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Essays in Empirical Development Economics: The Role of Income Shocks on Firm and Household Dynamics

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Essays in Empirical Development Economics:

The Role of Income Shocks on Firm and Household Dynamics

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This thesis consists of three essays that examine the causal effects that income shocks have on firm and household dynamics.

In the first chapter, I examine the role that income shocks have on the financial performance of small firms in Ecuador. To this purpose, I use the *menor cuantia* process, a government procurement mechanism that randomly selects winning bidders for public tenders. I use the exogenous variation created by the *menor cuantia* process to estimate the causal effects of income shocks on firm growth. I find that the effect on various measures of firm growth is significant, albeit temporary. The main contribution of this chapter to the literature is that it shows that the nature and duration of demand shocks, not just their magnitude, are an essential factor in explaining firm growth.

In the second chapter, I examine the role that income shocks have on household expenditures on human capital and non-durable consumption using the *menor cuantia* process as identification strategy. Overall, I find that household expenditure is highly sensible to temporary income shocks. Additionally, I find that, for shocks of higher monetary values, the effects are also observed the year after the shock. This chapter contributes to the literature by focusing on an unexpected, positive, and temporary income shock. Equally important, I provide estimates of the joint effects on human capital and non-durable consumption, areas which have traditionally been studied separately.

In the third chapter, co-authored with Nicolas Contreras, we examine the role that income shocks have on four key areas of education: school attendance, educational expenditures, child labor, and competency level in mathematics. We study this in the context of Uganda. Our empirical strategy relies on the exogenous variation in income created by deviations in localized rainfall. To interpret the results, we propose a simple theoretical framework which allows us to decompose income shocks into two opposing forces: an income effect and a substitution effect. We posit that the interaction of these two effects can lead to heterogeneous results for different types of households. We find that a higher household income increases the odds of children attending school, increases schooling expenditures, decreases the odds of child labor, and increases the odds for children to reach a higher level of proficiency in mathematics. When we break down the average estimates across household types, we find that income shocks have almost no effect on

school attendance and child labor for those households that rely on farming as their main source of income. The main contribution of this chapter is that it shows that, even within an ostensible homogeneous country, income shocks can have heterogeneous effects.

In the first two chapters, I use data from the *menor cuantia* process. Although not explicitly mentioned in the text, a significant amount of technical work was required to assemble this new dataset. The data from *menor cuantia* was publicly available but not easily accessible, and repeated requests for it went unanswered. Consequently, it was necessary to create an algorithm that searched individually over 40,000 public records. This process, which took over 13 months, required the use of artificial intelligence, optical recognition techniques, and manual data entry.

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Chapter 1
Letting Luck Decide: Government Procurement and the Growth of Small Firms

Abstract

I estimate the causal effects of demand shocks, stemming from government procurement, on the growth of small firms in Ecuador. I assemble a unique dataset using several new administrative sources and, as identification strategy, exploit a governmental procurement process that allocates public contracts through a randomized contest.

I find a positive and significant effect of demand shocks on firm growth. On average, an increase in demand of 10% will increase wage expenses by 4% and fixed assets by 5% during the year of the shock. I also find no evidence of spill-over effects from demand shocks on sales to the public or private sector. Finally, as in other studies, I show that demand positively impacts firm growth but, contrary to other findings, this effect is temporary and only observed during the year of the shock.

Keywords: Demand Shocks, firm growth, public procurement
J.E.L. Codes: H54, H57 D22

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1.1 Introduction

Small firms contribute up to 45% of total employment and 33% of GDP in developing countries (Kushnir et al., 2010). Despite this, the majority of small firms never grow beyond a few employees (Nichter and Goldmark, 2009). The importance of firm growth for economic and political reasons is evidenced by the number of public policies that have been created to promote it.

Economic theory provides two different approaches to explain firm growth. On one hand, firms can grow due to intrinsic factors such as: managerial ability (Lucas, 1978), increases in productivity (Jovanovic, 1982), and experience (Hopenhayn, 1992).[1] Public policies meant to address intrinsic factors include: access to credit, management development programs, and financial literacy programs. On the other hand, a set of recent papers suggest that demand factors, such as networking and reputation effects, might be equally important in explaining firm growth (Fishman and Rob, 2003; Syverson, 2004). In such cases, public policies that restrict competition and favor small enterprises might have a positive and significant impact on the development of small and medium enterprises (hereafter SMEs). Argentina's Ley 25.551 (2001) stipulates that goods provided by small firms receive a price margin of 7%; in Brazil, government purchases that are below a minimum threshold are exclusively destined to small firms (Lei Complementar N.123, 2006). The restriction of government procurement processes to certain, by assumption less competitive, firms implies that such programs have an opportunity cost. Are these demand-driven programs effective in promoting the growth of SMEs?

To empirically evaluate the effects of demand, the researcher needs to isolate it from other factors. This is a complicated prospect because the relation between demand and growth is unclear. On one hand, a firm may experience growth due to a shift of the demand curve induced by, for example, changes in preferences or exogenous price increases of substitute products. On the other hand, a firm that grows may benefit from an increase in market exposure and economies of scale, leading to an increase in demand. To overcome such identification problems, previous studies have relied on firm-level price data that allows to decompose demand from productivity shocks (Foster et al., 2008). When such detailed information is not available, researchers impose a structure on the demand and production functions and obtain estimates of unobserved demand shocks through the regression residuals (Pozzi and Schivardi, 2016). Hebous and Zimmermann (2016) exploit the timing of public government contracts and estimate that a one dollar increase in government purchases increases the capital investment of U.S. firms by 7 to 11 cents. Ferraz et al. (2016), whose work is the closest to the present one, use a quasi-experimental design based on the bidding process in Brazil. The authors find that winning a contract increases firm growth by 2.2% during the quarter of the shock.

In this study, I examine the short- and long-term impacts that demand shocks, stemming from

[1] Queiró (2016) presents evidence that the education of managers has a significant effect on firm size while Cabral and Mata (2003) find that experience is an important factor in determining firm size.

government purchases, have on the financial performance of SMEs. For this purpose, I exploit the *menor cuantia* process, a feature in Ecuador's public procurement law that awards contracts using a lottery. Using this process as a source of variation in firm demand, I assemble a unique dataset that combines firm-level financial information with public records for 1,179 firms that participated in the process for the years 2010-2012. I then compare the changes in balance sheet indicators between the winners and the losers of the contests, at the extensive and intensive margin.

I find that demand shocks significantly affect firms' short-term growth during the year of the shock. Firms that won a contract report, on average, 22% higher revenues and current assets, and 7% higher fixed assets than firms that did not win. The intensive margin analysis suggests that increasing demand by 10% will increase wage expenses by 4% and fixed assets by 5%. The effects of demand shocks are temporary and are only observed during the year of the shock. A year after winning a contract, gross revenues and current assets revert back to pre-shock levels and there are no differences in wage expenses and fixed assets between winners and runners-up of the contests. Moreover, I find that, outside the *menor cuantia* process, there are virtually no differences in sales to the government or the private sector between these two groups.

This paper contributes to the existing literature on the role of demand on firm growth and to the nascent literature that examines the role of government procurement on firm dynamics (Hoekman and Sanfilippo, 2018; Czarnitzki et al., 2018). The main contribution of this paper is that it highlights that the magnitude, nature, and duration of the shock are important factors to consider when analyzing how demand affects firm growth. Shocks that are perceived as temporary or unsustainable seem to only affect short-term measures of growth. Additionally, it provides an evaluation of a governmental preferential purchasing program for the particular case of SMEs.

The rest of this paper is divided as follows: section 1.2 explains the country context and procurement mechanism. Section 1.3 introduces the data. Section 1.4 discusses the identification strategy and empirical methodology. Section 1.5 provides the results and section 1.6 concludes.

1.2 Background

1.2.1 Public procurement in Ecuador

Ecuador is a small middle-income country with a 2016 population of 16 million people and a per capita income of $6,205. Since the year 2000, the official currency of Ecuador is the U.S. Dollar. Prior to the 2006 election, the country experienced political instability, a financial crisis, and ubiquitous cases of corruption. After the 2006 election, the new government vowed to restore public trust. As part of this plan, it enacted a new constitution, transparency laws and, in 2008, the Public Procurement Law (LONSCP, 2008). The Law reformed the procedures for the purchase of public goods and introduced provisions to safeguard the participation of SMEs in public procurement. The National Public Purchases Agency defines SMEs as a firm that has less than 100 employees and has sales lower than 2 million dollars (SERCOP, 2015).

The reform required that all government institutions procure all purchases through an online portal called Compraspublicas.[2] Before Compraspublicas, government procurement was done at a local level, with limited oversight and accountability. The Law stipulated that the process for the procurement of public works under a threshold, precisely 0.0007% of the government's budget, had to be done under the *menor cuantia* ("small amount") process.[3] This process contains two distinct features that are particularly relevant to this study: it is accessible only to SMEs and it grants contracts through a randomized lottery.

The *menor cuantia* process functions through Compraspublicas. The portal connects institutions who procure for services and products (hence projects) with firms, that bid for them. In order for a firm to bid on a project, it must first register in the portal. During this process, firms submit their personal and company information including: contact information, professional degrees and certificates, tax identification number, personal and company tax returns, inventory of physical capital, and industrial classification of the company. Once registered, firms are able to browse through the public contracts available and place their bids.

From the institution's side, the first step to procure a new public work is to create an entry in Compraspublicas.[4] The new project has to include: a description of the public work, location, budget, timeline, and project-specific requirements. These requirements include: technical and professional experience, qualification of employees, previous experience of the firm, education of managers, technical abilities, machinery, and financial capital.

