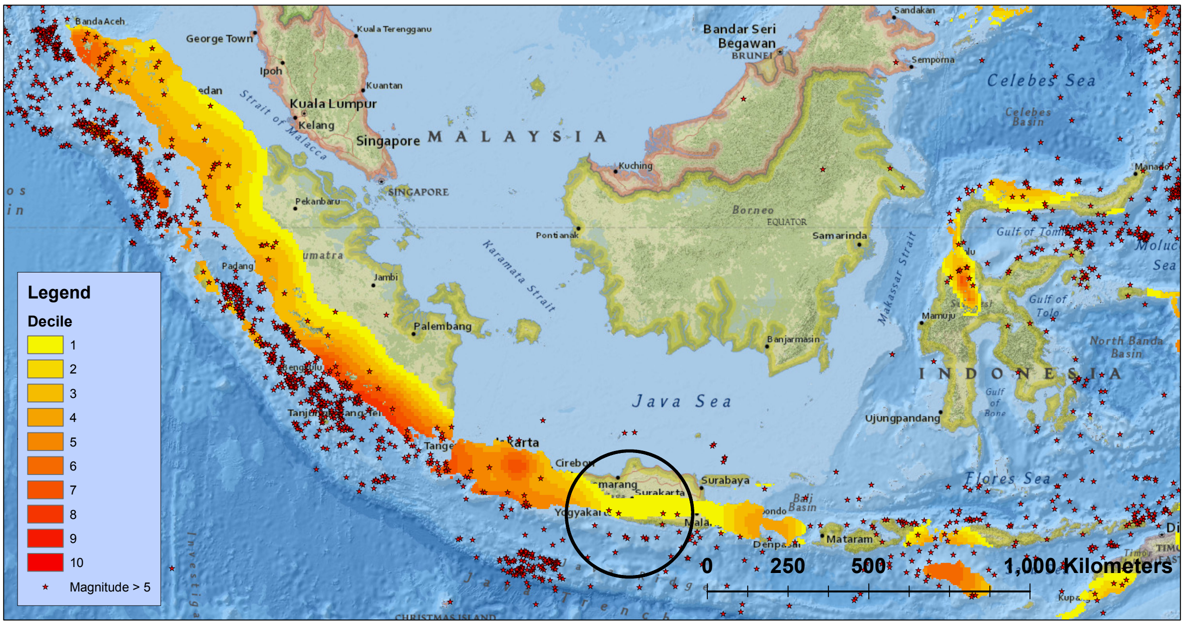
To investigate the effects of natural disasters on local labor markets, we study the effect of a large earthquake that hit Yogyakarta in Indonesia. Indonesia is one of the seismologically most active regions worldwide ranked third out of 153 countries in terms of absolute mortality risk from earthquakes (United Nations Office for Disaster Risk Reduction 2009). Since 2004, four seismic events alone affected 6.7 million people[4]. Indonesia is located on the boundary between the Sunda plate in the North-East and the Australia plate in the South-West. The Australia Plate is moving 50-60 mm per year northward with respect to the Sunda plate in the South-East and 40-50 mm per year northward in the North-West (US Geological Survey 2008). Inter-plate earthquakes (caused by the subduction of the Australia plate beneath the Sunda plate) and intra-plate earthquakes (caused by stresses generated in the subduction process) occur frequently.

Figure 2.1 shows earthquakes with a magnitude larger than 5 on the Richter scale in the region between 2000-2008 and the percentiles of peak ground acceleration values for areas that exhibit a 10% chance of exceeding a peak ground acceleration of 2 meters per second in a 50 year period[5]. Values of 2 meters per second and less were excluded. It is apparent from the map that Indonesia is exposed to a large number of earthquakes. Figure 2.1 also illustrates that despite differences in the predicted intensity of earthquakes, a large area in Indonesia is subject to substantial risk of future earthquakes. The impossibility to predict earthquakes and thus exogeneity of the earthquake is crucial for our identification strategy. The Yogyakarta earthquake took place on 27 May 2006 at 05:53:58 am with a magnitude of 6.3 and a shallow depth of 10 meters below sea level (US Geological Survey 2012). It was among the most

[4]The four events are: the 2004 Tsunami caused by an earthquake, the 2006 Yogyakarta earthquake, the 2009 Southern Sumatra earthquake, and the 2007 Southern Sumatra Tsunami (put EM-DAT source).

[5]When an earthquake happens the ground shakes, but also accelerates. Peak ground acceleration is the largest increase in velocity recorded on the ground.

Figure 2.1: Earthquakes during 2000-2008, and Earthquake Hazard



Notes: Figure is produced using ArcGIS 10; earthquakes with a magnitude larger than 5 on the Richter scale from the United States Geological Survey and earthquake hazard from the Center for Hazards and Risk Research (CHRR); Center for International Earth Science Information Network (CIESIN), Columbia University; International Bank for Reconstruction and Development/The World Bank.

costly natural disasters in developing countries in the past 10 years leading to damage and losses of about US$ 3.1 billion (International Recovery Platfrom 2009). More than 5700 people were killed, and about 280,000 houses were destroyed Java Reconstruction Fund (2007). However, the Indonesian governments' response was swift and coordinated and pooled donor funding was channeled through the Java Construction Fund. By June 2007, about 80% of the affected houses had been repaired or replaced (World Bank 2012).

We combine data from several sources. First, we use household level data from the Indonesia Family Life survey, a large-scale panel household survey conducted in 1993, 1997, 2000 and 2007. Being the only large-scale longitudinal survey available in Indonesia, it is suitable to study the dynamic behavior of individuals. The initial sample includes 321 communities and is representative of 83% of the Indonesian population living in 13 of the country's 26 provinces[6]. With a re-contact rate in 2007 of 93.6% of the original IFLS 1 (1993) households

[6]Indonesia's administrative levels are provinces (*provinsi* or *propinsi*) which are divided into districts, which are further divided into subdistricts. Districts can be cities (*kota*) or regencies (*kabupaten*). For the purpose of this study, *cluster* or *community* refers to the IFLS communities, which are the original 321 communities plus the communities of mover households.

it follows panel members equally well or better than surveys in developed countries (Strauss et al. 2009). In particular when studying the consequences of natural disasters, a low attrition rate is a pre-requisite. In this study we use data for individuals aged 20-55 in 2000 living in the following provinces: Central Java, Yogyakarta, East Java and West Java. This leaves us with a sample of 2,471 individuals in treatment and control districts as defined below for whom we have complete information for 2000 and 2007. They live in 127 of the original IFLS communities, 224 communities of split-off households, and across 84 districts. Round 3 was conducted between July-December 2000 and round 4 took place between October 2007-July 2008.

The wage reported for a respondent's primary job forms the basis for computing wages. Wages for privately employed individuals are measured as last month's salary including the value of all benefits. For self-employed individuals, wages are computed using last month's net profits[7]. Following Strauss et al. (2004), we also compute hourly wages on the basis of monthly reported earnings divided by the total hours worked last week multiplied by 4.33. We top code individuals who reported working more than a total of 126 hours per week to 126 (assuming a maximum work load of 18 hours per day for 7 days a week) and only include individuals with positive earnings in both years.

Following Thomas et al. (1999) we use a province-specific price deflator that is based on the price indices reported by Indonesia Statistics (BPS[8]) for 45 cities in Indonesia (43 cities until 2003), matching the BPS cities to the IFLS provinces and using a simple average of the price indices for provinces with more than one city[9]. All wages are expressed in 2007 Indonesian Rupiah.

[7]The results are robust to including yearly wages for those individuals who have missing monthly wages but we prefer to not aggregate across these different recall spans.

[8]The full name is Badan Pusat Statistik.

[9]Thomas et al. (1999) construct an alternative measure for inflation based on the price data collected in the IFLS community questionnaire and find that rural inflation was 5% higher than urban inflation; therefore, they decide to further inflate prices for rural residents. Given that the period between 2000 and 2007 has noted a far more stable price environment than pre-crisis, we only use the BPS price data. As will be explicit in the next section which outlines the empirical framework, we take first differences to account for location specific time invariant effects; further, we include a dummy variable if the household lives in an urban area to account for differential wage growth.

Over the past 20 years, the Indonesian labor market has gone through a number of phases. The 1990s, and before the Asian crisis, in 1997, have been marked by rising employment and wages and a shift of the workforce out of agriculture. Wages dropped sharply in the aftermath of the crisis, and since then employment and wage growth have been moderate, with a significant portion of the labor force employed in the informal sector. Indonesia's labor market is known to be among the region's as well as the world's most inflexible labor markets, with hiring and firing regulations further tightened in the 2003 Manpower Law. However, considering that 63% of the employed workforce works in the informal sector, and that only 20% of workers in the formal sector report working with a contract, it fails to protect the most vulnerable workers (World Bank 2010). For a detailed analysis of the Indonesian labor market see World Bank (2010).

Table 2.1 presents some basic descriptive statistics of the sample in 2007. The average age in 2000 is 36 years. Slightly less that half of the respondents have at most primary education, and for about 35% the highest level of education is secondary school. Between 11 and 12% has tertiary education. About half of the sample lives in urban communities. The Indonesian labor market is highly segmented, with about half of the individuals self-employed. Their share has even increased between 2000 and 2007, so that in 2007 they constitute the single largest category of employment, followed by private workers, government workers and firm owners. In terms of the sectoral distribution of workers, commercial services employ about a third of the sample, followed by social services, manufacturing, agriculture and construction.

There is substantial overlap between categories of employment and sectors. In 2000, about half of the workers in agriculture are self-employed, with the other half being wage workers. Almost all workers in the construction sector are wage workers. About 28% of workers in the manufacturing sector are self-employed and 69% of workers are wage workers. Employment in commercial services follows the opposite pattern: 69% of workers are self-employed, and 27% of workers are wage workers. The largest group in social services are wage workers with 46%, followed by government workers with 32% and self-employed with 20%. Firm owners comprise between 1-2% of each of these categories. The high level of

Table 2.1: Sample Characteristics

	2000	2007	Definition
Basic Characteristics			
Age	36.031		Age of respondent in 2000
Gender	0.633		Male=1, Female=0
Primary	0.482	0.478	=1 if highest level of school attended is elementary school, islamic elementary school (Madrasah Ibtidaiyah) or islamic school (Pesantren)
Secondary	0.356	0.346	=1 if highest level of school attended is junior/senior high, or islamic junior/senior high school (Madrasah Tsanawiyah, Madrasha Aaliyah)
Tertiary	0.106	0.118	=1 if highest level of school attended is university education
Urban	0.493	0.554	=1 if household lives in an urban location
Employment Category			
Self-employed	0.403	0.539	=1 if self-employed, self-employed with unpaid family worker/temporary worker and casual workers
Firm Owner	0.018	0.029	=1 if self-employed with permanent worker(s)
Government Worker	0.089	0.096	=1 if government worker
Private Worker	0.490	0.336	=1 if private worker
Employment Sector			
Agriculture	0.18	0.193	=1 if individual works in agriculture, forestry, fishery and hunting
Construction	0.088	0.075	=1 if individual works in construction, mining, electricity and gas, water
Manufacturing	0.203	0.179	=1 if individual works in manufacturing
Commercial Services	0.302	0.321	=1 if individual works in wholesale, retail restaurants and hotels; transportation, storage and communications; finance, insurance, real estate and business services
Social Services	0.227	0.231	=1 if individual works in social services
Contract Features			
Contract		0.062	=1 if individual works with a contract
Union		0.100	=1 if individual is member of a labor union or a business association
N	2471		

informality in the Indonesian workforce also becomes apparent when noting that only 6.2% of workers in our sample have a written contract. About 10% of workers are members of a union.

Differences in median levels of income and median growth are illustrated in tables 2.12

and 2.13 in the Appendix. Table 2.12 shows that government workers enjoy the highest hourly wages in both years, about four to five times the hourly wages of self-employed and wage workers and about one quarter more than firm owners. Given that firm owners work about 50 hrs per week compared to government employees who work 37 hours per week, monthly wages are fairly similar for government workers and firm owners in 2000 but substantially lower for firm owners in 2007. Self-employed have the lowest level of wages in both rounds, and the gap between wages of self-employed and wage workers has widened. Columns (4) and (5) show median growth rates of log of hourly and monthly wages, where the top panel conditions on the category of employment in 2000 and the bottom panel conditions on the category of employment in 2007. The highest growth of real wages has been enjoyed by government workers and private sector workers, while firm owners and self-employed either had very moderate growth or negative growth in the period between 2000 and 2007. Table 2.13 shows that differences in median hourly and monthly earnings are smaller across sectors. Both in 2000 and 2007, employees in the social services sector have the highest hourly and monthly wages, followed by the construction, manufacturing, commercial services and agriculture sector. Median wage growth was lowest or negative in the agriculture sector and highest in the social services sector, which is where 89% of government employees work.

We use two sources of data to measure the exposure to the earthquake. First, we use data from the Desinventar database for Indonesia, maintained by the Indonesian National Board for Disaster Management (BNPB[10]). The database contains information on the type of disaster, geographical location, as well as information on its effect on human life (deaths, missing individuals, injured, evacuated and relocated), property damage (destroyed and affected houses, crop destruction) and on infrastructure (transportation, industry, etc.). As a measure for the strength of a disaster, we use the number of destroyed houses. We use data from Indonesia's Statistical Agency for the population in each district in 2005 to account for differences in population density across districts.

Table 2.14 in the appendix shows all entries in the Desinventar database between 1972

[10]The full name is Badan Nasional Penanggulangan Bencana.

and 2009 and mean deaths, injured, houses destroyed and houses damaged per event. Floods, fires and landslides are the most frequently recorded type of natural disaster, followed by strong winds, droughts, earthquakes, surges eruptions and tsunamis. In terms of destruction, earthquakes and tsunamis stand out in their impact in terms of human and physical losses. The average number of deaths per entry is almost 50 deaths for earthquakes and 3,260 deaths for tsunamis. Physical asset destruction is also highest with 1,785 houses destroyed on average for earthquakes and 6,540 houses destroyed for tsunamis. The tsunami on 26 December 2004 accounts for most of the damage from tsunamis, with 27 entries and 99% of deaths from tsunamis and 99% of houses destroyed by tsunamis caused by this single event. The earthquake in Yogyakarta also accounts for a significant proportion of deaths and houses destroyed caused by earthquakes in Indonesia between 1972-2009. About 48% of deaths by earthquakes and about 27% of houses destroyed by earthquakes were caused by the Yogyakarta earthquake[11].

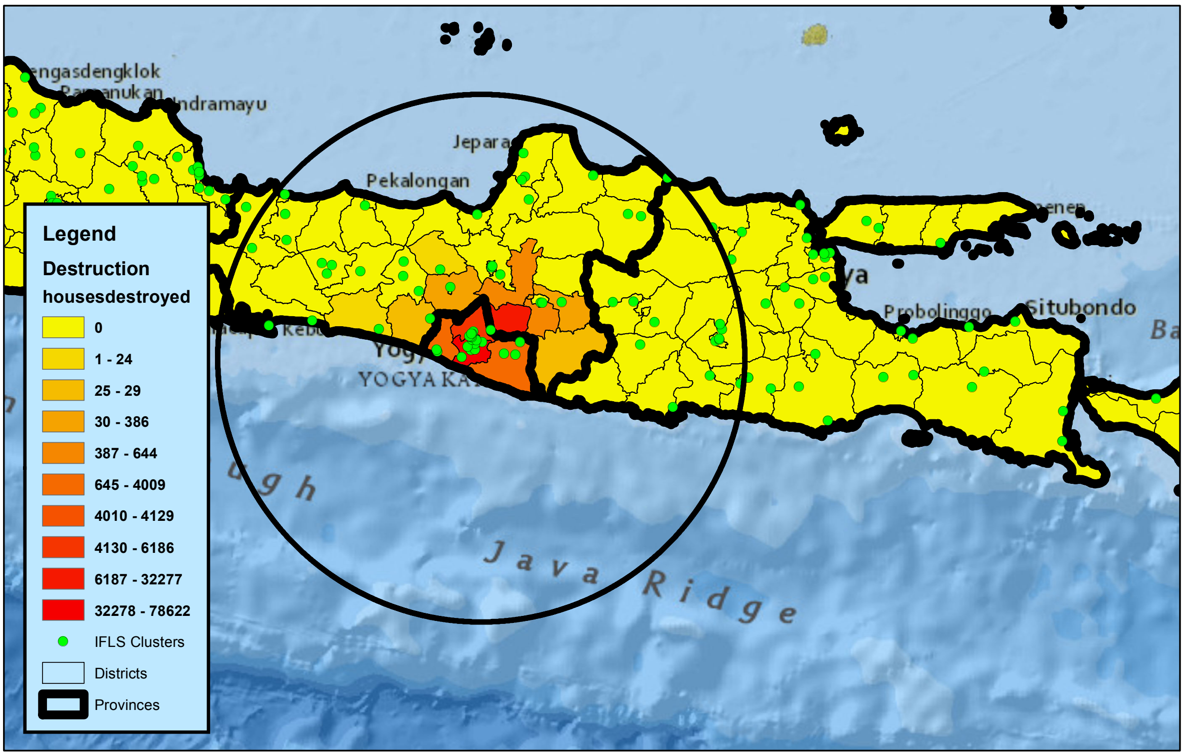
Figure 2.2 zooms into Java and shows the epicenter of the Yogyakarta earthquake. The green circles represent the locations of the original IFLS clusters; districts (provinces) are indicated by the thin (thick) boundaries. The different colors indicate the level of destruction caused by the earthquake in each district, ranging from no destruction (yellow) up to 78,622 houses destroyed (dark red). We use an individual's location in 2007 to link the IFLS data with the earthquake data.

Second, we use data on the characteristics of the ground shaking produced by the Yogyakarta earthquake from the United States Geological Survey[12]. In particular, we use the

[11]The number of houses negatively affected by the earthquake varies across reports from 154,000 houses destroyed and 260,000 damaged (BAPPENAS 2006), 280,000 houses destroyed(Java Reconstruction Fund 2007), 270,000 houses heavily damaged (International Recovery Platfrom 2009). According to the Desinventar database, there were 129,798 houses destroyed and 172,854 houses damaged. To ensure that our results are not driven by reporting bias, we also use a measure of the earthquake that is independent of reporting and relies on exogenous characteristics of the earthquake.

[12]There are different approaches in the literature to measure the effect of earthquakes. Yang (2008) constructs two distance bands from the epicenter of the earthquake, where he defines 'near' quakes as those within 100 kilometers of the epicenter of the first earthquake and 50 kilometers of epicenter of the second. Those in 'middle distance' to quakes are those within 125 kilometers of first epicenter and 75 kilometers of second epicenter (but not in 'near' area). Halliday (2006) constructs an index of destruction based on various damage measures. The methodology employed in Baez and Santos (2008) is most directly related to ours as they exploit the exogenous characteristics of the earthquake.

Figure 2.2: Yogyakarta Earthquake, 27 May 2006 at 05:53:58 AM



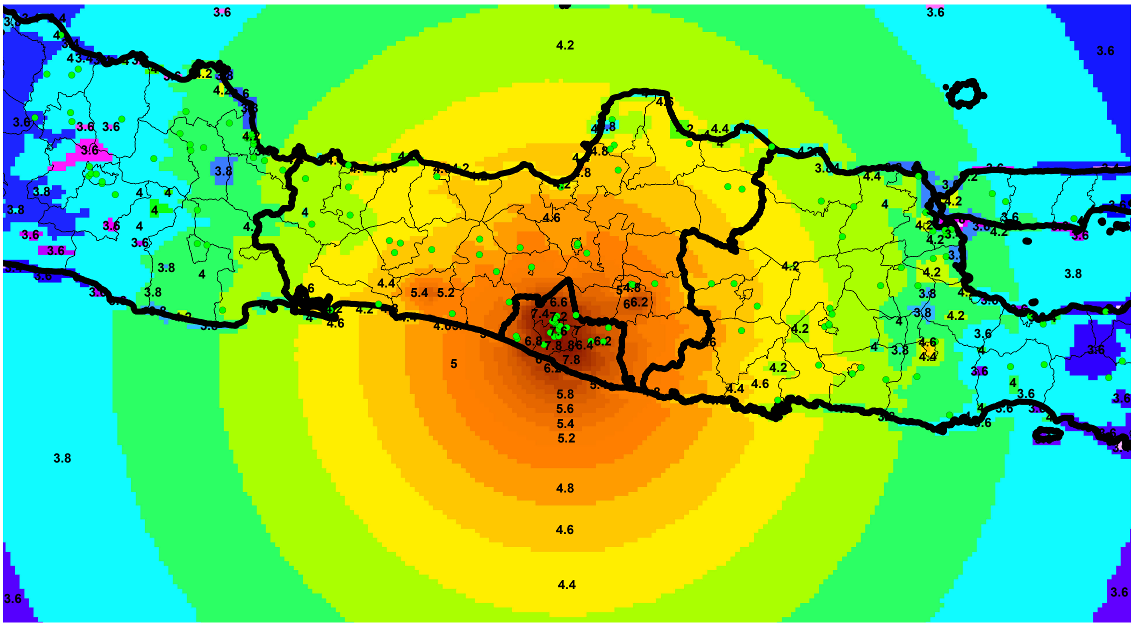
Source: ArcGIS 10; data from US Geological Survey and IFLS communities.

shakemap which is calculated based on peak ground velocity and peak ground acceleration. While an earthquake has only one magnitude and one epicenter, it leads to a range of intensities in the area around the earthquake[13]. The shakemap shapefile indicates instrumental intensities of the earthquake using the modified mercalli intensity scale. Figure 2.4 in the appendix overlays the map in figure 2.2 with the shakemap shapefile and shows that the contours for higher instrumental intensity correlate with the level of reported destruction. Compared to the magnitude and depth of the earthquake at the epicenter, the instrumental intensity is a more useful measure of the consequences of the earthquake in the area surrounding the epicenter. In contrast to the traditional mercalli intensity measure and other measures of the level of destruction of an earthquake, the advantage of the instrumental intensity scale is that it is derived uniquely from exogenous characteristics of the earthquake and not from observations and damage reports. It is therefore a more exogenous measure of the earthquake than any reported measure.

[13]For example, the Richter scale is a scale that measures the magnitude of the earthquake at the epicenter. To measure the intensity of an earthquake in the vicinity of the epicenter, the modified mercalli scale or the Rossi-Forrel scale are common.

We use ArcGIS 10.0 to link the shakemap with the household data. The instrumental intensity contour polygons are provided in 0.2 intensity units. We convert the polygons into a raster of 0.28 degrees (pixels of approximately 3.2 km by 3.2 km) and extract the modified mercalli intensity scale measure for each community. For individuals who moved outside their original clusters into a non-IFLS cluster we don't have the exact GPS location, but know their district of residence. We therefore extract the average mercalli intensity measure for each district using the zonal statistics tool[14]. The raster conversion is shown in figure 2.3 and figure 2.5 in the appendix shows the map zoomed into the epicenter of the earthquake. Table 2.15

Figure 2.3: Modified Mercalli Intensity Map, Yogyakarta Earthquake



Source: ArcGIS 10; data from US Geological Survey and IFLS communities.

in the appendix shows the number of houses destroyed and damaged in districts affected by the earthquake from the Desinventar database as well as the mercalli intensity scale and the population in 2005. High damage corresponds to high values of the mercalli scale. In the whole data set, the pairwise correlation of these two measures of earthquake intensity is 0.78 with a p-value of 0.000.

[14]This is in line with the literature using spatial data. For example, Nunn and Puga (2012) compute the average ruggedness of a country by averaging over a grid level index of ruggedness. Burgess et al. (2012) compute the number of pixels which were deforested in each province in Indonesia using satellite information on deforestation.

West Java, Central Java, Yogyakarta Province and East Java are densely populated areas as shown by figure 2.6 in the appendix. Mean population per district in 2008 was 1,109,765 with a standard deviation of 677,366.7. The smallest district is Kota Mojokerto with a population of 114,804 and the largest district is Bogor with a population of 4,219,324. Given the vast size of Indonesia and heterogeneity in terms of geography, income and population density it would not be suitable to use all individuals of the IFLS sample outside a certain radius as a comparison group. Rather, to have a sample that is very comparable to the treatment group we limit the sample to individuals in clusters or districts with an exposure of at least 3.7 on the mercalli scale[15]. As mentioned above, these individuals all live in West Java, Central Java, Yogyakarta Province and East Java, thereby within a radius of about 380 km of the earthquake's epicenter.

2.3 Conceptual Framework

This section sets out a simple framework outlining the effects a natural disaster can have on local labor markets. It combines approaches from the labor economics literature on local labor markets (Moretti 2011; Moretti 2010), work on sectoral labor market dynamics (Carrington 1996; Keane and Prasad 1996; Kline 2008) and the predominantly macro-focused literature on Dutch-disease type of effects (Corden and Neary 1982; Corden 1984; Collier and Gunning 1999). Assume a small open economy consisting of J communities. Goods and services can be divided according to 2 dimensions: tradable vs. non-tradable, and necessities vs. non-necessities. All goods and services are produced by firms in 5 sectors: agriculture, construction and utilities, manufacturing, commercial services and social services.

We now consider the effect of a destructive natural disaster on local labor markets. Assume that the natural disaster is a rapid-onset event such as a hurricane or an earthquake which has an immediate effect that wears off fairly quickly[16]. Neither firms nor workers can predict the event. Therefore, firms can not ex ante expand or contract or change their capital-labor

[15] We show that our results are robust to changes in the comparison groups.

[16] The opposite is what the disaster literature refers to as 'slow-onset disasters' such as a drought (Benson and Clay 2004). Potential behavioral responses by individuals and governments are very different for these two types of disasters.

ratios in order to reduce adjustment costs once the disaster strikes. The natural disaster can be thought of leading to two types of shocks to the labor market: a *destruction shock* due to the immediate effect of the disaster, and a *reconstruction shock* in the recovery phase. The strength of these two forces determines the overall effect on the labor market and economy.

2.3.1 Destruction Shock

The immediate effects of the disaster are (i) a downward shift in labor supply due to loss of lives and injuries; (ii) destruction of capital, such as private and public buildings, equipment and infrastructure, such as roads and bridges; and (iii) a shift in households' expenditure towards food due to the income effect of destruction of private property[17]. The decrease in the supply of labor due to human losses and injury is expected to shift down labor supply, thereby raising wages if labor supply is limited. The shift in the composition of expenditures leads to a drop in demand for non-food consumption goods. The destruction of capital will slow down production until substitutes are found. As Horwich (2000) pointed out, as long as human capital remains, production processes will be re-optimized, relying either on higher levels of labor or energy, for example. The destruction of infrastructure affects the tradability of goods and services leading to goods and services which were previously tradable suddenly becoming non-tradables. We expect this natural "trade restriction" to lead to downward pressure in prices of food in surplus areas, and upward pressure on prices in deficit areas (Dercon 1995). Surplus areas are defined as communities which produce more food than they consume, and deficit areas are defined as communities whose consumption of food is higher than their production.

[17]While the downward shift in labor supply and destruction of capital are directly observable and straightforward consequences of a natural disaster, the conjecture that we observe a shift in households' composition of expenditures towards food is based on Engel's Law, which suggests a negative relationship between income and food expenditure shares. It would imply that households whose property has been destroyed and who are temporarily unemployed face a decrease in their wealth and income which will lead to a larger share of expenditure being allocated to food. I am not aware of empirical evidence on the shifts in expenditure shares across different categories in the aftermath of natural disasters, so the third channel is as an assumption, rather than a direct consequence. Further, for the sake of simplicity, I refer to food as the main necessity in the discussion, but it could also be interpreted in the sense of "necessitities", which would include shelter.

2.3.2 Reconstruction Shock

In the aftermath of the disaster, significant resources are flowing into the affected region to provide emergency goods and services, and reconstruct houses and infrastructure. There will be two effects similar to a Dutch disease effect at the national level (Corden 1984): first, a spending effect due to the increase in spending on non-tradable goods and services, the booming sector being the construction sector; and second, a resource movement effect; if labor supply is limited, wages have to increase to facilitate the shift of workers from tradable sectors into non-tradable sectors. As the construction sector expands there are general equilibrium effects on the service sector and the non-tradables sector.

The demand for services increases due to two factors: (i) the increased size of the construction sector leads to an increase in the demand for intermediate goods produced both in the service and manufacturing sector. As services tend to be supplied locally and supply is inelastic in the short run, this leads to an increase in the wage premium paid in the service sector to accommodate the expansion of the sector; (ii) the increase in wages of individuals employed in the production of non-tradables leads to an increase in the demand for local services (provided that the income elasticity of demand for services is positive, the size of the effect depends on consumers' preferences over tradables and non-tradables); similar to the construction sector, wages in the sectors producing non-tradables increase until the wage premium has been driven to zero. Therefore, the increase in the ratio of non-tradables to tradables wages draws workers out of the tradable sector into the non-tradable sector.

As a consequence, the higher price level of local inputs into production leads to a decrease in the relative competitiveness of firms producing tradable goods as they have to compete with firms that are potentially able to produce at lower costs in other communities. Linked with the destruction of capital, we expect firms to downsize or relocate to unaffected communities and the tradable sector contracts. How strong the contraction is depends on three factors. First, the level of destruction of the shock. Second, on the tradability of inputs required for construction activities that are produced in the manufacturing sector, such as equipment and machinery. The more tradable inputs are, the stronger the contraction, as construction firms in the affected community can purchase inputs from other communities where firms produce manufactured goods at lower prices. Third, the effect on firms in the manufacturing and agriculture sector depends on individuals' preferences over tradable versus non-tradable goods. The lower individuals' income elasticity of demand for non-tradable goods the stronger the change in the relative prices and the more firms producing tradable goods are going to contract.

The combined effect of the destruction and reconstruction shock is therefore an empirical question and determined by the strength of these shocks. If the destruction shock dominates, the increase in wages due to a decrease in labor supply because of injuries, the drop in non-food consumption, and together with the change in the tradability of goods and services, will lead to an increase in the wage for individuals producing food in particular in communities which are net purchasers of the good. If the reconstruction shock is dominant, we expect an increase in wages in non-tradable sectors to facilitate shifts into non-tradable sectors if labor supply is limited, and a shift out of tradable sectors into non-tradable sectors.

Finally, given the characteristics of the Indonesian labor market presented in the previous section, it is also important to think through the effects a natural disaster could have on different employment categories. Informal workers might suffer larger losses from the shock as they lack employment protection, but they might also be more flexible in shifting to different sources of employment and taking advantage of arising opportunities. The effects are therefore theoretically ambiguous.

In this simple framework we have abstracted from a number of issues. For example, the destruction of firms' capital stocks by the natural disaster might affect firms' optimal capital labor ratios. If the natural disaster raises firm owners' expectations over the occurrence of another natural disasters in the future, this might lower the expected return to physical capital and raise the expected return to human capital, leading to a change in firms' optimal capital-labor ratios. Further issues include agglomeration effects that might arise due to the increase in production in the construction sector, the role of access to credit in facilitating the expansion of firms producing non-tradables, the difficulty in adjusting capital labor ratios particularly in the construction sector, and the role of heterogeneity in skills. There might be important composition effects if the additional workers required in the non-tradables sector are from either the higher or lower end of the skill distribution which in turn might change individuals' return to education and consequently their decision on how much to invest in their human capital. Finally we have abstracted from migration between affected and non-affected communities. With full mobility, we would expect any premium in wages to be driven away by the movement of workers between local labor markets. Evidence for a larger difference in sectoral wage premia after earthquakes is therefore evidence that labor markets are segmented.

2.4 Identification and Estimation

We start by outlining our methodology to investigate the effect of the earthquake on wage growth and heterogeneity in wage growth across categories of employment and sectors; before presenting the results, we also test for potential biases due to selection, migration and attrition. Our identification strategy relies on the exogenous nature of the earthquake. Let's denote the first round of the survey (July-December 2000) as $t = 1$ and the second round of the survey (October 2007-July 2008) as $t = 2$. We then assume that individual i's wages in $t = 1$ and $t = 2$ are as follows

$$\ln y_{i1} = a_1 + \boldsymbol{X}'_{i1}\, \boldsymbol{c}_1 + \boldsymbol{S}'_{i1}\, \boldsymbol{d}_1 + \boldsymbol{Z}'_{i1}\, \boldsymbol{e}_1 + (f_{p1} + g_i + u_{i1}) \tag{2.1}$$

$$\ln y_{i2} = a_2 + b_2\, H_i + \boldsymbol{X}'_{i1}\, \boldsymbol{c}_2 + \boldsymbol{S}'_{i1}\, \boldsymbol{d}_2 + \boldsymbol{Z}'_{i1}\, \boldsymbol{e}_2 + (f_{p2} + g_i + u_{i2}) \tag{2.2}$$

where

y_{i1} is the wage observed in $t = 1$.

y_{i2} is the wage observed in $t = 2$.

H_i is the time-invariant measure of destruction through the earthquake.

$\boldsymbol{X}_{i1}$ is a vector of individual or household characteristics in $t = 1$.

$\boldsymbol{S}_{i1}$ is a vector of dummy variables indicating the sector of employment in $t = 1$.

$\boldsymbol{Z}_{i1}$ is a vector of dummy variables indicating the category of employment in $t = 1$.

f_{p1} and f_{p2} are dummy variables for provinces.

g_i is a time invariant individual fixed effect.

u_{i1} and u_{i2} are idiosyncratic shocks.

First differencing then gives

$$\Delta \ln y_{i2} = \Delta a_2 + b_2 H_i + \boldsymbol{X}'_{i1} \Delta \boldsymbol{c}_2 + \boldsymbol{S}'_{i1} \Delta \boldsymbol{d}_2 + \boldsymbol{Z}'_{i1} \Delta \boldsymbol{e}_2 + (\Delta f_{p2} + \Delta u_{i2}) \tag{2.3}$$

which removes the individual fixed effect g_i and can be rewritten as

$$\Delta \ln y_{i2} = \alpha + \beta H_i + \boldsymbol{X}'_{i1} \boldsymbol{\gamma} + \boldsymbol{S}'_{i1} \boldsymbol{\delta} + \boldsymbol{Z}'_{i1} \boldsymbol{\theta} + (\phi_p + \varepsilon_{it}) \tag{2.4}$$

presenting our baseline specification.

To measure the effect of the earthquake shock, our main measures are the number of houses destroyed per population in 2005 and the mercalli measure of earthquake intensity. Individual and household characteristics include age, age squared, education, urban location, gender and hours worked; sectoral dummy variables indicate whether the individual is employed in agriculture, construction, manufacturing, commercial services (base category) or social services; the category of employment is denoted by dummy variables for whether the individual is self-employed (base category), firm owner, employed by the government or in the private sector. We also control for the time span between the earthquake on 27 May 2006 and the date of the household interview[18]. The median household was interviewed 631 days after the earthquake, with the first households interviewed 550 days after the earthquake, and the last households interviewed 760 days after the earthquake. Additionally, we add month dummies for both the surveys in 2000 and 2007 to account for the fact that wage growth between 2000 and 2007 might depend substantially on the season and therefore timing of

[18] If a household interview took place over several days, we use the first date of the interview.

the interviews.

As we condition on baseline characteristics in equation (2.2), equation (2.4) differs from a standard panel fixed effects model in that we condition on lagged characteristics. We prefer this specification for several reasons: first, the control for baseline characteristics in equation (2.2) is particularly relevant for variables that capture responses to the earthquake, such as sectoral shifts that are induced by the earthquake which are correlated with wages, biasing our estimate of d_2. It is similar to what Angrist and Pischke (2008) call 'bad controls', in that controlling for the sector of employment in period 2, or taking differences in sectoral dummies, would capture part of the response to the earthquake. Recognizing that this is our preferred specification, we also estimate the model using a fixed effects specification, and the results are robust.

Second, the potential benefit of fixed effects or first differences specification comes at the cost of identifying parameters solely relying on individuals who shift across sectors in a treatment area. Third, our main question is what the effects of a large shock are, conditional on having been employed in a certain sector. Finally, the identifying assumption in our model is that $E(\varepsilon_{it}|H_i, \boldsymbol{X}_{i1}, \boldsymbol{S}_{i1}, \boldsymbol{Z}_{i1}, \phi_p) = 0$, so that education, age, location, sector of employment and category of employment in 2000 are not correlated with unobservables determining wage growth between 2000 and 2007. It is not difficult to come up with a violation of this assumption, for example, more educated individuals being more able to cope with shocks to wage growth, and thereby having higher wage growth. However, we find this assumption still more convincing than assuming that current individual labor market characteristics are uncorrelated with current unobservables determining wages once time-invariant individual characteristics are controlled for, which is assumed in a standard fixed effects model. We nevertheless show that our results are virtually unchanged when we estimate the model as a fixed effects specification or a diff-in-diff specification. When we estimate the model as a fixed effects specification, we assume the following process for wages

$$\ln y_{it} = a + b\, H_{it} + \boldsymbol{X}'_{it}\, \boldsymbol{c} + \boldsymbol{S}'_{it}\, \boldsymbol{d} + \boldsymbol{Z}'_{it}\, \boldsymbol{e} + (f_{pt} + g_i + u_{it}) \tag{2.5}$$

for $t = 1, 2$ which differs from equation 2.4 in two respects: first, we replace H_{it} with zero in when $t = 1$; second, we now control for contemporaneous background characteristics $\boldsymbol{X}$, sectors $\boldsymbol{S}$ and categories $\boldsymbol{Z}$ rather than conditioning on lagged characteristics.

When estimating the model in a Diff-in-Diff specification, we assume the following process

$$\ln y_{it} = a_t + b\, H_i + D_t + w\, H_i * D_t + \boldsymbol{X}'_{it}\, \boldsymbol{c} + \boldsymbol{S}'_{it}\, \boldsymbol{d} + \boldsymbol{Z}'_{it}\, \boldsymbol{e} + (f_{pt} + u_{it}) \tag{2.6}$$

for $t = 1, 2$ which differs from equation 2.4 in three respects: first, as we have two equations now to estimate H_i appears twice. The coefficient b captures differences in wages between treatment and control areas; second, we now include a dummy variable D_t that is equal to one in $t = 2$. The coefficient on the interaction term, w therefore indicates the effect of the earthquake on wages. Third, as in equation (2.5), we control for contemporaneous characteristics.

Further, an important choice in the empirical specification relates to the inclusion of a lagged dependent variable, where the obvious trade-off between endogeneity due to the inclusion of an endogenous variable and endogeneity due to omitted variables is the central issue. As a robustness check, we therefore also estimate model (2.4) with a lagged dependent variable, and instrumenting for the lagged dependent variable using earnings in 1997. Our estimation sample becomes significantly smaller by doing this as we require individuals to earn wages in all of the three rounds, but it is a valuable test for the robustness of the identifying assumptions.

An immediate concern given the labor market structure is whether earthquakes are impacting self-employed and wage-employed individuals similarly. We therefore use the base model defined in equation (2.4) and interact the category of employment with the measure of destruction and estimate the following model

$$\Delta \ln y_{i2} = \alpha + \beta\, H_i + \boldsymbol{X}'_{i1}\, \boldsymbol{\gamma} + \boldsymbol{S}'_{i1}\, \boldsymbol{\delta} + \boldsymbol{Z}'_{i1}\, \boldsymbol{\theta} + (H_i * \boldsymbol{Z}_{i1})'\, \boldsymbol{\lambda} + (\phi_p + \varepsilon_i) \tag{2.7}$$

and then test whether $\boldsymbol{\lambda} = 0$ to assess whether the earthquake had a different effect depending on the sector of employment.

To determine heterogenous sectoral effects of the earthquake shock, we use the base model defined in equation (2.4) and interact the sector of employment in 2000 with the earthquake shock

$$\Delta \ln y_{i2} = \alpha + \beta H_i + \boldsymbol{X}_{i1}' \boldsymbol{\gamma} + \boldsymbol{S}_{i1}' \boldsymbol{\delta} + \boldsymbol{Z}_{i1}' \boldsymbol{\theta} + (H_i * \boldsymbol{S}_{i1})' \boldsymbol{\xi} + (\phi_p + \varepsilon_i). \tag{2.8}$$

The coefficient vector $\boldsymbol{\xi}$ indicates whether there is heterogeneity in the effect of the earthquake depending on the sector of employment of the individual before the earthquake.

2.4.1 Exogeneity of Earthquake

As figure 2.1 showed, a large area of Indonesia is exposed to substantial risks of earthquakes; the location of the Yogyakarta earthquake is actually in an area that does not fall into the highest deciles of peak ground acceleration values for areas that exhibit a 10% chance of exceeding peak ground acceleration of 2 meters per second in a 50 year period. We control for a large range of baseline characteristics determining wage growth, but we still worry that unobservables which are correlated with the incidence of the earthquake are biasing our results. For example, if the most productive individuals move to areas with minimal earthquake probability, the productivity of individuals affected by the earthquake is lower than in 'safe' areas. Unobserved productivity will then be negatively correlated with the earthquake; if productivity affects wage growth, we would falsely attribute lower wage growth in affected areas to the earthquake.

To test for this, we conduct a placebo experiment in which we test whether baseline wages are different before the earthquake. For this, we merge the earthquake exposure measures to individuals' baseline district and communities. Table 2.2 shows the correlates of baseline wages in 2000 for our two main measures for the earthquake shock: district level destruction and the mercalli measure of earthquake intensity. District level destruction measures the number of houses destroyed per person using the population in 2005. The highest level of destruction is in the district of Bantul, where 78,622 houses were destroyed and the population in 2005 was 839,536, so that 0.09 houses were destroyed per person. The mercalli measure

Table 2.2: Dependent Variable: Baseline Log of Monthly Wages

	ratio	ratio2	ratio2IV	mercalli1	mercalli2	mercalli3
	(1)	(2)	(3)	(4)	(5)	(6)
Houses dest/population	-2.028	-1.575*	-1.475			
	(1.597)	(0.889)	(2.683)			
Mercalli				0.027	-.029	-.120
				(0.075)	(0.053)	(0.123)
Controls	Age, Sex	Full Set	Full Set	Age, Sex	Full Set	Full Set
District Fixed Effects	NO	NO	NO	NO	NO	YES
Obs.	2471	2471	2471	2471	2471	2471

Notes: Full controls include baseline age, age squared, gender, education, sector of employment, category of employment, rural/urban location, month of the 2000 survey and province specific trends; all models include province fixed effects; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

ranges from a maximum exposure of 8 to a value of 3.8 for the households furthest away in the sample. Columns (1) and (4) control for age, age squared and the gender of the individual, and the remaining columns include the full set of baseline controls. For the district level destruction measure, we find a small and marginally significant negative effect of the placebo shock, suggesting that baseline wages were 1.5% lower when a district had a one percentage point higher destruction; however, the destruction measure is endogenous. If wages proxy for the level of development, and housing construction was of poorer quality in these areas, then we would expect subsequent destruction to be higher. In column (3), we instrument for the destruction measure using the mercalli measure[19]. We no longer find any significant effect anymore. When using our exogenous measure of the effect of the earthquake, the mercalli intensity scale, we do not find any significant differences in the wages of individuals affected by the earthquake. As there is district level variation in the mercalli intensity measure through linking communities' GPS coordinates with the pixels of instrumental intensity of the earthquake, we can add district dummy variables to account for differences in district level wage growth rates in column (6). Again, we do not observe any significant differences.

As the main specification considers the effect of the earthquake on wage growth, it is important to test whether wage growth was similar in treatment and control areas before the earthquake. For individuals for which we have positive wages in 1997, we have estimated the same equation using wage growth between 1997 and 2000; table 2.3 shows the result

[19]The Kleibergen-Paap Wald rk F statistic is 36.01, so that we can reject the null that the model is weakly identified.

of the same equations estimated above with log wages, but now for wage growth. The table illustrates that we do not find any significant differences in the level of wage growth for both earthquake measures which would violate the common trends assumption.

Table 2.3: Dependent Variable: Growth of Log Wages 1997-2000

	ratio	ratio2	ratio2IV	mercalli1	mercalli2	mercalli3
	(1)	(2)	(3)	(4)	(5)	(6)
Houses dest/population	0.617	0.67	1.710			
	(0.984)	(0.965)	(2.900)			
Mercalli				-.018	0.096	0.096
				(0.054)	(0.143)	(0.143)
Controls	Age, Sex	Full Set	Full Set	Age, Sex	Full Set	Full Set
District Fixed Effects	NO	NO	NO	NO	NO	YES
Obs.	1499	1499	1499	1499	1499	1499

Notes: Full controls include baseline age, age squared, gender, education, sector of employment, category of employment, rural/urban location, month of the 2000 survey and province specific trends; all models include province fixed effects; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

2.4.2 Selection into Labor Market

We only include individuals in our sample for which we have positive wages in both periods. A concern is that the earthquake causes endogenous selection into the labor market, or into recording non-zero wages. Suppose that individuals differ along their unobservable endowment of creative adaptiveness, so how quickly they adapt to a new situation and develop new solutions, and there are high-endowment and low-endowment individuals. Low-endowment individuals are then going to be more likely to drop out of the labor market after the earthquake, whereas high-endowment individuals are more likely to keep their jobs. But if high endowment individuals were more likely to enjoy higher wages independent of the earthquake, the effect of the earthquake would be biased upwards because we are missing these low-endowment individuals. We examine whether unobservable determinants of wages of individuals who earned a positive wage in 2000 but are not in our wage-earning sample in 2007 are correlated with the earthquake. To do this, we create a dummy variable that is equal to one if an individual earned positive wages in 2000 but not in 2007. We then interact this variable with baseline wages, which contains unobservable determinants of wages, as well as with baseline controls. We then regress our earthquake measures on controls, the dummy variable and the interaction of the dummy variable with wages and baseline controls. The intuition is that once we include all our baseline controls, the variable $\ln y_{i1}$ should only include unobservable determinants of wages, so that it proxies for residual wages. We can then test whether these unobservables are different for individuals who reported a positive wage in 2000 but not in 2007.

Table 2.4: Dependent Variable: Earthquake

	ratio	ratio2	mercalli1	mercalli2	mercallife
	(1)	(2)	(3)	(4)	(5)
$\ln y_{2000}$	-.0005	-.0005*	0.004	-.006	-.002
	(0.0004)	(0.0003)	(0.011)	(0.009)	(0.002)
$D_{yin2000>0andyin2007=.}$	-.0003	0.006	-.282	-.267	-.002
	(0.01)	(0.011)	(0.272)	(0.281)	(0.067)
$\ln y_{2000} * D_{yin2000>0andyin2007=.}$	0.0002	-.0002	0.0005	0.015	0.003
	(0.0004)	(0.0004)	(0.013)	(0.012)	(0.003)
Controls	Age, Sex	Full Set	Age, Sex	Full Set	Full Set
District Fixed Effects	NO	NO	NO	NO	YES
Obs.	3216	3216	3216	3216	3216

Notes: Full controls include baseline age, age squared, gender, education, sector of employment, category of employment, rural/urban location, month of the 2000 survey and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

There are 745 individuals in our sample who reported a positive wage in 2000 but not in 2007. Table 2.4 shows the correlation between the residual of the wage equation and earthquake intensity; columns (1) and (3) control for age, age squared and sex, while the remaining columns include the full set of controls. Column (5) adds district fixed effects. The third row shows that the interaction effect between baseline residual wages and the dummy for not reporting wages in 2007 is insignificant. In other words, individuals who reported positive wages in 2000 but did not report positive wages in 2007 did not have unobservable determinants of wages which are systematically correlated with the earthquake[20]. The control for baseline wages is significant and negative in column (2), but the coefficient is very small and the effect is not there when we the exogenous mercalli earthquake measure as the dependent variable.

[20]We have estimated the model in column (5) including interaction effects with the baseline sector of employment and category of employment; we do not that find individuals who reported positive wages in 2000 but not in 2007 who were working in a specific sector had unobservable determinants of wages which are systematically correlated with the earthquake.

2.4.3 Attrition and Migration

Attrition is a significant concern when analyzing longitudinal data sets, and particularly so in developing countries. Indeed, Thomas et al. (2012) show that households which were not interviewed in 2007 tended to have higher education, more highly educated parents and come from households with higher consumption at baseline in 1993. They further find that per capita expenditure of longer distance movers between 1993 and 1997 which were tracked was 75% higher compared to non-movers.

If the survey misses individuals with the steepest wage growth, we would underestimate the average growth in wages by leaving out mover households. Attrition and migration are important when considering the effect of natural disasters. When individuals in 2007 were asked in the migration section of the individual questionnaire, the three most frequently stated reasons for migration were work-related migration (34%), marriage (15%) and education (11%); only 0.33% of individuals give natural disasters as a reason for migration. Both Halliday (2006) and Yang (2008) find that two earthquakes in El Salvador reduced the probability that households send a migrant, due to either liquidity constraints or a higher need for family labor at home.

It is therefore important to test for differential migration and attrition depending on the proximity of household to the earthquake. We construct a variable that is equal to one if a household in our sample in 2000 moved from an earthquake affected district to a district not affected by the earthquake and zero otherwise[21]. In a linear probability model, we regress this measure on baseline wages and add controls in column (2), and column (3) includes district fixed effects. Similar to the test for selection, we can interpret the coefficient on the wage variable as a proxy for unobservable wages. Table 2.5 shows that individuals who moved outside the earthquake affected areas did not have significantly different unobservables determining baseline wages, so that that migration out of earthquake affected areas is not correlated with higher or lower unobservables.

[21] We define districts affected by the earthquake as those which had any houses destroyed.

Table 2.5: Dependent Variable: Whether Household Moved Away from Earthquake Affected District

	migrate1	migrate2	migrate3
	(1)	(2)	(3)
$\ln y_{2000}$	-.0009	-.002	-.002
	(0.002)	(0.003)	(0.002)
Controls	Age, Sex	Full Set	Full Set
District Fixed Effects	NO	NO	YES
Obs.	3216	3216	3216

Notes: Full controls include baseline age, age squared, gender, education, sector of employment, category of employment, rural/urban location, month of the 2000 survey and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Out of the all individuals for which we have positive wages in 2000, only 3% were living in households which were not found for the follow up interview in 2007, so that attrition is low for this sample. We tested whether attrition is more likely in earthquake affected areas, as well as whether it is more likely for individuals with lower baseline wages, and did not find any evidence for any systematic attrition related to the earthquake[22]. Therefore, there does not seem to be evidence that the earthquake led to higher migration or attrition of individuals at a specific location of the wage distribution, thereby biasing the results[23].

2.5 Empirical Results and Discussion

We start by presenting the base results in which we investigate overall wage growth, as well as heterogeneity with regard to the sector and category of employment of the individual before the earthquake. Second, we test the robustness of our results by using hourly wages instead of monthly wages, different recall periods and limiting the households in the control group. Following Leamer (1983)'s suggestion, we estimate a range of alternative models to show that our results are robust to different identifying assumptions. Third, we discuss possible mechanisms.

[22] Frankenberg et al. (2005), using the IFLS data, do not find evidence that forest fires led to differential attrition.

[23] We have also used the complete sample of all IFLS households who lived in the control and treatment areas in 2000 and merged them with their follow up households in the 2007 round. We then constructed an indicator whether a household interviewed in 2000 in the control and treatment areas was not found in 2007, and regressed the indicator on the earthquake measures. We did not find any relationship between exposure to the shock and subsequent probability of being in the sample, and there is no evidence that poorer households affected by the earthquake are less likely to be tracked in the survey in 2007. This suggests that there is no evidence that the earthquake led to differential patterns of attrition for lower and higher income families.

2.5.1 Base results

Table 2.6 shows the results for equation (2.4). Column (1) includes the number of houses destroyed per person and column (2) shows the log of the number of houses destroyed. For districts in which no houses were destroyed, we replace the variable with zero. The third column uses the mercalli intensity measure. The results show that households who were affected by the earthquake have on average significantly higher wage growth, and this result is robust to the measure of the earthquake shock.

Table 2.6: Dependent Variable: Changes in Log of Monthly Wages

	ratio	log	mercalli
	(1)	(2)	(3)
Houses dest/population	4.450***		
	(1.105)		
Log Housesdestroyed		0.053***	
		(0.014)	
Mercalli			0.14***
			(0.051)
Obs.	2471	2471	2471
R^2	0.071	0.07	0.069

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

For a one percentage point increase in the proportion of houses destroyed per population, wage growth was 3.9 percent higher. The coefficient on the log of houses destroyed is not deflated by population and indicates that for a 1 percent increase in the number of houses destroyed, wage growth was 0.05 percent higher. The third row uses the exogenous modified mercalli intensity scale and indicates that for a one unit increase in the shake intensity experienced by the individual, wage growth was on average 14% higher. As both, the number of houses destroyed and the log of houses destroyed are based on the same underlying destruction measure, we present the remainder of the results for the effect of housing destruction per population (denoted by ratio in the column header) as well as the modified mercalli intensity scale (denoted by mercalli in the column header)[24]. Table 2.16 in the appendix lists all explanatory variables except the month of interview dummy variables. The table shows that

[24]We prefer houses destroyed per population to take into account population density.

wage growth in construction and manufacturing was significantly lower than wage growth in commercial services. Wage growth was also lower for males illustrating that the gender wage gap is becoming smaller. Controlling for basic characteristics such as education, age, location, sector and category of employment wages were 40% higher for men at baseline in 2000. Wage growth is significantly higher for workers in urban areas. We do not find this result when looking at the cross sections in 2000 and 2007, but see the same effect when conditioning whether a worker was in an urban area in 2007. This suggests that the well documented urban wage premium operates in the sample through a higher growth rate rather than higher levels (Glaeser and Maré 2001). Wage growth is significantly faster for private sector workers and government workers compared to self-employed. Compared to a hypothetical worker in Yogyakarta unaffected by the earthquake shock, wage growth tends to be higher for workers outside Yogyakarta[25]. We do not find evidence for a significant wage effect dependent on the days between the earthquake and the survey. We have also experimented with higher order polynomials but this did not affect the results.

As the labor market is fragmented with a large proportion of individuals in self-employment, we now interact the earthquake measure with whether an individual is self-employed, employed by the government, or works in the private sector to determine whether the evolution of wage growth is different for individuals depending on their category of employment before the earthquake. Table 2.7 shows that there is a negative effect for government workers when using the destruction measure, but not when using the mercalli measure. There is no evidence, however, that self-employed individuals suffered lower wage growth after the earthquake.

Next, we interact the earthquake shock with the sector of employment of the individual in the period before the earthquake, taking commercial services as the base group. The results in table 2.8 suggest that the higher average wage growth is predominantly driven by workers in the agricultural sector obtaining higher wage growth compared to individuals employed in

[25] As we control for the exposure to the earthquake, the interpretation of the province dummies indicates differences holding earthquake exposure constant. As workers in Yogyakarta were all affected to varying degrees by the earthquake, the comparison group is a *hypothetical* worker unaffected by the earthquake.

Table 2.7: Dependent Variable: Changes in Log of Monthly Wages

	ratio	mercalli	mercallife
	(1)	(2)	(3)
Earthquake	4.702***	0.143**	0.035
	(1.336)	(0.059)	(0.125)
Earthquake*Firm Owner	0.199	0.009	0.05
	(5.039)	(0.103)	(0.106)
Earthquake*Government Worker	-3.168**	-.061	-.043
	(1.537)	(0.042)	(0.041)
Earthquake*Private Sector	0.146	-.002	0.021
	(1.468)	(0.04)	(0.038)
Obs.	2471	2471	2471
R^2	0.071	0.069	0.11

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 2.8: Dependent Variable: Changes in Log of Monthly Wages

	ratio	mercalli	mercallidfe
	(1)	(2)	(3)
Earthquake	1.902	0.096*	-.022
	(1.609)	(0.053)	(0.129)
Earthquake*Agriculture	9.161***	0.334***	0.301***
	(3.398)	(0.079)	(0.079)
Earthquake*Construction	2.493	0.087*	0.083*
	(1.937)	(0.049)	(0.049)
Earthquake*Manufacturing	4.258	0.027	0.031
	(2.616)	(0.062)	(0.064)
Earthquake*Social Services	1.754	0.035	0.049
	(2.484)	(0.044)	(0.044)
Obs.	2471	2471	2471
R^2	0.075	0.08	0.118
$H_0 : \xi_{agr} = \xi_{con}$	0.031	0.002	0.006
$H_0 : \xi_{agr} = \xi_{man}$	0.088	0.000	0.001
$H_0 : \xi_{agr} = \xi_{soc}$	0.012	0.000	0.001

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

commercial services. This effect is significant at the 1% level for both earthquake measures as shown in columns (1) and (2). We add district dummy variables to account for differences in district level wage growth rates in column (3); this does not affect the coefficients nor the significance level. The last three rows show the p-values of hypothesis tests where the null hypothesis is that the coefficient on the earthquake-agriculture interaction term is equal to the other earthquake-sector interaction terms. The tests suggest that we can reject at the 10% level when using the destruction measure, and at the 1% level when using the mercalli measure, that these coefficient are equal to each other. When the earthquake is measured with the mercalli scale in columns (2) and (3), we also find some evidence that individuals working in the construction sector before the earthquake experience higher wage growth, but the coefficient is not significantly different from the coefficient on the interaction term between the earthquake and the manufacturing or social services sector.

Table 2.9: Dependent Variable: Changes in Log of Monthly Wages

	ratio	mercalli
	(1)	(2)
Earthquake	1.902	0.096
Clustered s.e.	(1.609)	(0.053)*
Conley s.e.	(1.248)	(0.049)**
Earthquake*Agriculture	9.161	0.334
Clustered s.e.	(3.398)***	(0.079)***
Conley s.e.	(2.300)***	(0.076)***
Earthquake*Construction	2.493	0.087
Clustered s.e.	(1.937)	(0.049)*
Conley s.e.	(1.707)	(0.042)**
Earthquake*Manufacturing	4.258	0.027
Clustered s.e.	(2.616)	(0.062)
Conley s.e.	(2.498)*	(0.054)
Earthquake*Social Services	1.754	0.035
Clustered s.e.	(2.484)	(0.044)
Conley s.e.	(2.027)	(0.038)
Obs.	2471	2471

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

When analyzing a big shock like an earthquake, one also needs to be concerned about spatial dependence between observations. We always cluster standard errors by sampling cluster and the coefficients on the agriculture interaction in table 2.8 have small standard errors; we still need to make sure that this is not due to biased estimation of standard errors. We therefore also estimated the standard errors using Conley (1999)'s method which adjusts the estimated covariance matrix to allow for spatial correlation. We select a cut-off value of 0.25 decimal degrees (about 30 km) in each direction over which the correlation is assumed to decrease linearly with distance and after which the correlation is set equal to zero. Split-off households are assigned the coordinates of the centroid of the district polygon, as we do not have their exact coordinates. Table 2.9 compares the two methods and shows that the method to cluster standard errors does not significantly affect the results. If anything, Conley standard errors are slightly smaller than simple clustered standard errors. Both do not affect our results. However, Conley standard errors have the disadvantage that we impose that all split-off households live in the centroid of the polygon and thereby ignore potentially different correlation among individuals living in the same cluster, which is likely to lie outside the polygon centroid. Given the similarity in the size of the standard errors, for the remainder of the chapter, unless specified otherwise, we present standard errors clustered at the level of the sampling cluster.

2.5.2 Robustness

We show that the increased wage growth effects in the agricultural sector are robust to a number of different specifications (see appendix). Table 2.17 shows equation (2.8) using hourly wages as the dependent variable. In Table 2.18 we replace missing monthly wages if individuals reported last year's wages or profits by yearly wages or profits divided by 12; the results are substantively equivalent, but we prefer to refrain from aggregating across different recall periods. We also vary comparison groups to test whether different cut-offs in the modified mercalli scale limiting the comparison group affects the results. Columns (1)-(3) limit the sample to individuals with an exposure above 3.8, 4.1 and 4.2 on the mercalli scale. Table 2.19 indicates that the results are robust to different cut-offs, although the positive effect on the construction sector disappears when limiting the sample. Given that only about 6% of individuals work in the construction sector, limiting the sample reduces the precision of the estimates so that we are not able to identify sectoral differences in wage growth for sectors in which few individuals work. Finally, we test whether the results are robust to the identifying assumptions of our preferred specification by estimating the model using fixed effects, a diff-in-diff specification, a dynamic version of equation (2.4) which includes a control for wages in 2000 and a dynamic model instrumenting for the lagged dependent variable using the income from 1997.

The differential return to agriculture workers in the fixed effects results in table 2.20 and the diff-in-diff specification in table 2.21 are very similar to our baseline specification in table 2.6[26]. The dynamic model in table 2.22 yield slightly lower estimates. However, once we instrument for the lagged dependent variable using wages in the previous period in table 2.23 we see that the results are again very close to our baseline specification in equation (2.4). We have also estimated the model as a dynamic random effects model and as a dynamic fixed effects IV model using wages in 1997 as instruments and the coefficients and standard errors are virtually identical to the results presented here. As discussed in the previous section, we prefer equation (2.4) as it conditions on baseline characteristics which are not affected by potentially endogenous movement across sectors. However, the robustness exercise shows that the results are not due to selecting a particular set of identifying assumptions, but robust across various models[27].

A further concern is the measurement of wages in the agriculture sector. The household questionnaire records the net profit earned from farm businesses (or the share if the business is owned by multiple individuals); the individual level questionnaire, for which the wage data comes, asks individuals to report their profits at the individual level, but each respondent might also report the full profit. This only biases our results if for some reason the reporting of individual level profits has increased for individuals who were affected by the earthquake. We test whether self-employed agricultural workers are driving these results from several angles: first, we split the sample by work category; second, we drop self-employed agricultural workers. In both cases the significant positive effect of the earthquake on wages in agricul-

[26]In the diff-in-diff specification, we estimate the model including a time trend, the earthquake measure to control for pre-treatment differences, and the earthquake measure interacted with the time trend to obtain the treatment effect; we always include controls in levels.

[27]We have conducted a range of further robustness checks. First, we have estimated the base results instrumenting with the mercalli measure for the destruction measure, as well as the interaction terms; second, we have re-estimated all equations using the full sample of workers aged between 15 and 85; third, we have applied the attrition adjusted cross sectional individual sampling weights provided by the IFLS which make the 2007 IFLS sample of individuals representative for the 2007 population of individuals living in the original IFLS 13 provinces; our results remain robust.

ture remains. Finally, we estimate our base model in equation (2.4) but instead of estimating it at the individual level, we use changes in total household expenditure as the dependent variable, and control for the sector of employment of the household head in 2000[28]. In credit constrained environments, household expenditure and incomes are likely to be similar. Table 2.24 shows that households in which the household head was employed in the agricultural sector before the earthquake had significantly higher per capita expenditure, supporting that the positive effect on wages found in the wage regressions is not simply an artefact of reporting.

2.5.3 Mechanisms

While the higher wage growth for individuals working in the construction sector is intuitive given the upward shift in labor demand in the construction sector in the aftermath of the earthquake, explaining the increase in wage growth for agricultural workers is less obvious. In the conceptual framework in section 2.3 we referred to 'food' when discussing the effects on the price of necessities. We now explore in more detail why we might find an effect on agricultural wages. Profit maximizing firms will set wages equal to a workers' marginal product of labor multiplied by the price. Higher wage growth could be due to (i) higher agricultural prices or (ii) an increase in the marginal product of labor. We now investigate these channels in turn.

Increase in Prices of Agriculture Goods

The price of agricultural products could have increased due to the disruption in trade or the destruction of harvests; to explore the effect of trade disruptions on prices, we sketch the effects in a simple two-period framework borrowing ideas from Samuelson (1952)'s discussion of spatial price equilibrium. Assume that there are communities with excess demand for rice (net buyer communities) and communities which have excess supply (net seller communities), and the price for rice importing communities is equal to the producer price plus a transport cost. The earthquake increases transport costs for affected communities. It might also cause some communities to shift from being net exporters to being net importers due to

[28] Similar to wages, we convert per capita expenditure to 2007 Rupiah

destruction of harvests[29].

We first assume that the difference in autarchy prices of net seller and net buyer communities is larger than the increased transport cost so that communities continue to trade. The effect on price growth then depends on whether communities were net sellers or net buyers before and after the earthquake. We examine four types of communities, communities which shifted from being net sellers to being net buyers (SNB), communities which were always net buyers (ANB), communities which were always net sellers (ANS) and communities which shifted from being net buyers to being net sellers (SNS). Assume that the switch of SNB communities was caused either by a negative supply shock due to the earthquake (for communities which were affected by the earthquake), or due to an unobservable shock (for communities not affected by the earthquake), and is such that autarchy prices of the former net seller increase, which raises equilibrium prices.

We expect the highest increase in prices to be faced by communities which shifted from being net sellers to being net buyers. These communities did not pay for transport costs before, experienced the shock to supply and now face the increased transport cost after the earthquake. The second largest price effect is for communities which were always net buyers, both before and after the earthquake. Since the price of rice they faced before the earthquake already included transport costs, the growth in the price is by the additional transport cost caused by the destruction of infrastructure and the effect of the shock to SNB communities. For communities who were always net sellers, we only expect to see increase in price caused by the shock to SNB communities, since they do not face the increased transport costs. Finally, communities which shifted from being net buyers to being net sellers experience a higher price due the shock to SNB communities, but this is counteracted by not having to pay for transport costs anymore.

We expect the order of the price growth effects to be $\Delta p_{SNB} > \Delta p_{ANB} > \Delta p_{ANS} > \Delta p_{SNS}$. In the limit, if trade networks are completely destroyed, communities turn into little island

[29]According to International Recovery Platfrom (2009), 92% of damage in the agriculture sector was due to production losses, and 80% of damages to infrastructure occurred in provincial and district roads.

economies which do not trade anymore. In this case, we would expect a price drop for communities which were net sellers before the destruction, and an increase in the price for communities which were net buyers. We will keep the four groups for the empirical analysis to determine which of these scenarios is consistent with the data[30].

To test this mechanism, ideally we would have consumption, production and price data for a range of goods and services. In the data set, however, rice is the only good for which we have information on the level of prices per kg in both survey rounds, household level production and household level consumption. To proxy prices of agricultural goods, we therefore use information on rice prices from the community questionnaire of the IFLS survey. In 2000, up to three markets or sales outlets were visited to collect data on prices of basic goods. In 2007, interviewers collected prices from local markets, shops/stalls, and up to three informants were asked. For rice prices, the 2007 questionnaire records prices for high quality rice, average quality rice and low quality rice. Since we only have information on average quality rice in 2000, we use this variable to calculate prices. To calculate the price per kg, we multiply the price of a liter of rice by (1/0.89) and the price in grams by 1000. When the price was obtained by various sources, we calculate a simple average price over these sources.

We use the household questionnaire to get a measure of whether a community is a net set seller or a net producer of rice. From the household questionnaire we use farmers who record rice as the most valuable crop that the household farm produced for the market or for home consumption and aggregate the value of total production generated by the farm business (including produce for own consumption or giving to others) in the last 12 months at the community level. To measure total consumption, we aggregate the value of households' yearly consumption of rice (home-produced or bought from the market) at the community level. We classify the community as a net buyer if the ratio of total consumption over total production is larger than one in a particular period[31]; we then use this to define whether a community has always been either a net buyer or net seller, or whether it changed its net

[30] In what we discussed we do not explicitly account for general equilibrium effects of the destruction of transport infrastructure on communities not affected by the earthquake. In the empirical section we relax this assumption by using the continuous mercalli measure for the earthquake.

[31] We also show the results with different cut-offs.

position[32].

Since we need at least a reasonable sample of households per cluster to estimate aggregate production, we exclude communities which are not original IFLS communities (who will have few households living there in each round) which results in a sample of 126 communities. We then estimate the effect of the earthquake on the change in the price of rice using the following regression:

$$\begin{aligned}\Delta \ln p_{j2} =& \pi_0 + \pi_1 H_j + \pi_2 SNB_j + \pi_3 ANB_j + \pi_4 ANS_j \\ &+\pi_5 SNB_j * H_j + \pi_6 ANB_j * H_j + \pi_7 ANS_j * H_j + \varepsilon_{j2}\end{aligned} \tag{2.9}$$

for community $j = 1, \ldots, N$, where

p is the price of rice per kg.

H is a measure of destruction through the earthquake.

SNB is equal to one if a community shifted from being a net seller to being a net buyer of rice between 2000 and 2007/2008.

ANB is equal to one if a community was a net buyer of rice in both 2000 and 2007/2008.

ANS is equal to one if a community was a net seller of rice in both 2000 and 2007/2008.

Downward Shift in Labor Supply

The second channel through which agricultural wages could have increased is through a downward shift in labor supply in the agricultural sector, possibly due to job opportunities opening up in other sectors of the economy associated with reconstruction. To test this channel, we use the Indonesian Sub-National Growth and Governance data set which contains

[32]Another method to investigate how the earthquake shock has impacted integration and trade would be to look at the conintegrating relationship between price series of different clusters (Dercon 1995; Varela et al. 2012). However, we are not aware that district level or community level rice price data for Indonesia exist and we were told by BPS that such data do not exist. For the case of rice, our data construction method based on community price surveys has the advantage that we can hold quality of rice constant by looking at the price of rice of average quality. Convoluting product quality and price effects is a common problem when analyzing aggregate price series (Varela et al. 2012).

sectoral employment shares at the district level for the years 2001-2004 and 2007. The labor market data contained in the data set are computed from SUSENAS data, a large yearly national socio-economic survey which is representative at the district level. The individual questionnaire in the SUSENAS survey asks the employment sector of household members aged 10 and over. The employment share per sector is defined as the number of individuals in each district employed in a particular sector divided by the total working population in each district. We also include the number of individuals unemployed which are computed on the basis of employed individuals aged 15 and over divided by the total labor force which is defined as individuals working, temporarily absent from work but having a job, those who did not work but were looking for a job or were preparing for a job. As the labor market data for 2005 are missing and we do not have information on the exact timing of the survey in 2006, we compare changes in sectoral employment shares between 2004 and 2007 in earthquake affected and comparison districts. To estimate the impact of the earthquake on the share of individuals employed in each sector we use the following specification:

$$\Delta \ln prop_{d2} = \lambda_0 + \lambda_1 H_d + \varepsilon_{d2} \tag{2.10}$$

for district $d = 1, \ldots, N$, where

$prop$ is the proportion of individuals employed in a particular sector and the proportion of individuals unemployed.

H is a measure of destruction through the earthquake.

The dependent variable $\Delta \ln prop_{d2}$ refers to changes in the log of the proportion of individuals employed in a particular sector between 2004 and 2007. To address the correlation of the residuals of the sectoral share equations, we estimate the model as a system of seemingly unrelated equations. We test these two channels in turn.

Evidence on Mechanisms

Table 2.10 shows the effect of the earthquake on the change in log prices of rice at the community level. There is a significant and positive effect for both earthquake measures, so that

Table 2.10: Dependent Variable: Changes in Log of Rice Price

	ratio	ratio2	mercalli	mercalli2
	(1)	(2)	(3)	(4)
Earthquake	1.030***	0.273	0.021*	-.0003
	(0.173)	(0.367)	(0.012)	(0.011)
Earthquake*Shift to Net Buyer		1.274*		0.049**
		(0.753)		(0.024)
Earthquake*Always Net Buyer		1.234		0.011
		(3.059)		(0.015)
Earthquake*Always Net Seller		-.003		0.022
		(0.481)		(0.024)
Shift to Net Buyer		0.006		-.216
		(0.063)		(0.158)
Always Net Buyer		-.047		-.098
		(0.037)		(0.091)
Always Net Seller		0.031		-.079
		(0.041)		(0.124)
Obs.	126	126	126	126
R^2	0.03	0.107	0.043	0.136

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

communities which were affected by the earthquake had steeper growth in average rice prices. A 1 percent increase in the proportion of houses destroyed leads to a 1 percent higher growth rate in the price of rice, and a one unit increase in the mercalli measure leads 2.1 percent higher growth in the price of rice. However, this average effect possibly masks significant heterogeneity across communities. We test whether this effect is stronger for different types of communities. Columns (2) and (4) show the results where the omitted category is communities which were always net sellers. Indeed the effect is stronger for communities that became net buyers in the sample period. We do not find evidence for an average increase in prices across different types of communities. Communities which shifted from being net sellers to net buyers and were affected by the earthquake experienced about 5% higher growth in the price of rice for a one unit increase in the mercalli measure compared to communities which shifted to being net sellers.

We test for the robustness of this finding, by taking cut-offs in the ratio of consumption over production between 1 and 3 with 0.2 steps. Figure 2.7 and 2.8 in the appendix show the range of values of the coefficients on $\pi_1 + \pi_5$, $\pi_1 + \pi_6$ and $\pi_1 + \pi_7$ for both the destruction as well as the mercalli earthquake measure. Consistent with the expectation, the change in prices is significantly higher for communities which shifted to being net buyers in the sample period. The results are slightly cleaner when using the mercalli measure, most likely due to the finer measure when comparing across communities, since the destruction measure only varies at the district level, assigning the same value to all communities in the same district. What emerges, nevertheless, is that communities which became net buyers in this period experienced the highest growth in rice prices when focusing on the coefficients with p-values of 0.1 or less. The fact that we do not observe consistent evidence for decreases in the price for net seller communities and increases in the price for net buyer communities suggests that trade continued in the aftermath of the earthquake.

Table 2.11 shows the results from the district level sectoral shares equation, where each row shows the effect of the earthquake shock on the change in the proportion of individuals employed in a particular sector. We include the log of the number of houses in the second column as an alternative measure as our level of observation now is the district. The growth in

Table 2.11: Dependent Variable: Sectoral Shares

	ratio	ln(number houses)	mercalli
	(1)	(2)	(3)
Δ % Agriculture	-.535***	-.017**	-.0093
	(0.1373)	(0.0072)	(0.0068)
Δ % Construction	1.11***	.0200***	.0128**
	(0.1763)	(0.005)	(0.0053)
Δ % Manufacturing	-.048	-.0009	.0038
	(0.4267)	(0.0072)	(0.0066)
Δ % Commercial Services	-.417	.0027	-.0049
	(0.2786)	(0.0068)	(0.0070)
Δ % Social Services	-.0928	-.0042	-.0022
	(0.0990)	(0.0043)	(0.0031)
Δ % Unemployement	.159	-.0023	-.0006
	(0.1220)	(0.0042)	(0.0035)
Obs.	91	91	91

Notes: Coefficients from system of 6 seemingly unrelated regressions, indicating the effect of the earthquake on the change in the proportion of individuals employed in a particular sector for the three different earthquake measures; robust standard errors in parentheses; *, **, *** denote significance at 10%, 5% and 1% levels.

the district level share of the population employed in the agricultural sector decreased significantly when using our first two measures in column (1) and (2), implying that a 1% increase in the proportion of houses destroyed leads to a 0.54% lower growth in the percentage of individuals employed in agriculture. The effect is less precisely estimated when using the mercalli measure. There is also a strong and significant effect on the construction sector across the three measures. For example, a one percent higher proportion of houses destroyed during an earthquake led to a 1.1% higher growth rate in the proportion of individuals employed in construction[33].

It is important to examine how these two proposed mechanisms might interact. Higher price growth in agriculture due to trade limitations and the resulting higher wage growth would, if anything, draw workers back into agriculture, thereby biasing upwards λ_1 in the agricultural shares equation of specification (2.10). On the other hand, it is possible, that the higher growth rate in the price of rice is also caused by the labor shifts out of agriculture, rather than trade restrictions and changes in output.

If earthquakes lead to job creation outside the agricultural sector, and workers previously employed in agriculture take up job opportunities outside agriculture, this leads to a downward shift in labor supply in the agricultural sector and therefore an increase in wages. We would also observe higher wage growth in earthquake affected communities, but this would be caused by the higher demand for labor in non-agricultural sectors. One way to test this is by including the change in the proportion of workers employed in each sector in equation (2.9). If all the effect is coming through sectoral shifts, the earthquake and net position of the community should not be significant anymore. The results are substantially the same when including sectoral changes, which suggests that we can not rule out that trade limitations and damage to infrastructure had an effect.

The results therefore suggest that the increase in wages in the agricultural sector in the aftermath of the earthquake was driven by a combination of sharper increases in the price of

[33]The results are equivalent when we restrict the sample of districts to those in which a member of the IFLS sample lives.

rice, in particular for communities which shifted from being net producers to net purchasers as well as shifts out of the agricultural sector, thereby raising the marginal product of labor of agricultural workers.

2.6 Conclusion

This chapter explored how natural disasters affect labor markets, more specifically, wage growth across employment categories and sectors as well as changes in the sectoral composition of the labor force. Our identification relied on the exogenous nature of a large earthquake hitting Yogyakarta, Indonesia, on 27 May 2006. We used a panel of individuals from the Indonesia Family Life Survey living in the vicinity of the earthquake, and linked these with data on district level housing destruction, the modified mercalli intensity scale of the earthquake which takes into account peak ground velocity, peak ground acceleration and the topology of the region; data on community level rice prices and district level employment indicators.

We found that labor markets are remarkably resilient against such a large shock and on average wage growth was even higher in earthquake affected regions. We did not find strong evidence for differences in the effect of the earthquake according to whether individuals are self-employed, firm owners, government workers or employed in the private sector. Given that these employment categories have different levels of job protection and regulations, this result is rather surprising. However, we did find substantial heterogeneity with respect to the sectoral evolution of wages. Individuals who worked in the agricultural sector in areas that were strongly affected by the earthquake enjoyed a substantially higher earnings growth compared to individuals working in the commercial services sector, who nevertheless do not have any negative earnings growth effects. This suggests that local labor markets are fairly segmented and mobility is limited. In the agriculture sector this is likely to be the case since land as a factor of production is immobile, many farms are family farms, and monitoring of labor is relatively difficult in this sector. The result is robust to a range of specifications relying on alternative identifying assumptions compared to our preferred specification, including a differences-in-differences specification, fixed effects, a dynamic specification and a dynamic instrumental variables specification. A range of measures of the intensity of the earthquake shock and varying control groups also produce very consistent results.

We proposed two mechanisms for this result. First, the destruction of infrastructure led to increases in the price of food, particularly in areas which are net consumers of food. Second, a downward shift in the supply of labor due to fatalities and injuries and an increase in the demand for labor in sectors producing non-tradables in the aftermath of the disaster drew workers out of the agricultural sector (the low-wage sector) into higher-wage non-tradable sectors, leading to a rise in the marginal product of labor and wages in the agriculture sector. We find evidence for both mechanisms. The earthquake led to higher growth in the price of rice. We also show that growth of rice prices was higher in communities which switched from being net producers to being net consumers. Employment contracted in the agricultural sector and expanded in the construction sector in the aftermath of the earthquake. This suggests that both these effects resulted in higher wage growth for agricultural workers.

Even though this chapter provided evidence on a natural disaster in Indonesia, the findings are relevant for other lower middle income countries as well, and suggest that efficient responses to large scale shocks can even lead to positive effects on the evolution of wages. As the response to the earthquake has been regarded as fast and efficient, this finding resonates with Kahn (2005) who finds that institutional quality can mitigate the adverse effects of natural disasters. But since this chapter provided evidence on one particular natural disaster in Indonesia, further research in the following areas is still missing. First, how do local labor markets, in different contexts, respond to large scale shocks. For example, what type of labor market institutions are helpful in protecting wages and which institutions limit flexibility of labor. Second, how policy responses differ across contexts. To answer this question, an avenue for further research would then be to separately identify the effect of the destruction and the reconstruction shock, which we were not able to do in this chapter. Finally, in this study we focused on the short to intermediate term effects. Longer post-disaster time series data on earnings would allow us to investigate longer wage dynamics to test whether the effects we find are transitory or persistent. Given that the propensity of natural disasters is expected to rise, and with rapid urbanization the consequences are going to be larger, all these become increasingly important questions.

2.7 Appendix

Table 2.12: Median of Wages and Wage Growth by Employment Category

		Levels in 2000		Growth by Category in 2000	
	N	Hourly†	Monthly	Hourly†	Monthly
	(1)	(2)	(3)	(4)	(5)
Self-employed	996	2035.1	368,952.9	5.1%	7.5%
Firm Owner	44	6401.7	1,295,379.0	-5.9%	7.2%
Government worker	219	8115.1	1,286,428.0	32.2%	33.9%
Private Worker	1212	2219.0	454,797.8	26.8%	22.7%
Total	2471	2357.9	464,079.4	21.4%	19.9%

		Levels 2007		Growth by Category in 2007	
	N	Hourly†	Monthly	Hourly†	Monthly
	(1)	(2)	(3)	(4)	(5)
Self-employed	1332	2199.5	400,000.0	6.5%	4.5%
Firm Owner	71	5278.8	1,000,000.0	5.9%	8.1%
Government worker	237	10997.5	1,700,000.0	36.7%	37.4%
Private Worker	831	3079.3	600,000.0	31.6%	26.8%
Total	2471	2886.8	500,000.0	21.4%	19.9%

Notes: †hourly wages in 2007 missing for 2 individuals; employment categories are defined as follows: Self-employed includes self-employed with unpaid family worker/temporary worker, casual worker in agriculture, casual worker not in agriculture; firm owners are self-employed with permanent worker. Columns (4) and (5) show wage growth, where the top panel shows wage growth for workers employed in a particular category in 2000, and the bottom panel shows wage growth for workers employed in a particular category in 2007. All figures are in 2007 Indonesian Rupiah using the CPI for 43 cities in Indonesia.

Table 2.13: Median Wages and Wage Growth by Employment Sector

		Levels in 2000		Growth by Category in 2000	
	N	Hourly†	Monthly	Hourly†	Monthly
	(1)	(2)	(3)	(4)	(5)
Agriculture	444	1840.0	368,952.9	7.1%	7.5%
Construction	217	2485.2	553,429.3	22.4%	19.9%
Manufacturing	502	2143.6	421,949.2	18.7%	13.7%
Commercial Services	747	2143.6	417,671.4	19.9%	13.2%
Social Services	561	4019.2	649,711.1	27.5%	30.0%
Total	2471	2357.9	464,079.4	21.4%	19.9%
		Levels 2007		**Growth by category in 2007**	
	N	Hourly†	Monthly	Hourly†	Monthly
	(1)	(2)	(3)	(4)	(5)
Agriculture	476	1924.6	300,000.0	1.4%	-3.2%
Construction	186	3150.3	600,000.0	13.4%	19.9%
Manufacturing	443	2969.3	600,000.0	27.7%	23.5%
Commercial Services	794	2474.4	500,000.0	18.4%	12.2%
Social Services	572	4925.3	845,000.0	29.7%	29.8%
Total	2471	2886.8	500,000.0	21.4%	19.9%

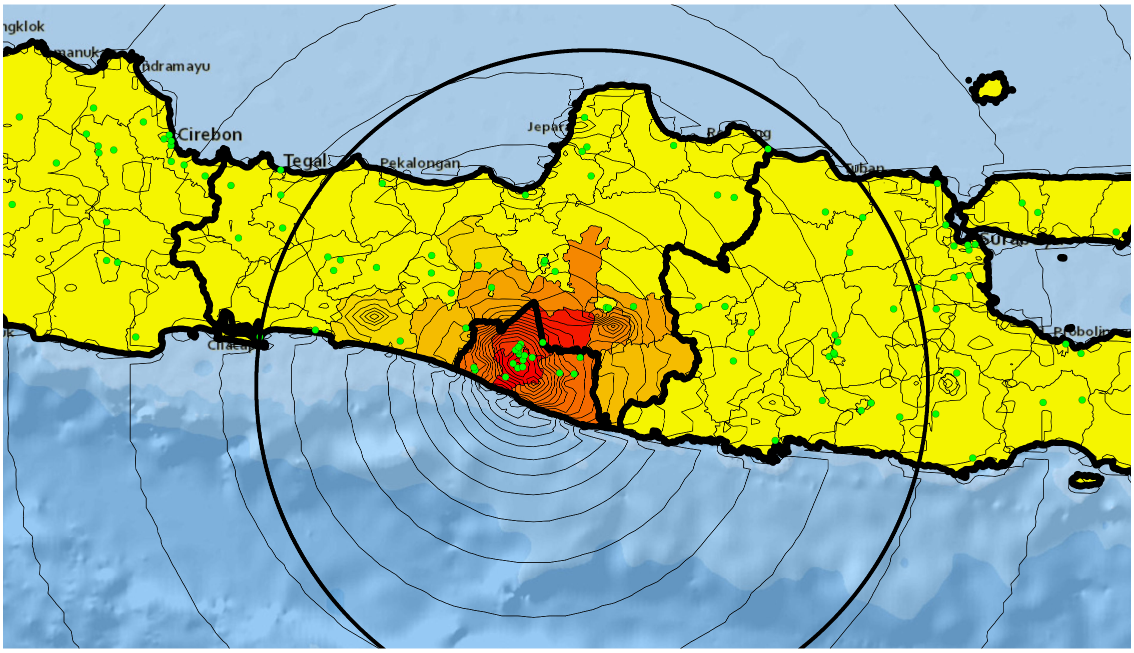
Notes: †hourly wages in 2007 missing for 2 individuals; employment sectors are defined as follows: agriculture includes forestry fishing and hunting; construction electricity, gas and water and mining; commercial services comprises wholesale, retail, restaurants, hotels, transportation, storage communications, finance, insurance, real estate and business services. Columns (4) and (5) show wage growth, where the top panel shows wage growth for workers employed in a particular sector in 2000, and the bottom panel shows wage growth for workers employed in a particular sector in 2007. All figures are in 2007 Indonesian Rupiah using the CPI for 43 cities in Indonesia.