After this step, the project enters into its first phase, acceptance of bids from firms. There are two ways used to notify firms of a new project. First, the system sends automatic notifications to providers. It does so through an algorithm that compares the requirements listed in the project with the competencies listed in the profile of providers. In addition to contacting providers directly, the system also posts the project on the database of the portal. During this stage, all registered providers are able to search and browse through the available projects and express their interest.[5]

In the second phase of the process, all providers that bid on the project must provide proof that they fulfill the requirements specified. They do this by uploading official documentation to Compraspublicas. For instance, if the project requires specific machinery, then providers must upload the registration and proof of purchase of the equipment. A notable feature of this part of the process is that the requirements for each public work are objective and, in some cases, the system does not allow the provider to complete this phase if they do not meet the minimum cutoffs.

[2] The website address is www.compraspublicas.gob.ec

[3] For the years 2009-2012, the threshold to use the process was around $150,000.

[4] Each project must be approved in the government budgetary process. This process is done during the previous fiscal year.

[5] In the year 2012, additional rules were added to the system that prevented certain providers from submitting bids. These rules were not in place during the time period used in this study.

Following this phase, a committee from the public institution evaluates all the providers that presented a bid. The committee's responsibility is to identify if each firm meets the minimum requirements for the project- effectively supplementing the verification process done by the system. To illustrate, suppose that a new construction project requires a minimum of 2 years of previous experience. An interior design firm could, theoretically, qualify for this process. In this case, it is the role of the committee to verify if the experience listed by the firm is relevant. The committee does not rank nor provide a numerical qualification of providers; it only determines if they are qualified to perform the project. The providers that qualify enter into a list. In the final phase of the process, the system automatically and randomly selects one provider from the list of qualified providers. This provider is the winner of the contest and is given the contract for the project.

The identification strategy in this study relies on the fact that the allocation of the contract is random. For a given public contract, all providers that qualify to participate in the lottery have, on average, comparable characteristics. The impartiality of the procurement process is ultimately an empirical question, and is addressed in the empirical section, where it is concluded that *menor cuantia* projects are, indeed, randomly assigned. Moreover, and regardless of any empirical considerations, there are two major features of the process that suggest that contracts are assigned randomly.

First, no negotiation between institutions and firms takes place at any stage of the process. The price for a given public work is predetermined and, as a result, no preference is given for one bid being more competitive than another. This is evidenced by comparing the budgeted and actual costs for a given project. In the *menor cuantia* process these values always coincide. In public work projects of higher amounts, which are allocated using different procedures, one can observe considerable variations between the estimated and actual costs. Second, the requirements that are set for each contract are defined in terms of objective criteria and must be verified by legal documents.[6]

1.3 Data

The data for this study consist of a panel of 1,179 firms that presented bids on a total of 5,475 public works performed under the *menor cuantia* process during the period between May 2009 and December 2012. Firm-level data were obtained from the National Bureau of Companies of Ecuador (SUPERCIAS) and include: contact information, yearly tax returns, and balance sheet

[6] A potential concern is the committee's discretion to qualify providers. A committee might try to provide preferential treatment to a firm by being stringent in their review of other firms and thus limiting the number of qualified providers. To overcome this potential limitation, I exclude from the sample a firm if, during any contest, it was the only one qualified into the pool.

information.[7] Data of public works performed under the *menor cuantia* process come from the Ecuadorian Procurement Agency (SERCOP) and include: contract information for each public work, the unique identification number of each firm that bid on each project, a list of qualified providers, and the winner of the contest.[8] At the time of this writing, all data for this project were publicly available but were not easily accessible. For this reason, the data were obtained by using a web scraping algorithm. The appendix provides a comprehensive overview of the data gathering process.

Table 1.1: Descriptive statistics of firms

	2009	2010	2011	2012	Total
Avg. age (years)	5.41	5.68	4.97	4.69	5.14
Avg. number of qualifications	2.16	6.76	5.68	4.67	5.41
Avg. number of winnings	0.52	0.88	0.82	0.77	0.80
Avg. gross yearly revenue (USD)	255,137	291,232	291,162	233,392	269,230
Avg. total assets (USD)	113,570	133,844	129,358	126,885	128,589
Avg. liabilities (USD)	90,084	105,213	100,211	91,743	98,202
Avg. wage expense (USD)	24,146	22,351	25,508	29,778	25,931

[1] Descriptive statistics of 1,179 registered firms participating in the *menor cuantia* process for the years in the sample. Values are arithmetic averages. Income, assets, liabilities, and wage expense are presented in U.S. dollars. Assets (liabilities) include fixed and current assets (liabilities). The source of the data are the balance sheet reports presented by firms to the tax authority.

The breakdown of qualified firms by year is as follows: 146 in 2009, 543 in 2010, 543 in 2011, and 546 in 2012. Table 1.1 presents descriptive statistics for the firms in the sample. The sample of companies in this study consists principally of small and medium sized firms in the construction industry. Based on their official registration record, 86% of firms report that their primary specialization is construction of buildings, real estate activities, architecture and engineering consulting, or civil engineering. The companies were categorized based on their size by SERCOP.[9] Medium

[7] All values are obtained from firms' balance sheet documents, as reported to the tax authority (Servicio de Rentas Internas).

[8] Firm level data can be found at http://www.supercias.gob.ec. Public works data can be found at https://www.compraspublicas.gob.ec.

[9] A micro firm has between 1 and 9 employees and gross sales and assets of less than $100,000. A small firm has between 10 and 49 employees and sales and assets between $100,000 and 1 million dollars. A medium firm has between 50 and 99 employees and sales between 1 and 2 million dollars.

sized companies make up 8% of the sample and have average gross revenues of $943,107. Small sized companies make up 44% and have average gross revenues of $244,590. Micro sized companies make 48% of the sample and have gross revenues of $84,458. Firms in the sample are young, the average age (years since registration) is 5.1 years. 90% of firms in the sample are less than 13 years old. For the period 2009-2012, each firm qualified to be part in the random drawing an average of 5.41 times per year, winning a contract, on average, 0.80 times per year. Financially, firms report to have average total assets of $128,589 and average liabilities of $98,202. The average wage expenditure is $25,931 and 90% of firms report less than $60,000 in wage expenditures.[10] Geographically, 55% of the firms in the sample are located in the 10 most populous cities in Ecuador, where approximately 50% of the total population live.

Table 1.2: Descriptive statistics of public works by year: 2009-2012

	2009	2010	2011	2012	Total
Avg. contract amount (USD)	39,794	46,960	53,468	54,600	50,160
Avg. duration of contract (days)	57	63	69	65	65
Avg. days to submit a bid	8	7	7	7	7
Avg. number of qualified providers per contest	12	19	19	14	17
N. of contracts awarded	468	2034	1626	1347	5475

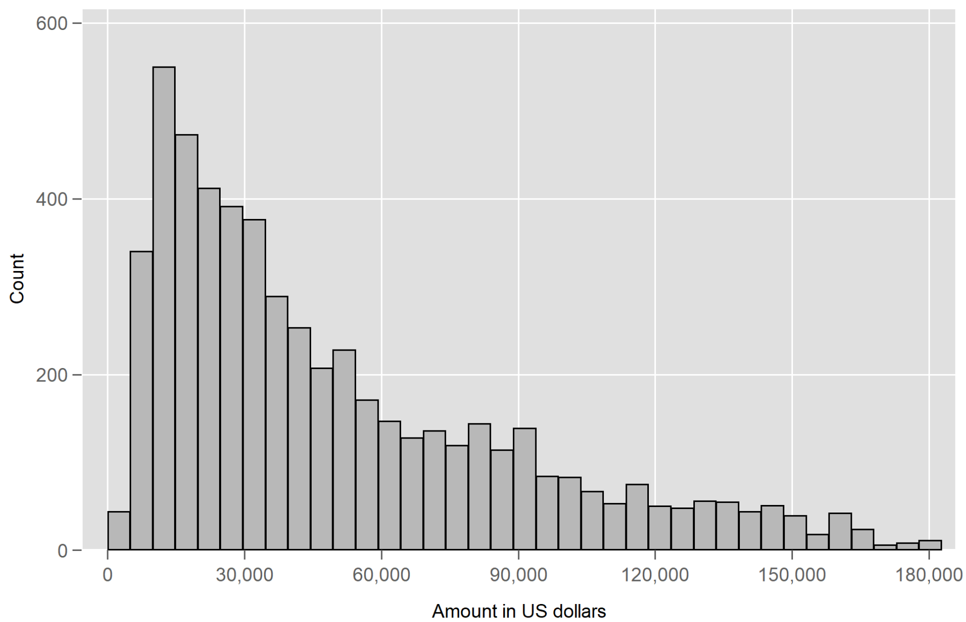
[1] Descriptive statistics of the 5,475 public works used in this study by year of procurement. Values are arithmetic averages of variables. Contract amount is measured in U.S. dollars. Length of contract is measured in days.

Table 1.2 provides the description of the 5,475 public works used in the study. The average contract amount is $50,160 and approximately 70% of contracts are below $60,000. Figure 1.1 shows the distribution of the values of public works for the years 2009-2012. The average contract duration (length of time required for a provider to complete the project) is 65 days and 90% of contracts last less than 96 days. The average contract has 6 requirements. On average, 17 providers qualified for the public contest per contract. The data obtained from the procurement agency suggests that all but 16 of the 5,475 public works were completed and delivered.[11]

[10] The information on the number of employees in a company is not available. However, a back-of-the-envelope calculation suggests that 90% of firms have less than 7 permanent employees.

[11] The remaining 16 public works were terminated unilaterally. There is no information that describes the reasons for the termination.

Figure 1.1: Contract amount of public works under *menor cuantia* process: 2009-2012



The figure above provides the contract amount of the 5,475 public works in the sample performed in the *menor cuantia* process for the years 2009-2012. The values for public works are presented in U.S. dollars.

1.4 Empirical Strategy

The purpose of this study is to estimate the causal effects of demand shocks on firm growth. To capture different areas of growth, I use four different measures: gross revenues, wage expenses and fixed and current assets.[12]

Assume that the relationship between firm growth and demand can be represented by the following reduced-form model:

$$\dot{y}_{it} = \beta_0 + \beta_1 d_{it} + X_{it}\beta_2 + \mu_i + \epsilon_{it} \tag{1}$$

where $\dot{y}_{it}$ denotes the growth of firm i during period t, d_{it} is the demand faced by the firm during year t, X_{it} is a matrix of firm-specific covariates, μ_i denotes unobserved time-invariant firm characteristics, and ϵ_{it} is the error term. I define $\dot{y}_{it}$ to be the difference in logs: $\dot{y}_{it} = ln(y_{it}) - ln(y_{it-1}) \forall\ y \in \ \{\ gross\ revenues,\ wage,\ and\ fixed\ and\ current\ assets\}$. Estimating this model by ordinary least squares will yield biased results if the demand faced by the firm is correlated with unobserved firm characteristics, μ_i, which is likely the case.

[12] For revenues I use total sales; for wages I use the total expenditure on salaries, wages, and commissions; for fixed and current assets I use the definition as stated in the International Financial Reporting Standards (IFRS).

To eliminate μ_i, one could transform the model by first differencing it. Even though this transformation eliminates μ_i, estimating the differenced model by OLS will provide a biased estimate if changes in demand are correlated with time-variant unobserved firm characteristics, i.e $\mathbf{E}[\Delta\epsilon_{it}, \Delta d_{it}] \neq 0$. To overcome this identification problem, one needs to identify an exogenous source of demand.

The increase in demand caused by winning a *menor cuantia* contest provides the source of exogenous variation needed to obtain unbiased estimates. Conditionally on qualifying, the random nature of the lottery ensures that the contract allocation is independent of firm specific characteristics. Firms that did not win the contract serve as an appropriate control group to obtain the effects of demand shocks on growth.

There are two main concerns with using the contracts allocated under *menor cuantia* as an exogenous source of demand. The first concern is that the lottery may not be random. This would occur if companies or the public institutions were able to manipulate the system. The second concern is participation. Firms can submit bids for multiple projects on a given year. To participate in a lottery, each firm must qualify to enter into the pool. If more productive firms qualify to more contests, then the probability of winning under the process increases. In this case, even if contracts are allocated randomly, they are not exogenous to firm-level characteristics.[13]

The randomness of the contest can be tested empirically. The probability of winning a contest at time t should be orthogonal to any firm-level characteristics observed at time $t-1$. Table 1.3 shows the results of a difference in means for the firms that qualified for the public contests during the years 2010-2012. There are no significant differences between winners and runners-up at the 10% significance level. Additional exercises (presented in the appendix) compare the theoretical and actual distributions of winners and runners-up over time.[14]

In addition to this evidence, the lottery is done through Compraspublicas. This portal is constantly audited by external reviewers and neither firms nor institutions have administrative access to the site. Finally, the sample in this study excludes a firm, if during any contest, they won because there was only 1 qualified provider in the lottery. All this evidence supports the claim that the assignment of contracts is in fact random. For this reason, I estimate the following reduced form model:

$$\dot{y}_{it} = \beta_0 + \beta_1 d_{it} + X_{it}\beta_2 + \epsilon_{it} \tag{2}$$

I proceed in two steps. First, I estimate equation 2 on the extensive margin, by comparing winners of the contests with those that did not win. In this specification $\dot{y}_{it}$ is the measure of growth for company i at time t, d_{it} equals 1 if the firm won a contract during year t and 0 otherwise,

[13]In all estimations, I control for the total number of qualifications and winnings by providers.

[14]The probability of winning a contest is inversely proportional to the number of providers that qualified to the contest.

and X_{it} represents firm-specific controls. I include as controls the age and location of the firm, a vector of controls that account for geographic characteristics, and regional GDP indicators. All specifications control for time and region fixed effects.

In the second step, I estimate the effect of demand shocks on the intensive margin. To measure the intensive margin, I estimate equation 2 defining d_{it} to be the log of sales from *menor cuantia*. The coefficient β_1 shows how percent changes in exogenous demand affect different measures of firm growth. To estimate if demand shocks have an effect beyond the year of the shock, I look at growth at different time intervals, $\dot{y}_{it+i} \forall\ i \in \{1, 2\}$.

What does $\dot{y}_{it}$ measure? During the year of the shock, $\dot{y}_{it}$ shows the difference in growth between winners and losers, with $t-1$ being the year of reference. A priori, one would expect to see significant differences in measures of growth between winners and losers. This is because winning an additional contract directly impacts balance sheet indicators such as sales and current asset during the year that the shock occurs. Nonetheless, it is still plausible to observe no differences between participants of the contest during the year of shock. For instance, if firms were capacity constrained, i.e. could only perform a limited number of contracts on a given year, then firms that win contracts from *menor cuantia* will not be able to perform additional work. Analogously, firms that did not win the contest, could seek work in the private sector. Under this scenario, firms replace private contracts with public ones, causing no overall changes in the total amount of work performed. It is worth noting, however, that the fact that firms apply to the *menor cuantia* contest suggests that they are not capacity constraint.[15]

[15] An additional explanation would be if firms could easily manipulate the balance sheet information, for instance to avoid taxation, then this would account for the lack of changes observed.

Table 1.3: Differences in means, by year

Variable	Runners-up	Winner	P-value
2010			
Log total assets (USD)	10.00	10.16	0.43
Log total liabilities (USD)	10.03	10.38	0.12
Log current assets (USD)	9.39	9.73	0.11
Log fixed assets (USD)	9.43	9.71	0.20
Log current liabilities (USD)	9.64	10.05	0.13
Log fixed liabilities (USD)	10.38	10.35	0.92
Log revenue (USD)	11.66	11.70	0.82
Log wage expenditure (USD)	9.19	9.49	0.14
Firm age (years)	5.57	5.82	0.60
2011			
Log total assets (USD)	10.17	9.76	0.12
Log total liabilities (USD)	10.25	9.93	0.14
Log current assets (USD)	9.69	9.38	0.14
Log fixed assets (USD)	9.55	9.44	0.59
Log current liabilities (USD)	9.98	9.66	0.12
Log fixed liabilities (USD)	10.23	10.02	0.54
Log revenue (USD)	11.46	11.42	0.85
Log wage expenditure (USD)	9.24	9.00	0.13
Firm age (years)	5.22	4.70	0.25
2012			
Log total assets (USD)	9.57	9.61	0.83
Log total liabilities (USD)	9.97	9.81	0.46
Log current assets (USD)	9.15	9.22	0.72
Log fixed assets (USD)	9.67	9.45	0.29
Log current liabilities (USD)	9.72	9.46	0.24
Log fixed liabilities (USD)	9.64	9.92	0.42
Log revenue (USD)	11.13	11.23	0.70
Log wage expenditure (USD)	9.37	9.29	0.59
Firm age (years)	4.86	4.51	0.43

[1] The following table presents the results from a Student t-test difference in means exercise for the firms participating in the *menor cuantia* contest. The term "Winners" refer to the firms that won in the *menor cuantia* process whereas the term "Runners-up" denotes the firms that did not win. The values refer to the first lags of the variables.

1.5 Results

I begin this section by presenting the effects of demand shocks on growth, at the extensive margin during the year of the shock, shown in Table 1.4. I estimate equation 2 by least squares, the independent variable *winner* takes the value 1 if a firm won a contest at time t and 0 otherwise. Each specification controls for time and region fixed effects and clusters errors at the firm-level. The dependent variable in columns 1 and 2 is revenue growth. Firms that experienced a demand shock report, on average, approximately 22% higher revenues than firms that did not experience a shock. The coefficient of .202 is significant at the 1% level and is robust to the addition of controls. Columns 3 and 4 present the results for growth of wage expense. The estimated coefficients suggest that firms that win a contract spend, on average, 5% more on wages than non winners. These results, however, are not robust to the inclusion of additional controls. Columns 4 and 5 report the results on growth of fixed assets. Firms that win a contract report, on average, 7% higher fixed-assets than non-winners. Columns 7 and 8 report the results on current assets. The coefficients are significant at the 1% level and similar in magnitude to the coefficients estimated for growth of revenues.