Table 2.14: Disasters, 1972-2009

Event	Freq.	Percent	Deaths	Injured	H destroyed	H damaged
Drought	799	11.54	0	0	0	0
Earthquake	277	4	46.86	233.19	1785.16	2491.95
Eruption	56	0.81	8.34	24.43	7.18	69.23
Fire	1,361	19.66	0.17	0.70	20.61	1.19
Flood	2,163	31.25	1.12	86.36	55.08	83.02
Landslide	1,135	16.4	2.85	36.18	46.14	61.78
Strong Wind	921	13.31	0.16	1.73	28.50	37.58
Surge	160	2.31	0.09	1.26	22.78	23.63
Tsunami	50	0.72	3357.94	38.44	6539.74	1944.42
Total	6,922	100	27.07	43.12	151.88	156.18

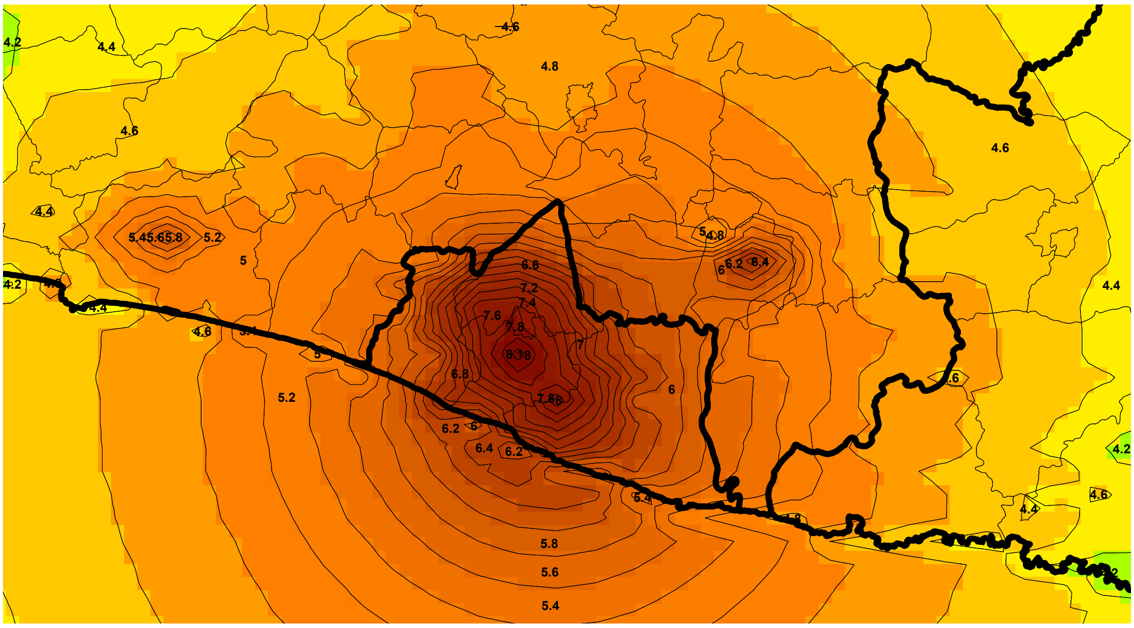
Notes: Complete sample from Desinventar database; deaths, injured, houses destroyed and houses damaged show means per (district-specific) data entry.

Figure 2.4: Yogyakarta Earthquake, 27 May 2006 at 05:53:58 AM



Source: ArcGIS 10; data from US Geological Survey and IFLS communities.

Figure 2.5: Modified Mercalli Intensity Map zoomed into the Epicenter



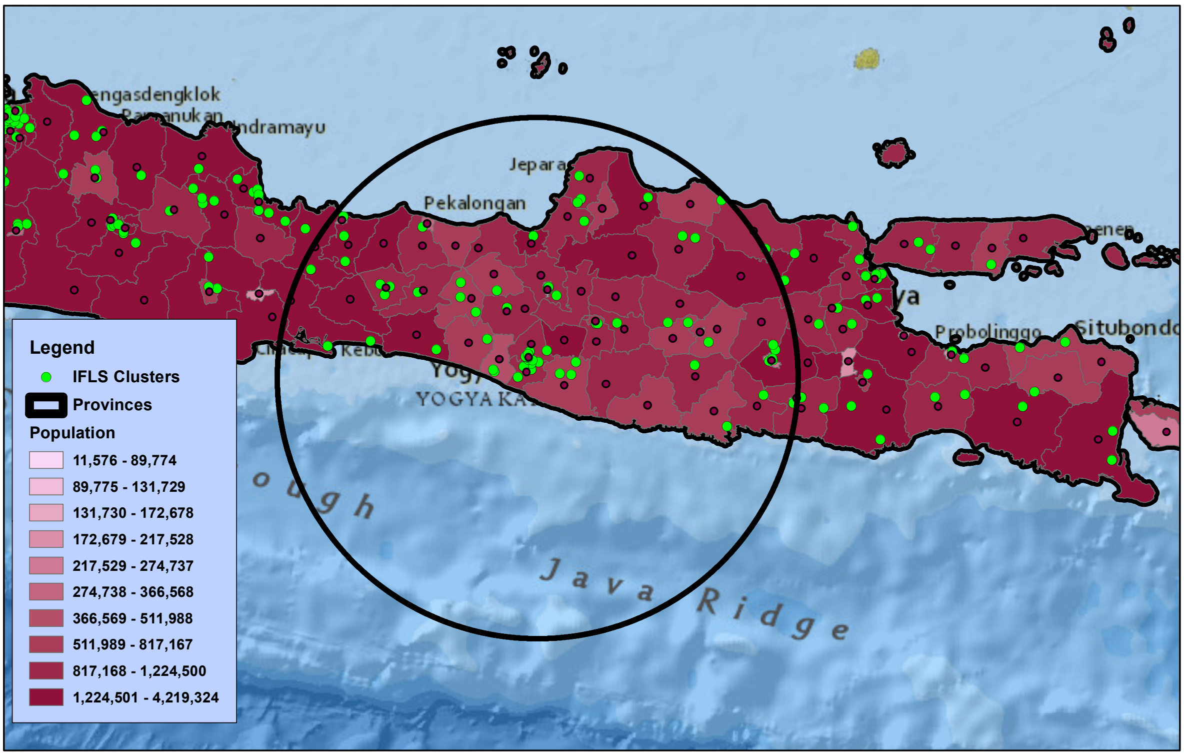
Source: ArcGIS 10; data from US Geological Survey.

Table 2.15: Housing Destruction per District

District	Houses Destroyed	Houses Damaged	Mercalli	Av.mercalli	Population 2005
	(1)	(2)	(3)	(4)	(5)
Bantul	78,622	69,818	7.6	7.7	871,203
Klaten	32,277	63,615	5.8	6.3	1,119,812
Sleman	6,186	16,065	6.6	6.8	999,586
Kota Yogyakarta	4,129	10,219	7.8	7.7	439,393
Kulon Progo	4,009	5,134	6.2	5.9	373,770
Gunung Kidul	2,957	5,783	6.2	6.4	681,554
Sukoharjo	644	885	5.6	5.6	805,096
Magelang	386	386	5.2	5.2	1,141,503
Karanganyar	66	75	4.8	5.0	791,177
Purworejo	29	347	5.2	5.4	713,149
Temanggung	24	61	4.8	4.9	686,851
Kebumen	3	0	4.8	5.0	1,193,854

Notes: Desinventar database and USGS modified mercalli intensity scale. Column (4) lists the average modified mercalli intensity scale per district. Column (5) shows the average modified mercalli intensity scale of the sample, replacing the data in column (4) with exact shaking values for individuals in the original IFLS communities.

Figure 2.6: Population Density



Source: ArcGIS 10; data from 2008 Village Potential Data, Badan Pusat Statistik.

Table 2.16: Dependent Variable: Changes in Log of Monthly Wages

	ratio	log	mercalli
	(1)	(2)	(3)
Houses dest/population	4.467***		
	(1.111)		
Log Housesdestroyed		0.053***	
		(0.014)	
Mercalli			0.14***
			(0.051)
Agriculture	-.143	-.136	-.139
	(0.104)	(0.105)	(0.104)
Construction	-.226**	-.216**	-.226**
	(0.088)	(0.088)	(0.089)
Manufacturing	-.226***	-.225***	-.226***
	(0.059)	(0.059)	(0.059)
Social Services	0.015	0.009	0.006
	(0.069)	(0.07)	(0.07)
Primary	-.095	-.092	-.107
	(0.113)	(0.111)	(0.112)
Secondary	-.089	-.100	-.113
	(0.123)	(0.121)	(0.122)
Tertiary	-.058	-.068	-.079
	(0.138)	(0.135)	(0.135)
Age	0.012	0.012	0.013
	(0.02)	(0.021)	(0.021)
Age Squared	-.0003	-.0003	-.0003
	(0.0003)	(0.0003)	(0.0003)
Urban	0.129*	0.17***	0.152***
	(0.075)	(0.045)	(0.046)
Male	-.130***	-.133***	-.127***
	(0.046)	(0.046)	(0.046)
Firm Owner	0.065	0.066	0.071
	(0.151)	(0.152)	(0.151)
Wage Worker	0.216**	0.214**	0.22**
	(0.097)	(0.098)	(0.098)
Government Worker	0.145**	0.143**	0.146**
	(0.06)	(0.061)	(0.061)
Central Java	0.084	0.341**	0.226
	(0.087)	(0.148)	(0.148)
East Java	0.222**	0.518***	0.443**
	(0.088)	(0.16)	(0.176)
West Java	0.107	0.402**	0.356*
	(0.099)	(0.165)	(0.186)
Hours Worked	-.005***	-.005***	-.005***
	(0.001)	(0.001)	(0.001)
Days since EQ	-.0004	-.0002	-.0003
	(0.003)	(0.003)	(0.003)
Const.	0.142	-.291	-.732
	(1.766)	(1.780)	(1.799)
Obs.	2471	2471	2471
R^2	0.071	0.07	0.069

Notes: All models control for month of each survey round; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 2.17: Dependent Variable: Changes in Log of Hourly Wages

	ratio	mercalli	mercallidfe
	(1)	(2)	(3)
Earthquake	2.122	0.056	-.189
	(2.219)	(0.064)	(0.147)
Earthquake*Agriculture	6.605*	0.309***	0.293***
	(3.613)	(0.086)	(0.09)
Earthquake*Construction	3.805	0.116*	0.12**
	(2.835)	(0.06)	(0.058)
Earthquake*Manufacturing	3.271	0.004	0.007
	(3.260)	(0.077)	(0.079)
Earthquake*Social Services	2.339	0.032	0.048
	(3.010)	(0.053)	(0.056)
Obs.	2469	2469	2469
R^2	0.051	0.055	0.095

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 2.18: Dependent Variable: Changes in Log of Monthly Wages, Month and Year Recall Combined

	ratio	mercalli	mercallidfe
	(1)	(2)	(3)
Earthquake	0.845	0.068	-.084
	(2.275)	(0.066)	(0.172)
Earthquake*Agriculture	8.348	0.321	0.302
	(3.077)***	(0.079)***	(0.082)***
Earthquake*Construction	1.027	0.031	0.022
	(3.993)	(0.081)	(0.082)
Earthquake*Manufacturing	3.114	-.009	-.011
	(2.629)	(0.079)	(0.08)
Earthquake*Social Services	2.633	-.003	0.005
	(3.086)	(0.064)	(0.066)
Obs.	2917	2917	2917
R^2	0.052	0.058	0.088

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 2.19: Dependent Variable: Changes in Log of Monthly Wages, Varying Control Groups

	more4	more42	more44
	(1)	(2)	(3)
Earthquake	0.084	0.084	0.137*
	(0.054)	(0.059)	(0.082)
Earthquake*Agriculture	0.274***	0.224***	0.188**
	(0.068)	(0.073)	(0.092)
Earthquake*Construction	0.053	0.031	-.032
	(0.051)	(0.054)	(0.074)
Earthquake*Manufacturing	0.025	0.041	0.034
	(0.066)	(0.069)	(0.075)
Earthquake*Social Services	0.052	0.026	-.014
	(0.047)	(0.05)	(0.065)
Obs.	2048	1616	1118
R^2	0.089	0.104	0.109

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels. Columns (1)-(3) limit the sample to individuals with an exposure above 3.8, 4.1 and 4.2 on the mercalli scale.

Table 2.20: Dependent Variable: Log of Monthly Wages, Fixed Effects

	ratio	ratio2	mercalli	mercalli2
	(1)	(2)	(3)	(4)
Earthquake	4.977***	1.677	0.136***	0.003
	(0.875)	(1.101)	(0.051)	(0.026)
Earthquake*Agriculture		10.452***		0.289***
		(3.434)		(0.084)
Earthquake*Construction		3.488*		0.102**
		(1.960)		(0.048)
Earthquake*Manufacturing		1.811		0.003
		(2.392)		(0.05)
Earthquake*Social Services		0.702		0.005
		(1.578)		(0.041)
Obs.	4940	4940	4940	4940
R^2	0.086	0.088	0.083	0.089

Notes: All models control for age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 2.21: Dependent Variable: Log of Monthly Wages, Diff-in-Diff

	ratio	ratio2	mercalli	mercalli2
	(1)	(2)	(3)	(4)
Earthquake	4.718***	1.481	0.069***	0.015
	(0.536)	(1.622)	(0.021)	(0.033)
Earthquake*Agriculture		9.496**		0.296***
		(4.619)		(0.098)
Earthquake*Construction		4.977*		0.13**
		(2.670)		(0.063)
Earthquake*Manufacturing		3.070		0.027
		(2.595)		(0.061)
Earthquake*Social Services		2.827		-.0009
		(2.724)		(0.062)
Obs.	4940	4940	4940	4940
R^2	0.281	0.284	0.278	0.284

Notes: All models control for age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 2.22: Dependent Variable: Changes in Log of Monthly Wages, Dynamic Model

	ratio	ratio2	mercalli	mercalli2
	(1)	(2)	(3)	(4)
Earthquake	3.215***	2.415**	0.107***	0.097**
	(0.97)	(1.145)	(0.04)	(0.042)
Earthquake*Agriculture		4.805***		0.187***
		(1.695)		(0.052)
Earthquake*Construction		0.829		0.035
		(1.575)		(0.041)
Earthquake*Manufacturing		0.667		-.040
		(1.631)		(0.043)
Earthquake*Social Services		0.328		0.023
		(1.271)		(0.029)
Obs.	2471	2471	2471	2471
R^2	0.346	0.347	0.345	0.349

Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 2.23: Dependent Variable: Changes in Log of Monthly Wages, Dynamic Model - IV

	ratio	ratio2	mercalli	mercalli2
	(1)	(2)	(3)	(4)
Earthquake	3.661***	1.981	0.074	0.03
	(1.196)	(1.784)	(0.053)	(0.057)
Earthquake*Agriculture		9.113***		0.335***
		(2.763)		(0.075)
Earthquake*Construction		1.246		0.056
		(2.020)		(0.052)
Earthquake*Manufacturing		1.847		-.020
		(1.855)		(0.05)
Earthquake*Social Services		0.788		0.038
		(1.698)		(0.039)
Obs.	1499	1499	1499	1499
R^2	0.262	0.268	0.261	0.28

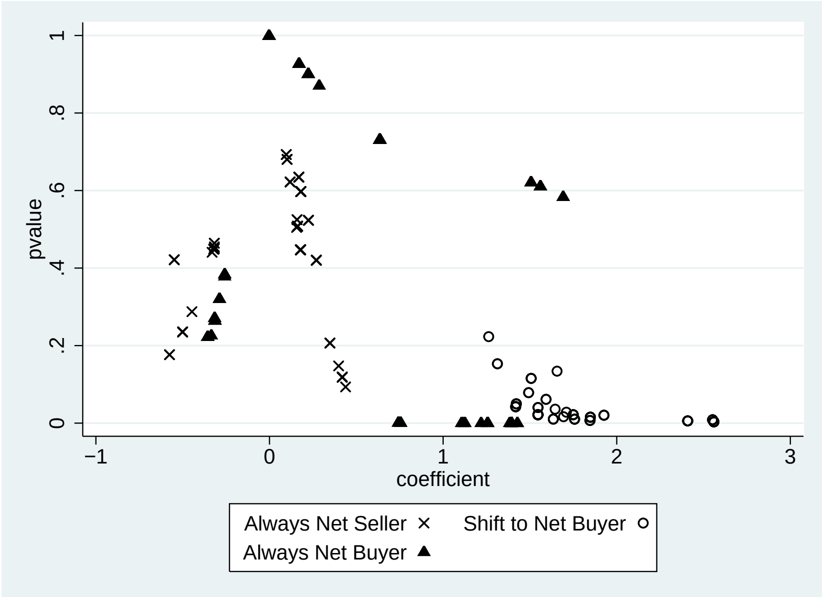
Notes: All models control for baseline age, gender, sector of employment, category of employment, hours worked, rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 2.24: Dependent Variable: Changes in Log of Monthly per capita Expenditures

	ratio	ratio2	mercalli	mercalli2
	(1)	(2)	(3)	(4)
Earthquake	1.138	0.292	0.042	0.053
	(1.386)	(1.613)	(0.06)	(0.061)
Earthquake*Agriculture		4.991***		0.119***
		(1.647)		(0.041)
Earthquake*Construction		-.680		-.023
		(2.064)		(0.049)
Earthquake*Manufacturing		3.380		-.005
		(2.922)		(0.059)
Earthquake*Social Services		-1.454		-.094**
		(2.067)		(0.046)
Obs.	1787	1787	1787	1787
R^2	0.05	0.058	0.05	0.064

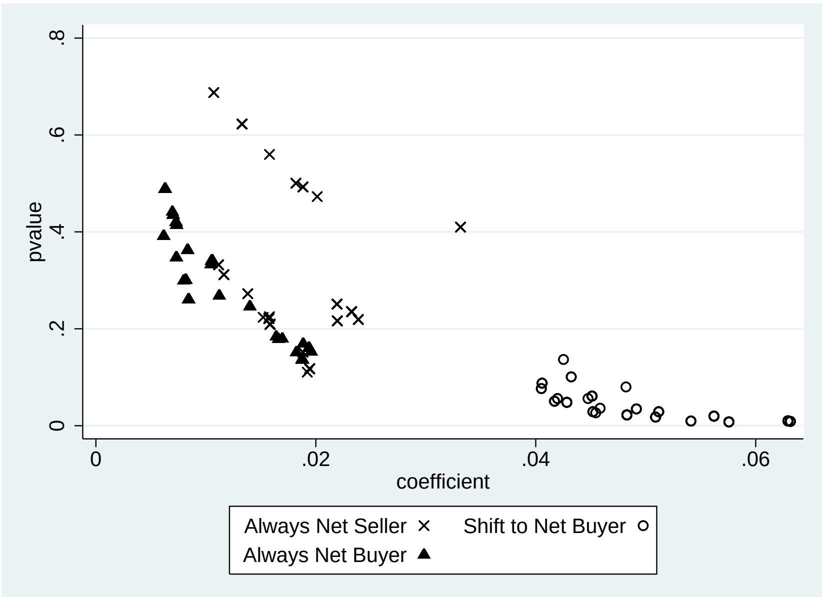
Notes: All models control for baseline age, gender, sector of employment, category of employment of the household head; rural/urban location, month of each survey round, time between the survey and the earthquake and province specific trends; robust standard errors in parentheses, clustered at the community level; *, **, *** denote significance at 10%, 5% and 1% levels.

Figure 2.7: Range of Coefficients with Varying Cut-offs (Destruction Measure)



Notes: Circles represent the coefficient for communities which shifted to net buyers ($\pi_1+\pi_5$); triangles represent the coefficient for communities which were net buyers in both periods ($\pi_1 + \pi_6$); crosses represent the coefficient for communities which were always net sellers ($\pi_1 + \pi_7$); communities which shifted to net sellers are the omitted category; standard errors clustered at the district level.

Figure 2.8: Range of Coefficients with Varying Cut-offs (Mercalli Measure)



Notes: Circles represent the coefficient for communities which shifted to net buyers ($\pi_1+\pi_5$); triangles represent the coefficient for communities which were net buyers in both periods ($\pi_1 + \pi_6$); crosses represent the coefficient for communities which were always net sellers ($\pi_1 + \pi_7$); communities which shifted to net sellers are the omitted category; standard errors clustered at the district level.

Chapter 3

Preferences over Leisure and Consumption of Siblings and Intra-household Allocation

3.1 Introduction

Children are often treated as passive members in the household and their preferences over consumption and leisure are rarely modelled. With few exceptions, household models in economics treat children as public goods or passive agents of the household, let alone allowing for preference heterogeneity among siblings[1]. In many developing country contexts, children are expected to perform unpaid or paid work inside or outside the house, but there is also a significant level of heterogeneity across children with regard to their attitudes and preferences towards work[2]. While parents certainly play a central role in deciding over a child's time allocation, Edmonds (2008, p. 3668) points out:

[1] Studies who consider children as decision makers in households include Moehling (2005), Lundberg et al. (2009), Kapan (2009) and Dauphin et al. (2011).

[2] Orkin (2011) presents qualitative evidence from children in rural Ethiopia supporting the idea that children have different preferences with regard to work as well as make decisions regarding their time. Furthermore, a recent experimental literature highlights heterogeneity in children's risk taking, attitudes towards ambiguity, time preferences, and competitiveness (Castillo et al. 2011; Andersen et al. 2013; Sutter et al. 2013). Castillo et al. (2011) and Sutter et al. (2013) show how differences in preferences elicited in experiments significantly correlate with differences in observed behaviors in real life, such as school referrals, smoking, alcohol consumption and saving of pupils in Georgia (United States) and Tyrol (Austria).

> *"Future research understanding the child's own role in her time allocation is perhaps the most pressing need in the child labor literature."*

Several economists have argued that trade sanctions and consumer boycotts as policies to fight child labor might backfire and raise child labor at least in the short run, and even contribute to its persistence in the long run (Edmonds and Pavcnik 2005; Basu and Zarghamee 2009; Doepke and Zilibotti 2010). If children have agency over their decisions even in relatively poor settings, considering their preferences is instrumental to understanding households' behavior in low income countries.

When considering children as economic agents with preferences over consumption and leisure, it becomes natural to apply standard models employed in the labor economics literature in which agents maximize utility from consumption and leisure subject to a budget constraint. If parents have equal levels of altruism towards their children, differences in within-household allocations among siblings would then be due to differences in preferences.

The psychology literature has long recognized the role of children in household decision making and studies on child development suggest a process of gradual increase of shared decision making towards decision autonomy from childhood into adolescence (Grotevant 1983; Dornbusch et al. 1985; Yee and Flanagan 1985). Harbaugh et al. (2003) play dictator and ultimatum games with children and find that they are good bargainers by the age of 7, in the sense that they are aware of their own and their partner's pay-offs in a specific situation. Evidence from an experiment conducted by Harbaugh et al. (2001) suggests that by the age of 11, children's choices are roughly as rational as choices by adults, so that their choices satisfy the Generalized Axiom of Revealed Preference[3]. Lundberg et al. (2009) show that there is a sharp increase in children's reported involvement in the decision making process between age 10-14. Most parents will also agree that children growing up in the same household can be very different in their personality traits and preferences (Daniels and Plomin 1985; Dunn

[3]Choices made by about 60% of 11 year old children and undergraduates are consistent with utility maximization, compared to about 25% of 7 year old children.

and Plomin 1990)[4].

The objective of this chapter is to view children as agents and to understand whether children's preferences over consumption and leisure determine allocations of assignable goods among siblings. The central contribution of the chapter is twofold. First, it develops a unitary model of the household focusing on intra-sibling allocation of consumption and leisure[5]. The model assume parents to be social planners taking into account children's preferences over leisure and consumption when making allocation decisions. The focus of this chapter is how allocations are driven conditional on children being in school rather than the tradeoff between work and school, so we abstract from schooling decisions[6]. The model provides insights into how heterogeneity in children's preferences and parental altruism affect allocations and yields testable propositions. The intuition is straightforward. Assume there is a family with two children, child A and child B, who face equal wages. If relative parental altruism towards child A and B drives allocation decisions and children's relative preferences over leisure and consumption are independently distributed, we expect the residuals of the relative expenditure and the relative leisure equation to be positively correlated, controlling for age and gender composition effects. The favorite child gets allocated a higher expenditure share and higher leisure share. On the other hand, if child A and child B's relative preferences for leisure are negatively correlated with their relative preferences for consumption, and there is no variation in parental altruism in the unobservables, conditional on age and gender composition effects, the residuals should be negatively correlated. Children who work longer hours get rewarded accordingly.

Second, we use detailed data on time use and assignable goods of a panel data set of children in Ethiopia, India, Peru and Vietnam to test the theoretical implications of the model. Data on both time use of children in the household and assignable expenditures from house-

[4]One of the earliest studies documenting the low correlation of personality inventories between siblings was Crook (1937) using the Bernreuter personality inventory.

[5]Our approach is most closely related to Browning and Gørtz (2012) who model the allocation of consumption and leisure between husband and wife.

[6]Our model therefore does not view child work and schooling as substitutes, which is in line with evidence found by Attanasio et al. (2010). They show that increases in schooling hours caused by the Familias en Acción program in Colombia did not map one to one into reductions in work hours; rather, the results suggest that leisure time of children decreased.

hold surveys is rare for adults (Browning and Gørtz 2012), and even more so for children. We use data on the amount of time children spend on leisure and work activities, and child-specific clothes expenditures. To our knowledge, this is the first paper that explicitly models within sibling variation in preferences over leisure and consumption and tests the predictions of the theoretical model with a data set of children who are in full time schooling and haven't entered the formal labor market yet in the context of four developing countries.

We find that conditioning on observable variables, the residuals of these simultaneous decisions are significantly negatively correlated. This suggests that differences in siblings' relative time and consumption allocations are driven by their relative preferences over leisure and consumption rather than differences in the relative altruism of parents vis-à-vis their children. This correlation is robust to excluding younger children and non-biological siblings. When we use relative work hours instead of relative leisure we observe a positive correlation in the residuals, supporting the hypothesis that preferences are driving allocations rather than altruism toward a particular child. We show that this finding persists when we only explore variation in the hours worked in the household, ruling out that the positive correlation between relative work and relative expenditure is due to children working outside the house and therefore needing more work-related clothes expenditures. We also do not find evidence that the relationship is driven by age-gender-location specific productivity differences, non-linear age effects, different levels of education and schooling hours, and a range of alternative hypotheses. Children seem to trade off leisure and consumption and are rewarded accordingly. As a result, the data is consistent with a model in which families behave as if they were an internal market in which children select their optimal consumption-leisure bundle.

The approach adopted in this chapter is based on the assumption that household allocations are efficient, an assumption embodied in unitary as well as collective household models, which explicitly assume the existence of an efficient intra-household decision making process (Becker 1981; Chiappori 1988; Browning and Chiappori 1998). Among the first to explicitly consider parent-children interactions was Becker (1981) with his well known Rotten Kid Theorem. Within the literature on intra-household allocations, the presence of children and their effect on household economic behavior has received increasing attention over the past 20 years (Browning 1992; Browning and Lechene 2003; Browning and Ejrnæs 2009; Bonke and Browning 2011; Blundell et al. 2005; Cherchye et al. 2012). A recent paper by Dunbar et al. (2013) uses semi-parametric restrictions to identify the resource shares in a household allocated to children with the goal of estimating children's poverty levels in Malawi. The data employed in this chapter allows us to *directly* use the expenditures for a specific good (clothes) allocated to specific children in the household for households with two children. Our starting point is therefore knowledge of the child-specific expenditures.

Our focus on within sibling allocation of resources by parents also relates to the literature on child quantity and quality trade-offs, parental investment, and parental preferences for equality among their children. Becker and Lewis (1973) highlight the interaction between the quantity and quality of children: a larger number of children increases the marginal cost of quality, and vice versa. Becker and Tomes (1976) show that when children have different endowments, and the return to human capital investment is higher for high-endowment children, parents exacerbate these differences by investing human capital more heavily in the child with the higher endowments[7]. Whether parents reinforce or compensate endowments is still an open question; there is evidence for compensatory behavior of parents (Behrman et al. 1982; Griliches 1979), as well as reinforcement (Behrman et al. 1994; Rosenzweig and Zhang 2009). Parents might also be both reinforcing and compensating differences in different dimensions. Conti et al. (2010) use data from Chinese twins and find that parents make compensating investments in health and reinforcing investments in education, and there is no effect on the time parents spend with children. Our paper differs from this literature in that we focus on a consumption good (clothes) rather than investment goods (i.e. education, health) and abstract from differences in initial endowments of children[8]. In our model, inequality in leisure and consumption among siblings can be due to differences in parental preferences as well as differences in children's preferences over leisure and consumption[9]. Finally, we do

[7]Behrman et al. (1995) highlight that this finding requires equal concern of parents, sufficiently high levels of resources allocated to children, and higher marginal as well as average returns to education for the more able child.

[8]Ideally we would like to test for the role of ability as well; unfortunately, our data only contains information of ability for the panel child but not the siblings.

[9]We do not make assumptions over what determines heterogeneity in parental altruism towards their children.

not explore the effect of family size due to limitations in the data: as we are able to identify expenditure shares and leisure time only for children with one other sibling in the age range of 5-17, we limit our sample to families with two children in this age group without younger siblings.

A few studies have departed from modeling children via caring preferences or as a household public good to consider them as agents in the household. Moehling (2005) shows that adolescents' labor force participation is positively correlated with their clothing expenditures using data from the Cost of Living Survey of 1917-1919 in the United States. Dustmann and Micklewright (2001) use data from sixteen year old adolescents from the British National Child Development Study and find that adolescents' labor force participation reduces parental transfers[10]. This focus of this chapter differs from these studies in that we are interested in how relative preferences of siblings and relative altruism of parents affect relative expenditures between siblings.

Dauphin et al. (2011) examine the demand systems of families with one child aged sixteen and over living with his or her parents using data from the United Kingdom; they find that the data are consistent with three decision makers for the complete sample, the sample of children aged 16-21 and for daughters (irrespective of their age). Kapan (2009) uses data from Turkey and finds that while the unitary model is not rejected for families in which the wife does not earn an income, it is strongly rejected when a son aged 12 and above is present in the household (but not for daughters). Instead of examining properties of demand systems to test whether the data are consistent with more decision makers when older children are present, our approach is to develop a model which delivers testable propositions on relative preferences and relative expenditures of siblings.

The chapter is structured as follows: section 3.2 presents the context and data. Section 3.3 develops a theoretical model. Section 3.4 focuses on identification and estimation of the

[10]Moehling (2005) argues that during the time of their data income of children entered the household budget so that it increased the bargaining power of children, while Dustmann and Micklewright (2001) argue that for their sample earnings of adolescents remain directly in the hands of the adolescent, so that parents respond by reducing transfers.

model parameters. Section 3.5 discusses the results and section 3.6 concludes.

3.2 Data

Detailed data on allocations of time and goods within families is very rare. In the majority of household surveys we observe total household expenditures for particular goods, where at most it is possible to assign a few goods to husband, wife and children after making assumptions about the characteristics of goods. Detailed data on time allocations across household members is even sparser. Having both pieces of information in the same survey is crucial for studying their interaction. We use data from the Young Lives Survey, a study of childhood poverty tracking two cohorts of children in Ethiopia, India, Peru and Vietnam. For the purpose of this chapter, we use data from the older cohort which is 7-8 years old when first interviewed in 2002. The second and third rounds took place in 2006/2007 and 2009/2010 and collected detailed information on expenditures as well as information on what activities all household members aged 5-17 spent time on during a usual workday.

The survey contains one 'panel' or 'index' child per family (which determines the panel dimension of the survey), but also collects detailed information on other family members in the household. Focusing on a cohort over time has the advantage that we can inspect how a relatively homogenous sample of children at two points of time interacts with siblings. From the whole data set we select our sample along four dimension: (i) as we can assign expenditures with certainty only to children with one other sibling, we use the sample of children with one other child below 18 years old in the household; (ii) since the time diary is available only for children between 5 and 17, we limit the sample to panel children with siblings between 5 and 17 years; (iii) given that we are interested in time allocations for children who are in school, we raise the age cutoff to 6 years; (iv) we then only keep children which are in full time schooling to abstract from the child labor-schooling tradeoff. Given that in both rounds, about 89% of the children in our sample are in full-time schooling, this restriction is not particularly reducing our sample. This leaves us with a total of 1,652 sibling pair observations for both rounds across four countries.

A first look at the data confirms that children in our sample feel that they have a significant amount of agency over their choices. As part of the child questionnaire in 2006, the index child was asked to name activities he or she did the day before the survey, and whether it was the child's choice to do that activity. Table 3.1 shows the most frequently listed activities and the percentage of children who say that it was their choice to do this activity for the four countries[11]. Children across the four countries named on average between three and four activities. On average, between 72-76 percent of children in Peru, India and Vietnam state that they did the activity they listed by choice. Ethiopian children lag behind with the average percentage of children doing a listed activity by choice being less than half. More than 92% of children across the four countries named school as an activity they did the day before the survey, but while 63 percent of children go there by choice in Peru, only 33 or 34 percent do so in Vietnam and Ethiopia. Similar heterogeneity is apparent for household chores. Domestic chores in the household are performed by choice by at least 80 percent of children in Vietnam and India, compared to 65 and 35 percent for children in Peru and Ethiopia. Collecting firewood is done by choice by 71 percent of Indian children, compared to 31 percent of Ethiopian

Table 3.1: Children's Time Use and Choice

	Ethiopia n=143		India n=394		Peru n=177		Vietnam n=430	
	named activity (1)	own choice (2)	named activity (3)	own choice (4)	named activity (5)	own choice (6)	named activity (7)	own choice (8)
School	0.92	0.34	0.99	0.59	0.98	0.63	0.97	0.33
Homework/Tuition	0.50	0.45	0.91	0.66	0.96	0.82	0.85	0.80
Domestic Chores within Home	0.68	0.35	0.25	0.85	0.49	0.65	0.66	0.81
Collecting Firewood or Water	0.26	0.31	0.11	0.71	0.03	0.50	0.02	0.57
Caring for Animals of hh	0.21	0.24	0.01	1.00	0.06	0.56	0.08	0.77
Leisure Time with Friends	0.40	0.88	0.69	0.96	0.03	1.00	0.51	0.95
Watching TV	0.14	0.64	0.56	0.93	0.60	0.96	0.65	0.95
Average Own Choice		0.43		0.76		0.76		0.72

Notes: Data from round 2 of Young Lives Data. The index child was asked to name activities he or she undertook the day before the survey and whether it was the child's choice to do that activity. Odd numbered columns show the percentage of children naming a particular activity; even numbered columns show the fraction of children who stated it was their choice to do the particular activity they listed.

[11]We limit the sample to answers of children which are part of our estimation sample either in 2006 or 2009, and exclude 25 duplicate entries which arose when an activity was named twice by the child with the same answer on whether it was a choice. In three cases the child named an activity twice, but with different answers whether she performed by choice, so we keep these three cases.

children. Leisure time with friends is an activity undertaken by at least 88 percent of children because they want to; this is similar for watching TV, with the exception of Ethiopia where only 64 percent of children state that they watch TV by choice. However, only 20 children in the Ethiopian sample stated that they watched TV the day before the survey, and out of these 4 children stated that they did not have a choice, and three children stated that they sometimes have a choice, so this is based on few observations.

Table 3.6 in the appendix shows the relationship of the second child in the household to the panel child. Ninety percent or more children are the biological siblings of the panel child in India, Peru and Vietnam and this is true for 76 percent in Ethiopia. The second largest group are half-siblings, who are mainly maternal, uncles/aunts and cousins. In the rest of the chapter we refer to the co-habitating child as the sibling, recognizing that a small proportion of the children in the sample are half-siblings or other relatives[12].

3.2.1 Time Allocation

The household questionnaire asks the main caretaker of the panel child how household members aged 5 to 17 years allocated their time across the following activities on a typical weekday in the last week[13]: sleeping, caring for others (younger siblings, ill household members), household chores (fetching water, firewood, cleaning, cooking, washing, shopping), non-paid activities outside the household (tasks on family farm, cattle herding, other family business, shepherding, piecework or handicrafts done at home), activities for pay/sale outside the household or for someone not in the household, at school (including traveling time), studying outside of school time (at home, extra tuition) and playtime/general leisure (including time taken to eating, drinking and bathing). Asking allocations on a typical weekday has the advantage that it provides a better picture of everyday activities of a child and is less

[12]In the robustness section we present the results only using sibling pairs with the same mother and the same father.

[13]We do not have data on the caretaker's reported time allocation for the panel child in India for 2009, so we use the child's reported time allocation. We tested the correlation between the caretaker's and the panel child's reported time allocation when both are available. Excluding data for 2009 for India, the correlation is 0.76 (with a p-value of 0.000) for leisure and 0.8180 (with a p-value of 0.000) for work. The results are stronger if we use the child's reported time allocation for the panel child. Given that we only have these for the panel child but not the sibling, we prefer to use the caretaker's reported time allocation for the main results.

vulnerable to particularities of the survey day than referring to activities the day before the survey[14].

Table 3.7 in the appendix shows the characteristics of the panel child in 2006 and 2009. The panel child is between 11 and 13 years old in 2006. The proportion of male panel children in 2006 is highest in Peru with 62 percent, compared to 53, 51 and 45 percent in Vietnam, India and Ethiopia. All children in our sample are in school, but there are differences in the number of hours children spend in school. Children in Vietnam spend the fewest number of hours at school with 4.59 hours, while kids in India spend 6.89 hours per day on average in 2006. When taking into account differences in studying hours, children in Ethiopia, Peru and Vietnam spend about 8 hours on school and study, compared to 10 hours in India. Play time is highest in Vietnam with an average across the two years of almost 5 hours, as opposed to 2.97 hours in Ethiopia, 3.72 hours in India and 2.86 hours in Peru. There is also substantial variation across children in the hours of leisure, with about 40% of panel children spending 3 or 4 hours on playing per day.

About 80% of children spend at least one hour per day contributing to the household economy by performing household chores, child care, non paid work and paid work. Aggregated across these categories, kids in Ethiopia work about 3.5 hours a day in 2006 and 4 hours a day in 2009, thereby working the longest number of hours. Children in Peru work for about 1.5 hours in 2006 and 2.2 hours in 2009, similar to children in Vietnam. Children in India work on average about one hour per day. In all countries the time allocated to working is higher in 2006 than in 2009. Sleeping accounts for about 8.5 to 9 hours and children sleep less when they get older.

Table 3.8 in the appendix presents the characteristics of the siblings of the panel child in 2006 and 2009. Siblings are between 6 and 17 years old, with an average between 12 and 13 years. The average age is not strictly increasing as we don't have a balanced data set: some

[14]It has the disadvantage that it does not convey information on a usual weekday when children are in school during the day if the survey took place during holidays. As we are interested in time allocations of children who are spending part of their day at school, we only kept children in the sample who have positive school hours recorded.

children exit the data set when their parents have a third child, and some children enter the data set through as their siblings when their siblings are above 18 years. About half of the siblings are male. The sibling data reflect the same patterns emerging from the panel children. Children in India spend the most hours on school and study, and work hours are highest in Ethiopia. Play time of siblings is about 4 hours in India and Vietnam, and 3 hours in Ethiopia and Peru.

3.2.2 Expenditure Allocation

The household questionnaire collects data on expenditures within the last 12 months. The 12 month recall has the disadvantage of recall bias but this is likely to be outweighed by the advantage of more complete reporting compared to diary-based data collection that only records expenditures over a few weeks. Assignable expenditures include clothes, footwear, school uniform, school fees, private classes, books, transportation to school, doctors, medicine and entertainment. We focus on children's clothes in this analysis, which account with an average of 6.2% for a sizeable share of total nonfood expenditures of households[15]. Parents are asked to state the total amount of expenditure on boy's and girl's clothes. If they are not able to recall the gender, they indicate the total amount spent on a good. Within these categories, they indicate the approximate fraction of expenditure on the index child (nothing, less than half, about a half, more than half but not all, and everything). To recover child specific expenditures we assume the following conversion: 0 if the stated share is "nothing", 0.25 if the stated share is "less than half", 0.5 if the stated share is "about a half", 0.75 if the stated share is "more than half but not all", and 1 if the stated share is "everything". Since we focus on families with two children, knowing the allocation share to the index child, we can assign the remainder to the sibling for same sex sibling pairs. Ruling out corner solutions, we only use the sample of children with some positive clothes expenditures for both siblings[16].