Table 1.4: Effects of demand shocks on firm growth: extensive margin

Dependent Variable	Revenue Growth		Wage Growth		Fixed Assets Growth		Current Assets Growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Winner	0.245***	0.202***	0.048*	0.043	0.081**	0.068*	0.254***	0.200***
	(0.062)	(0.064)	(0.029)	(0.028)	(0.037)	(0.038)	(0.068)	(0.071)
Age of Firm		-0.016		0.004		-0.001		-0.076***
		(0.012)		(0.006)		(0.009)		(0.013)
Contests participated		0.005**		0.002		0.002		0.006**
		(0.002)		(0.001)		(0.003)		(0.003)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size of firm	No	Yes	No	Yes	No	Yes	No	Yes
Regional controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1778	1771	1778	1771	1778	1771	1778	1771
R^2	0.014	0.023	0.025	0.044	0.005	0.013	0.029	0.050

[1] Least squares estimation of the effects of winning a procurement contract on firm growth. The dependent variables are: growth (log differences) of: revenue (columns 1 and 2), wage expense (columns 3 and 4), fixed assets (columns 5 and 6), and current assets (columns 7 and 8). The variable winner is a dummy variable taking the value 1 if a firm won a contest at time t and 0 otherwise. Standard errors (in parentheses) are clustered at the firm-level. Age of a firm is reported in years. Contest participated refers to the numbers of contests that a firm qualified for during a given year. The size of a firm are a set of dummies that control for the size (as defined by the National Bureau of Companies of Ecuador) of the firm. The regional controls include: local GDP and construction permits issued during the year. P-values $*p < .1, **p < .05, ***p < .01$.

Overall the results from Table 1.4 suggest that demand shocks affect firm growth in two distinct manners. For immediate measures of growth, such as revenues or current assets, there is a direct relationship between demand shocks and growth. To illustrate, given that the average yearly revenue of a firm for the sample is \$269,230, the estimated coefficient on revenue suggests that winning a contest increases the measure by approximately \$ 59,000 which is close to the average value of a *menor cuantia* contract (\$50,160). At the same time, the results show that for other measures of growth, such as wages and fixed assets, this relationship, while positive, has a lower a magnitude and statistical significance.

Next, I examine the effects of demand shocks on growth at the intensive margin. I estimate equation 2 by least squares, where the independent variable is the log of total yearly revenue received from *menor cuantia*. Table 1.5 presents the estimation results.

Columns 1 and 2 show the results for revenue growth, suggesting that an increase of 10% in sales will increase declared revenue by 10%. While ostensibly trivial, this result provides a good indication that the financial statements used in this study are a reliable source to measure the financial performance of firms. Columns 3 and 4 present the results for the growth of wage expense. The estimated coefficient of 0.05 is significant at the 1% level and does not change with the addition of controls. This suggests that an increase of 10% in the demand will increase wage expenses by 5%. Columns 5 and 6 present the results on growth of fixed assets, the coefficients suggest that an increase of 10% in the demand will increase wage expenses by 5%. Columns 7 and 8 report the results of current assets and suggest that an increase of 10% in the demand will increase current assets by 22%. Overall, the results from the intensive margin analysis are similar in magnitude and significance to the ones presented in Table 1.4.

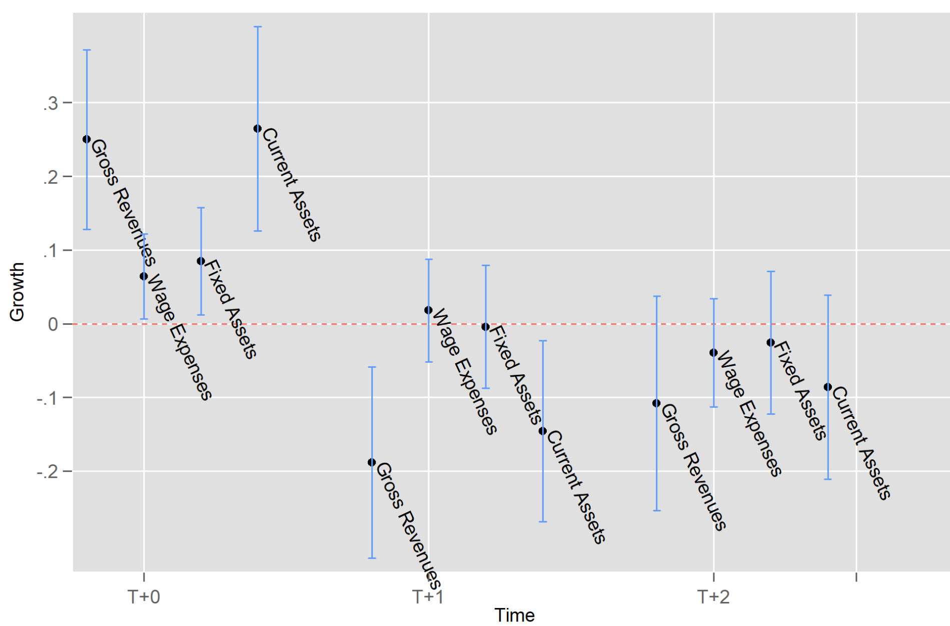
Table 1.5: Effect of demand shocks on firm growth: intensive margin

Dependent Variable	Revenue Growth		Wage Growth		Fixed Assets Growth		Current Assets Growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Revenue from menor cuantia	0.11***	0.09***	0.05***	0.04**	0.05**	0.05**	0.20***	0.21***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)
Age of firm		-0.00		-0.00		0.00		-0.00***
		(0.00)		(0.00)		(0.00)		(0.00)
Contests participated		0.00*		0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)		(0.00)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size of firm	No	Yes	No	Yes	No	Yes	No	Yes
Regional controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,380	1,380	1,380	1,380	1,380	1,380	1,380	1,380
R^2	0.017	0.025	0.029	0.058	0.006	0.012	0.050	0.060

[1] Least squares estimation of the effects of winning a procurement contract on firm growth. The dependent variables are the growth (log differences) of revenue (columns 1 and 2), wage expense (columns 3 and 4), fixed assets (columns 5 and 6), and current assets (columns 7 and 8). The variable revenue from *menor cuantia* is the log of revenues obtained from the *menor cuantia* contest. Standard errors (in parentheses) are clustered at the firm-level. Age of a firm is reported in years. Contest participated refers to the numbers of contests that a firm qualified for during the year. The size of a firm are a set of dummies that control for the size (as defined by the bureau of companies of Ecuador) of the firm. The regional controls include: local GDP and construction permits issued during the year. P-values $*p < .1, **p < .05, ***p < .01$.

Next, I examine the duration of the effects. This is of particular relevance given that the changes observed could be due to short-term reasons such as hiring more labor to fulfill the contract or renting machinery required for a project. Figure 1.2 shows the differences in growth rates between firms that won a *menor cuantia* contract and those that did not. The differences are shown for the first two years after the contest. The figure shows the coefficient for growth estimated using equation 2 with the 95% confidence interval. The dependent variable is the growth rate in gross revenues, wage expense, and fixed and current assets. The figure reveals two significant insights. First, the year after the shock, winners of the *menor cuantia* contest experience a decrease in gross revenues and current assets. The decrease the year after the shock is similar in magnitude than the increase experienced the year of the shock. No effect is observed the year after the shock for labor costs and fixed assets. Second, no statistically significant effects in any measure of growth are observed two years after the shock.

Figure 1.2: Firm Growth after winning a contract



The figure above contains the average growth rates $t + k, k \in (1, 2)$ years after winning a contract under the *menor cuantia process*. Growth is defined as log differences. The bars represent the 95% confidence interval. The figure was created using the results from estimating equation 2 by least squares. The dependent variable is a dummy variable taking the value 1 if a firm won a contest at time t and 0 otherwise.

One non-pecuniary benefit of winning a contract is that it gives firms experience, reputation, and contacts in the public sector. In this case, it is possible for winning firms to increase their sales to the government outside of the *menor cuantia* process. Table 1.6 provides the results of testing the difference in means of the sales to the government between the winners and runners-up. There are virtually no differences in sales to the government after the year of the shock.

Table 1.6: Average differences in government sales

Sales-Winners	Sales-Runners-Up	Difference	P-Value	Year
Year of shock				
43,659	120,620	-76,960	0.008343	2009
140,253	268,325	-128,071	0.064538	2010
121,272	203,820	-82,547	0.013566	2011
153,569	250,319	-96,749	0.12826	2012
1 Year after schock				
188,835	230,421	-41,586	0.686347	2009
192,870	226,931	-34,061	0.516806	2010
352,894	407,545	-54,651	0.657602	2011
191,365	270,290	-78,925	0.196067	2012
2 Years after schock				
187,444	238,895	-51,451	0.466527	2009
432,706	493,418	-60,711	0.708223	2010
233,369	328,853	-95,484	0.174268	2011

[1] The following table presents the results from a Student t-test difference in means. The term "Sales-Winners" and "Sales-Runner-Ups" refer to all government sales outside of the *menor cuantia* process for firms that won and lost in the *menor cuantia* process, respectively. The column "Difference" denotes the differences in sales between winners and runners-up.

I perform several robustness checks, presented in the appendix, to examine the sensitivity of the results. First, I estimate the results looking at each year individually. Second, I use an alternative definitions of growth. Third, I estimate the results defining the dependent variable in levels instead of growth. Fourth, I do a two stage estimation using the sales from *menor cuantia* as instrument for total yearly sales. The results are not affected by the use of these alternative specifications.

1.6 Discussion and conclusions

In this paper I estimate the causal effects of demand shocks on firm growth using as a source of exogenous variation the shocks from the *menor cuantia process*. I find that, in the short-term, demand shocks significantly affect firm growth. Firms that win the contest report higher revenues and assets and spend more on wages and short-term assets than those that did not. The short-term results are consistent with recent findings in Hebous and Zimmermann (2016) and Ferraz et al.

(2016). Contrary to their findings, however, there is no evidence of an increase in growth in the years following the shock. Similarly, no differences in additional sales to the government or the private sector are observed.

The evidence presented in this paper suggests that government procurement has limited long-term impact on the growth of small firms. There are, however, important caveats concerning the generalization of these results. The short and aleatory nature of the *menor cuantia* process may affect how firms perceived the shock. Firms may be hesitant to invest in long-term assets or hire permanent workers if the change in demand is perceived as unsustainable or temporary. Similarly, the small amount and short duration of the projects might imply that firms can accommodate the increase in demand by hiring temporary staff. Further studies are needed to understand how the nature, magnitude, and duration of the demand shocks impact the long-term growth of SMEs.

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A Robustness

I perform several robustness checks to examine the sensitivity of the results. In Table 1.7, I estimate the results looking at each year individually. In column Table 1.8, I estimate growth using an alternative definition of growth ,$\frac{y_t - y_{t-1}}{.5*(y_t + y_{t-1})}$ as discussed in Ferraz et al. (2016). In Table 1.9, I estimate the results defining the dependent variable in levels instead of growth. Finally, I do a two stage estimation using the sales from *menor cuantia* as instrument for total yearly sales (available upon request).

Table 1.7: Regression results by year

Dependent Variable	Revenue Growth		Wage Growth		Fixed Assets Growth		Current Assets Growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Results for 2010								
Winner	0.640***	0.645***	0.101	0.103	0.354**	0.353**	0.373**	0.349**
	(0.186)	(0.189)	(0.111)	(0.112)	(0.137)	(0.145)	(0.165)	(0.164)
Age of firm		-0.001		0.000	-0.000	-0.000		-0.001***
		(0.001)		(0.000)	(0.000)	(0.000)		(0.000)
Results for 2011								
Winner	0.490**	0.546***	0.255**	0.242**	-0.024	-0.005	0.306*	0.292*
	(0.199)	(0.202)	(0.123)	(0.121)	(0.135)	(0.133)	(0.161)	(0.162)
Age of firm		-0.000		-0.002***	-0.001***	-0.001**		-0.001
		(0.001)		(0.000)	(0.000)	(0.000)		(0.001)
Results for 2012								
Winner	0.363	0.249	-0.123	-0.100	0.185	0.208	0.382**	0.353**
	(0.263)	(0.257)	(0.106)	(0.104)	(0.150)	(0.163)	(0.168)	(0.171)
Age of firm		-0.001*		-0.001	-0.000	-0.000		-0.002***
		(0.001)		(0.000)	(0.000)	(0.000)		(0.001)

[1] Least squares estimation of the effects of winning a procurement contract on firm growth, by year. The dependent variables are: the growth (log differences) of: revenues (columns 1 and 2), wage expenses (columns 3 and 4), fixed assets (columns 5 and 6), and current assets (columns 7 and 8). The variable winner is a dummy variable taking the value 1 if a firm won a contest at time t and 0 otherwise. Standard errors (in parentheses) are clustered at the firm-level. Age of a firm is reported in years. P-values $*p < .1, **p < .05, ***p < .01$.

Table 1.8: Regression results, alternative growth definition

Dependent Variable	Revenue Growth		Wage Growth		Fixed Assets Growth		Current Assets Growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Winner	0.249***	0.225***	0.102*	0.079	0.154**	0.139**	0.256***	0.240***
	(0.072)	(0.071)	(0.061)	(0.059)	(0.065)	(0.065)	(0.055)	(0.055)
Age of firm		-0.001***		-0.001***	-0.001***	-0.001***		-0.001***
		(0.000)		(0.000)	(0.000)	(0.000)		(0.000)
Observations	1039	1039	899	899	870	870	1262	1262
R^2	0.012	0.064	0.003	0.058	0.033	0.041	0.016	0.047

[1] Least squares estimation of the effects of winning a procurement contract on firm growth. The dependent variables are the growth, defined as $(\frac{y_t - y_{t-1}}{.5*(y_t + y_{t-1})})$ of: revenues (columns 1 and 2), wage expenses (columns 3 and 4), fixed assets (columns 5 and 6), and current assets (columns 7 and 8). The variable winner is a dummy variable taking the value 1 if a firm won a contest at time t and 0 otherwise. Standard errors (in parentheses) are clustered at the firm-level. Age of a firm is reported in years. P-values $*p < .1, **p < .05, ***p < .01$.

Table 1.9: Regression results, levels

Dependent Variable	Revenue Growth		Wage Growth		Fixed Assets Growth		Current Assets Growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Winner	1.443***	1.337***	0.953***	0.922***	0.315	0.272	0.573***	0.488***
	(0.244)	(0.228)	(0.216)	(0.200)	(0.239)	(0.221)	(0.171)	(0.153)
Age of firm		0.003***		0.004***		0.005***		0.003***
		(0.001)		(0.001)		(0.001)		(0.001)
Observations	1778	1771	1778	1771	1778	1771	1778	1771
R^2	0.020	0.149	0.011	0.146	0.001	0.185	0.006	0.196

[1] Least squares estimation of the effects of winning a procurement contract on firm growth. The dependent variables is are the log dollar amount (as reported in the balance sheet) of revenues (columns 1 and 2), wage expenses (columns 3 and 4), fixed assets (columns 5 and 6), and current assets (columns 7 and 8). The variable winner is a dummy variable taking the value 1 if a firm won a contest at time t and 0 otherwise. Standard errors (in parentheses) are clustered at the firm-level. Age of a firm is reported in years. P-values $*p < .1, **p < .05, ***p < .01$.

B Random Assignment Tests

In this section, I perform several empirical tests to check the *menor cuantia* assignment mechanism. I start by constructing a theoretical distribution of the number of times that participants are expected to win a contest and compare this, using a $\chi 2$ test, with the realized distribution. It is important to note that the process involves both firms and individuals. As a result, I use all participants for this exercise. The construction of the theoretical distribution is based on the fact that the probability of winning a contest is inversely proportional to the number of qualified providers.

For any contest j held at time t, let $d_{kjt} = i,\ i \in \{1, 0\}$ be an indicator variable taking the value 1 if the provider k wins the contest and 0 otherwise. For each individual contest j, the probability of winning is the inverse of the number of participants n that qualify to enter $P(d_j = 1) = \frac{1}{n_j}$. It follows that the expected value of the number of contracts, $D_{it} = 1$, won by a provider can be represented by:

$$\mathbb{E}_k[D_i = 1] = \sum_{j}^{J} P(d_j = 1)$$

where $\mathbb{E}_k[D_i = 1]$ depends on two factors: the total number of contests J that a given provider participated in and the number of qualified providers participating in each contest. It is therefore possible to derive a theoretical distribution of the number of expected winnings by provider, and test the theoretical results with the observed data. Let X_i be firm specific covariates, then:

Proposition 1- *The probability of winning a contest at time t is orthogonal to firm-level characteristics X_i observed at time $t-1$.*

Proposition 2- *The theoretical and actual frequency distributions of provider winnings are not different.*

Note also that the process implies that events should be independent of time. As a result, it is expected that winning a contest during $t-1$ should not affect the probability of winning the contest at time t.

$$\mathbb{E}_k[D_{it}|D_{it-1}] = \mathbb{E}_k[D_{it}] = \sum_{j_t}^{J_t} P(d_j = 1)$$

Proposition 3- *Winning a contest during year t does not affect the probability of winning a contest during year k $\forall t, k \in (2009, 2010, 2011, 2012)$ where $t \neq k$.*

Proposition 1 is tested and presented in the text. Proposition 2 and 3 are tested by using the χ^2 test using the actual and theoretical distributions. I use all of the contest won by all providers during the 2009-2012. I pooled the providers that won more than 12 times. This was done as the number of expected providers in each of those categories was less than five. Proposition 3 is tested using a similar mechanism as in proposition 2 but only include those providers that qualified for a given contest in two given years. Results are presented in the following tables. I fail to reject the null hypothesis on all three cases at the 10% level.

Table 1.10: Realized vs. expected frequency distributions

Contracts won	*Expected*	*Actual*
0	2186	2173
1	1966	1955
2	872	888
3	423	477
4	272	271
5	154	155
6	105	118
7	73	66
8	40	52
9	25	27
10	21	24
11	16	19
12	12	6
+13	25	34

Pearson χ^2 *Pr= .242*

[1] The following table presents the results of a $\chi 2$ difference in distribution test between the theoretical and actual number of times providers in the *menor cuantia* process were expected to win contracts.

Table 1.11: Expected vs. Actual distribution

Year	*Expected vs actual*	
	2010	
2009	*Winner*	*Loser*
Winner	979-958	261-282
Runners-up	650-619	393-424
Pearson χ^2 Pr= .396		
	2011	
2010	*Winner*	*Loser*
Winner	2157-2151	630-636
Runners-up	447-468	535-514
Pearson χ^2 Pr= .816		
	2012	
2011	*Winner*	*Loser*
Winner	1817-1874	511-454
Runners-up	438-461	350-327
Pearson χ^2 Pr= .132		

[1] The following table presents the results of a $\chi 2$ difference in distribution test between the theoretical and actual number of times providers in the *menor cuantia* process were expected to win contracts. The test looks at individuals that qualified for a random contest during the years 2009 and 2010, 2010 and 2011, and 2011 and 2012.

C Data Gathering Process

The data gathering process was divided into three phases. The first phase consisted on obtaining detailed information on all the public purchases performed under the *menor cuantia* processes for the years 2008-2012. This provided information on each public purchase as well as all individuals and firms that submitted a bid to participate in each public work. The second phase of the project consisted on obtaining detailed information on each individual and firm that participated in the *menor cuantia* process during the sample period. The third and final phase of the project, consisted on cleaning and entering this information into a database.