Table 3.9 in the appendix shows that there is large variation children's clothes expenditures. Given that the interview is centered around the panel child, one might worry that

[15]The median is slightly lower with 4.6%.

[16]This implies that we exclude 160 observations for whom either one or both children have zero clothes expenditures.

parents report significantly higher amounts for the panel child compared to their siblings. We do not find evidence in support of systematically higher reporting for the panel child. Rather, we find that expenditures are on average significantly higher for the sibling for Ethiopia in 2006 and for India in both rounds. We come back to this issue when discussing sources of measurement error in the identification section 3.4.

3.2.3 Relative Leisure and Expenditure

Figures 3.2 to 3.5 in the appendix show relative expenditures and relative leisure of siblings for each country. A large proportion of parents is egalitarian, with the lower and upper bound given by 32.7 percent in Ethiopia and 58.7 percent in Peru of sibling pairs who have equal allocations of clothes expenditures. Leisure is less equally distributed than expenditures with the children in Peru having equal hours of leisure in 41.3 percent of sibling pairs, compared to 23.3 percent of sibling pairs in Vietnam. Unequal allocations are distributed between a factor of 0.1 and 20 for clothes and 0.125 and 8 for leisure.

The pairwise correlation coefficient of relative expenditures and relative leisure is equal to -0.16 for Peru and Vietnam (with p-values of 0.007 and 0.0001), -0.81 for India (with a p-value of 0.0560) and -0.755 (with a p-value of 0.2890) for Ethiopia. We therefore do not reject that relative leisure and consumption are significantly and negatively correlated in the data in India, Peru and Vietnam, as illustrated by the graph in the South West corner which shows a significant and negative relationship between relative leisure and relative expenditures for these countries. When we exclude observations who have ratios of 5 or more (this reduces the sample by a maximum of 4 observations per country), the negative correlation is even stronger for Peru and Vietnam with correlation coefficients of -0.22 and -0.21 and remains substantially unchanged for Ethiopia and India. We do not exclude these observations in the estimation, but it is important to check that the result is not driven by them. If anything, our results are stronger without outliers. The next section presents the theoretical model.

3.3 Theoretical Model

This section develops a simple unitary household model in which parents are social planners and allocate time and consumption within the household. We allow for heterogeneity in preferences over leisure and consumption of household members as well as heterogeneity in parental altruism towards a particular child. The model yields testable predictions on optimal relative consumption and leisure allocations across siblings.

Assume that a family consists of parents P and children K where we assume that $K = A, B$[17]. Children are assumed to be egoistic. Parents have a joint welfare function Ω^P with caring preferences which aggregates the utilities of household members, taking into account individual's preferences. Ω^P is therefore a function of the parents' own utility, U^P, child A and B's utilities, U^A and U^B, and how much weight the parents attribute their own utility, measured by α[18], as well as how much they care about their offspring through the caring parameter δ so that

$$\Omega^P = \alpha\, U^P + \delta\, U^A + (1-\delta)\, U^B \tag{3.1}$$

where we include δ and $(1-\delta)$ to allow for differences in child A and B's weight in the parents' utility function[19]. Ω^P can therefore be seen as a social welfare function $\Omega^P = \omega(U^P, U^A, U^B)$

[17] Behrman (1997) refers to this as *consensus parental preferences*.

[18] This differs from *child-neutral preferences* as employed by Becker and Tomes (1976) or *equal concern* of parents as employed by Behrman et al. (1982) where parents attribute equal weights to children.

[19] From the literature on intrahousehold allocation it has become clear that classical properties of demand systems (Slutksy symmetry and income pooling) are generally violated when households are composed of a husband and wife (Browning et al. 2011), suggesting that they rarely act as a unit. Our model can be generalized to allow for two parents and two children and with different bargaining weights among parents (which depend on prices and incomes). For example, as discussed in Browning et al. (2011), we could assume a household welfare function Ω'^P of the form

$$\Omega'^P = \mu\,(U^M + \kappa^M U^C) + (1-\mu)\,(U^F + \kappa^F U^C)$$

where U^M is the mother's utility, U^F is the father's utility, μ is the pareto weight, κ^M is the mother's weight for children, κ^F is the father's weight for children, and $U^C = \delta\, U^A + (1-\delta)\, U^B$ as above. This can be rewritten as

$$\Omega'^P = \mu\, U^M + (1-\mu)\, U^F + (\mu\,\kappa^M + (1-\mu)\,\kappa^F)\, U^C$$

which, as will become clear below, would leave the core predictions of our model unchanged. This allows for the bargaining power of mother and father to affect the weight of children in the household's problem, as often modeled theoretically and found empirically in studies investigating intra-household allocation outcomes as a function of the identity of the income earner (Attanasio and Lechene 2002; Basu 2006; Bobonis 2009; Duflo 2000; Duflo 2003; Lundberg et al. 1997; Reggio 2011; Thomas 1990; Ward-Batts 2008). What we still require is that the *relative* weights of child A and B are independent of the parents' pareto weights but this is significantly less restrictive than assuming that both parents have the same weights for children. To maintain a focus on the in the spirit of Samuelson (1956), where the weighting function ω depends on α and δ[20]. We assume that α and δ are independent of prices and incomes and that $0 < \delta < 1$ and $0 < \alpha < 1$. Further, we rule out that children can affect the level of altruism of the parents[21]. The parents' welfare function is thus strictly increasing in the utility of household members $m = P, A, B$ which is defined as

$$U^m = U^m(x_m, l_m) \tag{3.2}$$

where x is a private good and l is leisure[22].

We assume that $U^m_{x_m} > 0$, $U^m_{l_m} > 0$, U^m is continuous, and strictly quasi concave for $m = P, A, B$. The household faces the budget constraint

$$x_P + x_A + x_B = I + h_P\, w_P + h_A\, w_A + h_B\, w_B \tag{3.3}$$

where the price of the consumption good is normalized to one, w denotes wage income and I is non wage income; household members face the time constraints

$$l_m = T - h_m \quad \text{for } m = P, A, B \tag{3.4}$$

where T is the time endowment and h are hours worked. Substituting the time constraints into the budget constraint yields the full budget constraint

$$\underbrace{x_P + l_P\, w_P + x_A + l_A\, w_A + x_B + l_B\, w_B}_{\text{Value of Consumption}} = \underbrace{I + T(w_P + w_A + w_B)}_{\text{Value of Endowment}}. \tag{3.5}$$

Children's wages can be seen as either through working outside the household where income earned enters the household budget, or through doing housework which in turn allows the parents to participate in activities outside the household. In light of the descriptive statistics

core mechanisms, which is within-sibling allocation, we keep the model as parsimonious as possible.

[20]We can not distinguish whether the differences in the weight are due to differences in parental altruism because parents have a higher level of love for one child, or whether this is because one child is better at terrorizing the parents, thereby increasing her or his bargaining weight. For the purpose of the theoretical and empirical model we interpret δ as the parents' level of altruism for child A.

[21]This is relaxed in the literature on strategic behavior of adult children competing for transfers from parents (Chang 2009; Chang and Luo 2011). In Chang (2009) adult children are modeled as homogenous, while in Chang and Luo (2011) adult children differ in their wages; children's preferences over leisure and consumption are not modeled in these two papers.

[22]Preferences and utility functions are denoted with superscripts, choice variables with subscripts.

of the previous section, it is reasonable to assume that these children contribute to household income by carrying out work inside and outside the household. The utility function and budget and time constraints make a number of assumptions. First, any activity apart from work is considered as leisure. If children do not consider schooling as leisure, the total time endowment of children could therefore be defined as $T = 24 - s_m$ for $m = A, B$, where s represents time at school[23]. Alternatively, we could have an additional term for schooling s so that $l_m = T - s_m - h_m$ for $m = A, B$. Schooling valued at wages would appear as an additional term in the value of consumption, but leave the optimality conditions between leisure and consumption unchanged, and thus the main results of the model equivalent. Second, individuals do not derive any utility from working. Third, parents have deferential preferences, in that they care about children's utilities but allow them to decide on their optimal consumption bundle based on their preferences. An implication is that parents do not derive any direct utility from seeing their children consume goods or participate in work, other than through an increase in the child's utility. To render the model more realistic, following Browning and Gørtz (2012) we could have included household production of a public good. This would leave the core predictions of our model unchanged. Since both modifications, schooling as a separate term and production, do not affect our result, we opted for keeping the model as parsimonious as possible.

Parents function as social planners and maximize overall household welfare by solving the following maximization problem

$$\max_{x_P, x_A, x_B, l_P, l_A, l_B} \alpha\, U^P + \delta\, U^A + (1-\delta)\, U^B \text{ subject to} \tag{3.6}$$

$$x_P + l_P\, w_P + x_A + l_A\, w_A + x_B + l_B\, w_B = I + T(w_P + w_A + w_B)$$

[23] In the empirical section we only look at children who are in school. However, we also test whether treating hours spent at school as an additional choice variable affects the results.

The Lagrangean is

$$\mathscr{L} = \alpha\, U^P + \delta\, U^A + (1-\delta)\, U^B \tag{3.7}$$

$$-\lambda\, \{x_P + l_P\, w_P + x_A + l_A\, w_A + x_B + l_B\, w_B - I - T(w_P + w_A + w_B)\}$$

and the first order conditions are

$$\mathscr{L}_{x_P} = \alpha\, \frac{\partial U^P}{\partial x_P} - \lambda = 0 \tag{3.8}$$

$$\mathscr{L}_{x_A} = \delta\, \frac{\partial U^A}{\partial x_A} - \lambda = 0 \tag{3.9}$$

$$\mathscr{L}_{x_B} = (1-\delta)\, \frac{\partial U^B}{\partial x_B} - \lambda = 0 \tag{3.10}$$

$$\mathscr{L}_{l_P} = \alpha\, \frac{\partial U^P}{\partial l_P} - \lambda\, w_P = 0 \tag{3.11}$$

$$\mathscr{L}_{l_A} = \delta\, \frac{\partial U^A}{\partial l_A} - \lambda\, w_A = 0 \tag{3.12}$$

$$\mathscr{L}_{l_B} = (1-\delta)\, \frac{\partial U^B}{\partial l_B} - \lambda\, w_B = 0 \tag{3.13}$$

$$\mathscr{L}_{\lambda} = x_P + l_P\, w_P + x_A + l_A\, w_A + x_B + l_B\, w_B \tag{3.14}$$

$$-I - T(w_P + w_A + w_B) = 0. \tag{3.15}$$

We assume that individual utility functions are additive over consumption and leisure

$$U^m = \theta^m \ln x_m + \tau^m \ln l_m \quad \text{for } m = P, A, B \tag{3.16}$$

so that θ measures household member m's preferences for consumption and τ measures his or her preferences for leisure; without loss of generality we set $\tau^P = 1$. The use of a log linear utility function for parents P and children A and B has two desirable properties. First, it builds a concern for equity into the utilitarian welfare function Ω^P, without explicitly modeling it through an additional parameter. Second, it allows us to obtain closed form solutions which we can take directly to the data, establishing a clear link between the theoretical model and the estimated parameters. Deriving the utility function with respect to x_P, x_A, x_B, l_P, l_A and l_B, combined with the first order conditions, we get

$$\frac{x_A}{x_B} = \frac{\delta}{1-\delta}\,\frac{\theta^A}{\theta^B} \tag{3.17}$$

$$\frac{l_A}{l_B} = \frac{\delta}{1-\delta}\,\frac{w_B}{w_A}\,\frac{\tau^A}{\tau^B} \tag{3.18}$$

for siblings A and B, where $\delta/(1-\delta)$ measures parents' altruism towards child A compared to child B, θ_A/θ_B measures children's relative preferences for consumption, τ_A/τ_B measures children's relative preferences for leisure, and w_B/w_A measures children's relative wages. We can also see that individual members' optimal consumption labor choice, $U^m_x/U^m_l = 1/w_m$, can be achieved through a two stage budgeting process in which in the first stage income is distributed appropriately, and in the second stage household members maximize $U^m(x_m, l_m)$ subject to $x_m + l_m\, w_m = I_m + T\, w_m$ where I_m is determined by the sharing rule of non-labor income (Browning et al. 2011). Therefore, following the second welfare theorem a competitive outcome can be reproduced given appropriate redistribution of initial incomes.

The simple comparative statics follow from (3.17) and (3.18)

$$\frac{\partial(\frac{x_A}{x_B})}{\partial\frac{\theta^A}{\theta^B}} > 0 \qquad \frac{\partial(\frac{l_A}{l_B})}{\partial\frac{\theta^A}{\theta^B}} = 0 \tag{3.19}$$

$$\frac{\partial(\frac{x_A}{x_B})}{\partial\frac{\tau^A}{\tau^B}} = 0 \qquad \frac{\partial(\frac{l_A}{l_B})}{\partial\frac{\tau^A}{\tau^B}} > 0 \tag{3.20}$$

$$\frac{\partial(\frac{x_A}{x_B})}{\partial\frac{\delta}{1-\delta}} > 0 \qquad \frac{\partial(\frac{l_A}{l_B})}{\partial\frac{\delta}{1-\delta}} > 0 \tag{3.21}$$

$$\frac{\partial(\frac{l_A}{l_B})}{\partial\frac{w_B}{w_A}} > 0. \tag{3.22}$$

The comparative statics imply that A's consumption increases relative to child B's, the stronger siblings' relative preferences for consumption θ^A/θ^B and the higher relative parental altruism $\delta/(1-\delta)$. The higher τ^A/τ^B, so the stronger A's preference for leisure relative to B's, the more leisure A will have compared to B. Finally, as B's wages increase relative to A's wages, it is efficient to allocate higher leisure to A relative to B. The theoretical model can be readily extended to n children, yielding $n(n-1)/2$ optimality conditions per family. However, the estimation becomes substantially less straightforward due to diads at the family level as will be clear in the next section. Further, we can only identify resource allocation shares for a subset of families with three children. We therefore keep the model with 2 children and leave the application to larger families for future research.

3.4 Identification and Estimation

We now discuss substantive and functional form assumptions required to translate theory into our estimable equations. Before presenting the results, we also outline how we deal with measurement error, and discuss fixed effects and the non-linearity of the relative expenditures variable.

3.4.1 Substantive Assumptions

Equations (3.17) and (3.18) describe the relative expenditure and leisure allocations of sibling A and B which depend on relative preferences θ^A/θ^B and τ^A/τ^B, as well as on relative parental altruism $\delta/(1-\delta)$ and relative wages w_B/w_A at a particular point in time. Since we look at preferences of children, we want to relax the assumption that preferences are stable. We assume that relative parental altruism is fixed over time[24]. Let's therefore rewrite equations (3.17) and (3.18) with time subscripts on the child specific preference variables as well as the time and consumption allocations

$$\frac{x_{At}}{x_{Bt}} = \frac{\delta}{1-\delta}\,\frac{\theta_t^A}{\theta_t^B} \tag{3.23}$$

$$\frac{l_{At}}{l_{Bt}} = \frac{\delta}{1-\delta}\,\frac{w_{Bt}}{w_{At}}\,\frac{\tau_t^A}{\tau_t^B}. \tag{3.24}$$

[24]There are reasons to believe that relative parental altruism might be time-varying, i.e. parents having at birth stronger relative altruism towards boys, but reverting to stronger relative altruism for girls when the boys are in puberty. For simplicity, we assume that relative altruism is stable across time.

We now denote sibling pair A and B in a family with subscript i and get

$$x_{it} = \delta_i \, \theta_{it} \tag{3.25}$$

$$l_{it} = \delta_i \, \kappa_t^{-1} \, \tau_{it} \tag{3.26}$$

where $x_{it} = x_{At}/x_{Bt}$ is sibling pair i's relative consumption of a particular good at time t; in other words, sibling A's consumption of a particular good divided by sibling B's consumption of a particular good at time t. Similarly, we define $l_{it} = l_{At}/l_{Bt}$, $\theta_{it} = \theta_t^A/\theta_t^B$, $\tau_{it} = \tau_t^A/\tau_t^B$ and $\delta_i = \delta/(1-\delta)$ as parents' relative altruism towards child i. We have assumed that relative wages of sibling A and B are constant across children, so that $\kappa_t = w_{At}/w_{Bt}$[25]. Equations (3.25) and (3.26) illustrate that relative altruism δ_i affects both relative consumption and relative leisure of sibling pair i positively, so that parents with $\delta > 0.5$ will allocate a higher consumption as well as more leisure to child A, holding θ_{it} and τ_{it} constant. Further, as becomes clear from the theoretical model, the consumption and work decisions are simultaneous decisions; therefore, regressing relative leisure on relative consumption, or vice versa, would lead to biased estimates. We use an approach employed by Browning et al. (1994) and instead are interested in the correlation of the residuals of these two simultaneous equations, conditional on observable exogenous variables. In other words, conditioning on basic observable characteristics, we test whether unobservables from the time allocation decision are correlated with unobservables from the consumption decision.

3.4.2 Functional Form Assumptions

We model children's relative preferences for consumption and leisure at time t as a function of a vector of observable household and child characteristics $\boldsymbol{Z}_{it}$ which include age, gender, rural or urban location, and a time fixed effect; further, we assume the presence of unobservable time invariant individual fixed effects $\lambda_{\theta i}$ and $\lambda_{\tau i}$, as well as time-varying idiosyncratic error

[25] We relax this assumption in the empirical section where we proxy wages with years of education.

terms $\varepsilon_{\theta it}$ and $\varepsilon_{\tau it}$ unobserved by the econometrician, yielding

$$\theta_{it} = \exp\{\beta_{\theta_0} + \beta_\theta' \boldsymbol{Z}_{it} + \lambda_{\theta i} + \varepsilon_{\theta it}\} \tag{3.27}$$

$$\tau_{it} = \exp\{\beta_{\tau_0} + \beta_\tau' \boldsymbol{Z}_{it} + \lambda_{\tau i} + \varepsilon_{\tau it}\}. \tag{3.28}$$

A variable R_i measuring relative altruism needs to satisfy the exclusion restriction that the effect of the variable is equal to zero when included in a regression of the difference between log relative expenditure and log relative leisure on the vector of characteristics contained in $\boldsymbol{Z}_{it}$[26]. Birth order or relative birth order have proven to be important determinants of within household allocation (Black et al. 2005; Chesnokova and Vaithianathan 2008; Ejrnæs and Pörtner 2004; Patrinos and Psacharopoulos 1997). It would therefore be a natural candidate to model relative altruism. However, it is highly correlated with the age difference and does not satisfy the exclusion restriction. Another candidate variable that potentially affects altruism of parents is if the older sibling is the older son. We have 283 sibling pairs in our sample in which the oldest child is a boy with a younger brother. This variable satisfies the exclusion restriction[27]. Therefore, we assume that parents' relative altruism for child A versus child B is a function of whether the older child is male and he has a younger brother, as well as unobservable time invariant individual fixed effect[28] $\lambda_{\delta i}$

$$\delta_i = \exp\{\beta_{\delta_0} + \beta_\delta R_i + \lambda_{\delta i}\}. \tag{3.29}$$

[26]The exclusion restriction emerges from taking the ratio of equations (3.25) and (3.26), and taking logs. This removes δ_i so that we require $\beta_{\delta 1} = 0$ in

$$\ln x_{it} - \ln l_{it} = \beta_{\delta 0} + \beta_{\delta 1} R_i + \boldsymbol{\beta}_{\delta 2}' \boldsymbol{Z}_{it} + \varepsilon_{\delta it}.$$

In other words, conditional on $\boldsymbol{Z}_{it}$, a variable R_i proxying for altruism should not affect $\ln x_{it} - \ln l_{it}$.

[27]We have also tested including a dummy variable which is equal to one if the oldest sibling is a boy (unconditional on whether he has a younger brother or a sister) and if the oldest sibling is a boy with a sister, but the variables do not pass the exclusion restriction or only marginally pass it, so we do not include them.

[28]Given that our sample covers a short time span, this variable is practically time invariant. There are only two panel children for whom their status changes, when a younger cousin or uncle moves into the household, so that they become the oldest male of the two. In the robustness section we show that our results are robust to excluding non-biological siblings.

3.4.3 Measurement Error

Until now we assumed that we know the true level of expenditures and leisure. However, in addition to recall bias, due to the nature of the data there is a second source of likely measurement error, illustrated in detail in the appendix in section 3.7.1. We know the allocation to the panel child as a fraction of the expenditure category (boys or girls clothes). We therefore always denote the panel child as child A. However, expenditures allocated to the sibling of the panel child are vulnerable to measurement error, since we assume that parents list clothes for household members 18 and over in the adult clothes category. Therefore, we assume that expenditures on child A are correctly measured so that

$$x_A = x_A^* \tag{3.30}$$

where x_A denotes the data and x_A^* the true expenditure. For child B, we have

$$x_B = e^{\rho} x_B^* \tag{3.31}$$

where x_B indicates the data, x_B^* the true expenditure and ρ is the difference between the recorded and the true log expenditure. Plugging this into equation (3.17) and taking logs we can see that ρ will be contained in the error term, biasing the constant. When the dependent variable is measured with error, consistency requires that the measurement error ρ is independent of the explanatory variables (Wooldridge 2002). This seems plausible in our case, so that the age of children, gender, and location is not correlated with the presence of adolescents aged 18-25 in the household who parents consider as children. Further, we know when measurement error is going to be more likely. The cases particularly prone to measurement error are (i) when both children are of the same sex, and there are further siblings aged 18 and over of the same sex in the household who parents consider a child (denoted as case 1); (ii) when children are of the opposite sex, but there is a further member of the same sex as child B in the household aged 18 and over who the parents consider a child (denoted as case 2). On the other hand, measurement error is going to be less likely for same sex siblings whenever the over 18 year old sibling is of the opposite sex, and for mixed sex siblings whenever the over 18 year old sibling is of the opposite sex of sibling B. Relative expenditures x_A/x_B are therefore a lower bound estimate of true relative expenditures, since $x_B = \max\{0, x_B\}$ for those with older siblings. We can use this information to model measurement error ρ as

$$\rho = \beta_{\rho 0} + \beta_\rho O_{it} \tag{3.32}$$

where O_{it} is equal to the number of older siblings according to case (i) or (ii) in either round.

Plugging (3.27), (3.28), (3.29) and (3.32) into (3.25) and (3.26) while taking (3.30) and (3.31) into account, and taking logs we get the following structural equations

$$\begin{aligned} \ln x_{it} =& (\beta_{\theta 0} + \beta_{\delta_0} + \beta_{\rho_0}) + \boldsymbol{\beta}'_\theta \boldsymbol{Z}_{it} + \beta_\delta R_i + \beta'_\rho O_{it} && (3.33) \\ & + (\lambda_{\theta i} + \lambda_{\delta i}) + \varepsilon_{\theta it} \\ \ln l_{it} =& (\beta_{\tau_0} + \beta_{\delta_0}) + \beta'_\tau \boldsymbol{Z}_{it} + \beta_\delta R_i && (3.34) \\ & + (\lambda_{\tau i} + \lambda_{\delta i}) + \varepsilon_{\tau it}. \end{aligned}$$

We can not separately identify the effect of $\ln \kappa_t$ and the coefficient on the time trend contained in $\boldsymbol{Z_{it}}$, due to our assumptions on the constant ratio across sibling pairs, so that it is part of $\boldsymbol{Z_{it}}$. We then get the two linear reduced forms

$$\ln x_{it} = \Pi_{x0} + \boldsymbol{\Pi}'_{x\theta} \boldsymbol{Z}_{it} + \Pi_{x\delta} R_i + \Pi'_{x\rho} O_{it} + \epsilon_{xit} \tag{3.35}$$

$$\ln l_{it} = \Pi_{l0} + \boldsymbol{\Pi}'_{l\tau} \boldsymbol{Z}_{it} + \Pi_{x\delta} R_i + \epsilon_{lit}. \tag{3.36}$$

Identification of $\Pi_{x\theta}$, $\Pi_{l\tau}$, $\Pi_{x\rho}$, and $\Pi_{x\delta}$ requires that $\boldsymbol{Z}_{it}$, R_i and O_{it} are uncorrelated with the composite error terms ϵ_{xit} and ϵ_{lit}. This is not an implausible assumption given that age, gender and location are out of the control of the child. We test the two following propositions adopted from Browning and Gørtz (2012):

Proposition 1 (Differences in children's preferences) *If θ_{it} and τ_{it} are negatively correlated, there is no variation in δ_i and $w_{Bt} = w_{At}$, then x_{it} and l_{it} will be negatively correlated.*

Proposition 2 (Differences in parental altruism) *If there is variation in δ_i while θ_{it} and τ_{it} are independent of each other and $w_{Bt} = w_{At}$, x_{it} and l_{it} will be positively correlated.*

Proposition 1 and 2 present the extreme cases and intermediate cases will be a weighted average of the two. The empirical model shows that if 'differences in parental altruism' drive allocations and preferences for leisure and consumption are independent, we expect the residuals to be positively correlated due to the fact that they both contain $\lambda_{\delta i}$ and altruism affects consumption and leisure positively. If heterogeneity is due to 'differences in children's tastes' where $corr((\lambda_{\theta i} + \varepsilon_{\theta i}), (\lambda_{\tau i} + \varepsilon_{\tau i})) < 0$ and $\lambda_{\delta i} = 0$, then we would expect that x_{it} and l_{it} to be negatively correlated. However, in either case we can not rule out that both, parental altruism and children's preferences, are operating. For example, a strong negative correlation in the residuals does not mean that necessarily parents do not have different weights for their children. It only indicates that differences in preferences are a more significant driver of allocations than differences in parental altruism.

3.4.4 Estimation: Fixed Effects and Non-Linearity of the Expenditure Variable

Despite having a panel, a consistent estimation of the fixed effects $(\lambda_{\theta i} + \lambda_{\delta i})$ and $(\lambda_{\tau i} + \lambda_{\delta i})$ is not feasible. First, with two time periods, the estimate of the fixed effect is inconsistent (Wooldridge 2002). Second, several of the preference parameters are time invariant; even for more time periods we would only be able to identify a combination of the fixed effect and the coefficient on the time invariant variables. Instead of using the natural logarithm, we follow Browning et al. (1994) and transform x_{it} and l_{it} using the inverse hyperbolic sine. The main advantage of this transformation is that the inverse hyperbolic sine is always positive and linear for low values, but very similar to the natural logarithm for high values. This avoids having highly negative values when relative expenditure and relative leisure are very low. Even though it is defined for the whole real line, so including zero, we do not include relative expenditure or leisure that is equal to zero[29].

[29]Our results are substantively unchanged when using the natural logarithm instead of the inverse hyperbolic sine; the choice between the inverse hyperbolic sine and the natural logarithm is therefore not fundamental for the results.

Inspection of the distribution of x_{it} and l_{it} in figures 3.2 to 3.5 also showed that these variables are clumped at specific values, which is particularly true for x_{it}. The nature of the questionnaire is the reason for this clumping at various points. As discussed in the previous section, parents were asked to indicate the approximate fraction of expenditures that went to the index child, measured by a variable ranging from 1 to 5. In order to take into account the non-continuous nature of the variable, we also model relative expenditures and relative leisure as ordered variables, taking on three values

$$v_{it}^{*} = \begin{cases} 0 & \text{if } v_{it} < 1 \\ 1 & \text{if } v_{it} = 1 \\ 2 & \text{if } v_{it} > 1 \end{cases} \tag{3.37}$$

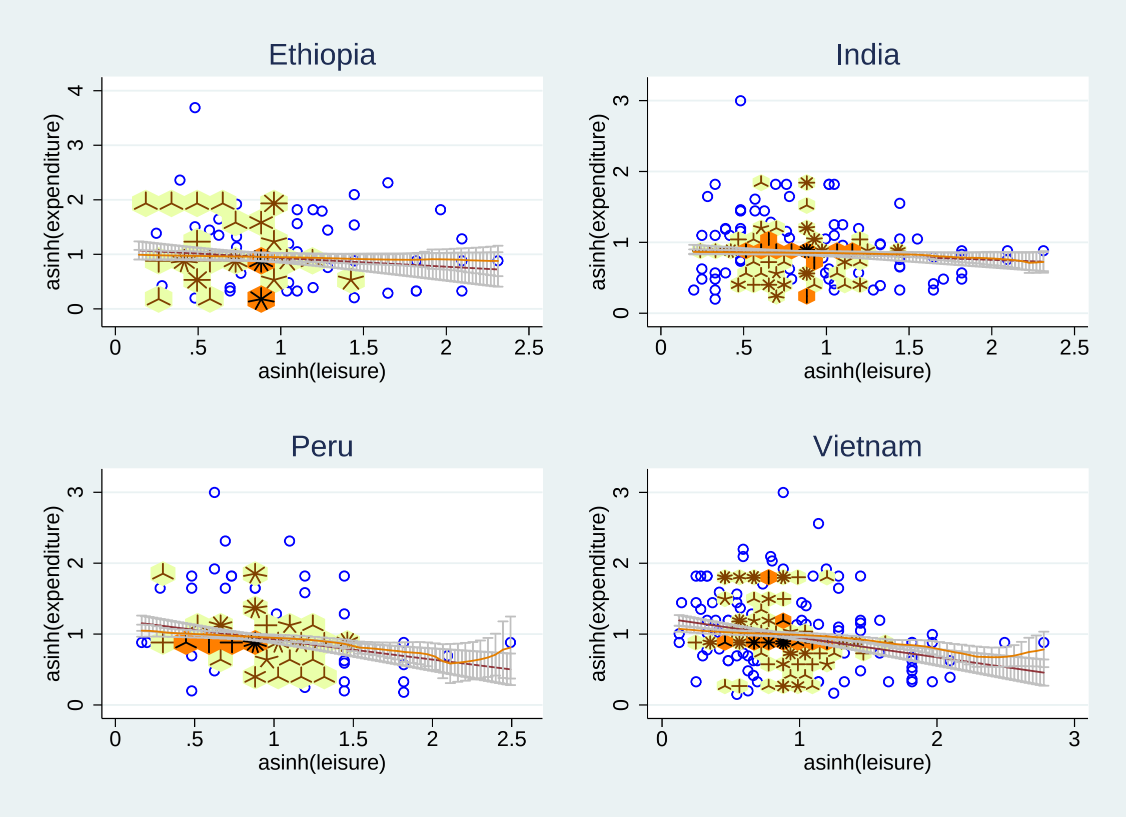
for $v = l, x$. We present estimates for treating both variables as continuous, x_{it} as an ordered variable and l_{it} as continuous, and both variables as ordered. For all models, we jointly estimate equations (3.35) and (3.36) with full information maximum likelihood, assuming that the errors have a bivariate normal distribution, and then test the correlation of the error terms of the two equations. The estimation is performed using the command `cmp` as developed by Roodman (2009).

3.5 Empirical Results and Discussion

3.5.1 Base Results

We start by looking at the unconditional distribution of leisure and consumption. Figure 3.1 shows the joint distribution of relative expenditure and leisure overlaid with a linear and a local polynomial regression and a 95 percent confidence interval. The figures show that there is a significant, negative, and fairly linear relationship between siblings' relative consumption and leisure for India, Peru and Vietnam. For the empirical model, we present results for the different specifications of the dependent variables. Column (1) presents the results for both variables modeled as continuous, column (2) models x_{it} as ordered and l_{it} as continuous, and column (3) models both variables as ordered. The correlation of the residuals is presented following the estimated coefficients.

Figure 3.1: Unconditional Joint Distribution of $\ln x_{it}$ and $\ln l_{it}$



Notes: Y-axis shows relative expenditure using the inverse hyperbolic sine transformation; x-axis shows relative leisure using the inverse hyperbolic sine transformation. The figure contains circles and hexagons. Circles represent individual data points; in a light hexagon each line from the centre represents one observation; in a dark hexagon, each line from the centre represents four observations; overlaid are a linear regression and a local polynomial regression with 95% confidence intervals.

The correlations of the residuals of a model including an intercept only are shown in table 3.2 for each of the countries, supporting what figure 3.1 already suggested. To take into account correlation across errors for panel children which are in the sample in two rounds (about 50% of the sibling pairs), all standard errors are clustered at the panel child level. There is a significant negative correlation between the residuals of the leisure and the consumption equations for India, Peru and Vietnam, and this negative correlation is robust across the three estimation methods. The fact that the correlation in Ethiopia is less significant could be due to the smaller sample size, or due heterogeneity, which would be consistent with the findings in table 3.1 which suggests that children in Ethiopia state that they feel substantially less agency over their choices compared to the other three countries. The last row of table 3.2

Table 3.2: Correlation ρ of Residuals of an Intercept-only Model

	$\ln x_{it}$ continuous $\ln l_{it}$ continuous	x_{it} ordered $\ln l_{it}$ continuous	x_{it} ordered l_{it} ordered
	(1)	(2)	(3)
Ethiopia (n=199)	-.1072	-.125	-.1581
	(.0778)	(.0847)	(.0939)*
India (n=554)	-.077	-.1180	-.114
	(.0379)**	(.0470)**	(.0543)**
Peru (n=271)	-.238	-.2901	-.2937
	(.0569)***	(.0646)***	(.0782)***
Vietnam (n=628)	-.2243	-.2955	-.3798
	(.0346)***	(.0416)***	(.0466)***
Pooled (n=1652)	-.1594	-.2064	-.2471
	(.0242)***	(.0273)***	(.0305)***

Notes: Robust standard errors in parenthesis, clustered at child level; *, **, *** denote significance at 10%, 5% and 1% levels.

shows that the correlation is significant for all three models when the data is pooled across countries. The results are virtually identical when including a time trend, but there is no a priori reason to expect that the ratios change significantly over time. These findings lend support to proposition 1 which states that if θ_{it} and τ_{it} are negatively correlated, there is no variation in δ_i and $w_{Bt} = w_{At}$, then x_{it} and l_{it} will be negatively correlated. In other words, differences in children's preferences drive allocations. If differences in parental altruism δ_i were driving allocations while θ_{it} and τ_{it} are independently distributed and $w_{Bt} = w_{At}$ as outlined in proposition 2, we would expect x_{it} and l_{it} to be positively correlated.

For the main empirical model we pool the data across the four countries, while staying fully flexible by including a range of interaction effects to allow for differences in the slope of the parameters by country and time. The main advantage of pooling the data is that we have more power when testing the correlation of the residuals.

Table 3.3 shows the basic results for equations (3.35) and (3.36) where we include separate intercepts for each of the countries and a time dummy variable. The upper panel shows the relative expenditure equation, and the lower panel shows the relative leisure equation. Before interpreting the coefficients, we test for a number of restrictions to arrive at a more parsimonious specification. The theoretical model does not prescribe the functional form

Table 3.3: Base Model

	$\ln x_{it}$ continuous $\ln l_{it}$ continuous	x_{it} ordered $\ln l_{it}$ continuous	x_{it} ordered l_{it} ordered
	(1)	(2)	(3)
Relative Expenditure			
A's age	0.017	0.077	0.078
	(0.02)	(0.059)	(0.059)
B's age	-.036***	-.135***	-.135***
	(0.003)	(0.011)	(0.011)
A=male, B=male	-.019	0.187**	0.188**
	(0.036)	(0.096)	(0.096)
A=male, B=female	-.003	0.077	0.077
	(0.03)	(0.085)	(0.085)
A=female, B=male	0.044	0.308***	0.308***
	(0.028)	(0.081)	(0.081)
Urban	0.028	0.106	0.106
	(0.022)	(0.066)	(0.066)
Oldest Son	0.011	-.284***	-.285***
	(0.038)	(0.1)	(0.1)
Measurement Error	-.129***	-.383***	-.384***
	(0.032)	(0.1)	(0.1)
Obs.	1652	1652	1652
$R^{2\dagger}$	0.1508	0.0872	0.0872
Relative Leisure			
A's age	-.018	-.018	-.045
	(0.015)	(0.015)	(0.059)
B's age	0.037***	0.037***	0.158***
	(0.003)	(0.003)	(0.01)
A=male, B=male	-.030	-.030	0.034
	(0.028)	(0.028)	(0.113)
A=male, B=female	0.069***	0.069***	0.34***
	(0.022)	(0.022)	(0.087)
A=female, B=male	-.072***	-.072***	-.265***
	(0.021)	(0.021)	(0.082)
Urban	-.008	-.008	-.014
	(0.018)	(0.018)	(0.069)
Oldest Son	0.049	0.049	0.091
	(0.03)	(0.03)	(0.126)
Obs.	1652	1652	1652
$R^{2\dagger}$	0.1889	0.1889	0.1144
Correlation ρ	-.0304	-.0480*	-.0562*
	(.0258)	(.0289)	(.0336)

Notes: All models include country and time intercepts. †Pseudo R^2 for ordered probit. Robust standard errors in parenthesis, clustered at child level; *, **, *** denote significance at 10%, 5% and 1% levels.

through which gender affects preferences. Additionally, the gender of the denominator and nominator child switches according to the sibling pair, where child A always denotes the index child. To impose as few restrictions as possible on sibling-interactions, we first entered dummy variables for all gender combinations, leaving a female-female sibling pair as the base category. We then jointly test for both, the leisure and expenditure equation, whether the coefficient on the male-female dummy variable is equal to the negative of the coefficient on the female-male sibling dummy variable. This restriction is not rejected by the data when modeling both dependent variables as linear, but it is rejected when we model relative expenditures as an ordered variable and relative leisure as a continuous variable, and when we model both dependent variables as ordered. For ease of exposition, we therefore do not impose it in the three models, but this does not affect our results. With regard to age, we tested jointly for both equations whether the coefficient on the age of child A is equal to the negative of the coefficient on the age of child B which is not rejected in any of the models. We can therefore impose the restriction that age affects relative expenditure and leisure through the difference in age of child A and B[30].

We now discuss the parsimonious specification presented in table 3.4. The results show that the coefficients on relative age are statistically significantly different from zero in both the leisure and the expenditure equation, and this holds for any specification of the dependent variables. We find that the larger the age difference between child A and B, the higher is relative expenditure and the lower is relative leisure. For mixed sibling pairs, an interesting pattern arises. When the index child is female and has a brother, she enjoys significantly higher expenditure and significantly lower leisure compared to a female index child with a sister. The effect is significant also for male index children who have a sister, who enjoy significantly higher leisure compared to female index children with a sister. We find that relative expenditures are significantly lower when the index child is the oldest male with a brother, suggesting that there is no evidence that these boys are positively discriminated with regard to clothes expenditures and leisure. The control for whether the child lives in an urban area

[30]When testing these restrictions with a set of likelihood ratio tests, we are not able to cluster standard errors at the child level. We have also estimated the models without imposing any restrictions and the results remain robust.

Table 3.4: Parsimonious Model

	$\ln x_{it}$ continuous $\ln l_{it}$ continuous	x_{it} ordered $\ln l_{it}$ continuous	x_{it} ordered l_{it} ordered
	(1)	(2)	(3)
Relative Expenditure			
Relative Age	0.033***	0.127***	0.127***
	(0.003)	(0.011)	(0.011)
A=male, B=male	-.030	0.161*	0.161*
	(0.037)	(0.095)	(0.095)
A=male, B=female	-.004	0.075	0.075
	(0.03)	(0.085)	(0.085)
A=female, B=male	0.043	0.303***	0.303***
	(0.028)	(0.081)	(0.081)
Urban	0.026	0.1	0.101
	(0.022)	(0.066)	(0.066)
Oldest Son	0.029	-.240**	-.240**
	(0.039)	(0.101)	(0.101)
Measurement Error	-.129***	-.376***	-.378***
	(0.032)	(0.1)	(0.1)
Obs.	1652	1652	1652
$R^{2\dagger}$	0.1409	0.0828	0.0828
Relative Leisure			
Relative Age	-.036***	-.036***	-.150***
	(0.002)	(0.002)	(0.01)
A=male, B=male	-.024	-.024	0.059
	(0.029)	(0.029)	(0.113)
A=male, B=female	0.069***	0.069***	0.338***
	(0.022)	(0.022)	(0.088)
A=female, B=male	-.071***	-.071***	-.260***
	(0.021)	(0.021)	(0.083)
Urban	-.006	-.006	-.003
	(0.018)	(0.018)	(0.069)
Oldest Son	0.039	0.039	0.041
	(0.03)	(0.03)	(0.126)
Obs.	1652	1652	1652
$R^{2\dagger}$	0.1830	0.1830	0.1102
Correlation ρ	-.0406	-.0571*	-.0680**
	(.0264)	(.0290)	(.0337)

Notes: All models include country and time intercepts. †Pseudo R^2 for ordered probit. Robust standard errors in parenthesis, clustered at child level; *, **, *** denote significance at 10%, 5% and 1% levels.

is insignificant which suggests that there are no systematic differences across urban and rural settings that would lead to more or less equal relative expenditure or relative leisure patterns. Additionally, the coefficient on the variable capturing measurement error is negative, in line with our conjecture, indicating that our measure of relative expenditure is systematically lower when one of the two outlined cases of measurement error takes place.

The negative correlation in the relative leisure-consumption relationship we observed in the unconditional distribution graphs could have been driven simply by the fact that older children have less leisure if they get a younger sibling due to longer hours of caretaking, but they get higher expenditures since they are the oldest and parents need to build up a stock of children's clothes and other child-related items. In the same logic, younger children could get more leisure (playing time) as they are younger and less clothes expenditures due to the fact that their older sibling passes them on clothes. However, this does not appear to be the case as even after controlling for the age difference and gender composition, the negative correlation of the residuals persists. The last row in table 3.4 shows that the correlation of the residuals is substantially lower with a correlation of about -0.05 compared to -0.2 in table 3.2 but it remains negative, and is statistically significantly different from zero when estimating the model as a an ordered probit with a linear model in column (2), or as two ordered probit equations in column (3). The correlation in the residuals is negative as well in column (1) when both variables are modeled as continuous variables, although statistically not significantly different from zero. Given the discontinuous distribution of in particular the expenditure variable, it is not surprising that the model performs better when taking the structure of the data into account. Thus, our preferred specification is column (2). The results, modeling both variables as ordered variables, are very similar.