C.1 Phase I

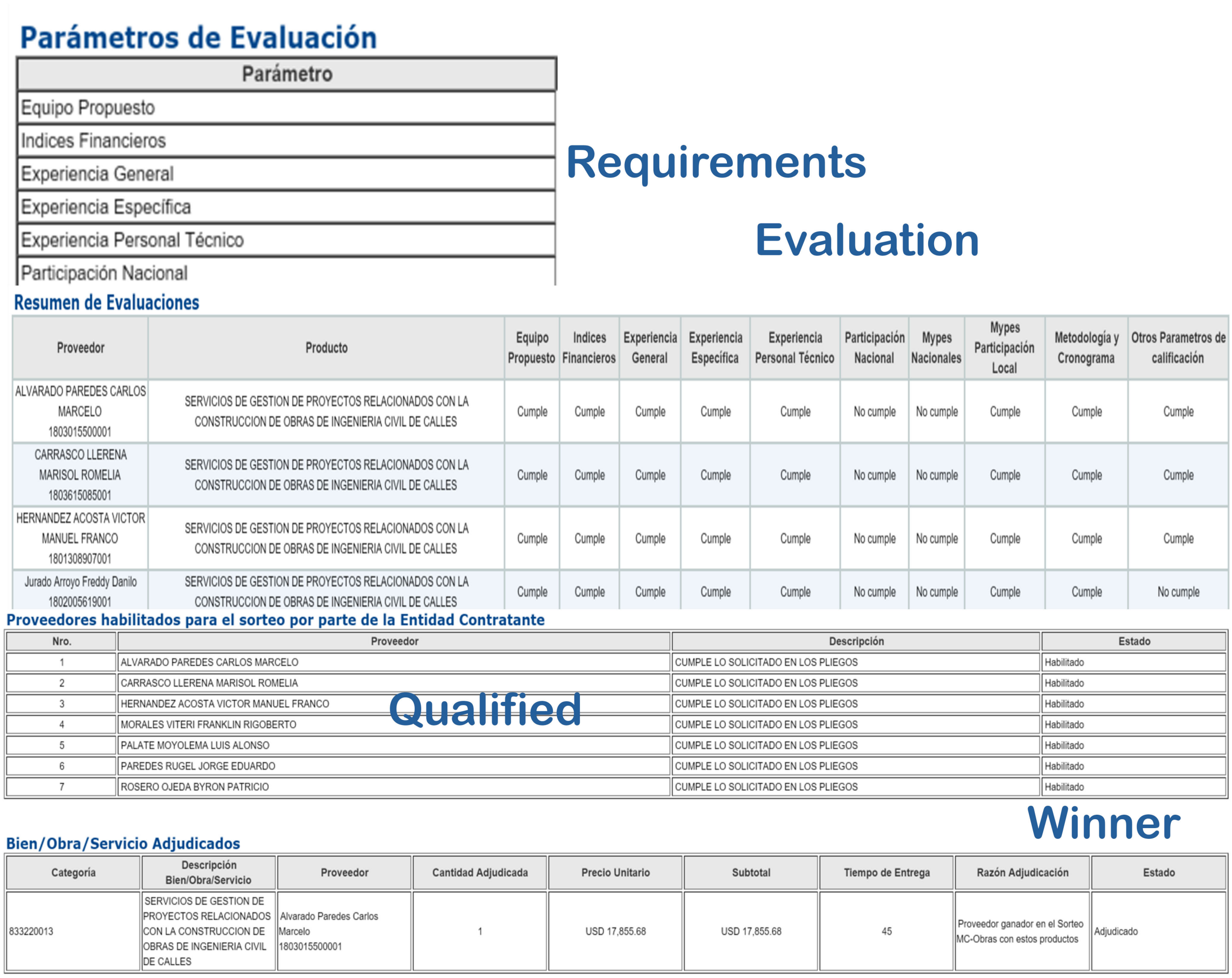
The purpose of this phase was to obtain all public works done under the *menor cuantia* process for the years 2008-2012. To do this, I first downloaded a master file that contained all purchases done by public institutions in Ecuador for the years 2009-2015. The file was downloaded from the website of the public procurement agency (SERCOP)[16]

The master file contained all purchases done by the government; including those done under processes other than the *menor cuantia*. Next, I selected the universe of all purchases under *menor cuantia*, which include their respective dates of publication. For each purchase, the file made available a description of the procurement process used, a purchase code, dates of the purchase, and other information. This file, however, did not provide the level of detail needed for the project. To obtain this additional information, I created a data scrapping code that searched and downloaded all meta-data. This required doing a personalized search for each public work in the sample. The gathering was restricted to the purchases which 1) were finalized 2) had a unique id number and 3) were awarded to only one contractor. 28,957 out of the total 32,551 public works in the *menor cuantia* met this criteria and form the universe of public works for the project.

The process above was done in three different batches during the year 2015. The first batch was a pilot project done in March 2015. The second batch took place between April and June 2015. The third batch was done in August 2015. For each of the 28,957 files, there were 9 pages that were downloaded: 1) basic information on the contract including length, terms of payment, and contacts, 2) information on the important dates of the public work, 3) information on the providers that had been invited, 4) information on the requirements for the public works, 5) information on the results of the contest, and 6) information on the providers that were qualified, 7) information on the products or services that were required, 8) a section for questions and answers, and 9) an archive with all files for the process.

[16]The website link is: http://portal.compraspublicas.gob.ec/serc op/analisis-sercop/. After opening the link, it is necessary to click under "Reportes del Sistema de Contratación Pública" which will provide a login to the database. Once inside the database, one can choose to download a report containing all information. This file was obtained on February 15th, 2015

Figure 1.3: Sample search result for menor cuantia



Parámetros de Evaluación

Parámetro
Equipo Propuesto
Indices Financieros
Experiencia General
Experiencia Específica
Experiencia Personal Técnico
Participación Nacional

Resumen de Evaluaciones

Proveedor	Producto	Equipo Propuesto	Indices Financieros	Experiencia General	Experiencia Específica	Experiencia Personal Técnico	Participación Nacional	Mypes Nacionales	Mypes Participación Local	Metodología y Cronograma	Otros Parametros de calificación
ALVARADO PAREDES CARLOS MARCELO 1803015500001	SERVICIOS DE GESTION DE PROYECTOS RELACIONADOS CON LA CONSTRUCCION DE OBRAS DE INGENIERIA CIVIL DE CALLES	Cumple	Cumple	Cumple	Cumple	Cumple	No cumple	No cumple	Cumple	Cumple	Cumple
CARRASCO LLERENA MARISOL ROMELIA 1803615085001	SERVICIOS DE GESTION DE PROYECTOS RELACIONADOS CON LA CONSTRUCCION DE OBRAS DE INGENIERIA CIVIL DE CALLES	Cumple	Cumple	Cumple	Cumple	Cumple	No cumple	No cumple	Cumple	Cumple	Cumple
HERNANDEZ ACOSTA VICTOR MANUEL FRANCO 1801308907001	SERVICIOS DE GESTION DE PROYECTOS RELACIONADOS CON LA CONSTRUCCION DE OBRAS DE INGENIERIA CIVIL DE CALLES	Cumple	Cumple	Cumple	Cumple	Cumple	No cumple	No cumple	Cumple	Cumple	Cumple
Jurado Arroyo Freddy Danilo 1802005619001	SERVICIOS DE GESTION DE PROYECTOS RELACIONADOS CON LA CONSTRUCCION DE OBRAS DE INGENIERIA CIVIL DE CALLES	Cumple	Cumple	Cumple	Cumple	Cumple	No cumple	No cumple	Cumple	Cumple	No cumple

Proveedores habilitados para el sorteo por parte de la Entidad Contratante

Nro.	Proveedor	Descripción	Estado
1	ALVARADO PAREDES CARLOS MARCELO	CUMPLE LO SOLICITADO EN LOS PLIEGOS	Habilitado
2	CARRASCO LLERENA MARISOL ROMELIA	CUMPLE LO SOLICITADO EN LOS PLIEGOS	Habilitado
3	HERNANDEZ ACOSTA VICTOR MANUEL FRANCO	CUMPLE LO SOLICITADO EN LOS PLIEGOS	Habilitado
4	MORALES VITERI FRANKLIN RIGOBERTO	CUMPLE LO SOLICITADO EN LOS PLIEGOS	Habilitado
5	PALATE MOYOLEMA LUIS ALONSO	CUMPLE LO SOLICITADO EN LOS PLIEGOS	Habilitado
6	PAREDES RUGEL JORGE EDUARDO	CUMPLE LO SOLICITADO EN LOS PLIEGOS	Habilitado
7	ROSERO OJEDA BYRON PATRICIO	CUMPLE LO SOLICITADO EN LOS PLIEGOS	Habilitado

Bien/Obra/Servicio Adjudicados

Categoría	Descripción Bien/Obra/Servicio	Proveedor	Cantidad Adjudicada	Precio Unitario	Subtotal	Tiempo de Entrega	Razón Adjudicación	Estado
833220013	SERVICIOS DE GESTION DE PROYECTOS RELACIONADOS CON LA CONSTRUCCION DE OBRAS DE INGENIERIA CIVIL DE CALLES	Alvarado Paredes Carlos Marcelo 1803015500001	1	USD 17,855.68	USD 17,855.68	45	Proveedor ganador en el Sorteo MC-Obras con estos productos	Adjudicado

The figure above presents the search results of a public work. The top part presents the requirements for the contest. The evaluation part presents, for each bidder, a note stating if they satisfy the requirements. The qualified sections shows those providers that qualified for the contest. The winner section presents the winner of the contest.

C.2 Phase II

In phase II of the project, I obtained financial information on the firms and individuals that participated in the *menor cuantia* process. The meta-data, gathered in the previous phase, provided information on all providers that submitted a bid to perform the public work. Each provider has a unique identification number used for tax purposes (RUC or registro único del contribuyente). There are two different types of providers: firms and self-employed. By law, financial information for firms is available at the Superintendencia de Companias, (SUPERCIAS). SUPERCIAS is a government institution and all companies must provide financial records, tax statements, and contact information to them. SUPERCIAS makes this information publicly available through their website.

Repeated requests to obtain the data on companies went unanswered. As a result, an automated program was created to obtain this information.[17] I downloaded two types of data. The first included basic company information and was scrapped directly from the website. The second included all yearly financial statements on record for that company.

C.3 Phase III

In this phase of the project, I had to enter the financial information into a database. The statements were stored as PDF documents in two different formats: 1) a scanned image and/or 2) a structured document. To obtain the financial data from the structured document, I ran several scripts to do so automatically. Figure 1.4 provides a sample of this type of balance. For balances that were scanned copies of documents, the data was entered manually and verified by at least an additional worker and was tested using accounting principles. Figure 1.5 and Figure 1.6 provide an example of the financial information available as scanned documents.

The final phase involved testing all information gathered to ensure it was consistent.

[17]In order to minimize the risk of skipping some companies, I performed the scraping 3 times on those companies I was not able to find.

Figure 1.4: Sample financial information

SUPERINTENDENCIA DE COMPAÑÍAS

RAZÓN SOCIAL	CONSTRUCTORA GARCIA SALTOS CIA. LTDA.
DIRECCIÓN	JOSE MARIA VELASCO IBARRA S/N Y 10 DE NOVIEMBRE
EXPEDIENTE	385
RUC	1891735428001
AÑO	2011
FORMULARIO	SC.NEC.385.2011.1
FECHA DE LA JUNTA QUE APROBÓ LOS ESTADOS FINANCIEROS (DD/MM/AAAA)	10/04/2013

ESTADO FINANCIERO BAJO NEC PARA LA SUPERINTENDENCIA DE COMPAÑÍAS

OPERACIONES CON PARTES RELACIONADAS DEL EXTERIOR EN EL EJERCICIO ECONÓMICO

CUENTA	CÓDIGO	VALOR US$
ACTIVO CON PARTES RELACIONADAS DEL EXTERIOR	11	
PASIVO CON PARTES RELACIONADAS DEL EXTERIOR	12	
INGRESO CON PARTES RELACIONADAS DEL EXTERIOR	13	
EGRESO CON PARTES RELACIONADAS DEL EXTERIOR	14	
TOTAL OPERACIONES CON PARTES RELACIONADAS DEL EXTERIOR	15	

BALANCE GENERAL (NEC 1)

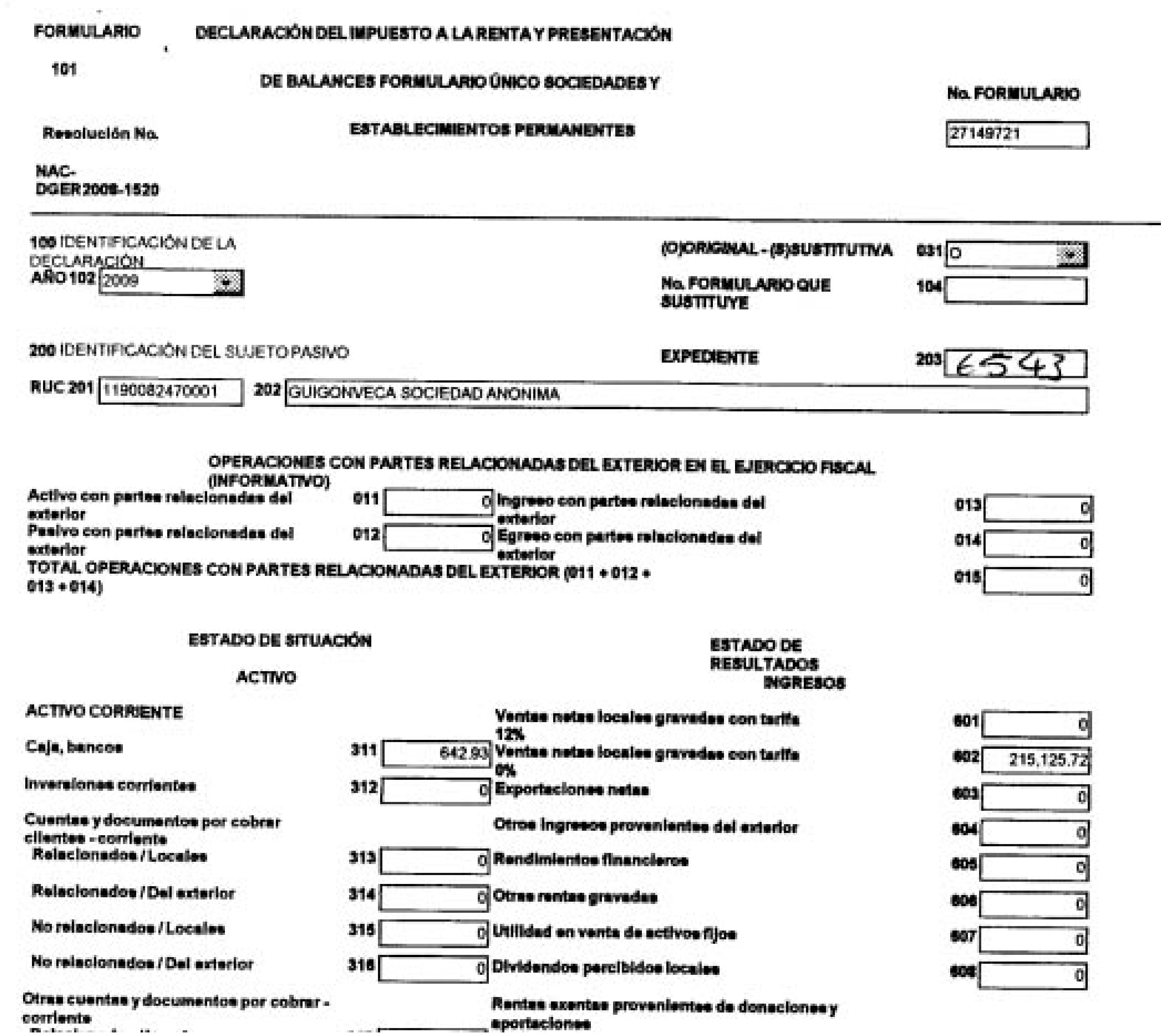
CUENTA	CÓDIGO	VALOR US$
CAJA - BANCOS	311	4.737,69
INVERSIONES CORRIENTES	312	
CUENTAS Y DOCUMENTOS POR COBRAR CLIENTES CORRIENTE RELACIONADOS LOCALES	313	
CUENTAS Y DOCUMENTOS POR COBRAR CLIENTES CORRIENTE RELACIONADOS DEL EXTERIOR	314	
CUENTAS Y DOCUMENTOS POR COBRAR CLIENTES CORRIENTE NO RELACIONADOS	315	

ESTADO DE RESULTADOS (NEC 1)

CUENTA	CÓDIGO	VALOR US$
VENTAS NETAS LOCALES GRAVADAS CON TARIFA 12%	601	78.252,27
VENTAS NETAS LOCALES GRAVADAS CON TARIFA 0%	602	
EXPORTACIONES NETAS	603	
OTROS INGRESOS PROVENIENTES DEL EXTERIOR	604	
RENDIMIENTOS FINANCIEROS	605	
OTRAS RENTAS GRAVADAS	606	

The figure above presents a financial return available as a structured format. The data from this balance was extracted using automated script.

Figure 1.5: Sample financial information



FORMULARIO 101

DECLARACIÓN DEL IMPUESTO A LA RENTA Y PRESENTACIÓN DE BALANCES FORMULARIO ÚNICO SOCIEDADES Y ESTABLECIMIENTOS PERMANENTES