3.5.2 Robustness

We perform a battery of robustness checks testing specifications, assumptions, samples and alternative explanations. Table 3.5 presents the correlation of the residuals for each of the robustness tests. The first row repeats the correlation found in the parsimonious specification. First, given that we are pooling countries with a range of political, economic and ideological beliefs, we also test whether the results are robust to a fully flexible specification in which we interact all explanatory variables with the country fixed effects. We find that our findings remain substantively the same for the three columns.

Table 3.5: Robustness Checks

	$\ln x$ continuous $\ln l$ continuous	x ordered $\ln l$ continuous	x ordered l ordered
	(1)	(2)	(3)
Correlation parsimonious model	-.0406	-.0571*	-.0680**
	(.0264)	(.0290)	(.0337)
Full set of interaction effects (n=1652)	-.0349	-.0549*	-.0566*
	(.0261)	(.0287)	(.0339)
Education included (n=1623)	-.0339	-.0521*	-.0657*
	(.0266)	(.0293)	(.0335)
Schooling as simultaneous choice (n=1652)	-.0406	-.0571**	-.0670**
	(.0264)	(.0290)	(.0337)
Non-linear age effect (n=1652)	-.0422	-.0568*	-.0679**
	(.0266)	(.0291)	(.0338)
Heterogeneity in age effect (n=1652)	-.0327	-.0483*	-.0563*
	(.0259)	(.0289)	(-.0563)
Biological siblings only (n=1565)	-.0397	-.0614**	-.0604*
	(.0254)	(.0290)	(.0342)
Productivity differences (n=1652)	-.0396	-.0569*	-.0638*
	(.0265)	(.0293)	(.0339)
11-17 year olds only (n=1063)	-.0543	-.0646*	-.0685*
	(.0346)	(.0360)	(.0401)
Work as dependent variable			
Correlation parsimonious model (n=1080)	.0437	.0676**	.0855*
	(.0322)	(.0343)	(.0420)
Work and productivity (n=1080)	.0416	.0618*	.0829*
	(.0327)	(.0345)	(.0423)
Excl. work outside the house (n=1016)	.0590*	.0653*	.0784*
	(.0355)	(.0361)	(.0439)
Excl. children working outside (n=765)	.0698*	.0736*	.0962**
	(.0397)	(.0403)	(.0486)

Notes: All models include country and time intercepts. Robust standard errors in parenthesis, clustered at child level; *, **, *** denote significance at 10%, 5% and 1% levels.

Second, in the theoretical model we assumed that the relative wage of child A and child B is constant across children, so that the term $\ln \kappa_t$ is captured by the time dummy variable. We now relax this assumption and rewrite κ_t as κ_{it} where we assume that the relative wage of child B to child A is determined by the relative number of years of schooling of child A and B at time t. We then re-estimate the model including the level of schooling of child A and B separately in the analysis, which does not affect the negative correlation in the residuals. Given that schooling choice is likely to be correlated with factors unobserved by the econometrician, we prefer to include the schooling variable only in the robustness check. The base model only includes variables exogenous to the sibling pair such as age, age order, gender composition and location of the household. Third, differences in the amount of hours spent on schooling might be correlated with unobservables determining relative leisure and relative consumption. These differences are rather small, with 67 percent of sibling pairs spending equal amounts of hours in school. Eighty percent of sibling pairs have not more than a 20 percent difference, and 92 percent of children have a maximum of a 30 percent difference. As a robustness check, we nevertheless include a third simultaneous equation for schooling, which does not affect the estimated correlation between relative expenditure and relative leisure.

Fourth, the model so far imposed linearity in the age difference effect which embeds two assumptions: first, the effect of an age gap of two years is half the effect of an age gap of four years; and second, the effect of age differences is independent of when the age gap occurs, so that the age gap between an 11 and 13 year old child is the same as the age gap between a 15 and 17 year old child. Given the importance of the age variable, we test whether the results are sensitive to inclusion of up to a third order polynomial, as well as a model in which I include the age of child A and B separately, as well as interaction terms between the age difference and the age of child A and B. I find that both robustness checks do not affect the residual correlation. Fifth, family dynamics might be systematically different when non-biological siblings are part of the family. We test whether it is these cases that are driving the results by limiting the sample to siblings with same mother and same father, excluding 87 observations.

Sixth, our findings could be due to a more mechanical relationship in which children are more or less productive at different ages and therefore perform different activities, rather than to do with the model's assumptions of differences in preferences. Edmonds (2006) finds that child labor in Nepal is consistent with comparative advantage of children. Although we control for the age difference between siblings, unobserved heterogeneity due to interactions between the age difference, gender and location could be substantial. For example, older girls might be substantially more productive caretakers than older boys, which would point towards an interaction effect between gender and age difference. We include interaction terms between location (whether the household lives in an urban area), age difference and gender combinations as well as the cross interaction terms in the relative leisure equation to test whether the correlation of the residuals is driven by gender-age-location specific combinations which are driving relative leisure. The residual correlation remains so that we can reject that unobserved heterogeneity due to interactions between gender, age and location leading to differences in productivity drive the results. Next, one could argue that for children below age 10 the type of activities they can undertake is likely to be more limited as their productivity is very low, and we would expect differences in preferences to be less developed at an earlier stage. We therefore limit the age range of siblings by excluding children below the age of 10 years. The results suggest that our findings were not driven by sibling pairs with large age gaps which are now excluded, as they are stable even when we drop a large number of children from the sample.

Eight, we undertake the whole analysis using relative work hours instead of leisure hours as the dependent variable. For this, we aggregate the number of household chores, child care, non-paid work and paid work of children into a work variable. We would now expect the opposite effects. If differences in children's preferences are the dominant driver, then the residuals would be positively correlated. Whoever works longer hours, receives higher consumption. On the other hand, if differences in parental altruism determine allocations and there is no correlation in preferences, then the residuals would be negatively correlated. The preferred child would work less but enjoy higher consumption. The results are consistent with the previous findings of differences in children's tastes being the dominant force. The residuals of the work and expenditure equations are positively correlated and are very similar in magnitude, so that children who work relatively more hours are rewarded with higher relative expenditures. The next row estimates the model with gender-age-location interaction terms to capture productivity differences but now with relative work as the dependent variable, and the correlation of the residuals persists. If we use work hours we lose 572 observations (about 20 percent of index children do not work, and about 34 percent of siblings do not work and we can not use a sibling pair if one of the two siblings does not work), which given our sample size is a loss of more than a third of the observations. We therefore prefer to use leisure in the analysis because of the higher number of non-zero observations.

Finally, an alternative explanation generating the positive correlation between work and clothes expenditure could be that children who work outside the house need more clothes to perform the work. To test whether this is the case, we redefine work only as household chores and child care (excluding non-paid work and paid work), both tasks which we would not expect to significantly raise clothes requirements. We estimate two specifications: first, we keep all children, simply replacing the work variable as zero unless children performed work in the household. Thereby, we only compare the workload of siblings in the household. The correlation of the residuals is not driven by this mechanical relationship. Second, we drop from the sample children who work outside the household, and estimate the model again, only examining variation in the hours worked by children in the household. This specification is most costly in that we lose about half of the sample. Despite the substantially smaller sample size and use of a completely different subsample, the magnitude of the correlation and significance level are almost unchanged. Overall, the correlation of the residuals is remarkably robust to different samples, and testing for different alternative explanations which could generate the results.

3.6 Conclusion

This chapter considered children as agents with their own preferences over leisure and consumption and built a theoretical and empirical model for children's time and consumption allocations. To our knowledge, this is the first paper that theoretically and empirically models within sibling distribution of preferences over leisure and consumption. The simple theoretical model allowed for heterogeneity in parental altruism as well as children's preferences over leisure and consumption and develops testable propositions. We kept the model as parsimonious as possible to highlight predictions generated simply by differences in relative preferences of children and relative altruism by parents. This comes at the cost of imposing sometimes fairly strict assumptions. For example, we imposed that parents' relative bargaining weights in the family do not affect the weight of specific children (i.e., girls versus boys) in the household's problem. We also assumed that children's work hours do not affect their parents' altruism.

We tested these propositions with a panel data set of children from Ethiopia, India, Peru and Vietnam which contains detailed information on time use and allocations of assignable goods for sibling pairs. We found that after conditioning on observable variables, the residuals of these simultaneous decisions are significantly negatively correlated. This correlation is robust to excluding younger children, non-biological siblings, and using relative work allocations instead of relative leisure. We also do not find evidence that the relationship is driven by age-gender-location specific productivity differences, non-linear age effects, different levels of education and schooling hours, and a range of alternative hypotheses. This suggests that differences in siblings' relative time and consumption allocations are driven by their relative preferences over leisure and consumption rather than differences in parents' relative altruism. Children seem to trade off leisure and consumption and are rewarded accordingly. As a result, the data are consistent with a model in which families behave as if they were an internal market in which children select their optimal consumption-leisure bundle.

One implication of this finding is that in order to understand households' behavior in low income countries, it is important to consider children as active agents within the family. Given the stringent data requirements, we were able to undertake this analysis for families with two children between the ages of 6-17 years in four developing countries. To investigate the generalizability of the results, future research should focus on extending the analysis to families with more than two children and application to further countries.

3.7 Appendix

Table 3.6: Relationship of Sibling to Panel Child

	Ethiopia	India	Peru	Vietnam
Brother/sister (both parents the same)	0.764	0.991	0.900	0.987
Half-sibling (same father)	0.005		0.004	0.005
Half-sibling (same mother)	0.085		0.059	0.002
Adoptive brother/sister	0.005			0.002
Uncle/aunt	0.035		0.015	
Cousin (including cousin-brother & cousin	0.070	0.007	0.015	0.005
Nephew/niece	0.010	0.002	0.007	
Brother/sister-in-law (spouse of sibling)	0.010			
Other relative	0.010			
Servant (farm-worker, maid, etc.)	0.005			

Notes: Relationship of sibling to panel child from household roster.

Table 3.7: Panel Child Characteristics

	2006				2009			
	mean	sd	min	max	age	sd	min	max
Ethiopia								
Age	11.49	0.50	11	12	14.50	0.50	14	15
Male	0.45	0.50	0	1	0.53	0.50	0	1
School	5.99	1.24	4	10	6.23	1.35	3	10
Study	1.89	0.93	0	5	2.25	1.23	0	7
Play	3.25	1.48	1	8	2.69	1.53	1	8
Child Care	0.11	0.40	0	2	0.38	0.75	0	4
Household Chores	2.44	1.59	0	8	2.58	1.47	0	6
Non Paid	0.80	1.46	0	5	0.98	1.68	0	8
Paid	0.11	0.59	0	4	0.21	0.89	0	6
Any Work†	3.45	1.91	0	8	4.15	1.76	1	9
Sleep	9.17	1.03	6	12	8.67	1.17	5	11
	n=95				n=104			
India								
Age	11.72	0.45	11	12	14.69	0.46	14	15
Male	0.51	0.50	0	1	0.52	0.50	0	1
School	6.89	1.06	4	10	8.26	1.29	1	13
Study	2.33	1.44	0	8	2.68	1.27	0	7
Play	3.86	1.81	1	9	3.58	1.45	1	8
Child Care	0.08	0.30	0	2	0.18	0.43	0	3
Household Chores	0.69	0.80	0	4	1.11	0.96	0	4
Non Paid	0.06	0.28	0	3	0.10	0.45	0	3
Paid	0.00	0.00	0	0	0.04	0.36	0	5
Any Work†	0.83	0.94	0	4	1.43	1.35	0	8
Sleep	8.92	0.89	6	11	8.05	0.92	5	10
	n=285				n=269			
Peru								
Age	11.88	0.44	11	13	14.41	0.57	13	17
Male	0.62	0.49	0	1	0.59	0.49	0	1
School	5.57	0.70	5	9	6.52	0.94	5	10
Study	2.14	0.94	0	6	2.42	0.94	0	6
Play	2.41	1.09	1	7	3.30	1.32	1	7
Child Care	0.34	0.67	0	4	0.49	1.05	0	6
Household Chores	0.95	0.61	0	3	1.32	0.84	0	4
Non Paid	0.24	0.71	0	4	0.32	0.81	0	4
Paid	0.06	0.43	0	3	0.05	0.24	0	2
Any Work†	1.6	1.29	0	7	2.18	1.7	0	8
Sleep	9.24	1.01	6	12	8.92	1.02	6	12
	n=141				n=130			
Vietnam								
Age	11.71	0.47	11	13	14.72	0.46	14	16
Male	0.53	0.50	0	1	0.46	0.50	0	1
School	4.59	0.63	2	8	5.48	0.86	4	10
Study	3.00	1.57	0	8	3.99	1.56	1	8
Play	5.92	1.83	1	10	4.03	1.47	1	8
Child Care	0.08	0.32	0	2	0.07	0.34	0	2
Household Chores	1.11	0.82	0	5	1.42	0.78	0	4
Non Paid	0.47	1.07	0	6	0.46	1.08	0	9
Paid	0.02	0.25	0	3	0.03	0.37	0	6
Any Work†	1.67	1.36	0	7	1.99	1.34	0	11
Sleep	8.81	0.79	7	11	8.54	1.04	5	12
	n=356				n=272			

Notes: Activities are measured in hours; †Any work is the sum of child care, household chores, non paid and paid work.

Table 3.8: Sibling Characteristics

	2006				2009			
	mean	sd	min	max	age	sd	min	max
Ethiopia								
Age	12.31	3.71	6	17	11.76	2.47	6	17
Male	0.55	0.50	0	1	0.63	0.49	0	1
School	6.07	1.44	4	11	6.16	1.26	4	10
Study	1.75	1.12	0	5	1.76	1.03	0	6
Play	3.34	1.76	1	8	3.40	1.61	1	8
Child Care	0.06	0.24	0	1	0.11	0.42	0	2
Household Chores	2.09	1.77	0	8	2.02	1.46	0	6
Non Paid	1.11	1.82	0	6	1.38	2.00	0	7
Paid	0.16	0.76	0	4	0.06	0.44	0	4
Any Work†	3.42	2.16	0	8	3.57	1.94	0	10
Sleep	9.11	1.12	7	12	9.11	1.34	6	12
	n=95				n=104			
India								
Age	11.58	3.03	6	17	13.18	2.48	6	17
Male	0.56	0.50	0	1	0.61	0.49	0	1
School	6.84	1.07	3	10	8.11	1.02	5	12
Study	2.34	1.51	0	9	2.16	1.06	0	5
Play	4.08	1.97	1	12	4.20	1.50	1	9
Child Care	0.05	0.24	0	2	0.12	0.38	0	2
Household Chores	0.53	0.74	0	3	0.74	0.82	0	4
Non Paid	0.04	0.23	0	2	0.05	0.25	0	2
Paid	0.01	0.12	0	2	0.01	0.12	0	2
Any Work†	0.62	0.9	0	5	0.91	1.01	0	5
Sleep	9.01	1.00	6	12	8.62	0.86	6	11
	n=285				n=269			
Peru								
Age	11.73	3.46	6	17	12.17	3.13	6	17
Male	0.55	0.50	0	1	0.51	0.50	0	1
School	5.52	0.78	4	10	6.28	0.97	4	10
Study	2.21	1.01	0	6	2.37	0.97	0	6
Play	2.44	1.20	1	6	3.52	1.21	1	7
Child Care	0.18	0.47	0	3	0.06	0.37	0	3
Household Chores	0.89	0.73	0	4	1.27	0.89	0	5
Non Paid	0.19	0.58	0	3	0.25	0.79	0	4
Paid	0.11	0.57	0	4	0.07	0.47	0	5
Any Work†	1.37	1.4	0	7	1.65	1.3	0	6
Sleep	9.26	1.10	7	12	9.16	1.11	6	13
	n=141				n=130			
Vietnam								
Age	12.12	3.60	6	17	11.97	3.54	6	17
Male	0.56	0.50	0	1	0.56	0.50	0	1
School	4.73	1.08	3	10	5.24	1.04	3	10
Study	2.96	1.77	0	8	3.47	1.63	0	9
Play	0.04	0.24	0	2	4.97	1.81	1	11
Child Care	0.04	0.24	0	2	0.02	0.18	0	2
Household Chores	0.93	0.92	0	4	0.92	0.86	0	5
Non Paid	0.39	0.97	0	6	0.31	0.90	0	6
Paid	0.01	0.16	0	3	0.03	0.38	0	6
Any Work†	1.38	1.38	0	6	1.27	1.46	0	10
Sleep	8.84	1.00	6	12	9.11	1.16	5	12
	n=356				n=272			

Notes: Activities are measured in hours; †Any work is the sum of child care, household chores, non paid and paid work.

Table 3.9: Clothes Expenditure per Child

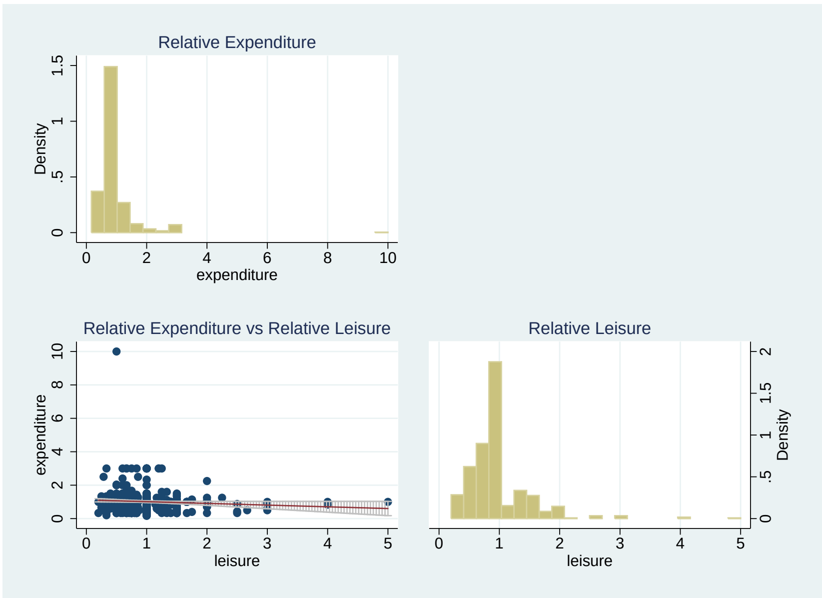
Ethiopia	2006				2009			
	mean	sd	min	max	mean	sd	min	max
Ethiopia								
Index Child								
Clothes	75.9	52.5	7.5	337.5	164.9	166.3	4.25	1000
male	72.0	50.7	7.5	235	151.9	121.1	4.25	600
female	79.2	54.3	19	337.5	179.4	206.0	25	1000
Sibling								
Clothes	112.3	114.2	2.5	640	159.7	158.9	12.75	750
male	123.2	134.2	2.5	640	169.2	161.3	12.75	710
female	99.2	83.6	5	400	143.9	155.7	20	750
India								
Index Child								
Clothes	584.1	424.8	50	2500	1104.4	1133.6	100	13500
male	603.5	412.3	120	2500	1072.9	666.3	200	5000
female	564.3	437.7	50	2500	1138.6	1485.4	100	13500
Sibling								
Clothes	655.0	550.9	60	5000	1285.7	1287.4	50	15000
male	584.5	538.7	60	5000	1260.8	1027.2	50	8000
female	745.2	555.3	100	3000	1325.3	1621.8	100	15000
Peru								
Index Child								
Clothes	106.2	91.1	6	750	162.4	201.8	8	1300
male	104.3	73.2	6	300	157.8	218.6	8	1300
female	109.1	114.9	20	750	169.0	176.5	10	1000
Sibling								
Clothes	108.2	90.6	9	525	138.7	156.1	8	1000
male	107.7	95.6	15	525	161.4	244.0	15	1500
female	108.7	85.0	9	500	149.9	203.7	8	1500
Vietnam								
Index Child								
Clothes	198.4	189.9	15	2000	489.4	790.4	20	10000
male	180.6	151.9	45	1500	489.9	712.1	37.5	7000
female	218.6	224.2	15	2000	488.9	854.7	20	10000
Sibling								
Clothes	212.0	231.7	15	3000	408.7	767.7	12.5	10000
male	220.8	284.8	15	3000	383.6	613.4	12.5	7000
female	200.5	135.0	30	750	440.2	926.7	20	10000

Notes: Measured in local currencies.

Figure 3.2: Relative Leisure and Consumption in Ethiopia

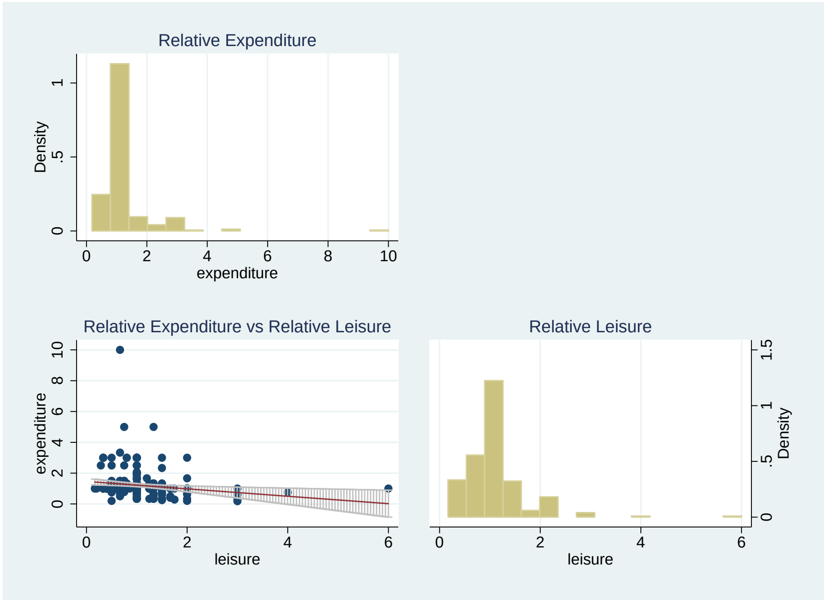
Notes: Linear regression of relative leisure on relative consumption with 95% confidence interval in the South-West panel.

Figure 3.3: Relative Leisure and Consumption in India



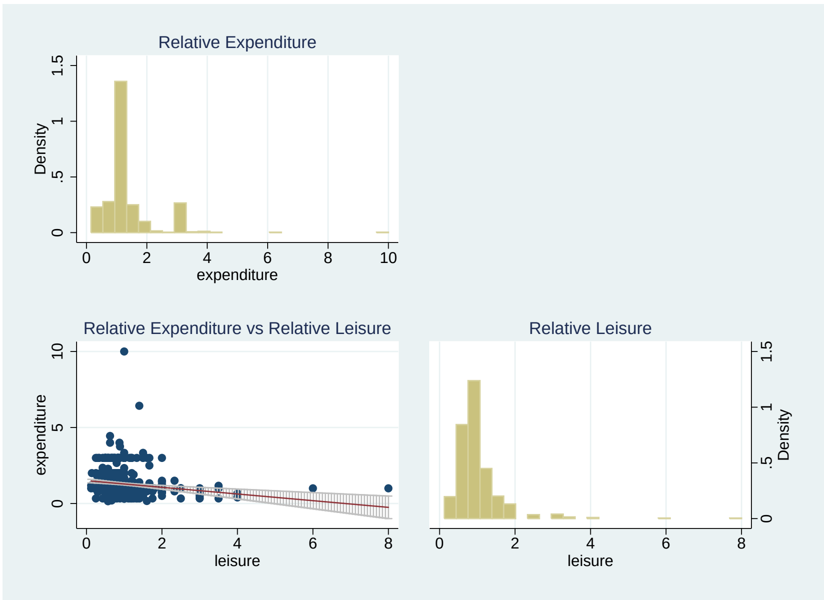
Notes: Linear regression of relative leisure on relative consumption with 95% confidence interval in the South-West panel.

Figure 3.4: Relative Leisure and Consumption in Peru



Notes: Linear regression of relative leisure on relative consumption with 95% confidence interval in the South-West panel.

Figure 3.5: Relative Leisure and Consumption in Vietnam



Notes: Linear regression of relative leisure on relative consumption with 95% confidence interval in the South-West panel.

3.7.1 Measurement Error

Measurement error in the expenditure data is due to the fact that we only know the allocation to child A with certainty, while we assign the remainder of children's expenditures to child B. In the presence of older siblings aged 18 and over who parents nevertheless regard as children, this will lead to an upward biased estimation of expenditures to child B, so that x_A/x_B is the lower bound. Below we discuss hypothetical cases for three children, A, B and C to illustrate when we can and can not identify expenditure shares.

Table 3.10: Identified Cases

	A	B	C	boy's x	girl's x	share A
Case 1						
Gender	male	male	female	100	50	0.5
Age	12	14	20			
Assignment	50	50	0			
Case 2						
Gender	male	female	male	100	50	0.5
Age	12	14	20			
Assignment	50	50	50			

Table 3.10 gives examples of cases when we can identify the share of expenditures with certainty. Case 1 is when the index child (A) is male, with a brother (B) and an older sister (C). Since we know the allocation to boy's clothes, and the share to the index child, we can assign the residual expenditures to child B. Clothes expenditures for the older sister would then be recorded either under adult expenditures of girl's expenditures, not affecting the allocations to child A and B. Case 2 is when the index child is male and child B is female, but there is an older brother in the family. We then know the allocation to child A from the questionnaire, and can assign girls expenditures to child B. The same cases hold for the opposite gender combinations.

Table 3.11 gives examples of cases when we are likely to measure the share of expenditures with measurement error if the parents consider males and females aged 18-25 as children when recording expenditures. Case 1 presents the scenario when the index child is male, with a brother aged 14 and an older brother aged 20. In this case, we assume that the residual expenditures (total expenditures minus the allocation share to the index child) is for

Table 3.11: Under-identified Cases

	A	B	C	boy's x	girl's x	share A
Case 1						
Gender	male	male	male	100	0	0.5
Age	12	14	20			
Assumed assignment B	50	50	0			
Alternative assignment B (i)*	50	0	50			
Alternative assignment B (ii)*	50	25	25			
Case 2						
Gender	male	female	female	100	150	1
Age	12	14	20			
Assumed assignment B	100	150	0			
Alternative assignment B (i)*	100	0	150			
Alternative assignment B (ii)*	100	100	50			

Note: * illustrates hypothetical alternative assignments.

child B, while alternative assignments for child B could be lower as illustrated if the parent record clothes expenditures for the 20 year old brother under boy's expenditures and not male adult expenditures. Case 2 presents the scenario when the index child is male, with a sister aged 14 and an older sister aged 20; again, the table shows that our assumed assignment is lower if the parents consider the 20 year old sister C as a child. The same logic applies to the opposite sex combinations.

We use these cases to model when measurement error is going to be more likely as illustrated in the examples. The cases particularly prone to measurement error are (i) when both children are of the same sex, and there are further siblings aged 18-25 of the same sex in the household who parents consider a child (denoted as case 1); (ii) when children are of the opposite sex, but there is a further member of the same sex as child B in the household aged 18-25 who the parents consider a child (denoted as case 2). We include a dummy variable that is equal to one if we observe either case (i) or case (ii) in the data which is case in 12% of the sample.

Chapter 4

The Cost of Road Infrastructure in Developing Countries

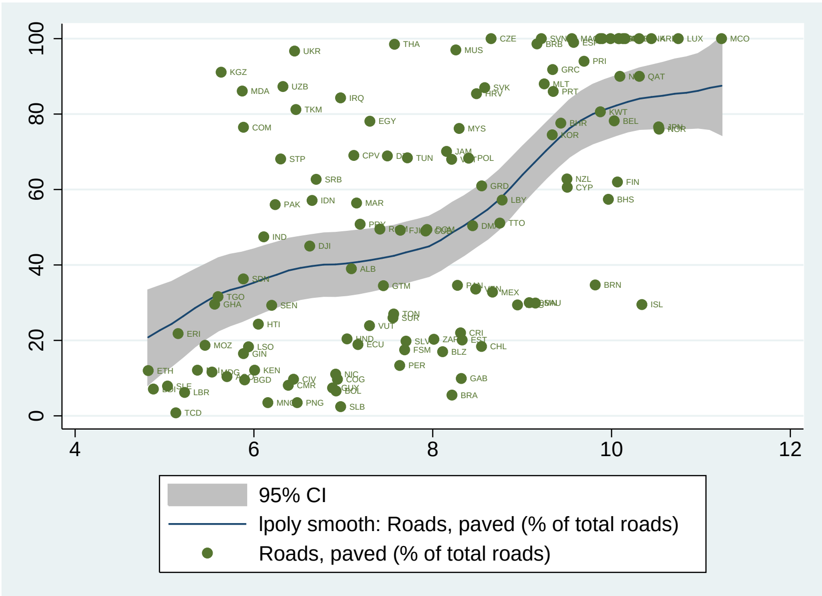
4.1 Introduction

This chapter analyzes a new and highly detailed global dataset on the unit costs of road construction and maintenance. Roads are archetypal of public economic infrastructure. While telecoms, power and railways are often privately financed, the practical scope for private financing of roads in developing countries has proved to be extremely limited. Yet over recent decades donors have shifted their support from such infrastructure, which was the initial rationale for aid, to social priorities, as exemplified by the Millennium Development Goals. In low-income counties this may have contributed to the deterioration in provision: for example, there is evidence that since the 1980s the African road stock has actually contracted (Teravaninthorn and Raballand 2009).

Unsurprisingly, the road stock is associated with the level of income. One practical measure is the proportion of the stock which is paved. As shown in figure 4.1, by the time a country has reached OECD levels of development (a GDP per capita of about US$26,000) around 80 percent of roads are paved, whereas in a country with a per capita income level of US$2,70 such as Togo, only around 30 percent are paved.

If roads complement private investment, it is reasonable to think of the massive public investment implied by such a transformation as not merely a consequence of development, but as integral to it. Yet as indicated by figure 4.1, the pace at which roads are paved appears to lag rather than lead general development. Between a GDP per capita of US$90 to US$3,000 investment in paving roads looks to stall before accelerating as countries approach the OECD level of income. Costs are important because they can lead to an income and a substitution effect. First, countries can afford fewer roads when the cost per km is high; second, investments projects failing to produce a high enough net present value or internal rate of return, will be likely to lose out to other projects.

Figure 4.1: Correlation between % of Paved Roads and Log of GDP per Capita in 2000



Notes: World Development Indicators 2012.

The contribution of this chapter is threefold. First, we introduce a new data set of 3,322 unit costs of road work activities across 99 countries. To our knowledge this is the first paper that provides clear quantitative evidence on the unit cost of building public road infrastructure across a large set of countries in the context of development. To make meaningful comparisons of unit costs of construction data, requirements are fairly stringent. At a minimum, one needs detailed information on the year and location of the work activity, type of costs (estimated, actual or contracted) and the specificities of the construction or maintenance activity (what type of road work activity it is). All these variables are present in our data set. Second, we examine whether there is residual variation in unit costs once we control for obvious cost drivers such as terrain ruggedness and access to markets. We focus on two dimensions of the environment a firm operates: conflict and corruption. Finally, based on these findings, we propose a research agenda.

Our analysis yields five main findings. First, we show that there is a large dispersion in unit costs across countries for comparable road work activities. For example, the difference between countries of an asphalt overlay of 40 to 59 mm amounts to a factor of three to four. Second, we find that after accounting for environmental drivers of costs such as terrain ruggedness and proximity to markets, residual unit costs are significantly higher in conflict countries. Countries which are in conflict have about 30% higher unit costs. This result is robust to different measures of conflict and political instability. Third, we also find evidence that costs are higher in countries with higher levels of corruption. Moving a country from the 75th percentile of corruption to the 25th percentile of corruption is associated with 6.3% lower unit costs. Countries with corruption levels as measured by the Worldwide Governance Indicators above the median in the sample have about 12% higher costs. Fourth, these effects are robust to controlling for a country's public investment capacity and business environment. Finally, we find that higher unit costs are significantly associated with lower levels of infrastructure provision.

This chapter is at the intersection of several strands of the literature. First, there is a growing literature on the effect of transport infrastructure on transport costs, trade volume, market development, productivity, and poverty and consumption. Limao and Venables (2001) find that the cost of shipping a 40-foot container from Baltimore to various locations is higher the poorer the infrastructure of the destination and transit country. Estimating a gravity model including an infrastructure variable, they find that poor infrastructure significantly reduces trade flows. Further, they find that doubling transport costs from the median reduces trade volume by 45 percent. Donaldson (2013) using micro data from colonial India finds that railroads decreased transport costs, increased trade, and raised real income levels. Mu and van de Walle (2011) show that rural roads in Vietnam have a significant effect on market development, and this effect is stronger for initially less developed markets. Shiferaw et al. (2011) evaluate the effect of two Road Sector Development Programs during 1997-2009 in Ethiopia and find that improved road accessibility increases value added per worker. Dercon et al. (2009) show that access to an all-weather road in rural Ethiopia reduced poverty by 6.9 percentage points and increased consumption by 16.3 percentage points. Khandker et al. (2009) find that Bangladesh's Rural Development Project and the Rural Roads and Markets Improvement and Maintenance Project led to poverty reductions of 3-4% and 5-6%, respectively. Jacoby and Minten (2009) find that an elimination of transport costs would substantially lower poverty in their study region in Madagascar. Stifel et al. (2012) apply Jacoby and Minten's methodology to a region in Ethiopia and arrive at a similar conclusion.

Second, while substantial progress is being made on evaluating the benefits of infrastructure, research on the cost side is lagging behind. The chapter relates to the recent effort in collecting data on unit costs of different types of infrastructure investments across countries. It is is complementary to the following studies: AFRICON (2008) analyze 115 road contracts in Sub-Saharan Africa and find significant economies of scale for projects covering a length longer than 50 km. Given the relatively small number of contracts, they have to aggregate various work activities into fairly coarse groups to create comparisons. In addition to coverage of contracts of all regions worldwide, the advantage of our paper is that we can control for systematic differences in the cost of construction by including fixed effects at the very detailed work activity level. Two studies by Alexeeva et al. (2008) and Alexeeva et al. (2011) examine evidence for corruption in the roads sector, using data on 109 road work contracts and 76 supervision consultancy contracts in 13 Sub-Saharan African countries, and a sample of 200 completed and ongoing road contracts in 14 European and Central Asian countries, respectively. This chapter differs from these two studies in that we focus on differences across countries, rather than the link between the bidding process, input costs and the unit cost of particular road work contracts[1]. Buys et al. (2010) use a subset of 465 roads contracts in Sub-Saharan African countries from the ROCKS database to argue that upgrading of the

[1]Ideally we would have liked to test their hypotheses on the larger data set we employ in our study; unfortunately, detailed bidding information was only collected for a small number of contracts in the database.

roads network could lead to an expansion of trade by US$250 billion over 15 years, at a cost of US$20 billion for upgrading and US$1 billion annually for maintenance costs.

Third, the chapter relates to a fairly recent literature on government procurement processes and waste associated with it. Bandiera et al. (2009) test for active (for example, corruption) and passive waste (for example, the inability of the civil servant to select the cheapest product) in the procurement of 21 generic goods by Italian public bodies and find substantial heterogeneity in prices paid by different types of bodies, with the average ministry paying about 40% higher prices compared to semi-autonomous bodies; passive waste is found to account for about 83% of waste. Di Tella and Schargrodsky (2003) find that a crack-down on corruption led to a 10-15% decline in prices paid by hospitals in Buenos Aires for basic supplies compared to the pre-crack-down period. Several studies investigate the bidding behavior of firms and efficiency of auctions in public procurement. Hyytinen et al. (2007) study the procurement of cleaning contracts in municipalities in Sweden and find that in 58% of the time, the lowest bidder does not win the auction and then contrast the behaviors of left-wing and right-wing governments. Huysentruyt (2011) examines 457 completed DFID contracts and compares for-profit and non-profit firms' bidding and contract implementation characteristics. She finds that contract renegotiations take place in 60% of all contracts, with the cost of renegotiations being about 30-50% higher when contracting with for-profit organization compared to non-profit organizations. Increasing attention has also been attributed to infrastructure auctions in developing countries. Estache and Iimi (2009) find joint bidding to be pro-competitive, especially when involving local entreprises from analysing 86 road work contracts. Estache and Iimi (2010) use data from 45 auctions in the roads sector of projects by the World Bank and the former Japan Bank for International Cooperation and find that in the roads sector bids submitted by entrant bidders are substantially more aggressive.

Finally, we aim to contribute to the literature on conflict and corruption. To our knowledge, the only study quantitatively investigating the link between conflict and the cost of transport infrastructure is Benamghar and Iimi (2011) who use data on 157 rural road projects in Nepal and show that the number of security incidents is significantly and and positively correlated with the value of submitted bids, cost overruns, and project delays. Considering corruption in transport infrastructure, Olken (2007) finds that missing expenditures amounted to on average 24% of the total cost of the road in his experiment in Indonesia. See Blattman and Miguel (2010) for a recent review on the literature on conflict and Olken and Pande (2012), Zitzewitz (2012) and Banerjee et al. (2012) on corruption in developing countries.

The chapter is organized as follows. Section 4.2 sets the scene for our focus on conflict and corruption. Section 4.3 presents a theoretical framework for analyzing the drivers of unit costs of road construction and maintenance. Section 4.4 describes our data. Section 4.5 outlines the econometric specification; section 4.6 discusses the results and sketches avenues for further research; the final section concludes.

4.2 Conflict and Corruption in the Roads Sector

The focus of our analysis is on the link between conflict and corruption and unit costs of road work activities. The focus on conflict is motivated by the fact that 1.5 billion people live in conflict-affected or fragile states, and these states lag behind on measures like poverty reduction and other developmental outcomes (World Bank 2011b). If these finance constrained states face high road construction costs, and roads construction and a better network reduce conflict by raising the opportunity cost of joining rebel groups through employment, as well as improved economic outcomes through better connectivity, then they might be trapped in an equilibrium with high costs of transport infrastructure and instability. Further, public work contracts, including roads, are subject to substantial levels of corruption. According to Transparency International's Bribe Payers Survey of over 3,000 business executives worldwide, public works contracts and construction is the sector with the highest propensity of paying bribes to officials and other firms (Transparency International 2011). As this chapter attempts to establish a first set of facts on differences in costs, a focus on the link between corruption and costs is a natural priority.

A review by the World Bank's Transport Research Support Program on the roads sector in conflict countries states that "*...projects that take place in conflict settings would almost always be more costly than in other settings because of challenges such as insecurity and low government capacity*" (Rebosio and Wam 2011). Higher costs can be due to the costs of monitoring of the security situation of an area, potentially undergoing substantial risks to visit the construction site, and the associated limited planning possible. In addition to protection of the staff working on the particular roads project, firms also risk that supplies are cut off due to disruptions of transport networks. If conflict takes place along ethnic lines, road construction firms might need to ensure to employ an ethnically balanced workforce, in order not to further fuel the conflict or becoming targets of violence themselves. Consultations with communities, while helpful, are also significantly adding to the cost of construction. Not only the construction but also the procurement process can be riskier in conflict countries. Rebosio and Wam (2011) and Benamghar and Iimi (2011) give evidence for these effects on risks and costs from Nepal: a government employed road engineer was killed in the Terai regions; road construction teams were constantly monitoring the security situation and adjusting their operations accordingly; in certain regions violence and intimidation were employed during the bidding process to prevent firms from submitting a bid for profitable project.

Allegations of fraud, corruption or collusion were made in about one fourth of the 500 approved World Bank financed projects with a road component between 2000-2010 (World Bank 2011a). Roads contracts procured through the World Bank are usually awarded in a one stage sealed bid auction, with the lowest bidder winning the auction. Alexeeva et al. (2011) find that in about 20% of the auctions in their sample of 200 contracts in Europe and Central Asia, at least 50% of firms who acquired bidding documents do not bid, the winning bid is not selected for detailed examination, or there is a time overrun of more than 30% of the contracted period. The estimates of costs of collusion and cartels in the road sector are large and range between 8% and 60% (World Bank 2011a). Considering that substantial resources are allocated to road construction and maintenance (US$56 billion between 2000-2010 by the World Bank alone), this represents a massive waste of funds. Further evidence from investigations discussed in (World Bank 2011a) is striking: in Bangladesh, companies paid officials up to 15% of the contract value in exchange for award of the contract. In an

African country, fraudulent claims such as cement contents and thinner layers than specified accounted for 15-20% of the bid price; the use of substandard materials imposes costs ex-post through higher maintenance costs and costs on vehicle drivers due to worse road conditions and might eventually lead to even negative rates of return of a particular project (Kenny 2009).

4.3 Theoretical Framework

This section develops a simple theoretical framework with the purpose of guiding the empirical analysis. Consider a particular type of road work activity, for example, a construction of a new 2 lane highway. Denote the length of the highway as q. Firms employ labor x_1 and capital x_2 in the production of highways and minimize a cost function

$$\min_{x_1,x_2} w_1 x_1 + w_2 x_2 \text{ subject to } q = f(x_1, x_2) \tag{4.1}$$

where w_1 is the price of labor and w_2 is the price of capital. Firms are assumed to be price takers in input markets. Further, assume that the firm has a Cobb-Douglas production function so that $f(x_1,x_2) = A^{-\delta} x_1^{\alpha} x_2^{\beta}$, where $A^{-\delta}$ is an inefficiency parameter, $0 < \alpha < 1$, and $0 < \beta < 1$[2].

The conditional factor demands from the firm's minimization problem for x_1 and x_2 are

$$x_1(w_1, w_2, q) = A^{\frac{\delta}{\alpha+\beta}} \left(\frac{w_2}{w_1} \frac{\alpha}{\beta} \right)^{\frac{\beta}{\alpha+\beta}} q^{\frac{1}{\alpha+\beta}} \tag{4.2}$$

$$x_2(w_1, w_2, q) = A^{\frac{\delta}{\alpha+\beta}} \left(\frac{w_1}{w_2} \frac{\beta}{\alpha} \right)^{\frac{\alpha}{\alpha+\beta}} q^{\frac{1}{\alpha+\beta}}. \tag{4.3}$$

Plugging these back into the cost function and rearranging gives

$$C(w_1, w_2, q) = w_1 x_1(w_1, w_2, q) + w_2 x_2(w_1, w_2, q) \tag{4.4}$$

$$C(w_1, w_2, q) = A^{\frac{\delta}{\alpha+\beta}} q^{\frac{1}{\alpha+\beta}} \theta w_1^{\frac{\alpha}{\alpha+\beta}} w_2^{\frac{\beta}{\alpha+\beta}} \tag{4.5}$$

[2]The choice of a Cobb-Douglas production function is for expositional simplicity and to shape our thinking, rather than reflecting the precise production technology underlying road work activities.

where $\theta = \left(\frac{\alpha}{\beta}\right)^{\frac{\beta}{\alpha+\beta}} + \left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha+\beta}}$ is just a parameter.

The average cost per kilometer can then be obtained by simply dividing the cost function by the kilometers of road built:

$$\frac{C(w_1, w_2, q)}{q} = A^{\frac{\delta}{\alpha+\beta}}\, q^{\frac{1-(\alpha+\beta)}{\alpha+\beta}}\, \theta\, w_1^{\frac{\alpha}{\alpha+\beta}}\, w_2^{\frac{\beta}{\alpha+\beta}}. \tag{4.6}$$

We can use (4.6) to test several hypotheses. Only the second term in equation (4.6) depends on q, and $\alpha+\beta$ indicates returns to scale in construction projects. If $\alpha+\beta > 1$, $\frac{\partial(\frac{C(w_1,w_2,q)}{q})}{\partial q} < 0$ so that an increase in the quantity of road produced will lower average costs. Unit costs are lower in countries in which the price of labor is low. Similarly, unit costs will depend on the price of capital. Given that developing countries often have to import machinery and equipment, we expect the price of capital to be higher in countries facing high transportation costs.

We use $A^{\frac{\delta}{\alpha+\beta}}$ to examine two dimensions of the environment in which a construction firm operates which potentially affect their costs: state fragility and corruption. Firms operating in a conflict or post-conflict country have to take into account the risks associated with termination of their contract, expropriation, and default on the side of the government to deliver their obligations of the contract. Assume that the cost function for this typical road in equation (4.6) gets shifted by an amount $A^{\frac{\delta}{\alpha+\beta}}$. Alternatively, if the firm needs to pay a bribe to government officials to get a construction permit, $A^{\frac{\delta}{\alpha+\beta}}$ can also represent these additional costs. We assume that both A and δ are exogenous to the firm's minimization problem; they are determined by the level of state fragility and corruption prevailing in the country the firm is operating in. Both, bribe payments and the risk premium required by firms to operate in conflict countries will drive up unit costs[3].

We are aware that conflict can also affect prices through changes in the market structure when firms are driven out of business, or through a price boom following the end of a conflict as demand for reconstruction increases. Further, corruption in the roads sector can be at three levels, with varying effects on efficiency. First, it can take at the level of the government when

[3]For example, Compte et al. (2005) argue that "...as firms expect to be paying a bribe, a mechanical effect of corruption is to increase the contract price by an amount corresponding to the anticipated bribe".

government officials receive side-payments to either select a contract from a particular firm, or to process documents of the operating firm. This results in higher unit costs and allocative inefficiency if contracts are not awarded to the most competitive firm. Second, individuals working for companies in the construction sector might inflate costs and use part of of these resources to extract side payments for themselves. The higher unit cost in turn decreases the likelihood of the project to be selected ex-ante by lowering the net present value or rate of return. Third, companies might not respect the contracted standards by using fewer or inferior materials. Here we only focus on the first level. We discuss further hypotheses how conflict and corruption affect roads construction costs in the final section as avenues for future research.

It is also worth highlighting several issues relevant to the procurement of roads which we do not consider in our simple model[4]. First, the market structure of the road construction sector and tender procedures affect how many firms will submit bids for a project, thereby determining *ex-ante competition* and the value of bids (Li and Zheng 2009). Second, if firms collude in the tendering phase, they can affect the price of the road contract (Pesendorfer 2000). Third, once a government has signed a contract with a firm for a road construction project, the firm can extract rents from the government, a problem referred to as hold-up in the literature (Board 2011). In the absence of data on the market structure, values of submitted bids for work activities as well as the difference in costs between contracted and actual costs for each work activity, we are not able to uncover these effects. The main rationale for the simple cost minimization framework is to inform our way of thinking about the deeper determinants of costs and input prices in an economy and to serve as a guide for the estimation. We return to market structure, collusion and hold up problems when discussing avenues for further research.

[4]See Moavenzadeh (1978) for a discussion how the construction sector is generally differs from other sectors.

4.4 Data

We use unit cost data from the Roads Cost Knowledge System (ROCKS), Version 2.3, developed by the World Bank's Transport Unit. Motivated by the lack of comparable information on costs of road work activities across countries, the database was started in 2001 with the aim of developing "an international knowledge system on road work costs - to be used primarily in developing countries - to establish an institutional memory, and obtain average and range unit costs based on historical data that could ultimately improve the reliability of new cost estimates and reduce the risks generated by cost overruns" (World Bank 2006). The focus of this section is on describing the data; we discuss issues due to selection in detail in the next section. The data stems from World Bank financed projects and is collected in collaboration with road agencies in the respective countries using information from Implementation Completion Reports, Pavement Management Systems Review Reports, Works Contracts, Appraisal Reports and Highway Development and Management Studies.

The data collection exercise was first conducted in five pilot countries, Bangladesh, India, Thailand, Viet Nam, Philippines; in 2002 a second set of countries was added including Ghana, Uganda, Poland, Armenia; in 2004, Lao, Kyrgyz, Kazakhstan, Ethiopia, Nigeria, and Serbia and Montenegro were added. As Table 4.1 shows, the current version of the database contains data from 3,322 work activities in 99 low and middle income countries out of which 23% are located in low income countries[5]. Contracts date between 1984 and 2008, with 82% of contracts taking place between 1996 and 2006. Tables 4.20 and 4.21 in the appendix show the distribution of projects by country over time.

The ROCKS database is based on 5 concepts (World Bank 2006). First, to allow for comparability of similar activities, road works are classified into categories: road development works and road preservation works. Within these two categories, projects are further divided into

[5]We exclude duplicates of 31 contracts for which we have the same entry for country, date, cost per km, cost type, work activity, length, width, shoulder and lanes. We also drop two contracts for Reconstruction Bituminous (one in India and one in Bangladesh) for which the recorded costs were US$218 and US$2,289; the median cost of the 595 Reconstruction Bituminous work activities of our database is US$195,516 per km so these two entries are likely to be incorrect.

Table 4.1: Complete ROCKS Database for Low and Middle Income Countries

	N	Percent
Low income	780	23.48
Lower middle income	1,352	40.70
Upper middle income	1,190	35.82
Total	3,322	100

Notes: income classification based on World Development Indicators 2012.

work class, work type and work activity. The detailed list of these sub-categories is presented in Tables 4.15 and 4.16 in the appendix. Second, comparisons are made possible through unit costs which are defined either as costs per square meter or costs per km. Third, the ROCKS database defines a minimum data requirement which is required to make the data comparable (e.g. country, date, project or source name, currency, unit cost, work type, cost type). Fourth, to add flexibility, road agencies are able to enter highly recommended data (e.g. predominant work activity, total cost, length and duration, carriage width, terrain type) and optional data (e.g. number of bidders, value of individual bids, unit costs of asphalt concrete, Portland cement concrete). Unit costs include civil works costs such as mobilization, pavement drainage, major structures and line markings; they exclude agency costs such as design, land acquisition, resettlement and supervision. Fifth, these costs are deflated to the year 2000 using the domestic consumer price index, and then converted into US$ using the exchange rate in 2000[6]. Bringing unit costs back to the same reference year and the same currency is crucial to allow for comparison across projects.

Unit costs are provided for programs or sections; a program is a part of a loan or credit, or a number of road sections combined. Sections define unit costs for road works on particular segments of a road. In either case, we have information on the name of the project the program or section is part of. Considering that a range of reports is used for the data collection,

[6]As the database does not contain consumer price indices and exchange rates after 2004, we recalculate all conversions using the official exchange rate (LCU per US$, period average) and the consumer price index from the World Development Indicators 2012. Projects denominated in currencies other than US$ were first deflated or inflated to the reference year 2000, and then converted into US$. Projects denominated in US$ were deflated to the reference year 2000 using the consumer price index of the United States. The costs are very similar to the ones provided in the database, with 93% (91%) of costs per km (square meter) lying within 2% of the original data provided. Azerbaijan, Ghana and Venezuela devalued their currencies since 2000, so for these countries we use the unit cost data provided in the database.

44% of entries are estimated costs, 27% are contracted costs, and 29% are actual costs. For some projects the database contains costs on all of the three categories. We include all of the available cost data. Unit costs from these different sources often differ by a large extent, so knowledge of the source is critical to compare unit costs. Individual road works activities also sometimes form part of a larger roads project. In order to account for the fact that there might be various costs types for the same projects, as well as various different work activities for the same project, we cluster the standard errors by country to allow for arbitrary correlation of costs within the same country.

Tables 4.17 to 4.19 in the appendix show the mean, median, maximum and minimum cost of various work types and work activities for both preservation and development works. The most expensive development work type is a new six lane expressway followed by a four lane expressway, while for preservation works the most expensive work type is concrete pavement restoration followed by strengthening. Zooming one level further in we see that the most expensive development activity has been further classified as a new bituminous six lane expressway, and the most expensive preservation work activity is a concrete slab replacement followed by reconstruction in bituminous and concrete.

Table 4.2 shows the range of average unit costs for a precisely defined work activity: asphalt overlays between 40 to 59 mm between 1996-1998 and 2006-2008 ranked by the cost in US$ per km. We limit the time window in order not to conflate differences in unit costs with changes in input prices which might affect economies differently. What is striking is that even for a narrowly defined time window and work activity, there are differences in unit costs of a factor between three to four. Using these unit costs, an asphalt overlay for a length of 100 km would cost US$3,300,000 in the Dominican Republic in 1997, compared to US$11,000,000 in Tanzania in 1996, or US$10,500,000 in Pakistan in 1998. Two sources of heterogeneity remain. While costs per square kilometer of a precisely defined work activity in a short time window are likely to be comparable, one could argue that different road widths might contribute to higher unit costs. Table 4.22 in the appendix shows that the ranking is

Table 4.2: Unit Costs per km of Asphalt Overlays 40 to 59 mm

Country	Cost per km in $1000	Number	Year	Country	Cost per km in $1000	Number	Year
			Work activities undertaken between 1996-1998				
Dominican Republic	33.5	1	1997	Argentina	69.7	1	1997
Ghana	42.9	5	1998	Brazil	74.4	1	1998
Lithuania	44.4	1	1996	Argentina	74.9	1	1996
Indonesia	48.5	1	1996	Cameroon	76.8	4	1997
Lithuania	49.7	1	1998	Bangladesh	79.1	26	1998
Mexico	50.7	1	1997	Vietnam	79.6	2	1998
Ghana	52.7	1	1996	Bangladesh	83.6	1	1997
Costa Rica	57.9	1	1996	Panama	84.1	1	1997
Armenia	60.7	1	1997	Nigeria	95.1	1	1997
Brazil	62.5	2	1996	El Salvador	102.2	1	1998
Bolivia	67.4	1	1997	Pakistan	105.0	1	1997
India	68.1	3	1997	Tanzania	111.7	1	1996
			Work activities undertaken between 2005-2007				
Paraguay	31.2	1	2005	Botswana	68.0	1	2006
India	35.9	2	2006	Nigeria	73.0	1	2007
Bulgaria	40.7	1	2006	Argentina	76.2	3	2006
Ecuador	41.6	1	2005	Georgia	82.6	1	2006
India	45.6	1	2005	Brazil	82.9	2	2005
Burkina Faso	48.0	1	2007	Georgia	84.9	1	2005
Brazil	55.2	3	2006	Vietnam	85.4	1	2005
Brazil	58.2	1	2007	Macedonia	85.7	1	2007
Thailand	59.5	1	2005	Rwanda	90.6	1	2006
Philippines	60.8	1	2006	Philippines	94.8	1	2005
Bosnia and Herzegovina	61.9	2	2006	Chile	98.9	1	2006
Nepal	63.1	1	2006				

Notes: costs per km of asphalt overlays 40 to 59 mm; all costs are in 2000 US$; number denotes the number of work activities in a given country over which a simple average is taken.

largely unaffected when using unit costs per square meter in 1996-1998[7]. Second, we pool across different sources of costs here, so the costs could be estimated, contracted or actual costs. However, the difference in unit costs of a factor of three to four is unlikely to be due to just differences in the source of costs[8]. We do not have enough observations for narrow work activities within these different cost types to separately show the differences for a large set of countries. To account for systematic differences across cost types, we have also compared the cost of construction projects, after partialling out the effects of cost types in a regression. The order of countries as well as range of unit costs remains substantively the same.

[7]Costs per square meter are missing for many observations in 2006-2008, so we only show unit costs of work activities from the earlier period.

[8]Flyvbjerg et al. (2003) find average cost overruns for roads are about 20% for projects in Europe and North America; Alexeeva et al. (2008) find average cost overruns by country for the DRC, Malawi, Tanzania, Mozambique, Ghana and Nigera to be between 12.05% and 39.72%; Alexeeva et al. (2011) find average cost overruns by country for Georgia, Serbia, Estonia, Armenia, Macedonia, Albania, Azerbaijan and Kazakhstan to be between 6% and 47%.

The database also contains bidding information for a subset of 266 work activities across 35 countries and the 5 regions. The minimum number of bidders is 1 and the maximum number is 25, with the median being 5 bidders. About 10% of contracts are awarded based on one or two bidders, which is similar to what Alexeeva et al. (2008) find. The value of each submitted bid is available for 188 contracts across 25 countries. The ratio of the maximum bid to the minimum bid varies substantially across countries up to a factor of 16.6 with a median of 1.34. A regression of the ratio of the maximum bid to the minimum bid on region dummies and dummies for the income categories shows that the ratio is about 2.5 lower in middle income countries compared to low income countries, indicating weaker competition in poorer countries. Alexeeva et al. (2008) conclude from their study on 13 countries in Sub-Saharan Africa that the roads sector is dominated by a few companies which undertake large-scale projects and that the highest value of contracts is awarded to Chinese companies.

Table 4.3 lists the variables we use from the ROCKS database and the main additional variables we have compiled. Table 4.14 in the appendix shows the descriptive statistics. Measures of corruption and conflict employed in the empirical literature are to varying degrees subjective measures, based on perceptions on individuals working in the private and public sector. To test whether the results are sensitive to the particular measure employed, we use measures from three sources. If we find patterns that are robust across a range of indicators, we are more confident that the results reflect a particular pattern.

First, our most direct measure for conflict episodes comes from the version 4-2012 of the UCDP/PRIO Armed Conflict Dataset, published by the Uppsala Conflict Data Program (UCDP) and the International Peace Research Institute, Oslo (PRIO)[9]. Readers are referred to Gleditsch et al. (2002), Themnér and Wallensteen (2012) and the Dataset Codebook for details. UCPD defines conflict as "a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths". We follow Miguel et al. (2004) and focus

[9]The other potential conflict data set is the Correlates of War data set. Due to concerns over transparency and consistency as well as a high threshold of deaths (Miguel et al. 2004) we prefer the Armed Conflict Dataset (ACD).

Table 4.3: Description of Main Data and Sources

Variable	Description	Source
Log of Cost	Log of unit cost of a particular road work activity (1984-2008)	ROCKS dataset, World Bank
Estimate	=1 if estimated costs	ROCKS dataset, World Bank
Contract	=1 if contracted costs	ROCKS dataset, World Bank
Actual	=1 if actual costs	ROCKS dataset, World Bank
Flat	=1 if terrain is flat	ROCKS dataset, World Bank
Hilly	=1 if terrain is hilly	ROCKS dataset, World Bank
Mountainous	=1 if terrain is mountainous	ROCKS dataset, World Bank
Rolling	=1 if terrain is rolling	ROCKS dataset, World Bank
Log of Ruggedness	Log of Terrain Ruggedness Index, representing the average ruggedness of a country measured as hundred of meters of elevation difference for grid points 926 meters apart	Nunn and Puga (2012)
Log of Distance to the nearest ice free coast	Log of average distance to nearest ice-free coast (1000 km)	Nunn and Puga (2012)
Log of Rainfall	Log of yearly precipitation in 100s mm, 2000-2008	Dell et al. (2012)
Population Density	Population Density (100 people per square km), 1960-2012	World Development Indicators
Log of Surface Area	Log of Surface Area (1,000 square kilometers)	World Development Indicators
Log of GDP	Log of GDP per capita (1984-2008), constant 2000 US$	World Development Indicators
ACD Conflict	=1 if country is in a conflict	Armed Conflict Dataset
WGI Instability	Index of political instability and violence from World governance Indicators (1996-2012), redefined to: -1.26 (lowest) to 2.21 (highest)	World Governance Indicators
TI Corruption	Corruption index from Transparency International, survey 2008, rescaled to 0.1 (lowest corruption), 5.6 (highest corruption)	Transparency International
WGI Corruption	Index of corruption from World Governance Indicators (1996-2012), redefined to: -1.45 (lowest corruption) to 1.6 (highest corruption)	World Governance Indicators
PIMI	Public Investment Management Index, 2011, measured on scale from 0 (worst) to 4 (best)	Dabla-Norris et al. (2011)
Log of DB Contract	Number of days it takes to enforce a contract, from Doing Business Indicators 2007	Doing Business Indicators

on internal armed conflicts between the government and an internal party with and without outside intervention which accounts for 88.5% of the conflicts recorded in the database. We define a project as being carried out in a conflict state if the state is in conflict in the year the road work activity is recorded; a country is likely not to return to full stability after the end of a conflict, so we also create a variable that defines the country as being in a post conflict period for 5 years after the end of a conflict, or until the country reverted back into conflict.

There are 187 conflict and post-conflict periods in the countries covered in our data.

Second, we use data from the Worldwide Governance Indicators (WGI) which are based on data from household and firm surveys, commercial business information providers, non-governmental organizations and public sector organizations. Six indicators capture different aspects of governance in 200 countries since 1996. We use the variables on 'control of corruption' and 'political stability and absence of violence/terrorism'. The control of corruption variable measures "perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests" and the variable political stability and absence of violence/terrorism reflects "perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism" (Kaufmann et al. 2010). These indicators are measured between -2.5 and 2.5 where higher numbers reflect lower levels of corruption and political instability. We multiply the variables by (-1) and rename the variables 'Corruption' and 'Political Instability' so that higher numbers reflect higher levels of corruption and political instability.

Third, we use Transparency International's 2008 Corruption Perception Index which allocates scores to countries from 1 to 10, where 0 equals the highest level of perceived corruption and 10 equals the lowest level of perceived corruption. We rescale the variable so that 10 is the highest level of corruption. Graf Lambsdorff (2005) and Thompson and Shah (2005) underscore that the Corruption Perception Index is inappropriate for comparison of countries across time, due to changes in methodology as well as data sources underlying the index. We use 2008 because this is the earliest year with the highest number of countries covered. We have also assembled the index for the years 1998-2011 and our results are robust to using the indicator from earlier years (1998-2007) and later years (2009-2012)[10].

[10]A popular source, due to its coverage across countries and time, for perception based data on institutions is the International Crisis Research Group (for example, Alesina and Weder (2002), Fisman and Miguel (2007), Ahmed (2013), Svensson (2005), Wei (2000)). The International Crisis Research Group compiles yearly data on 22 indicators measuring political, financial and economic risk between 1984 and 2012. Corruption is measured from 0 (high corruption) to 6 (low corruption) as a component of political risk. We do not include this measure for several reasons. First, Treisman (2007) has highlighted various questionable scores in the corruption indicator, both in the cross-section of countries as well as jumps in the indicator over time which do not seem correspond

The correlation between the WGI political instability indicator and the ACD conflict dummy is 0.58, and the correlation between the Transparency International measure and the WGI corruption measure is 0.81. Both correlations are significant at the 1 percent level. For the empirical analysis we create lagged three year averages of the two WGI measures. The data for our other explanatory variables are described in section 4.8.1 in the appendix.

4.5 Estimation and Identification

To obtain an estimable equation, we take logs of equation (4.6) and get

$$\ln \frac{C(w_1, w_2, q)}{q} = \frac{\delta}{\alpha+\beta} A + \ln\theta + \frac{1-(\alpha+\beta)}{\alpha+\beta} \ln q + \frac{\alpha}{\alpha+\beta} \ln w_1 + \frac{\beta}{\alpha+\beta} \ln w_2. \tag{4.7}$$

Rewriting average costs $\frac{C(w_1,w_2,q)}{q}$ as c, denoting $\frac{\delta}{\alpha+\beta} = \gamma$, $\frac{1-(\alpha+\beta)}{\alpha+\beta} = \phi_1$, $\frac{\alpha}{\alpha+\beta} = \phi_2$, $\frac{\beta}{\alpha+\beta} = \phi_3$, adding an error term and fixed effects for work activities, time and region as well as subscripts

to specific country level policies. We highlight some additional peculiarities here. For example, in 2000, Austria had the same level of corruption (a score of 4/6) as Congo, Iran, Libya and the United States. In the same year, Transparency International gives Austria a score of 7.7/10 where 10 is the least corrupt, Congo has it's earliest ranking in 2004 with 2.3/10, Iran gets 3.3/10, Libya has 2.1/10 in 2003, and the United States receives 7.8/10. There are also large discrepancies with the Worldwide Governance Indicators. We divide the set of countries into deciles for the year 2000 where higher deciles correspond to less corruption, and show that the difference in the location of countries is up to 8 deciles. For instance, Ireland ranks in the 10th decile in the WGI score, while it falls into the second decile according to the ICRG's ranking. Contrarily, the Congo falls within the eight decile in fighting corruption according to the ICRG measure, while it falls into the second lowest decile of corruption according to the WGI measure. For some countries there are large jumps. For example, in 1989 Niger's corruption measure was with 4 on par with Italy's, dropped to 3 in 1991 and then to 0 in 1997. Kenya's ICRG score dropped from 3.46 in 2003 to 0.5 in 2006. Lebanon's score dropped from 4 in 1995 to 1.75 in 1996. The average of the cross sectional correlation across the full set of countries between 1996-2011 is 0.86, for our sample of low and middle income countries the average cross sectional correlation is 0.59, ranging from 0.37 in 1998 to 0.70 in 2011. Yearly changes are uncorrelated for 4 periods, with an average correlation of 0.2 for the remaining periods in the full sample and similar patterns in the our sample of countries. Wei (2000) uses an average of the ICRG measure between 1991-1993, and Svensson (2005) uses either an average between 1982-2001 or the year 2001 in a cross section of countries. Given that cross-sectional variation is rather high, in these settings different measures produce similar results. Using these measures in a panel setting has been seriously questioned (Treisman 2007; Graf Lambsdorff 2005). Alesina and Weder (2002) use five-year averages for their main results, but emphasize that results in first differences should be interpreted 'very cautiously'. Ahmed (2013) does not show the robustness of his results when using alternative measures of corruption in his regressions using country fixed effects. Finally, Graf Lambsdorff (2005) notices that the ICRG Corruption variable reflects the *political risk* associated with corruption, rather than a country's level of corruption; the ICRG website does not provide information on how the scores are constructed. We therefore rely on the WGI and the TI corruption measures.

for work activities, work types, countries and time, we obtain

$$\ln c_{apit} = \gamma A_{it} + \ln\theta + \phi_1 \ln q_{apit} + \phi_2 \ln w_{1apit} + \phi_3 \ln w_{2apit}$$
$$+ \kappa_{apit} + \omega_a + \tau_t + \xi_{pt} + \rho_{ap} + \epsilon_{apit} \quad (4.8)$$

for work activity $a = 1,\ldots,A$, work type $p = 1,\ldots,P$, country $i = 1,\ldots,N$, and time $t = 1,\ldots,T$, where c is the cost per kilometer and q is a dummy variable that is equal to one if the length of the road is above 50 km; we do not have data on the cost of labor and capital for each construction project. Rather than estimating the technological parameters, our controls are selected to control for the deep determinants of factor prices. The cost of capital is going to be a function of transport costs, so we include the distance to the nearest ice-free coast from Nunn and Puga (2012) as a measure of the price of capital and equipment. For about half of the road work activities we know whether the terrain on which the road works are undertaken is flat, mountainous, hilly or rolling. We include these as dummy variables, and additionally include a measure of country-level ruggedness to account for higher input costs required on more rugged terrain. Given that unit costs might be higher in countries with high levels of rainfall, we include the three year average of lagged precipitation. We further include the log of GDP per capita to proxy for the price of labor and capital. We then use our measures of corruption and conflict to proxy for A, and include two dummy variables indicating that a country is above the median level of conflict or corruption of the sample[11]. Due to high levels of correlation between these measures, we enter them in separate regressions. Appreciating that road work contracts require a substantial amount of time to negotiate, we lag time varying country level controls by one period.

To account for differences in the source of unit costs and procurement, κ_{apit} is a vector of dummy variables capturing whether the source of costs is estimated or contracted costs with the base category being actual costs. All models include work activity fixed effects ω to control for systematic differences in costs across work activities, year fixed effects τ to account for worldwide construction industry trends, interaction terms between work type and 5-year

[11] We take the median of distinct country-year observations we have in the sample.

dummies ξ to allow for differences in the evolution of costs for different work types, region fixed effects ρ, and an error term ϵ[12]. We have missing values for certain countries for some of the explanatory variables. In this case, we follow a procedure known as modified zero-order regression outlined by (Greene 2003, p.60) in which we include a dummy variable that is equal to one if the variable is missing, and replace the missing observations with zero. We are not interested in the coefficients of the missing dummy variables, so do not report them when discussing the results[13].

In order to interpret the coefficient estimates on the included variables as causal relationships, we would require that $E(X_{apct}|\epsilon_{apit} = 0)$ where X_{apit} denotes a vector of all included controls. This is an implausible assumption. While it is unlikely that there is reverse causality from unit costs to the control variables, omitted variables might still bias our parameter estimates. Unfortunately, many of the controls are time invariant, and we do not have enough variation over time to include country fixed effects to account for time invariant unobservable characteristics and still identify the coefficient estimates of time-varying variables. The parameters estimates should therefore be interpreted as statistical associations, which still contain valuable insights. As a robustness check we will also estimate equation (4.8) with country fixed effects to test whether the road work activity characteristics, which have substantial within country variation, remain significant.

4.5.1 Selection

Our unit cost sample is selected along three dimensions. First, we only observe road work activities for which the World Bank provided a loan[14]. Given that this is the only available large database, our findings need to be interpreted in the context of this subset of work activities

[12]Table 4.23 in the appendix shows the coefficients of the work type dummy variables including and excluding country level controls. In the discussion of the results in the next section, we always control for work activity fixed effects, but do not discuss the differences in unit costs across these categories as this is not the main focus of this chapter.

[13]Section 4.6.1 discusses the robustness of our results to alternative ways of dealing with missing variables.

[14]It is not clear in which direction this would bias our estimates. If the World Bank, through its procurement guidelines, is able to impose stricter procedures in more corrupt countries than the government, we would underestimate the effect of corruption. Without the stringent guidelines, the government would have to pay a higher premium in high corruption countries. On the other hand, governments in corrupt countries are potentially better able to limit the magnitude of side payments necessary to carry out a work activity; this would indicate that our estimates of the effect of corruption are higher than the cost faced by governments.

conducted in collaboration with the World Bank.

Second, from inspection of tables 4.20 and 4.21 in the appendix it becomes clear that the distribution of road work activities is not a random sample of contracts per country for each year. Rather, as mentioned in section 4.4, the data are clustered around pilot countries, with additional countries being added gradually. We have been told from the responsible for the database that selection into the database out of the population of projects carried out by the World Bank does not follow any specific pattern, so that we regard it as random. To capture time invariant unobservables determining selection as a pilot country, we also include a dummy variable that is equal to one if a country belongs to the first two sets of pilot countries[15].

Third, we only observe costs for projects that were implemented, so out of the population of potential road work activities we miss projects which have not been started[16]. Considering that the net present value of a project at time=0 is $NPV_0 = -I_0 + (B_1 - C_1)/(1+r)^1 + \ldots + (B_T - C_T)/(1+r)^T$, projects which appear in the database must have low enough costs (initial costs I_0 as well as maintenance costs C) or high enough benefits B. We therefore observe a truncation of the response variable (those with high project costs and low benefits). We can examine the bias introduced by such truncation. Assume that the true model is $c = \beta_0 + \beta_1 x + u$ where c are unit costs, β_0 is a constant, β_1 is our coefficient of interest, and u is an error term. Consider a project with the same level of benefits in two countries. Let x be corruption, assume that corruption increases costs so that $\beta_1 > 0$, and that one country has a high level of corruption, while the other country has a low level of corruption. While the project is undertaken in the low corruption country, it might fail to generate a high enough NPV in the high corruption country. We therefore miss projects with high x and high u. Thus, thus x and u will be negatively correlated in the truncated sample and the OLS estimate of β_1 will be downward biased (towards zero), *underestimating* the effect of corruption on unit costs. Similarly, assume that x is a measure of flatness of the terrain, so that higher values

[15]These countries are Armenia, Bangladesh, Ghana, Philippines, Thailand, Uganda, Vietnam, India.

[16]For work activities in the sample for which we have estimated or contracted costs, we do not have information whether they were completed.

correspond to flatter terrain, and lower values to mountainous terrain. Since it is cheaper to build a road on flat terrain, $\beta_1 < 0$. Consider again a project yielding the same level of benefits in a flat and in a mountainous country. Following the logic above, a project yielding the same benefits is more likely to be in our sample in flat terrain (high x) and we will tend to miss out on projects in mountainous areas, so that x and u will be positively correlated in the truncated sample and the OLS estimate of β_1 will be upward biased, i.e. again towards zero. In this case, we will under-estimate the cost-reducing effect of flat terrain. This suggests that we will tend to underestimate effects in general so that our estimates can be viewed as conservative. If the benefits of a project are a function of the individuals affected by the improved road, and congestion costs are important, we would expect the benefit of transport infrastructure to be higher in densely populated areas, so that projects are more likely to be selected even if costs are higher than in an otherwise equivalent context. Unfortunately, we do not have information on projects which have not been carried out. We are therefore limited to controlling for population density to account for selection on observables.

4.6 Empirical Results and Discussion

We start by presenting the main results from equation (4.8) including our measures of conflict, and then turn to corruption in the second set of results. We examine the correlations with these measures separately, because they are highly correlated, and the effect of conflict holding corruption constant, and vice versa, is difficult to identify, and not the object of interest. Columns (1)-(3) in table 4.4 include the conflict variables without controls for GDP per capita, columns (4)-(6) include GDP per capita for one year before the road work activity (we refer to this as contemporaneous GDP per capita), and columns (7)-(9) include predetermined GDP per capita in 1985. While GDP per capita in the year of the road work activity is a more precise proxy for factor prices, it is likely to be correlated with other contemporaneous variables affecting unit costs. Therefore, we also show the results controlling for GDP per capita in 1985.

There is a robust and significant relationship between violent conflict and its legacy and unit costs. Countries which are in conflict have about 30% higher unit costs. Although the coefficient on the post-conflict dummy is positive, it is not significantly different from zero. We find evidence for the higher costs in politically unstable countries also when using the political instability measure from the Worldwide Governance Indicators (where we use the continuous measure as well as a dummy variable for whether the measure is above the median of the sample). Countries which are above the median of the sample in terms of political instability, face about 13% higher costs. The size and significance of the coefficients is robust to omitting GDP per capita, or controlling for contemporaneous or predetermined GDP per capita. The magnitude of the effect appears in line with Benamghar and Iimi (2011), who find that halving security incidents would reduce procurement costs by 10% and cost overruns by 15%.

Unsurprisingly, geography matters. The ruggedness of the terrain in a country, surface area and population density of a country are significantly and positively associated with unit costs. Building a road in a more rugged terrain is likely to involve higher unit costs of construction and maintenance. Column (1) suggests that a one percent increase in the ruggedness of a country is associated with about 0.09 percent higher unit costs. The surface area and distance to the nearest ice-free coast are collinear, so that when we include the surface area we cannot estimate the coefficient on the distance to the nearest ice-free coast precisely anymore. The positive coefficient on the surface area therefore is likely to pick up both the effects of being landlocked, leading to higher transport costs, as well as the fact that perhaps constructing and maintaining roads in larger countries involves higher organizational costs. Population density is also positively and significantly associated with unit costs, indicating that unit costs rise by about ten percent for an increase of 100 people per square kilometer. Finally, we turn to the work activity specific control variables. The estimates suggest that there are significant economies of scale. Unit costs are about ten percent lower when road work activities cover a length of at least 50 km. This is close to an estimate by AFRICON (2008) who find that median unit costs are 15-20% lower for road contracts that are larger than 50 km. There is no evidence that estimated costs and actual costs are significantly different[17]. There is some

[17]Unfortunately, data on the type of procurement is missing for more than half of the sample. For the unit costs for which we have data, the procurement was done by international competitive bidding in 62%, national competitive bidding in 36%, with the remaining 26 work activities procured via single source selection, force

evidence that contracted and estimated costs are lower than actual costs, but the effect is not significantly different from zero.

We now turn to corruption in table 4.5. As before, columns (1)-(3) exclude the control for GDP per capita, columns (4)-(6) include contemporaneous GDP per capita, and columns (7)-(9) include lagged GDP per capita. The pattern is consistent for the corruption variables from Transparency International and the Worldwide Governance Indicators. We find that Transparency International's measure of corruption is significantly correlated with unit costs, so that a one point increase in corruption on a ten-point scale is associated with an increase in costs by about 6-7%. The WGI measure suggests that moving a country from the 75th percentile of corruption to the 25th percentile of corruption is associated with 6.3% lower unit costs. Unit costs in countries with a level of corruption above the median as measured by the Worldwide Governance Indicator indicator of corruption have on average 12% higher costs[18]. The effects of the other control variables are stable when comparing their coefficients and standard errors with table 4.4.

Table 4.24 in the appendix shows a model without controls for conflict and corruption, and some of the omitted controls which are still of interest. Pilot countries have on average lower costs, but the coefficient is not significantly different from zero. There is substantial regional variation. Unit costs in East Asia and the Pacific, Latin America and the Carribean, the Middle East and North Africa, and South Asia are all significantly lower than in costs in the base category, Sub-Saharan Africa. These differences in costs range between the 49% lower costs in East Asia and the Pacific, to 18% lower costs in Latin America and the Caribbean. Subsequently, we use column (1) of table 4.24 to explore omitted variables.

account or limited international bidding. We have also tried including a dummy variable that is equal to one if procurement was done via international competitive bidding and zero otherwise, as well as a dummy variable that is equal to one if we miss procurement information. The results suggest that work activities awarded through an international auction have 35-38% higher costs (significant at the 5 percent level) compared to national bidding process, single source selection or force account. Alexeeva et al. (2008) find, when analyzing 109 contracts in 13 Sub-Saharan African countries, that local firms have a cost advantage over international firms, likely due to lower management and overhead costs. However, local firms perform worse in the implementation of the project, including longer delays and higher cost overruns. We do not have data related to the implementation of the project, so we cannot test whether we find the same with our data.

[18]We also tested whether estimated or contracted costs are significantly lower compared to actual costs in countries which suffer from conflicts, or countries with high levels of corruption, but we do not find any evidence for this.

Table 4.4: Conflict

	ACDI	WGII	WGImedI	ACDII	WGIII	WGImedII	ACDIII	WGIIII	WGImedIII
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ACD Conflict	0.306***			0.308***			0.31***		
	(0.064)			(0.069)			(0.064)		
ACD Post-Conflict	0.04			0.033			0.054		
	(0.057)			(0.058)			(0.055)		
WGI Instability		0.086*			0.083			0.096**	
		(0.045)			(0.051)			(0.046)	
WGI Instability > Median			0.135**			0.13**			0.153**
			(0.06)			(0.065)			(0.061)
Log Ruggedness	0.086***	0.129***	0.128***	0.082***	0.127***	0.126***	0.088***	0.13***	0.125***
	(0.029)	(0.034)	(0.033)	(0.029)	(0.035)	(0.034)	(0.028)	(0.035)	(0.033)
Log of Rainfall	-.088	-.070	-.072	-.104	-.080	-.083	-.093	-.082	-.091
	(0.065)	(0.071)	(0.07)	(0.065)	(0.072)	(0.071)	(0.065)	(0.07)	(0.071)
Log dist to coast	-.010	-.031	-.030	-.021	-.040	-.042	-.003	-.025	-.031
	(0.041)	(0.047)	(0.047)	(0.044)	(0.05)	(0.049)	(0.042)	(0.047)	(0.046)
Population Density	0.122***	0.102***	0.097***	0.118***	0.099***	0.094***	0.125***	0.105***	0.097***
	(0.018)	(0.019)	(0.017)	(0.019)	(0.019)	(0.018)	(0.018)	(0.019)	(0.017)
Log of Surface Area	0.052**	0.07***	0.075***	0.058**	0.075***	0.083***	0.05**	0.067***	0.075***
	(0.021)	(0.022)	(0.021)	(0.023)	(0.025)	(0.023)	(0.022)	(0.023)	(0.021)
Length > than 50 km	-.116***	-.090**	-.094**	-.127***	-.098**	-.104***	-.118***	-.092**	-.100**
	(0.036)	(0.039)	(0.038)	(0.036)	(0.04)	(0.038)	(0.037)	(0.04)	(0.039)
Estimate	-.025	-.026	-.028	-.019	-.020	-.024	-.020	-.021	-.023
	(0.056)	(0.058)	(0.058)	(0.055)	(0.057)	(0.057)	(0.055)	(0.058)	(0.057)
Contract	-.074	-.079	-.086	-.076	-.081	-.089*	-.070	-.076	-.085
	(0.055)	(0.054)	(0.054)	(0.055)	(0.054)	(0.054)	(0.054)	(0.053)	(0.053)
Log of GDP per capita				-.038	-.032	-.041			
				(0.037)	(0.041)	(0.04)			
Log of GDP pc (1985)							0.004	0.002	-.017
							(0.044)	(0.045)	(0.043)
Obs.	3322	3322	3322	3322	3322	3322	3322	3322	3322
R^2	0.898	0.896	0.896	0.898	0.896	0.896	0.898	0.896	0.896

Notes: Dependent variable is the log of cost per km; all models control for work activity fixed effects, year fixed effects, an interaction between work type and 5-year period fixed effects and region fixed effects; base categories are actual costs; robust standard errors in parentheses, clustered at the country; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 4.5: Corruption

	TI	WGI	WGImed	TIII	WGIII	WGImedII	TIIII	WGIIII	WGImedIII
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TI Corruption	0.063***			0.062**			0.076***		
	(0.023)			(0.025)			(0.025)		
WGI Corruption		0.084**			0.072			0.101**	
		(0.043)			(0.052)			(0.043)	
WGI Corruption > Median			0.122**			0.112*			0.142***
			(0.051)			(0.064)			(0.051)
Log Ruggedness	0.137***	0.149***	0.147***	0.135***	0.146***	0.146***	0.137***	0.151***	0.152***
	(0.034)	(0.033)	(0.032)	(0.035)	(0.034)	(0.033)	(0.035)	(0.034)	(0.033)
Log of Rainfall	-.059	-.049	-.038	-.068	-.058	-.045	-.076	-.061	-.043
	(0.07)	(0.066)	(0.069)	(0.071)	(0.067)	(0.07)	(0.071)	(0.067)	(0.069)
Log dist to coast	-.051	-.039	-.044	-.055	-.048	-.049	-.048	-.036	-.035
	(0.05)	(0.048)	(0.047)	(0.052)	(0.051)	(0.05)	(0.05)	(0.048)	(0.046)
Population Density	0.09***	0.098***	0.089***	0.087***	0.096***	0.088***	0.09***	0.099***	0.091***
	(0.019)	(0.019)	(0.018)	(0.02)	(0.019)	(0.019)	(0.019)	(0.019)	(0.018)
Log of Surface Area	0.083***	0.085***	0.092***	0.085***	0.091***	0.095***	0.081***	0.084***	0.09***
	(0.022)	(0.021)	(0.022)	(0.024)	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)
Length > than 50 km	-.088**	-.091**	-.096**	-.093**	-.100**	-.102***	-.090**	-.093**	-.097**
	(0.038)	(0.038)	(0.038)	(0.039)	(0.039)	(0.039)	(0.04)	(0.04)	(0.04)
Estimate	-.030	-.031	-.022	-.025	-.026	-.018	-.026	-.028	-.018
	(0.058)	(0.059)	(0.058)	(0.057)	(0.058)	(0.057)	(0.058)	(0.058)	(0.057)
Contract	-.086	-.080	-.076	-.087	-.083	-.078	-.084	-.078	-.071
	(0.055)	(0.054)	(0.053)	(0.054)	(0.054)	(0.053)	(0.053)	(0.053)	(0.052)
Log of GDP per capita				-.018	-.038	-.024			
				(0.041)	(0.043)	(0.047)			
Log of GDP pc (1985)							0.0007	0.0009	0.017
							(0.044)	(0.045)	(0.047)
Obs.	3322	3322	3322	3322	3322	3322	3322	3322	3322
R^2	0.896	0.896	0.896	0.896	0.896	0.896	0.897	0.896	0.896

Notes: Dependent variable is the log of cost per km; all models control for work activity fixed effects, year fixed effects, an interaction between work type and 5-year period fixed effects and region fixed effects; base categories are actual costs; robust standard errors in parentheses, clustered at the country; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 4.6: Conflict and Corruption

	TI	WGI	WGImed	TIII	WGIII	WGImedII	TIIII	WGIIII	WGImedIII
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TI Corruption	0.051**			0.055**			0.064***		
	(0.02)			(0.022)			(0.021)		
WGI Corruption		0.049			0.047			0.067	
		(0.041)			(0.047)			(0.041)	
WGI Corruption > Median			0.096**			0.094*			0.117**
			(0.045)			(0.055)			(0.046)
ACD Conflict	0.283***	0.289***	0.284***	0.294***	0.296***	0.293***	0.282***	0.288***	0.284***
	(0.057)	(0.06)	(0.059)	(0.059)	(0.063)	(0.061)	(0.056)	(0.06)	(0.058)
Log Ruggedness	0.077**	0.087***	0.086***	0.072**	0.083***	0.082***	0.078***	0.09***	0.091***
	(0.03)	(0.029)	(0.03)	(0.031)	(0.03)	(0.03)	(0.03)	(0.029)	(0.03)
Log of Rainfall	-.113*	-.102	-.096	-.130**	-.117*	-.109*	-.128**	-.112*	-.100
	(0.066)	(0.063)	(0.064)	(0.066)	(0.063)	(0.065)	(0.065)	(0.062)	(0.064)
Log dist to coast	-.034	-.020	-.028	-.036	-.027	-.030	-.030	-.015	-.017
	(0.041)	(0.041)	(0.04)	(0.042)	(0.042)	(0.041)	(0.042)	(0.041)	(0.04)
Population Density	0.11***	0.119***	0.11***	0.105***	0.115***	0.107***	0.111***	0.12***	0.112***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.02)	(0.02)	(0.019)	(0.019)	(0.019)
Log of Surface Area	0.056***	0.056***	0.063***	0.054**	0.059***	0.063***	0.054**	0.055**	0.061***
	(0.02)	(0.02)	(0.021)	(0.023)	(0.022)	(0.022)	(0.022)	(0.021)	(0.022)
Length > than 50km	-.112***	-.114***	-.118***	-.117***	-.124***	-.124***	-.113***	-.115***	-.118***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.037)	(0.037)	(0.037)
Estimate	-.033	-.032	-.026	-.024	-.024	-.018	-.029	-.030	-.022
	(0.054)	(0.055)	(0.054)	(0.053)	(0.054)	(0.053)	(0.054)	(0.054)	(0.053)
Contract	-.081	-.075	-.072	-.079	-.076	-.072	-.078	-.072	-.067
	(0.055)	(0.054)	(0.053)	(0.054)	(0.054)	(0.053)	(0.053)	(0.053)	(0.051)
Log of GDP per capita				-.005	-.028	-.013			
				(0.038)	(0.04)	(0.043)			
Log of GDP pc (1985)							0.008	0.007	0.022
							(0.042)	(0.043)	(0.044)
Obs.	3322	3322	3322	3322	3322	3322	3322	3322	3322
R^2	0.898	0.898	0.898	0.898	0.898	0.898	0.898	0.898	0.898

Notes: Dependent variable is the log of cost per km; all models control for work activity fixed effects, year fixed effects, an interaction between work type and 5-year period fixed effects and region fixed effects; base categories are actual costs; robust standard errors in parentheses, clustered at the country; *, **, *** denote significance at 10%, 5% and 1% levels.

To test whether corruption and conflict matter both, we include the Armed Conflict Dataset Indicator alongside the various corruption measures in table 4.6[19]. The results show that the association between conflict and costs is slightly lower when we include both both conflict and corruption in the regression, but it remains significant at the 1% level in all specifications. The coefficient on the corruption variables decreases in size, but remains significant when looking at the Transparency International measure and the WGI dummy variable for countries above the median.

4.6.1 Robustness

We now perform a number of robustness checks on our results. First, we introduce country fixed effects in table 4.7. This is a very limited test because most of our variables are country-specific and so drop out. As Kaufmann et al. (2010) point out, most countries in the Worldwide Governance Indicators have high persistence in these indicators over time, and changes in indicators are both due to changes in measurement as well as in the performance of a country. However, we have within country level variation in the conflict variable due to the different timing of the road work activities and conflicts, and this variable does not suffer from changes in measurement. The coefficients on those variables that can be tested are not significantly affected. The scale effect remains significant, negative, higher in magnitude, and coincides even closer with the results of AFRICON (2008). The coefficient on the conflict variable remains significant and positive but slightly lower in size, suggesting that countries undertaking road works during times of violence face 21% higher costs.

Second, we also estimate the models with costs per square meter instead of costs per km and find that the results are substantively the same. We prefer to use costs per km as we loose 500 observations when using the cost per square meter. Third, instead of the three-year lagged average of the WGI measures, we also use the variable in the year before the road work activity, as well as taking 5-year averages; the results are not affected. Fourth, one concern with the ACD conflict measure is that it has a cut-off of at least 25 battle-related deaths so that we might be picking up conflicts in remote areas in large countries which do not actually

[19]We prefer to test this measure as it is not based on ratings but a clear indicator of conflict in a country.

Table 4.7: Robustness Checks

	FE1	FE2
	(1)	(2)
Estimate	0.007	0.008
	(0.059)	(0.059)
Contract	-.056	-.051
	(0.056)	(0.056)
Length > than 50 km	-.129***	-.128***
	(0.038)	(0.038)
ACD Conflict		0.213*
		(0.114)
ACD Post-Conflict		0.064
		(0.104)
Obs.	3322	3322
R^2	0.908	0.908

Notes: Dependent variable is the log of cost per km; all models control for work activity fixed effects, year fixed effects, an interaction between work type and 5-year period fixed effects and region fixed effects; base categories are actual costs; robust standard errors in parentheses, clustered at the country; *, **, *** denote significance at 10%, 5% and 1% levels.

affect the whole country. To test whether this is driving the results, we interact the conflict and the post conflict dummy variables with the size of the country. We perform a joint significance test on these two interaction terms and find that we fail to reject the null hypothesis that they are jointly equal to zero, suggesting that this is not driving the results.

Fifth, we test whether our results are robust to alternative ways of dealing with missing data. In the analysis so far we employed three different types of controls: (i) geographic controls and GDP; (ii) project specific controls; and (iii) measures of conflict and corruption. We discuss missing values in turn for these four categories. Geographic controls and GDP data[20] are from various other data sets and with some exceptions completely available for all countries. The main reason for GDP in 1985 being missing for 17 countries is that many of them did not exist in 1985, such as Bosnia and Herzegovina, Kazakhstan, Kyrgyz Republic and Russia. The project specific controls[21] with the largest number of missing values are ter-

[20]Ruggedness, population, land area, distance to the nearest ice-free coast and region are available for all countries and years; precipitation is available for all countries except the West Bank and Gaza from 2000-2008; road projects before this date are assigned the 2000 value; GDP is available for all countries except Afghanistan; GDP in 1985 is not available for 17 countries or 337 road projects.

[21]The type of costs (estimate, contract or actual) and work type is available for all road work activities; work activity (one classification below work activity) is available for 2,926 work activities; terrain is available for 1,587 work activities; length of the project is available for 2,452 work activities.

rain and the length of the road work activity. Our coverage of the conflict and corruption[22] indicators is extensive in terms of countries covered. Our main approach to missing data has been modified zero-order regression, which is equivalent to replacing missing variables with means of the available observations. An alternative approach is to use 'listwise deletion', where we only use variables for which we have complete data (Cameron and Trivedi 2005). We therefore dropped any missing values in GDP, length of the road, Transparency International's measure for corruption, terrain and rainfall, and re-estimated the equations; our results are substantively the same. Due to the overlapping nature of the missing data the listwise deletion approach leads to a drop in the number of observations from 3,322 to 1,042. As a second alternative, we use the modified zero-order regression for the base controls (geographic controls and project-specific controls), and then use pair-wise deletion by dropping observations in which the corruption measure is missing, for equations in which there are missing values in the corruption measure. Third, we individually drop observations with missing data one by one and re-estimate our model each time, and our results are robust. Given that the specific terrain is recorded for less than half of the sample, we also estimated the model without the work activity associated terrain fixed effect and only include the country level ruggedness variable. Overall, the results are remarkably robust to these various specifications.

4.6.2 Omitted Variables

Having established that conflict and corruption are associated with higher costs, our main concern that prevents us from interpreting the coefficient estimates as causal are omitted variables. We have shown that the inclusion of per capita GDP does not substantially alter the results, which suggests that conflict and corruption are correlated with unit costs not simply through the level of income. However, conflict and corruption might be correlated with other unobserved variables. For example, conflict states are likely to both have weak government public investment management capacity, as well as an unfriendly business environment. We therefore use information on the Public Investment Management Index and data from the

[22]The ACD conflict and post-conflict variables cover all countries and time periods; WGI indicators for political instability and corruption are available for all countries; the Transparency International measure of corruption is missing only for Fiji (1 road work activity) and the West Bank and Gaza (3 road work activities)

Doing Business Indicators in 2007 to test whether these two dimensions capture part of the higher costs. We use variables which are underlying the Business Indicators: the time it takes to start a business, obtain a construction permit, import and export, register property, and enforce a contract. The Public Investment Management Index is measured on a scale from 1 to 4, with higher values reflecting better public investment management capacity. If our results are not affected by their inclusion, this does not imply a causal relationship, but it weakens the argument that our conflict and corruption variables are simply proxying for a weak business environment and government capacity. Table 4.8 shows the coefficients on these variables when added in separate regressions to the base model in column (1) of table 4.24. The only

Table 4.8: Omitted Variables

Public Investment Management Index	-.031 (0.068)
Log of DB Start Business	0.091 (0.059)
Log of DB Construction Permit	-.014 (0.076)
Log of DB Import+Export	0.083 (0.095)
Log of DB Register Property	0.004 (0.03)
Log of DB Enforce Contract	0.436*** (0.1)

Notes: Base model from column (1) of table 4.24. Each entry represents a separate regression; robust standard errors in parentheses, clustered at the country; *, **, *** denote significance at 10%, 5% and 1% levels.

significant correlation between costs is with time it takes to enforce a contract. A 10% increase in the number of days it takes to enforce a contract is associated with 4.4% higher unit costs. The coefficient on the Public Investment Management Index (PIMI) is insignificant but negative, suggesting that a one unit increase in the PIMI is associated with 3.1% lower unit costs. As we would like to test both a measure for the capacity of the government as well as the private sector environment, we now test whether the inclusion of these two measures affects our coefficients on conflict and corruption.

Table 4.9 presents the results for conflict, where the upper panel includes the Public Investment Management Index, and the lower panel includes the Doing Business variable.

Table 4.9: Conflict - Omitted Variables

	ACDI	WGII	WGImedI	ACDII	WGIII	WGImedII	ACDIII	WGIIII	WGImedIII
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ACD Conflict	0.308***			0.313***			0.311***		
	(0.067)			(0.07)			(0.066)		
ACD Post-Conflict	0.038			0.034			0.051		
	(0.06)			(0.059)			(0.057)		
WGI Instability		0.088*			0.089*			0.098**	
		(0.05)			(0.054)			(0.049)	
WGI Instability > Median			0.14**			0.143**			0.161**
			(0.069)			(0.071)			(0.068)
Public Investment Management Index	-.010	-.001	0.005	0.006	0.013	0.023	-.018	-.006	0.007
	(0.055)	(0.065)	(0.067)	(0.059)	(0.068)	(0.069)	(0.058)	(0.067)	(0.069)
Log of GDP per capita	NO	NO	NO	YES	YES	YES	NO	NO	NO
Log of GDP pc (1985)	NO	NO	NO	NO	NO	NO	YES	YES	YES
Obs.	3322	3322	3322	3322	3322	3322	3322	3322	3322
R^2	0.898	0.896	0.896	0.898	0.896	0.896	0.898	0.896	0.896
ACD Conflict	0.256***			0.259***			0.261***		
	(0.06)			(0.064)			(0.06)		
ACD Post-Conflict	0.047			0.04			0.057		
	(0.058)			(0.059)			(0.056)		
WGI Instability		0.082**			0.083**			0.089**	
		(0.036)			(0.041)			(0.036)	
WGI Instability > Median			0.118**			0.115**			0.131**
			(0.051)			(0.056)			(0.052)
Log of DB Enforce Contract	0.344***	0.423***	0.416***	0.348***	0.428***	0.421***	0.325***	0.402***	0.395***
	(0.081)	(0.087)	(0.088)	(0.083)	(0.089)	(0.09)	(0.084)	(0.091)	(0.093)
Log of GDP per capita	NO	NO	NO	YES	YES	YES	NO	NO	NO
Log of GDP pc (1985)	NO	NO	NO	NO	NO	NO	YES	YES	YES
Obs.	3322	3322	3322	3322	3322	3322	3322	3322	3322
R^2	0.899	0.898	0.898	0.899	0.898	0.898	0.899	0.898	0.898

Notes: Dependent variable is the log of cost per km; all models control for work activity fixed effects, year fixed effects, an interaction between work type and 5-year period fixed effects and region fixed effects, dummy variables for actual and contracted costs, type of terrain, ruggedness, distance to the nearest ice-free coast, population density, log of surface area, dummy for lenght>50 km; robust standard errors in parentheses, clustered at the country; *, **, *** denote significance at 10%, 5% and 1% levels.

Contemporaneous GDP per capita and lagged GDP per capita are again added gradually to test the sensitivity of the results to its inclusion. All models also include baseline controls from the previous tables. The coefficient on the Public Investment Management Index is never significantly different from zero and its inclusion does not affect the size and significance of the conflict variables. The business environment reveals a more consistent correlation with road works costs. A 10% increase in the number of days it takes to enforce a contract, is associated with a 2-4% increase in unit costs, and the results are robust to including contemporaneous and lagged GDP per capita or excluding GDP per capita. Its inclusion slightly reduces the size of the conflict variables. The most direct measure of conflict from the ACD drops in size from a premium of 30.6% to 25.6% in column (1) when accounting for the business environment. The Worldwide Governance Indicator measure also slightly drops in size from 14% higher costs for countries above the median of political instability to 12% in column (3). The results are not sensitive to the inclusion of contemporaneous or lagged GDP per capita.

Table 4.10 shows the same exercise for corruption and table 4.11 shows the results including both conflict and corruption. Both the inclusion of the Public Investment Management Index and the Doing Business variable do not substantively affect the size nor the significance of the coefficients, suggesting that there is a significant association with corruption after controlling for the business environment and the public investment capacity. Overall, the findings suggest that our measure of the business environment explains some of the premium charged by firms operating in conflict countries with little effect of either of the two measures on corruption.

Table 4.10: Corruption - Omitted Variables

	TI	WGI	WGImed	TIII	WGIII	WGImedII	TIIII	WGIIII	WGImedIII
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TI Corruption	0.062***			0.062**			0.076***		
	(0.024)			(0.025)			(0.025)		
WGI Corruption		0.076*			0.068			0.093**	
		(0.044)			(0.051)			(0.044)	
WGI Corruption > Median			0.12**			0.113*			0.138***
			(0.053)			(0.064)			(0.053)
Public Investment Management Index	-.014	-.025	-.005	-.007	-.014	0.002	-.019	-.030	-.012
	(0.063)	(0.064)	(0.064)	(0.067)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)
Log of GDP per capita	NO	NO	NO	YES	YES	YES	NO	NO	NO
Log of GDP pc (1985)	NO	NO	NO	NO	NO	NO	YES	YES	YES
Obs.	3322	3322	3322	3322	3322	3322	3322	3322	3322
R^2	0.896	0.896	0.896	0.896	0.896	0.896	0.897	0.896	0.896
TI Corruption	0.06***			0.062***			0.07***		
	(0.02)			(0.023)			(0.021)		
WGI Corruption		0.096**			0.093*			0.108**	
		(0.042)			(0.053)			(0.043)	
WGI Corruption > Median			0.13***			0.127**			0.145***
			(0.048)			(0.06)			(0.049)
Log of DB Enforce Contract	0.425***	0.442***	0.442***	0.429***	0.446***	0.446***	0.396***	0.423***	0.42***
	(0.092)	(0.097)	(0.102)	(0.093)	(0.099)	(0.104)	(0.095)	(0.101)	(0.105)
Log of GDP per capita	NO	NO	NO	YES	YES	YES	NO	NO	NO
Log of GDP pc (1985)	NO	NO	NO	NO	NO	NO	YES	YES	YES
Obs.	3322	3322	3322	3322	3322	3322	3322	3322	3322
R^2	0.898	0.898	0.898	0.898	0.898	0.898	0.898	0.898	0.898

Notes: Dependent variable is the log of cost per km; all models control for work activity fixed effects, year fixed effects, an interaction between work type and 5-year period fixed effects and region fixed effects, dummy variables for actual and contracted costs, type of terrain, ruggedness, distance to the nearest ice-free coast, population density, log of surface area, dummy for lenght>50 km; robust standard errors in parentheses, clustered at the country; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 4.11: Conflict and Corruption - Omitted Variables

	TI	WGI	WGImed	TIII	WGIII	WGImedII	TIIII	WGIIII	WGImedIII
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TI Corruption	0.056**			0.059***			0.07***		
	(0.022)			(0.023)			(0.022)		
WGI Corruption		0.05			0.05			0.067	
		(0.044)			(0.047)			(0.043)	
WGI Corruption > Median			0.103**			0.101*			0.121**
			(0.049)			(0.056)			(0.048)
ACD Conflict	0.292***	0.293***	0.29***	0.303***	0.302***	0.3***	0.291***	0.292***	0.29***
	(0.059)	(0.062)	(0.061)	(0.06)	(0.064)	(0.062)	(0.058)	(0.061)	(0.059)
Public Investment Management Index	0.015	-.0009	0.021	0.025	0.014	0.03	0.009	-.007	0.013
	(0.054)	(0.055)	(0.056)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
Log of GDP per capita	NO	NO	NO	YES	YES	YES	NO	NO	NO
Log of GDP pc (1985)	NO	NO	NO	NO	NO	NO	YES	YES	YES
Obs.	3322	3322	3322	3322	3322	3322	3322	3322	3322
R^2	0.898	0.898	0.898	0.898	0.898	0.898	0.899	0.898	0.898
TI Corruption	0.051***			0.056**			0.062***		
	(0.02)			(0.023)			(0.02)		
WGI Corruption		0.066			0.068			0.078*	
		(0.041)			(0.05)			(0.042)	
WGI Corruption > Median			0.108**			0.109**			0.124***
			(0.044)			(0.054)			(0.044)
ACD Conflict	0.233***	0.234***	0.23***	0.243***	0.242***	0.24***	0.235***	0.235***	0.232***
	(0.054)	(0.056)	(0.054)	(0.055)	(0.057)	(0.055)	(0.053)	(0.056)	(0.053)
Log of DB Enforce Contract	0.342***	0.354***	0.357***	0.343***	0.357***	0.359***	0.311***	0.334***	0.333***
	(0.077)	(0.081)	(0.085)	(0.078)	(0.083)	(0.086)	(0.08)	(0.085)	(0.087)
Log of GDP per capita	NO	NO	NO	YES	YES	YES	NO	NO	NO
Log of GDP pc (1985)	NO	NO	NO	NO	NO	NO	YES	YES	YES
Obs.	3322	3322	3322	3322	3322	3322	3322	3322	3322
R^2	0.899	0.899	0.899	0.899	0.899	0.899	0.899	0.899	0.899

Notes: Dependent variable is the log of cost per km; all models control for work activity fixed effects, year fixed effects, an interaction between work type and 5-year period fixed effects and region fixed effects, dummy variables for actual and contracted costs, type of terrain, ruggedness, distance to the nearest ice-free coast, population density, log of surface area, dummy for lenght>50 km; robust standard errors in parentheses, clustered at the country; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 4.12 summarizes the effect of progressively adding the various controls using the Transparency International measure for corruption and the ACD measure of conflicts; baseline controls (not shown) from the model in column (1) of table 4.24 are always included. Column (3) shows that both the conflict variable as well as the corruption variable decrease in size when they are jointly included, suggesting that part of the higher costs of conflict affected countries is because these countries also have higher levels of corruption, and vice versa. The control for the number of days it takes to enforce a contract mainly reduces the correlation of unit costs and the conflict variable, leaving the coefficient on the corruption variable virtually unchanged. Finally, the Public Investment Management Index does not further affect the conflict and corruption effects.

Table 4.12: Incremental Specification

	eq1	eq2	eq3	eq4	eq5
	(1)	(2)	(3)	(4)	(5)
ACD Conflict	0.297***		0.283***	0.233***	0.235***
	(0.06)		(0.057)	(0.054)	(0.056)
TI Corruption		0.063***	0.051**	0.051***	0.054***
		(0.023)	(0.02)	(0.02)	(0.021)
Log of DB Enforce Contract				0.342***	0.382***
				(0.077)	(0.08)
Public Investment Management Index					-.029
					(0.053)
Obs.	3322	3322	3322	3322	3322
R^2	0.898	0.896	0.898	0.899	0.899

Notes: Regression includes all controls (not shown) from the base model in column (1) of table 4.24; dependent variable is the log of cost per km; all models control for work activity fixed effects, year fixed effects, an interaction between work type and 5-year period fixed effects; base categories are actual costs; robust standard errors in parentheses, clustered at the country; *, **, *** denote significance at 10%, 5% and 1% levels.

4.6.3 How do Costs relate to Provision?

The core of this chapter has been to investigate the relationship between unit costs, conflict and corruption. Finally, we investigate whether higher unit costs are associated with lower outcomes as measured by the log of kilometers of roads paved per person and the performance of a country in the quality of trade and transport related infrastructure index which measures the quality which measures the quality of trade infrastructure such as ports, railroads, roads and information technology. The data on the log of kilometers of roads paved per person is constructed from the three variables taken from the World Development Indicators: the kilometres of paved road, the percentage of roads paved, and the population. The quality of trade and transport related infrastructure index is part of the logistics performance index compiled by the World Bank. The underlying data of the index stem from online questionnaires completed by international logistics professionals who were asked to rate a the quality of various areas of logistics performance on an ordered scale from one (very low) to five (very high). About 800 logistics professionals responded to interviews, and each of them answered questions on 8 countries. For more information on the selection rule of countries for respondents see (Arvis et al. 2007). The subcomponent on trade infrastructure is one of six main indicators underlying the logistics performance index and is measured on a continuous scale between one and five[23].

As road work activities are heterogenous, we first want to net out variation that is related to the road work activity, time effects as well as region fixed effects. We can then use the residual of this cost regression as a measure of residual unit costs and use it as a control in a regression of provision on unit costs, and a vector of controls. We prefer to directly estimate the coefficient by regressing the outcome measure on unit costs, while controlling for the vector of controls employed in the baseline regression in column (1) of table 4.24. Table

Table 4.13: Correlation between Unit Costs and Infrastructure Provision

	pavedroad	infrastructure
	(1)	(2)
Log of Cost per km (2000 US$)	-.068**	-.042**
	(0.028)	(0.017)
Obs.	3322	3269
R^2	0.681	0.668

Notes: Dependent variable as follows: log of km of paved road per person in column (1); quality of trade and transport related infrastructure index in column (2); both equations include all controls employed in column (1) of table 4.24; standard errors are clustered at the country level; *, **, *** denote significance at 10%, 5% and 1% levels.

4.13 shows the correlation between unit costs and transport infrastructure outcomes. We find evidence that higher costs are associated with a worse infrastructure. A ten percent increase in unit costs is associated with a 0.68% reduction in the kilometers of paved roads per person in a country and a 0.4 reduction in the quality of trade and transport related infrastructure index component of the logistics performance index. At the median value (2.23) this change

[23] For access to the data see http://lpisurvey.worldbank.org/

corresponds to a move almost into the top quartile. The regression in table 4.13 includes the same controls as column (1) of table 4.24, but the results remain the same when we control for contemporaneous per capita GDP or per capita GDP in 1985.

4.6.4 Future Research

This section reviews our core results and discusses avenues for further research. First, one possible area of future research is to examine the mechanisms through which state fragility affects costs. In this chapter, we modeled this in the cost function as a premium that firms require to cover costs due to disruption and risk. However, an alternative explanation is that fewer firms are left in the market after conflicts as they get driven out of business; if the supply of firms providing road works decreases by more than the contraction of demand, this will lead to higher prices. In this context, a combination of insuring risks of construction firms in fragile states and lifting of constraints to firms entering the construction sector might be helpful to increase competition and to reduce unit costs. Little is known also about the evolution of prices in post-conflict settings when investment accelerates so that there is increased pressure on the construction sector, foreign companies are eager to enter the new market and there might be delays in tendering due to aid conditionalities[24]. Here the effect is ambiguous: if the growth in demand outstrips the growth in supply, prices will increase; if large foreign companies, which are able to operate on losses in the short run, undercut prices in order to enter a market, this might even lead to lower prices.

Second, our results present evidence that there is a correlation between corruption and unit costs and our simple theoretical framework assumed that this is due to bribe payments to officials to obtain permits. A main drawback of perception based measures is that they might reflect overall governance quality of a country rather than being specifically related to the level of corruption (Kenny 2009). Olken (2009) finds that for road projects in Indonesia, although perceptions are correlated with his estimate for corruption, the correlation is fairly weak. Country level perception measures also do not allow us to distinguish between the lev-

[24]The issues associated with the positive demand shock also apply to countries experiencing windfalls from natural resources that trigger spending booms.

els of corruption across different sectors, petty corruption vs grand corruption, cartellization of the industry, or misreporting of expenditures. Sector specific measures of corruption from firm level surveys would allow establishing a tighter link between corruption and unit costs of transport infrastructure as well as the extent of corruption.

Third, this chapter finds that the time it takes to enforce a contract is significantly correlated with costs. One interpretation of this finding is that the time it takes to enforce a contract reflects the strength of legal institutions in a country. If relational contracts allow the buyer to efficiently contract when courts are weak, but road contracts are allocated via a one stage sealed bid auction independent of the strength of the court system, governments in countries with weak law enforcement pay higher prices. This implies that there is scope for research into how companies which are honest and deliver efficiently could be rewarded positively, while not sacrificing competition[25].

This chapter was agnostic about several other determinants of unit costs: first, the costs of inputs into production, such as equipment, raw materials, as well as human resources. Information on input prices would allow a better understanding of which part of the premium experienced in conflict and corrupt countries is due to higher input prices, and which part is due to rents obtained by firms undertaking the road work activities[26] The construction sector PPP of the International Comparison Project 2011 has collected detailed information on a range of comparable input prices, which could be used as a first step to explore differences in unit costs across countries. Second, an important area this chapter did not tackle due to data limitations is the market structure of the local construction industry and collusion among construction sector firms[27]. Finally, this chapter and the main discussion was centered on

[25] Krasnokutskaya and Seim (2011) evaluate the effects of a bid preference programs for small firms bidding for highway projects in California and find that the preference program significantly affects firms decisions to submit bids, and raises project costs between 1.5-2.3% once endogenous entry to bid is taken into account. To reduce time overruns (amounting to 130% in Ethiopia, 106% in Tanzania and 97% in Malawi (Construction Sector Transparency Initiative 2011)), Lewis and Bajari (2011) suggest score based auctions which are designed to internalize the costs of time overruns to construction sector firms.

[26] Cartels do not only take place on the construction firm side, but also on the input side. For example, Hüschelrath et al. (2013) finds that cement prices dropped by 25% higher following the break-up of the German cement cartel.

[27] Data and analysis on market structure are scattered, for example see Lan (2010) for China and Dantata (2007) for Nigeria; Ofori (2007) underlines that in addition to the inadequate knowledge of the market structure

transport infrastructure. A better understanding of unit costs of construction of other types of projects, for example, residential and commercial housing, is another avenue for further research.

4.7 Conclusion

This chapter presented a first systematic analysis of drivers of unit costs across countries. Our analysis yielded five main findings. First, we showed that there is a large dispersion in unit costs across countries for comparable road work activities. For example, the difference between countries of an asphalt overlay of 40 to 59 mm amounts to a factor of three to four. Second, we found that after accounting for environmental drivers of costs such as terrain ruggedness and proximity to markets, residual unit costs are significantly higher in fragile countries. Countries which are in conflict have about 30% higher unit costs. This result is robust across a range of measures of conflict and political instability. Third, we also find evidence that costs are higher in countries with higher levels of corruption. Countries with corruption levels as measured by the World Governance Indicators above the median in the sample have about 12% higher costs. Given that corruption and collusive practices might be even higher for projects undertaken directly by governments without the need to respect procurement procedures of the World Bank, the higher costs in corrupt environments are potentially a lower bound of the estimate. Fourth, the premium charged by firms in conflict and corrupt countries remains when we control for the government's public investment capacity and the business environment. Finally, we found that higher unit costs are significantly associated with lower levels of infrastructure provision. Based on these findings, we laid out a research agenda.

of the local construction industry in developing countries, little attention has been given to the contribution of the informal sector to construction.

4.8 Appendix

4.8.1 Data Sources for Additional Variables

Ruggedness

Our measure of ruggedness is taken from Nunn and Puga (2012) which in turn is based on Riley et al (1999). It represents the average ruggedness of a country and is measured in hundreds of meters of elevation difference for grid points about 926 meters apart. The lowest level of ruggedness is in Mauritania with an index of 0.115, and the highest is Bhutan, with an index of 6.740.

Rainfall

Our measure for rainfall is taken from Dell et al. (2012) and is defined as population weighted country level precipitation in 100s millimeters.

Basic Socio-economic Data

For the total population, total surface area, and GDP per capita for each country we use the World Development Indicators.

Public Sector Management Capacity

To measure the capacity of the public sector to execute projects we use the Public Investment Management Index (PIMI) collected by Dabla-Norris et al. (2011). The Public Investment Management Index is measured on a scale from 0 to 4.

The Business Environment

To measure the business environment of the country, we use data from the Doing Business Indicators in 2007 and measure costs in terms of time the number it takes to enforce a contract. We use 2007 because this is the first year for which we have complete coverage.

Tables 4.14 shows the descriptive statistics of the control variables. Some variables are not available for the year of the construction project. We therefore distinguish between the following cases: first, if the variable is only available at one point of time we assign the available value to the construction project; second, if the variable is available for at least two years we distinguish between the following three cases: (i) when the construction project took place before the year the variable becomes available, we use data from the first year of the variable; (ii) when the construction project took place after the last time the explanatory variable is recorded, we then use the value of the last available observation; (iii) if the construction project took place in a year for which there are data points both before and after, we linearly interpolate the explanatory variable.

Table 4.14: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Road activity controls					
Cost per km (2000 US$)	261741.12	558093.15	50.57	7810495.02	3322
Estimate	0.44	0.5	0	1	3322
Contract	0.27	0.44	0	1	3322
Actual	0.28	0.45	0	1	3322
International Bid	0.63	0.48	0	1	1471
Proc info missing	0.56	0.5	0	1	3322
Length > than 50 km	0.37	0.48	0	1	2452
Missing: Length	0.26	0.44	0	1	3322
Flat	0.38	0.49	0	1	1587
Hilly	0.09	0.29	0	1	1587
Mountainous	0.27	0.44	0	1	1587
Rolling	0.26	0.44	0	1	1587
Missing: Terrain	0.52	0.5	0	1	3322
Geographic controls					
Log Ruggedness	4.46	0.92	2.44	6.51	3322
Log of Rainfall	2.43	0.5	0.36	3.62	3319
Missing: Rainfall	0	0.03	0	1	3322
Log dist to coast	-1.45	1.21	-5.85	0.79	3322
Log of Surface Area	6.17	1.65	0.62	9.75	3322
Population Density	1.43	2	0.02	9.76	3322
Log of GDP per capita	6.72	1.14	4.53	9.07	3310
Missing: Log of GPD per capita	0	0.06	0	1	3322
Log of GDP pc (1985)	6.39	1.17	4.76	8.72	2985
Missing: Log of GPD pc (1985)	0.1	0.3	0	1	3322
East Asia & Pacific	0.21	0.41	0	1	3322
Europe & Central Asia	0.09	0.28	0	1	3322
Latin America & Caribbean	0.24	0.42	0	1	3322
Middle East & North Africa	0.03	0.17	0	1	3322
South Asia	0.14	0.35	0	1	3322
Sub-Saharan Africa	0.29	0.46	0	1	3322
Conflict and corruption controls					
ACD Conflict	0.25	0.43	0	1	3322
ACD Post-Conflict	0.12	0.32	0	1	3322
WGI Instability	0.56	0.63	-1.26	2.21	3322
TI Corruption	3.91	1	0.1	5.60	3318
Missing: TI Corruption	0	0.03	0	1	3322
WGI Corruption	0.48	0.46	-1.45	1.6	3322
WGI Corruption > Median	0.51	0.5	0	1	3322
Public investment capacity and DB controls					
Public Investment Management Index	1.92	0.6	0.27	3.53	2113
Missing: Public Investment Management Index	0.36	0.48	0	1	3322
Log of DB Start Business	3.64	0.62	1.79	5.31	3322
Log of DB Construction Permit	5.31	0.52	0	6.51	3322
Log of DB Register Property	3.98	1.16	0.69	6.53	3322
Log of DB Import+Export	4.08	0.42	2.89	5.19	3322
Log of DB Enforce Contract	5.39	2.2	0	6.89	3322

4.8.2 Tables and Figures

Table 4.15: Preservation Works

Work Class	Work Type	Predominant Work Activity
Routine	Routine Maintenance	Routine Maintenance Earth Road Routine Maintenance Gravel Road Routine Maintenance Block 2L Highway Routine Maintenance Bituminous 2L Highway Routine Maintenance Concrete 2L Highway Routine Maintenance Bituminous > 2L Highway Routine Maintenance Concrete > 2L Highway Routine Maintenance Bituminous Expressway Routine Maintenance Concrete Expressway
Periodic	Grading	Light Grading Heavy Grading
	Gravel Resurfacing	Regravelling
	Concrete Pavement Preventive Treatment	Concrete Pavement Preventive Treatment
	Bituminous Pavement Preventive Treatment	Fog Seal Rejuvenation
	Unsealed Preventive Treatment	Unsealed Preventive Treatment
	Surface Treatment Resurfacing	Slurry Seal or Cape Seal Single Surface Treatment Double Surface Treatment Triple Surface Treatment
	Asphalt Mix Resurfacing	Asphalt Overlay < 40 mm Asphalt Overlay 40 to 59 mm
Rehabilitation	Strengthening	Asphalt Overlay 60 to 79 mm Asphalt Overlay 80 to 99 mm Asphalt Overlay > 99 mm Mill and Replace Bonded Concrete Overlay Unbounded Concrete Overlay
	Concrete Pavement Restoration	Concrete Slab Replacement Concrete Slab Repair Concrete Diamond Grinding
	Reconstruction	Reconstruction Earth Reconstruction Gravel Reconstruction Block Reconstruction Bituminous Reconstruction Concrete

Table 4.16: Development Works

Work Class	Work Type	Predominant Work Activity
Improvement	Partial Widening	Partial Widening to Gravel 2L Partial Widening to Block 2L Partial Widening to Bituminous 2L Partial Widening to Concrete 2L
	Partial Widening and Reconstruction	Partial Widening and Reconstruction to Gravel 2L Partial Widening and Reconstruction to Block 2L Partial Widening and Reconstruction to Bituminous 2L Partial Widening and Reconstruction to Concrete 2L
	Widening	Widening Adding Bituminous 1L Widening Adding Bituminous 2L Widening Adding Bituminous 4L Widening Adding Concrete 1L Widening Adding Concrete 2L Widening Adding Concrete 4L
	Widening and Reconstruction	Widening and Reconstruction Adding Bituminous 1L Widening and Reconstruction Adding Bituminous 2L Widening and Reconstruction Adding Bituminous 4L Widening and Reconstruction Adding Concrete 1L Widening and Reconstruction Adding Concrete 2L Widening and Reconstruction Adding Concrete 4L
	Upgrading	Upgrading to Earth 2L Upgrading to Gravel 2L Upgrading to Block 2L Upgrading to Bituminous 2L Upgrading to Concrete 2L
New Construction	New 1L Road	New Earth 1L Road New Gravel 1L Road New Block 1L Road New Bituminous 1L Road New Concrete 1L Road
	New 2L Highway	New Earth 2L Highway New Gravel 2L Highway New Block 2L Highway New Bituminous 2L Highway New Concrete 2L Highway
	New 4L Highway	New Bituminous 4L Highway New Concrete 4L Highway
	New 6L Highway	New Bituminous 6L Highway New Concrete 6L Highway
	New 4L Expressway	New Bituminous 4L Expressway New Concrete 4L Expressway
	New 6L Expressway	New Bituminous 6L Expressway New Concrete 6L Expressway

Table 4.17: Cost per km for Different Work Types, by Work Category

Development						
	N	mean	p50	sd	min	max
New 6L Expressway	1	5,571,488	5,571,488	.	5,571,488	5,571,488
New 4L Expressway	65	2,838,562	2,495,592	1,474,420	937,499	7,810,495
New 4L Highway	11	2,195,810	2,213,333	1,159,299	660,242	4,561,035
New 6L Highway	2	1,990,155	1,990,155	991,449	1,289,094	2,691,215
Widening and Reconstruction	108	874,209	776,071	752,950	178,494	6,532,523
Widening	138	842,697	776,071	742,325	8,751	5,785,612
New 2L Highway	68	750,396	696,537	399,828	22,403	1,985,876
Partial Widening and Reconstruct	117	261,380	252,202	129,635	8,219	682,508
Upgrading	360	250,472	218,863	171,322	3,551	940,837
Partial Widening	12	137,773	148,321	29,027	67,299	168,278
New 1L Road	7	91,788	81,244	36,153	58,151	167,702
Total	889	678,283	358,293	930,798	3,551	7,810,495

Preservation						
	N	mean	p50	sd	min	max
Concrete Pavement Restoration	4	539,348	650,623	321,650	68,558	787,587
Reconstruction	745	220,287	169,668	209,577	1,973	2,615,657
Strengthening	422	139,371	120,799	75,097	27,473	553,857
Asphalt Mix Resurfacing	458	64,551	60,356	29,538	12,350	211,000
Surface Treatment Resurfacing	230	25,090	18,767	23,520	3,409	176,682
Gravel Resurfacing	275	18,169	13,198	15,765	1,872	112,950
Bituminous Pavement Preventive Treatment	47	7,355	5,534	6,190	1,147	30,653
Unsealed Preventive Treatment	101	4,347	4,385	1,319	2,009	8,402
Routine Maintenance	119	2,144	1,897	1,383	277	8,685
Grading	23	515	151	771	51	2,542
Total	2,424	109,930	67,561	149,738	51	2,615,657

Table 4.18: Cost per km for Development Works, by Work Activity

Development work activity	N	mean	p50	sd	min	max
New Bituminous 6L Expressway	1	5,571,488	5,571,488	.	5,571,488	5,571,488
Widening Adding Bituminous 4L	2	4,643,333	4,643,333	1,615,426	3,501,055	5,785,612
New Bituminous 4L Expressway	65	2,838,562	2,495,592	1,474,420	937,499	7,810,495
New Concrete 4L Highway	1	2,213,333	2,213,333	.	2,213,333	2,213,333
New Bituminous 4L Highway	10	2,194,058	2,177,899	1,221,993	660,242	4,561,035
New Bituminous 6L Highway	2	1,990,155	1,990,155	991,449	1,289,094	2,691,215
Adding Bituminous 4L	8	1,855,587	1,832,513	186,580	1,568,359	2,088,700
Widening Adding Concrete 1L	2	1,641,940	1,641,940	21,358	1,626,837	1,657,043
New Block 2L Highway	1	1,264,231	1,264,231	.	1,264,231	1,264,231
Widening and Reconstruction Adding Bituminous 2L	61	1,085,967	989,080	790,232	241,875	6,532,523
New Bituminous 2L Highway	43	828,245	764,706	378,909	224,882	1,985,876
Widening Adding Bituminous 2L	120	812,194	611,882	573,139	163,469	3,497,181
Widening Adding Concrete 2L	2	626,842	626,842	163,489	511,238	742,446
New Concrete 2L Highway	4	467,990	460,773	61,948	408,051	542,364
Widening and Reconstruction Adding Bituminous 1L	36	304,665	257,007	126,310	178,494	616,324
Upgrading to Concrete 2L	13	302,035	356,189	149,254	55,523	465,583
Upgrading to Bituminous 2L	283	276,508	241,148	166,059	29,897	940,837
Partial Widening and Reconstruction to Bituminous 2L	114	267,427	259,679	125,657	28,052	682,508
Widening Adding Bituminous 1L	7	265,241	260,115	287,751	8,751	702,651
Upgrading to Block 2L	13	168,742	165,477	66,341	42,710	325,644
Partial Widening to Bituminous 2L	12	137,773	148,321	29,027	67,299	168,278
New Gravel 2L Highway	5	124,079	111,650	103,110	22,403	232,864
New Gravel 1L Road	2	112,926	112,926	77,464	58,151	167,702
New Bituminous 1L Road	1	99,800	99,800	.	99,800	99,800
New Earth 1L Road	4	79,215	76,864	9,152	71,800	91,335
Upgrading to Gravel 2L	32	58,825	52,491	32,724	15,940	161,949
Partial Widening and Reconstruction to Gravel 2L	3	31,614	13,288	36,219	8,219	73,334
Upgrading to Earth 2L	6	12,683	13,432	6,593	3,551	20,377
Total	853	682,288	348,307	947,126	3,551	7,810,495

Table 4.19: Cost per km for Preservation Works, by Work Activity

Preservation work activity	N	mean	p50	sd	min	max
Concrete Slab Replacement	3	696,277	684,879	86,177	616,367	787,587
Reconstruction Bituminous	595	247,848	196,167	216,894	20,165	2,615,657
Reconstruction Concrete	31	236,432	222,319	119,577	50,890	487,139
Asphalt Overlay > 99 mm	91	183,925	167,059	76,022	56,275	478,158
Asphalt Overlay 80 to 99 mm	140	136,484	118,752	70,626	38,583	553,857
Mill and Replace	38	130,524	105,147	76,856	48,892	353,720
Asphalt Overlay 60 to 79 mm	54	91,572	87,437	30,920	27,473	180,761
Asphalt Overlay 40 to 59 mm	298	71,637	69,905	27,668	20,073	211,000
Reconstruction Block	2	51,816	51,816	37,039	25,626	78,007
Reconstruction Gravel	86	44,158	39,356	28,482	5,086	131,778
Asphalt Overlay < 40 mm	81	41,963	38,078	17,396	12,350	95,148
Double Surface Treatment	71	31,918	29,446	21,376	10,246	176,682
Single Surface Treatment	61	21,431	18,254	14,773	5,295	106,457
Double Surface Treatment	2	21,351	21,351	11,604	13,146	29,556
Reconstruction Earth	7	20,834	17,724	17,029	1,973	56,561
Regravelling	233	16,420	12,242	13,397	1,872	65,038
Slurry Seal or Cape Seal	48	13,917	10,575	9,230	3,409	35,805
Fog Seal	9	8,313	6,915	4,612	2,805	15,783
Unsealed Preventive Treatment	99	4,277	4,343	1,236	2,009	8,402
Routine Maintenance Block 2L Highway	2	2,728	2,728	1,736	1,500	3,956
Routine Maintenance Bituminous > 2L Highway	2	2,241	2,241	1,797	970	3,512
Routine Maintenance Bituminous 2L Highway	71	2,232	1,964	1,232	332	5,580
Routine Maintenance Concrete 2L Highway	1	1,483	1,483	.	1,483	1,483
Routine Maintenance Earth Road	2	1,185	1,185	1,216	325	2,045
Heavy Grading	9	1,144	591	948	323	2,542
Routine Maintenance Gravel Road	17	1,110	1,229	616	277	2,042
Light Grading	14	111	110	47	51	205
Total	2,067	116,228	71,896	156,977	51	2,615,657

Table 4.20: List of Countries (1)

	1984-1990	1991-1995	1995-2000	2001-2005	2005-2008	Total
Afghanistan	0	0	0	12	0	12
Albania	0	5	31	20	3	59
Algeria	0	3	3	0	0	6
Angola	0	0	0	8	0	8
Argentina	0	64	17	15	19	115
Armenia	0	3	48	0	0	51
Azerbaijan	0	0	0	2	0	2
Bangladesh	0	49	110	29	0	188
Belize	0	0	0	3	0	3
Benin	0	0	0	2	0	2
Bhutan	0	0	0	4	3	7
Bolivia	2	4	20	11	0	37
Bosnia and Herzegovina	0	0	0	1	7	8
Botswana	0	1	0	0	4	5
Brazil	8	42	33	32	33	148
Bulgaria	0	0	0	0	6	6
Burkina Faso	0	0	0	24	2	26
Burundi	0	0	0	3	2	5
Cambodia	0	0	0	11	4	15
Cameroon	0	4	12	13	0	29
Cape Verde	0	7	0	8	0	15
Chad	0	2	0	3	0	5
Chile	9	12	11	0	7	39
China	1	25	37	61	5	129
Colombia	0	13	0	0	0	13
Comoros	0	0	2	0	0	2
Congo	0	0	0	0	1	1
Costa Rica	0	0	6	0	0	6
Dem. Rep. Congo	0	0	0	16	1	17
Djibouti	0	0	5	6	0	11
Dominican Republic	1	4	36	2	0	43
Ecuador	0	1	0	12	0	13
El Salvador	0	0	4	0	0	4
Ethiopia	0	0	38	33	3	74
Fiji	0	0	1	0	0	1
Georgia	0	0	0	3	3	6
Ghana	2	29	217	38	1	287
Guatemala	0	3	0	0	0	3
Guinea	0	1	0	9	0	10
Haiti	0	0	1	7	0	8
Honduras	0	12	6	0	14	32
India	13	7	84	63	11	178
Indonesia	0	9	8	21	1	39
Iran	0	0	0	0	1	1
Jamaica	0	1	0	0	0	1
Jordan	0	4	4	0	0	8
Kazakhstan	0	0	17	7	0	24
Kenya	0	1	0	34	6	41
Kyrgyz Republic	0	2	5	7	0	14
Lao PDR	3	10	35	46	6	100

Table 4.21: List of Countries (cont.)

	1984-1990	1991-1995	1995-2000	2001-2005	2005-2008	Total
Latvia	0	0	6	0	0	6
Lebanon	0	14	9	25	0	48
Lesotho	0	0	4	3	0	7
Lithuania	0	0	5	0	0	5
Macedonia	0	0	2	13	3	18
Madagascar	0	1	1	8	0	10
Malawi	0	3	0	15	0	18
Malaysia	0	1	0	0	0	1
Mali	0	2	3	2	1	8
Mauritania	0	0	0	1	0	1
Mauritius	0	2	0	0	0	2
Mexico	3	8	49	2	0	62
Moldova	0	0	0	0	2	2
Mongolia	0	0	1	7	0	8
Morocco	0	2	0	2	0	4
Mozambique	0	0	0	21	3	24
Namibia	0	0	0	3	0	3
Nepal	0	8	7	7	7	29
Nicaragua	0	8	11	20	0	39
Niger	0	0	3	6	1	10
Nigeria	0	11	22	11	9	53
Pakistan	0	0	22	34	0	56
Panama	0	0	12	33	0	45
Papua New Guinea	0	4	1	29	0	34
Paraguay	0	5	5	13	0	23
Peru	0	14	8	5	0	27
Philippines	5	26	61	52	10	154
Romania	0	0	1	3	0	4
Russia	0	44	17	0	0	61
Rwanda	0	0	0	1	5	6
Samoa	0	0	1	0	0	1
Senegal	0	0	3	14	0	17
Serbia	0	1	0	0	0	1
Sierra Leone	0	6	0	7	0	13
South Africa	0	0	0	3	0	3
Sri Lanka	0	0	4	0	0	4
Swaziland	0	0	0	1	0	1
Tanzania	0	2	25	8	1	36
Thailand	0	29	116	25	0	170
Tunisia	0	6	2	4	0	12
Turkey	0	0	2	24	0	26
Uganda	0	11	173	18	0	202
Uruguay	0	11	61	0	0	72
Venezuela	0	1	47	1	0	49
Vietnam	0	3	14	18	7	42
West Bank and Gaza	0	0	3	0	0	3
Yemen	1	4	3	2	0	10
Zambia	0	16	0	15	0	31
Zimbabwe	0	4	0	0	0	4
Total	48	565	1,495	1,022	192	3,322

Table 4.22: Unit Costs per Square Meter of Asphalt Overlays 40 to 59 mm

Country	Cost per Square Meter	Number	Year	Country	Cost per Square Meter	Number	Year
Work activities undertaken between 1996-1998							
Dominican Republic	4.8	1	1997	Argentina	10.3	1	1996
Lithuania	6.1	1	1996	Cameroon	10.5	4	1997
Ghana	6.1	5	1998	India	10.5	3	1997
Lithuania	6.8	1	1998	Bangladesh	10.8	26	1998
Indonesia	6.9	1	1996	Vietnam	11.4	2	1998
Mexico	7.0	1	1997	Bangladesh	11.5	1	1997
Ghana	7.5	1	1996	Panama	11.5	1	1997
Armenia	8.3	1	1997	Nigeria	13.0	1	1997
Brazil	8.6	2	1996	Pakistan	14.4	1	1997
Bolivia	9.2	1	1997	El Salvador	14.6	1	1998
Argentina	9.6	1	1997	Tanzania	14.9	1	1996
Brazil	10.2	1	1998				

Notes: Costs per square meter of asphalt overlays 40 to 59 mm; all costs are in 2000 US$; number denotes the number of contracts in a given country over which a simple average is taken.

Table 4.23: Differences in Unit Costs across different Work Types

	eq1	eq2
	(1)	(2)
Preservation Works		
Routine Maintenance	-4.289***	-4.256***
	(0.143)	(0.174)
Grading	-6.396***	-6.305***
	(0.352)	(0.374)
Gravel Resurfacing	-2.275***	-2.207***
	(0.117)	(0.159)
Bituminous Pavement Preventive Treatment	-3.076***	-2.989***
	(0.134)	(0.18)
Unsealed Preventive Treatment	-3.375***	-3.441***
	(0.179)	(0.193)
Surface Treatment Resurfacing	-1.981***	-1.917***
	(0.135)	(0.185)
Asphalt Mix Resurfacing	-.848***	-.862***
	(0.092)	(0.143)
Strengthening	-.117	-.174
	(0.085)	(0.15)
Concrete Pavement Restoration	1.000	1.045*
	(0.629)	(0.553)
Reconstruction	0.073	0.029
	(0.102)	(0.157)
Development Works		
Partial Widening and Reconstruction	0.258	0.405***
	(0.224)	(0.151)
Widening	1.410***	1.415***
	(0.171)	(0.21)
Widening and Reconstruction	1.539***	1.485***
	(0.142)	(0.188)
Upgrading	0.271**	0.229
	(0.118)	(0.162)
New 1L Road	-.349**	-.027
	(0.148)	(0.191)
New 2L Highway	1.529***	1.450***
	(0.199)	(0.245)
New 2L Highway	1.529***	1.450***
	(0.199)	(0.245)
New 4L Highway	2.542***	2.502***
	(0.297)	(0.305)
New 6L Highway	2.464***	2.405***
	(0.097)	(0.162)
New 4L Expressway	2.824***	2.735***
	(0.072)	(0.156)
New 6L Expressway	3.682***	3.406***
	(0.127)	(0.224)
Obs.	3322	3322
R^2	0.83	0.841

Notes: Omitted category is partial widening; column (1) includes year dummies and contract characteristics included in all models; column (2) also includes country characteristics; standard errors brackets, clustered at the country level; *, **, *** denote significance at 10%, 5% and 1% levels.

Table 4.24: Baseline Results

	BASEI	BASEII	BASEIII
	(1)	(2)	(3)
Estimate	-.024 (0.059)	-.022 (0.058)	-.020 (0.058)
Contract	-.080 (0.054)	-.085 (0.055)	-.078 (0.054)
Geography			
Log Ruggedness	0.155*** (0.035)	0.151*** (0.037)	0.157*** (0.036)
Log of Rainfall	-.028 (0.07)	-.041 (0.071)	-.036 (0.071)
Log dist to coast	-.023 (0.051)	-.040 (0.054)	-.020 (0.051)
Population Density	0.105*** (0.019)	0.103*** (0.02)	0.107*** (0.02)
Log of Surface Area	0.081*** (0.022)	0.092*** (0.024)	0.081*** (0.022)
Length > than 50 km	-.093** (0.038)	-.105*** (0.039)	-.096** (0.039)
Log of GDP per capita		-.056 (0.038)	
Log of GDP pc (1985)			-.005 (0.046)
Pilot Country	-.095 (0.074)	-.096 (0.079)	-.099 (0.075)
East Asia & Pacific	-.490*** (0.096)	-.449*** (0.107)	-.486*** (0.103)
Europe & Central Asia	-.133 (0.09)	-.060 (0.103)	-.076 (0.105)
Latin America & Caribbean	-.175* (0.098)	-.066 (0.127)	-.167 (0.141)
Middle East & North Africa	-.438*** (0.106)	-.340** (0.141)	-.372*** (0.113)
South Asia	-.445*** (0.114)	-.431*** (0.121)	-.455*** (0.115)
Obs.	3322	3322	3322
R^2	0.896	0.896	0.896

Notes: Dependent variable is the log of cost per km; all models control for work activity fixed effects, year fixed effects, an interaction between work type and 5-year period fixed effects; base categories are actual costs; robust standard errors in parentheses, clustered at the country; *, **, *** denote significance at 10%, 5% and 1% levels.

Chapter 5

Conclusion

This thesis analyzed the labor market effects of a large earthquake in Indonesia, intra-household allocation of consumption and leisure among siblings in Ethiopia, Peru, India and Vietnam, and differences in the unit costs of road infrastructure in 99 low and middle income countries. To conclude, I briefly summarize each chapter.

The first chapter explored the labor market effects of a large earthquake in Indonesia. We argued that the natural disaster can be thought of leading to two types of shocks to the labor market: a *destruction shock* due to the immediate effect of the disaster, and a *reconstruction shock* in the recovery phase. The strength of these two forces determines the overall effect on the labor market and economy. We combined a comprehensive data set including data from the Indonesia Family Life Survey, the Desinventar database, the US Geological Survey and district level employment indicators and showed that the large destructive shock resulted in significantly higher wage growth for agricultural workers. This result is robust to a range of identifying assumptions. We proposed two mechanisms for this result: a higher growth rate of the price of rice in agricultural communities which switch from being net sellers to net buyers of rice and a downward shift in the supply of workers in the agricultural sector. We showed evidence for both mechanisms. This is important as the damage from natural disasters has been rising in the past two decades (United Nations and World Bank 2010) and labor markets play a vital role in determining individual's and household's welfare. In order to optimally design responses, it is therefore crucial to understand the labor market consequences of such shocks. We pointed towards avenues of future research. These include examining labor market responses of natural disasters, in different contexts, for different types of shocks, over longer time horizons and examining the role of aid inflows separately from the destruction shock.

The second chapter investigated the intra-household allocation of leisure and consumption among siblings. The paper considered children as agents with their own preferences over leisure and consumption and builds a theoretical and empirical model for children's time and consumption allocations in a household. We tested the predictions of the model with data from Ethiopia, India, Peru and Vietnam which contain detailed information on time use and allocations of assignable goods for sibling pairs. We found that conditioning on observable variables, the residuals of these simultaneous decisions are significantly negatively correlated. This suggests that differences in siblings' relative time and consumption allocations are driven by their relative preferences over leisure and consumption rather than differences in parents' relative altruism. Families seem to function as market economies in which children trade off leisure and consumption, select their optimal bundle, and are rewarded by their parents accordingly. This finding implies that in order to understand household behavior in low income countries, children should be treated as agents. Our analysis focused on families with two children in four countries. Future research should extend the analysis to families with more than two children and application to further countries.

The third chapter examined differences in unit costs of transport infrastructure. To our knowledge, this is the first paper that examines drivers of unit costs of construction of transport infrastructure with a large dataset of 3,322 unit costs of road work activities in 99 low and middle income countries. We found that: (i) there is a large dispersion in unit costs for comparable road work activities; (ii) after accounting for environmental drivers of costs such as terrain ruggedness and proximity to markets, residual unit costs are significantly higher in fragile countries; (iii) there is evidence that costs are higher in countries with higher levels of corruption; (iv) these effects are robust to controlling for a country's public investment capacity and business environment; (v) higher unit costs are significantly negatively correlated with infrastructure provision. Given the limited research available in this field, we suggested a number of avenues for future research. These include modeling different aspects of the costs of conflict and corruption than we do, researching the effectiveness of different policies to limit various forms of corruption, the role of input prices, and a better knowledge of the construction sector in general.

Bibliography

AFRICON (2008). Unit costs of infrastructure projects in sub-saharan africa, africa infrastructure country diagnostic. Background Paper No. 11 (Phase I) Africa Infrastructure Country Diagnostic, The World Bank.

Ahmed, F. Z. (2013). Remittances deteriorate governance. *Review of Economics and Statistics 95*(4), 1166–1182.

Alesina, A. and B. Weder (2002). Do corrupt governments receive less foreign aid? *The American Economic Review 92*(4), 1126–1137.

Alexeeva, V., C. Queiroz, and S. Ishihara (2008). Monitoring road works contracts and unit costs for enhanced governance in sub-saharan africa. Transport Paper 21, The World Bank.

Alexeeva, V., C. Queiroz, and S. Ishihara (2011). Monitoring road works contracts and unit costs for enhanced governance in europe and central asia. Transport Paper 33, The World Bank.

Alvarez-Cuadrado, F. and M. Poschke (2011, September). Structural change out of agriculture: Labor push versus labor pull. *American Economic Journal: Macroeconomics 3*(3), 127–58.

Andersen, S., S. Ertac, U. Gneezy, J. A. List, and S. Maximiano (2013). Gender, competitiveness and socialization at a young age: evidence from a matrilineal and a patriarchal society. *Review of Economics and Statistics 95*(4), 1438–1443.

Angrist, J. D. and J.-S. Pischke (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Arvis, J.-F., M. Mustra, L. Ojala, T. Naula, and J. Panzer (2007). Connecting to compete - trade logistics in the global economy: The logistics performance index and its indicators.

Attanasio, O., E. Fitzsimons, A. Gomez, M. I. Gutierrez, C. Meghir, and A. Mesnard (2010). ChildrenŠs schooling and work in the presence of a conditional cash transfer program in rural colombia. *Economic Development and Cultural Change 58*(2), 181–210.

Attanasio, O. and V. Lechene (2002). Tests of income pooling in household decisions. *Review of Economic Dynamics 5*(4), 720–748.

Baez, J. and I. Santos (2008). On shaky ground: The effects of earthquakes on household income and poverty. RPP-LAC - MDGs and Poverty - 02/2008, RBLAC-UNDP, New York.

Bandiera, O., A. Prat, and T. Valletti (2009). Active and passive waste in government spending: Evidence from a policy experiment. *The American Economic Review 99*(4), 1278–1308.

Banerjee, A., S. Mullainathan, and R. Hanna (2012). Corruption. NBER Working Paper No. 17968.

BAPPENAS (2006). Preliminary Damage and Loss Assessment: Yogyakarta and Central Java Natural Disaster. Report prepared for the 15th Meeting of the Consultative Group on Indonesia, Jakarta, June 14, 2006.

Basu, K. (2006). Gender and say: a model of household behaviour with endogenously determined balance of power. *The Economic Journal 116*(511), 558–580.

Basu, K. and H. Zarghamee (2009). Is product boycott a good idea for controlling child labor? a theoretical investigation. *Journal of Development Economics 88*(2), 217–220.

Becker, G. (1981). *A Treatise on the Family*. Harvard Univ Press.

Becker, G. S. and H. G. Lewis (1973, Part II,). On the interaction between the quantity and quality of children. *Journal of Political Economy 81*(2), S279–88.

Becker, G. S. and N. Tomes (1976). Child endowments and the quantity and quality of children. *The Journal of Political Economy 84*(4), S143–S162.

Behrman, J. R. (1997). Intrahousehold distribution and the family. *Handbook of Population and Family Economics 1*, 125–187.

Behrman, J. R., R. A. Pollak, and P. Taubman (1982). Parental preferences and provision for progeny. *The Journal of Political Economy*, 52–73.

Behrman, J. R., R. A. Pollak, and P. Taubman (1995). *From parent to child: Intrahousehold allocations and intergenerational relations in the United States*. University of Chicago Press.

Behrman, J. R., M. R. Rosenzweig, and P. Taubman (1994). Endowments and the allocation of schooling in the family and in the marriage market: the twins experiment. *Journal of Political Economy*, 1131–1174.

Belasen, A. R. and S. Polachek (2009). How Disasters Affect Local Labor Markets: The Effects of Hurricanes in Florida. *Journal of Human Resources 44*(1), 251.

Belasen, A. R. and S. W. Polachek (2008, May). How hurricanes affect wages and employment in local labor markets. *American Economic Review 98*(2), 49–53.

Benamghar, R. and A. Iimi (2011). Efficiency in public procurement in rural road projects of nepal. World Bank Policy Research Working Paper 5736.

Benson, C. and E. Clay (2004). *Understanding the economic and financial impacts of natural disasters*. World Bank Publications.

Black, D., T. McKinnish, and S. Sanders (2005). The Economic Impact Of The Coal Boom And Bust. *The Economic Journal 115*(503), 449–476.

Blattman, C. and E. Miguel (2010). Civil war. *Journal of Economic Literature 48*(1), 3–57.

Blundell, R., P.-A. Chiappori, and C. Meghir (2005, December). Collective labor supply with children. *Journal of Political Economy 113*(6), 1277–1306.

BNPB et al (2009). West sumatra and jambi natural disasters: Damage, loss and preliminary needs assessment. Joint report by the BNPB, Bappenas, and the Provincial and District/City Governments of West Sumatra and Jambi and international partners.

Board, S. (2011). Relational contracts and the value of loyalty. *American Economic Review 101*(7), 3349.

Bobonis, G. (2009). Is the allocation of resources within the household efficient? New evidence from a randomized experiment. *Journal of Political Economy 117*(3), 453–503.

Bonke, J. and M. Browning (2011). Spending on children: Direct survey evidence. *The Economic Journal 121*(554), F123–F143.

Browning, M. (1992). Children and household economic behavior. *Journal of Economic Literature*, 1434–1475.

Browning, M., F. Bourguignon, P. Chiappori, and V. Lechene (1994). Income and outcomes: a structural model of intrahousehold allocation. *Journal of Political Economy 102*(6), 1067–1096.

Browning, M. and P. Chiappori (1998). Efficient intra-household allocations: A general characterization and empirical tests. *Econometrica 66*(6), 1241–1278.

Browning, M., P. Chiappori, and Y. Weiss (2011). Family Economics. Unpublished Textbook Manuscript, Tel Aviv University.

Browning, M. and M. Ejrnæs (2009). Consumption and children. *The Review of Economics and Statistics 91*(1), 93–111.

Browning, M. and M. Gørtz (2012). Spending time and money within the household. *The Scandinavian Journal of Economics 114*(3), 681–704.

Browning, M. and V. Lechene (2003). Children and demand: direct and non-direct effects. *Review of Economics of the Household 1*(1), 9–31.

Burgess, R., M. Hansen, B. A. Olken, P. Potapov, and S. Sieber (2012). The political economy of deforestation in the tropics*. *The Quarterly Journal of Economics 127*(4), 1707–1754.

Buys, P., U. Deichmann, and D. Wheeler (2010). Road network upgrading and overland trade expansion in sub-saharan africa. *Journal of African Economies 19*(3), 399–432.

Cameron, A. C. and P. K. Trivedi (2005). *Microeconometrics: methods and applications*. Cambridge University Press.

Carrington, W. (1996). The Alaskan labor market during the pipeline era. *Journal of Political Economy 104*(1), 186–218.

Castillo, M., P. J. Ferraro, J. L. Jordan, and R. Petrie (2011). The today and tomorrow of kids: Time preferences and educational outcomes of children. *Journal of Public Economics 95*(11), 1377–1385.

Chang, Y. (2009). Strategic altruistic transfers and rent seeking within the family. *Journal of Population Economics 22*(4), 1081–1098.

Chang, Y.-M. and Z. Luo (2011). Endogenous division rules as a family constitution: Strategic altruistic transfers and sibling competition. mimeo.

Cherchye, L., B. De Rock, and F. Vermeulen (2012, September). Married with children: A collective labor supply model with detailed time use and intrahousehold expenditure information. *American Economic Review 102*(7), 3377–3405.

Chesnokova, T. and R. Vaithianathan (2008). Lucky last? intra-sibling allocation of child labor. *The BE Journal of Economic Analysis & Policy 8*(1).

Chiappori, P. (1988). Rational household labor supply. *Econometrica: Journal of the Econometric Society*, 63–90.

Collier, P. and J. Gunning (1999). *Trade Shocks in Developing Countries: Africa*. Oxford University Press, USA.

Compte, O., A. Lambert-Mogiliansky, and T. Verdier (2005). Corruption and competition in procurement auctions. *Rand Journal of Economics*, 1–15.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of econometrics 92*(1), 1–45.

Construction Sector Transparency Initiative (2011). Report on baseline studies: International comparison. Technical report, Construction Sector Transparency Initiative.

Conti, G., J. J. Heckman, J. Yi, and J. Zhang (2010). Early health shocks, parental responses, and child outcomes. Unpublished manuscript.

Corden, W. (1984). Booming sector and Dutch disease economics: survey and consolidation. *Oxford Economic Papers 36*(3), 359–380.

Corden, W. and P. Neary (1982). Booming sector and de-industrialization in a small open economy. *Economic Journal 92*, 368.

Crook, M. (1937). Intra-family relationships in personality test performance. *The Psychological Record*.

Dabla-Norris, E., J. Brumby, A. Kyobe, Z. Mills, and C. Papageorgiou (2011). Investing in public investment: an index of public investment efficiency. IMF Working Paper WP/11/37.

Daniels, D. and R. Plomin (1985). Differential experience of siblings in the same family. *Developmental Psychology 21*(5), 747.

Dantata, S. (2007). *General overview of the Nigerian construction industry*. Ph. D. thesis, Massachusetts Institute of Technology.

Dauphin, A., E. Lahga, B. Fortin, G. Lacroix, et al. (2011). Are children decision-makers within the household?*. *The Economic Journal 121*(553), 871–903.

De Mel, S., D. McKenzie, and C. Woodruff (2012). Enterprise recovery following natural disasters. *The Economic Journal 122*(559), 64–91.

Dell, M., B. F. Jones, and B. A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics 4*(3), 66–95.

Dercon, S. (1995). On market integration and liberalisation: method and application to ethiopia. *The Journal of Development Studies 32*(1), 112–143.

Dercon, S. (2004, August). Growth and shocks: evidence from rural ethiopia. *Journal of Development Economics 74*(2), 309–329.

Dercon, S., D. O. Gilligan, J. Hoddinott, and T. Woldehanna (2009). The impact of agricultural extension and roads on poverty and consumption growth in fifteen ethiopian villages. *American Journal of Agricultural Economics 91*(4), 1007–1021.

Di Tella, R. and E. Schargrodsky (2003). The role of wages and auditing during a crackdown on corruption in the city of buenos aires. *Journal of Law and Economics 46*(1), 269–292.

Doepke, M. and F. Zilibotti (2010). Do international labor standards contribute to the persistence of the child-labor problem? *Journal of Economic Growth 15*(1), 1–31.

Donaldson, D. (2013). Railroads of the raj: Estimating the impact of transportation infrastructure. *American Economic Review*. Forthcoming.

Dornbusch, S., J. Carlsmith, S. Bushwall, P. Ritter, H. Leiderman, A. Hastorf, and R. Gross (1985). Single parents, extended households, and the control of adolescents. *Child Development*, 326–341.

Duflo, E. (2000). Child health and household resources in south africa: Evidence from the old age pension program. *The American Economic Review 90*(2), 393–398.

Duflo, E. (2003, June). Grandmothers and granddaughters: Old-age pensions and intrahousehold allocation in south africa. *World Bank Economic Review 17*(1), 1–25.

Dunbar, G. R., A. Lewbel, and K. Pendakur (2013). Children's resources in collective households: Identification, estimation, and an application to child poverty in malawi. *The American Economic Review 103*(1), 438–471.

Dunn, J. and R. Plomin (1990). *Separate lives: Why siblings are so different.* Basic Books.

Dustmann, C. and J. Micklewright (2001). Intra-household transfers and the part-time work of children. CEPR Discussion Paper No. 2796.

Edmonds, E. (2006). Understanding sibling differences in child labor. *Journal of Population Economics 19*(4), 795–821.

Edmonds, E. (2008). Child labor. *Handbook of Development Economics 4*, 3607–3709.

Edmonds, E. and N. Pavcnik (2005). The effect of trade liberalization on child labor. *Journal of International Economics 65*(2), 401–419.

Ejrnæs, M. and C. Pörtner (2004). Birth order and the intrahousehold allocation of time and education. *Review of Economics and Statistics 86*(4), 1008–1019.

Estache, A. and A. Iimi (2009). Joint bidding, governance and public procurement costs: a case of road projects. *Annals of Public and Cooperative Economics 80*(3), 393–429.

Estache, A. and A. Iimi (2010). Bidder asymmetry in infrastructure procurement: Are there any fringe bidders? *Review of Industrial Organization 36*(2), 163–187.

Fisman, R. and E. Miguel (2007). Corruption, norms, and legal enforcement: Evidence from diplomatic parking tickets. *Journal of Political Economy 115*(6), 1020–1048.

Flyvbjerg, B., M. K. Skamris Holm, and S. L. Buhl (2003). How common and how large are cost overruns in transport infrastructure projects? *Transport Reviews 23*(1), 71–88.

Fomby, T., Y. Ikeda, and N. V. Loayza (2013). The growth aftermath of natural disasters. *Journal of Applied Econometrics 28*(3), 412–434.

Frankenberg, E., D. McKee, and D. Thomas (2005). Health consequences of forest fires in indonesia. *Demography 42*(1), 109–129.

Glaeser, E. L. and D. C. Maré (2001). Cities and skills. *Journal of Labor Economics 19*(2), 316–342.

Gleditsch, N., P. Wallensteen, M. Eriksson, M. Sollenberg, and H. Strand (2002). Armed conflict 1946-2001: A new dataset. *Journal of peace research 39*(5), 615–637.

Government of Haiti et al (2010). Haiti Earthquake PDNA: Assessment of damage, losses, general and sectoral needs, Annex to the Action Plan for National Recovery and Development of Haiti. Working paper prepared by the Government of Haiti with support from the International Community.

Graf Lambsdorff, J. (2005). Determining trends for perceived levels of corruption. Technical report, Passauer Diskussionspapiere: Volkswirtschaftliche Reihe.

Greene, W. H. (2003). *Econometric analysis*, Volume 5. Prentice hall Upper Saddle River, NJ.

Griliches, Z. (1979). Sibling models and data in economics: Beginnings of a survey. *The Journal of Political Economy*, S37–S64.

Grotevant, H. (1983). The contribution of the family to the facilitation of identity formation in early adolescence. *The Journal of Early Adolescence 3*(3), 225.

Halliday, T. (2006, July). Migration, risk, and liquidity constraints in el salvador. *Economic Development and Cultural Change 54*(4), 893–925.

Harbaugh, W., K. Krause, and T. Berry (2001). GARP for kids: On the development of rational choice behavior. *American Economic Review 91*(5), 1539–1545.

Harbaugh, W., K. Krause, and S. Liday (2003). Bargaining by children. Economics department working paper, University of Oregon.

Hochrainer, S. (2009). Assessing The Macroeconomic Impacts Of Natural Disasters. Policy Research Working Paper 4968, World Bank.

Horwich, G. (2000). Economic lessons of the kobe earthquake. *Economic Development and Cultural Change 48*(3), 521.

Hüschelrath, K., K. Müller, and T. Veith (2013). Concrete shoes for competition: The effect of the german cement cartel on market price. *Journal of Competition Law and Economics 9*(1), 97–123.

Huysentruyt, M. (2011). Development aid by contract: Outsourcing and contractor identity. mimeo.

Hyytinen, A., S. Lundberg, and O. Toivanen (2007). Politics and procurement: Evidence from cleaning contracts. Discussion Paper No 233, Helsinki Center of Economic Research.

International Recovery Platfrom (2009). The Yogyakarta and Central Java Earthquake 2006. Recovery Status Report.

Jacoby, H. G. and B. Minten (2009). On measuring the benefits of lower transport costs. *Journal of Development Economics 89*(1), 28–38.

Java Reconstruction Fund (2007). One Year after the Java Earthquake and Tsunami: Reconstruction Achievements and the Results of the Java Reconstruction Fund. Progress Report.

Jayachandran, S. (2006, June). Selling labor low: Wage responses to productivity shocks in developing countries. *Journal of Political Economy 114*(3), 538–575.

Kahn, M. E. (2005). The death toll from natural disasters: The role of income, geography, and institutions. *Review of Economics and Statistics 87*(2), 271–284.

Kapan, T. (2009). Patriarchal households are unitary: New evidence. mimeo, Columbia University.

Kaufmann, D., A. Kraay, and M. Mastruzzi (2010). The worldwide governance indicators: methodology and analytical issues. World Bank Policy Research Working Paper 5430.

Keane, M. and E. Prasad (1996). The employment and wage effects of oil price changes: a sectoral analysis. *The Review of Economics and Statistics 78*(3), 389–400.

Kellenberg, D. and A. M. Mobarak (2011). The economics of natural disasters. *Annual Review of Resource Economics 3*(1), 297–312.

Kenny, C. (2009). Measuring corruption in infrastructure: Evidence from transition and developing countries. *The Journal of Development Studies 45*(3), 314–332.

Khandker, S. R., Z. Bakht, and G. B. Koolwal (2009). The poverty impact of rural roads: evidence from bangladesh. *Economic Development and Cultural Change 57*(4), 685–722.

Kline, P. (2008). Understanding Sectoral Labor Market Dynamics: An Equilibrium Analysis of the Oil and Gas Field Services Industry. mimeo.

Kochar, A. (1999). Smoothing consumption by smoothing income: hours-of-work responses to idiosyncratic agricultural shocks in rural India. *Review of Economics and Statistics 81*(1), 50–61.

Krasnokutskaya, E. and K. Seim (2011). Bid preference programs and participation in highway procurement auctions. *The American Economic Review 101*(6), 2653–2686.

Lan, Y. (2010). The expansion of chinese construction companies in the global market. Msc thesis, University of Kansas School of Engineering.

Leamer, E. (1983). Let's take the con out of econometrics. *The American Economic Review*, 31–43.

Lewis, G. and P. Bajari (2011). Procurement contracting with time incentives: Theory and evidence. *The Quarterly Journal of Economics 126*(3), 1173–1211.

Li, T. and X. Zheng (2009). Entry and competition effects in first-price auctions: Theory and evidence from procurement auctions. *The Review of Economic Studies 76*(4), 1397–1429.

Limao, N. and A. J. Venables (2001). Infrastructure, geographical disadvantage, transport costs, and trade. *The World Bank Economic Review 15*(3), 451–479.

Loayza, N., E. Olaberría, J. Rigolini, and L. Christiaensen (2012). Natural disasters and growth: Going beyond the averages. *World Development 40*(7), 1317–1336.

Lundberg, S., R. Pollak, and T. Wales (1997). Do husbands and wives pool their resources? Evidence from the United Kingdom child benefit. *The Journal of Human Resources 32*(3), 463–480.

Lundberg, S., J. Romich, and K. Tsang (2009). Decision-making by children. *Review of Economics of the Household 7*(1), 1–30.

McIntosh, M. F. (2008). Measuring the labor market impacts of hurricane katrina migration: Evidence from houston, texas. *American Economic Review 98*(2), 54–57.

McKinsey (2013). Infrastructure productivity: How to save $1 trillion a year. Technical report, McKinsey Global Institute, McKinsey Infrastructure Practice.

Miguel, E., S. Satyanath, and E. Sergenti (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of Political Economy*, 725–753.

Moavenzadeh, F. (1978). Construction industry in developing countries. *World Development 6*(1), 97–116.

Moehling, C. (2005). 'She Has Suddenly Become Powerful': Youth Employment and Household Decision Making in the Early Twentieth Century. *The Journal of Economic History 65*(02), 414–438.

Moretti, E. (2010). Local multipliers. *American Economic Review 100*(2), 373–77.

Moretti, E. (2011). Local labor markets. *Handbook of labor economics 4*, 1237–1313.

Mu, R. and D. van de Walle (2011). Rural roads and local market development in vietnam. *The Journal of Development Studies 47*(5), 709–734.

Mueller, V. and A. Quisumbing (2010). Short- and long-term effects of the 1998 bangladesh flood on rural wages. IFPRI Discussion Paper 00956, International Food Policy Research Institute.

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics 88*(2), 221–231.

Nunn, N. and D. Puga (2012). Ruggedness: The blessing of bad geography in africa. *Review of Economics and Statistics 94*(1), 20–36.

Ofori, G. (2007). Construction in developing countries. *Construction Management and Economics 25*(1), 1–6.

Olken, B. A. (2007). Monitoring corruption: Evidence from a field experiment in indonesia. *Journal of Political Economy 115*(2).

Olken, B. A. (2009). Corruption perceptions vs. corruption reality. *Journal of Public Economics 93*(7), 950–964.

Olken, B. A. and R. Pande (2012). Corruption in developing countries. *Annu. Rev. Econ. 4*(1), 479–509.

Orkin, K. (2011). "See first, think later, then test": how children's perspectives can improve economic research. *European Journal of Development Research 23*(5), 774–791.

Patrinos, H. A. and G. Psacharopoulos (1997). Family size, schooling and child labor in peru–an empirical analysis. *Journal of population economics 10*(4), 387–405.

Paxson, C. H. (1992, March). Using weather variability to estimate the response of savings to transitory income in thailand. *American Economic Review 82*(1), 15–33.

Pesendorfer, M. (2000). A study of collusion in first-price auctions. *The Review of Economic Studies 67*(3), 381–411.

Premand, P. (2008). Hurricane mitch and consumption growth of nicaraguan agricultural households. CSAE WPS/2008-06.

Rebosio, M. and P. E. Wam (2011). Violent conflict and the road sector: Points of interaction. Technical report, The World Bank.

Reggio, I. (2011). The influence of the mother's power on her child's labor in mexico. *Journal of development economics 96*(1), 95–105.

Roodman, D. (2009). Estimating fully observed recursive mixed-process models with cmp. Working Paper 168, Center for Global Development.

Rose, E. (2001). Ex ante and ex post labor supply response to risk in a low-income area. *Journal of Development Economics 64*(2), 371–388.

Rosenzweig, M. R. and J. Zhang (2009). Do Population Control Policies Induce More Human Capital Investment? Twins, Birth Weight and China's "One-Child" Policy. *The Re-*

view of Economic Studies 76(3), 1149–1174.

Samuelson, P. (1956). Social indifference curves. *The Quarterly Journal of Economics 70*(1), 1.

Samuelson, P. A. (1952). Spatial price equilibrium and linear programming. *The American economic review 42*(3), 283–303.

Shiferaw, A., M. Soederbom, E. Siba, and G. Alemu (2011). Road networks and enterprise performance in ethiopia: Evidence from the road sector development program. IGC Working Paper 12/0696.

Silva, D. G. D., R. P. McComb, Y.-K. Moh, A. R. Schiller, and A. J. Vargas (2010). The effect of migration on wages: Evidence from a natural experiment. *American Economic Review 100*(2), 321–26.

Stifel, D., B. Minten, and B. Koro (2012). Economic benefits and returns to rural feeder roads: Evidence from a quasi-experimental setting in ethiopia. ESSP II Working Paper 40, Ethiopia Strategy Support Program II.

Strauss, J., K. Beegle, A. Dwiyanto, Y. Herawati, D. Pattinasarany, E. Satriawan, B. Sikoki, B. Sukamdi, and F. Witoelar (2004). *Indonesian living standards three years after the crisis: evidence from the Indonesia Family Life Survey*. RAND Corporation.

Strauss, J., F. Witoelar, B. Sikoki, and A. Wattie (2009). The fourth wave of the indonesia family life survey: Overview and field report. RAND Labor and Population Working Paper WR-675/1-NIA/NICHD, RAND.

Strobl, E. (2011). The economic growth impact of hurricanes: evidence from US coastal counties. *Review of Economics and Statistics 93*(2), 575–589.

Sutter, M., M. G. Kocher, D. Glätzle-Rüetzler, and S. T. Trautmann (2013). Impatience and uncertainty: Experimental decisions predict adolescents' field behavior. *American Economic Review*. Forthcoming.

Svensson, J. (2005). Eight questions about corruption. *The Journal of Economic Perspectives 19*(3), 19–42.

Teravaninthorn, S. and G. Raballand (2009). *Transport Prices and Costs in Africa: A Review of the Main International Corridors*, Volume 772. World Bank Publications.

Themnér, L. and P. Wallensteen (2012). Armed conflicts, 1946–2011. *Journal of Peace Research 49*(4), 565–575.

Thomas, D. (1990). Intra-household resource allocation: An inferential approach. *The Journal of Human Resources 25*(4), 635–664.

Thomas, D., K. Frankenberg, E.and Beegle, and G. Teruel (1999). Household budgets, household composition and the crisis in indonesia: evidence from longitudinal household survey data. Mimeo.

Thomas, D., F. Witoelar, E. Frankenberg, B. Sikoki, J. Strauss, C. Sumantri, and W. Suriastini (2012). Cutting the costs of attrition: Results from the indonesia family life survey. *Journal of Development Economics 98*(1), 108–123.

Thompson, T. and A. Shah (2005). Transparency international's corruption perceptions index: Whose perceptions are they anyway? mimeo.

Townsend, R. M. (1994, May). Risk and insurance in village india. *Econometrica 62*(3), 539–91.

Transparency International (2011). Bribe payer's index 2011. Technical report, Transparency International.

Treisman, D. (2007). What have we learned about the causes of corruption from ten years of cross-national empirical research? *Annual Review of Political Science 10*, 211–244.

Udry, C. (1995, December). Risk and saving in northern nigeria. *American Economic Review 85*(5), 1287–1300.

United Nations and World Bank (2010). *Natural hazards, unnatural disasters: the economics of effective prevention*. World Bank Publications.

United Nations Office for Disaster Risk Reduction (2009). Risk and poverty in a changing climate: Invest today for a safer tomorrow. Global Assessment Report on Disaster Risk Reduction.

US Geological Survey (2008). Seismic hazard of western indonesia. National Earthquake Information Center.

US Geological Survey (2012). http://earthquake.usgs.gov/earthquakes /eqinthenews/2006/usneb6/. National Earthquake Information Center.

Varela, G., E. Aldaz-Carroll, and L. Iacovone (2012). Determinants of market integration and price transmission in indonesia. World Bank Policy Research Working Paper 6098, World Bank.

Ward-Batts, J. (2008). Out of the wallet and into the purse: Using micro data to test income pooling. *Journal of Human Resources 43*(2), 325–351.

Wei, S.-J. (2000). How taxing is corruption on international investors? *Review of economics and statistics 82*(1), 1–11.

Wooldridge, J. (2002). *Econometric analysis of cross section and panel data*. The MIT Press.

World Bank (2006). Road Costs Knowledge System (ROCKS) Version 2.3 User's Guide. Transport and Urban Development Department, The World Bank.

World Bank (2010). Indonesia jobs report: Towards better jobs and security for all. World Bank Office Jakarta.

World Bank (2011a). Curbing fraud, corruption, and collusion in the roads sector. Technical report, Washington, DC: World Bank.

World Bank (2011b). *World development report 2011: Conflict, Security and Development*. Washington, DC: World Bank.

World Bank (2012). Implementation Completion and Results Report. Report No: ICR2246.

World Bank (2013). *World development report 2013: Jobs*. Washington, DC: World Bank.

Yang, D. (2008). Risk, Migration, and Rural Financial Markets: Evidence from Earthquakes in El Salvador. *Social Research: An International Quarterly 75*(3), 955–992.

Yee, D. and C. Flanagan (1985). Family environments and self-consciousness in early adolescence. *The Journal of Early Adolescence 1*(5), 59–68.

Zitzewitz, E. (2012). Forensic economics. *Journal of Economic Literature 50*(3), 731–69.