Resolución No. NAC-DGER2009-1520

No. FORMULARIO 27149721

100 IDENTIFICACIÓN DE LA DECLARACIÓN

AÑO 102 2009

(O)ORIGINAL - (S)SUSTITUTIVA 031 O

No. FORMULARIO QUE SUSTITUYE 104

200 IDENTIFICACIÓN DEL SUJETO PASIVO

EXPEDIENTE 203 6543

RUC 201 1190082470001 202 GUIGONVECA SOCIEDAD ANONIMA

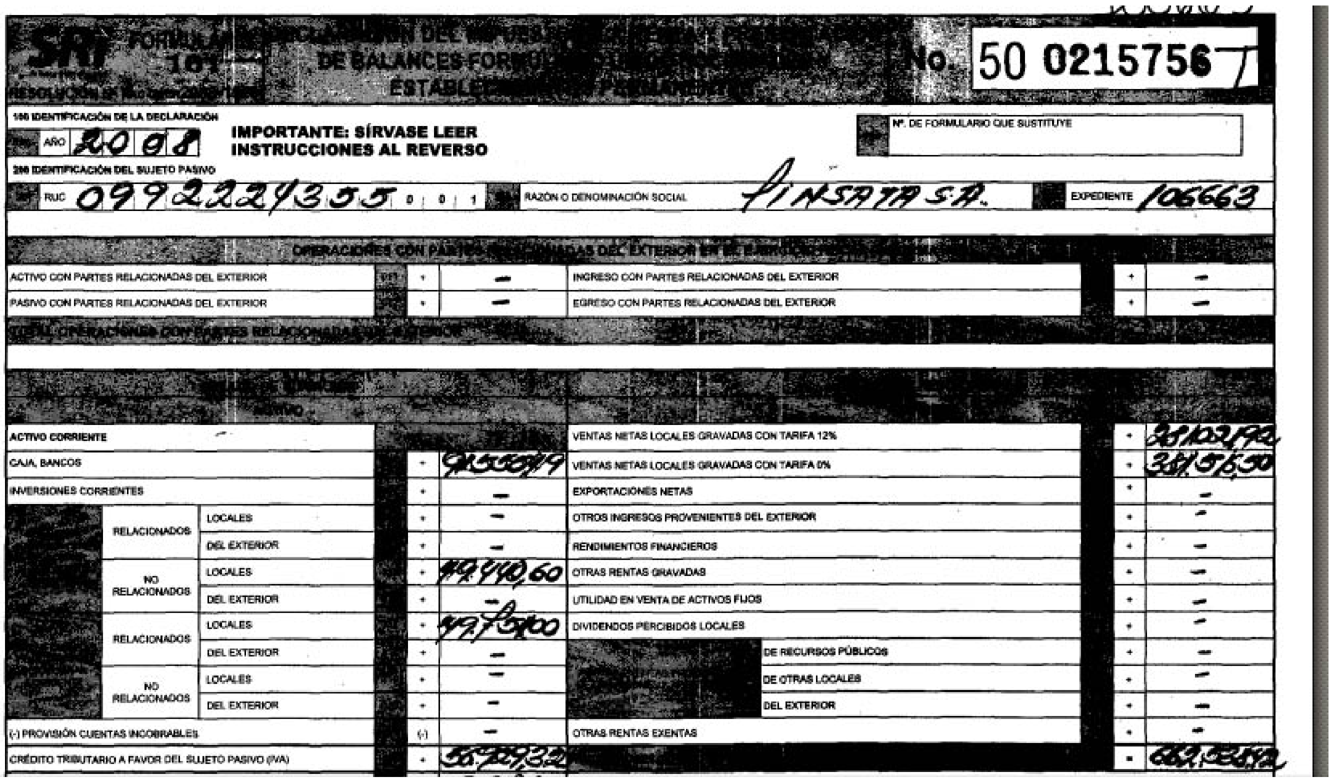
OPERACIONES CON PARTES RELACIONADAS DEL EXTERIOR EN EL EJERCICIO FISCAL (INFORMATIVO)

Activo con partes relacionadas del exterior	011	0	Ingreso con partes relacionadas del exterior	013	0
Pasivo con partes relacionadas del exterior	012	0	Egreso con partes relacionadas del exterior	014	0
TOTAL OPERACIONES CON PARTES RELACIONADAS DEL EXTERIOR (011 + 012 + 013 + 014)				015	0

ESTADO DE SITUACIÓN – ACTIVO			ESTADO DE RESULTADOS – INGRESOS		
ACTIVO CORRIENTE			Ventas netas locales gravadas con tarifa 12%	601	0
Caja, bancos	311	642.93	Ventas netas locales gravadas con tarifa 0%	602	215,125.72
Inversiones corrientes	312	0	Exportaciones netas	603	0
Cuentas y documentos por cobrar clientes - corriente			Otros ingresos provenientes del exterior	604	0
Relacionados / Locales	313	0	Rendimientos financieros	605	0
Relacionados / Del exterior	314	0	Otras rentas gravadas	606	0
No relacionados / Locales	315	0	Utilidad en venta de activos fijos	607	0
No relacionados / Del exterior	316	0	Dividendos percibidos locales	608	0
Otras cuentas y documentos por cobrar - corriente			Rentas exentas provenientes de donaciones y aportaciones		

The figure contains a financial return available as scanned copies. The data from this balance was obtained via manual entry.

Figure 1.6: Sample financial information


No. 50 0215756

100 IDENTIFICACIÓN DE LA DECLARACIÓN

AÑO 2008

IMPORTANTE: SÍRVASE LEER INSTRUCCIONES AL REVERSO

Nº. DE FORMULARIO QUE SUSTITUYE

200 IDENTIFICACIÓN DEL SUJETO PASIVO

RUC 0992224355 0 0 1

RAZÓN O DENOMINACIÓN SOCIAL FINSATA S.A.

EXPEDIENTE 106663

ACTIVO CON PARTES RELACIONADAS DEL EXTERIOR	+	–	INGRESO CON PARTES RELACIONADAS DEL EXTERIOR	+	–
PASIVO CON PARTES RELACIONADAS DEL EXTERIOR	+	–	EGRESO CON PARTES RELACIONADAS DEL EXTERIOR	+	–

ACTIVO CORRIENTE					VENTAS NETAS LOCALES GRAVADAS CON TARIFA 12%	+	38102,90
CAJA, BANCOS			+	91555,49	VENTAS NETAS LOCALES GRAVADAS CON TARIFA 0%	+	38157,50
INVERSIONES CORRIENTES			+	–	EXPORTACIONES NETAS	+	–
	RELACIONADOS	LOCALES	+	–	OTROS INGRESOS PROVENIENTES DEL EXTERIOR	+	–
		DEL EXTERIOR	+	–	RENDIMIENTOS FINANCIEROS	+	–
	NO RELACIONADOS	LOCALES	+	49440,60	OTRAS RENTAS GRAVADAS	+	–
		DEL EXTERIOR	+	–	UTILIDAD EN VENTA DE ACTIVOS FIJOS	+	–
	RELACIONADOS	LOCALES	+	497500	DIVIDENDOS PERCIBIDOS LOCALES	+	–
		DEL EXTERIOR	+	–	DE RECURSOS PÚBLICOS	+	–
	NO RELACIONADOS	LOCALES	+	–	DE OTRAS LOCALES	+	–
		DEL EXTERIOR	+	–	DEL EXTERIOR	+	–
(-) PROVISIÓN CUENTAS INCOBRABLES			(-)	–	OTRAS RENTAS EXENTAS	+	–
CRÉDITO TRIBUTARIO A FAVOR DEL SUJETO PASIVO (IVA)			+	56929,32		=	669,358,92

The figure contains a financial return available as scanned copies. The data from this balance was extracted via-manual entry.

D Sample selection

A total of 1,920 registered firms participated in the process. To obtain the firm's financial information, I used the unique tax identification number and performed a search on the Superintendencia de Compañias' (SUPERCIAS) website. I was able to obtain information on 1836 firms. The remaining 84 firms did not have a record. Out of the 1836, there were 661 firms that won, at least once, a contest where there was only one qualified participant for the lottery. These 661 firms participated in a total of 3,160 public contests. I exclude from the sample these firms. The total sample for public works under menor cuantia to be 1,175 firms participating in 5,475 public works.

Chapter 2
The Effects of Temporary Income Shocks on Household Expenditures

Abstract

I study how household expenditures on non-durable consumption and human capital change in response to a positive and temporary income shock. I examine a sample of one-income earning Ecuadorian households where the income earner participated in a procurement process that uses a random lottery to select winning bidders for public tenders. I use a unique dataset that combines the results from the lottery with confidential tax-level data. I find that income shocks cause households to increase spending in education and health by 8%, and in food and clothing by 11% during the year of the shock. I also find that households that received shocks of higher magnitudes smooth their expenditures over time.

In addition to providing a measure of the propensity to consume for households in Ecuador, this study contributes to the literature by focusing on an unexpected, positive and temporary income shock. Additionally, this study estimates the joint effects on non-durable consumption and human capital, areas which have traditionally been studied separately.

Keywords: Human capital, income shocks, non-durable consumption
J.E.L. Codes: H57, I38, C13

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2.1 Introduction

Understanding how households react to changes in income has been a perennial area of research in development economics.[1] Research on this subject can be used at a macro and micro economic level to help, for instance, estimate monetary and fiscal multipliers and model the effects of public policies. To properly address this question, it is essential to identify if the shock is expected or unexpected and if it is temporary or permanent (Jappelli and Pistaferri, 2010; Blundell et al., 2008). Equally important, the researcher must account for measurement error, especially when examining more than one variable at a time (Pistaferri, 2015). Addressing both issues concurrently remains a challenge in the literature.

In this paper, I estimate the causal effects of temporary and unexpected income shocks on expenditures in non-durable consumption and human capital. To this purpose, I use confidential tax deduction data from the National Tax Collection Agency of Ecuador and examine the expenditures claimed by 2,902 single-income households on education and health (human capital) and clothing and food (non-durable consumption) for the years 2009-2012. The heads of the households in the sample provided services to the Ecuadorian government under a process that selects vendors using a random lottery. I use the exogenous variation in household income created by the lottery to causally estimate the impact of income shocks on expenditures at the extensive and intensive margin.

The unique dataset and setting are particularly relevant to answer this empirical question. The increase in household income for households that benefited from the lottery is exogenous, temporary, and unexpected. Therefore, households that did not benefit from the lottery serve as an appropriate counterfactual to obtain unbiased estimates of income shocks. Tax deductions provide a reliable measure of expenditure as they reflect actual purchases and must be accompanied by receipts. As a result, I am able to jointly estimate expenditures in non-durable consumption and human capital.[2]

I find that during the year of the shock, households that benefited from the lottery spend, on average, between 11% more in non-durable consumption and 8% more in human capital as compared to those households that did not win. At the intensive margin, the results suggest an income elasticity of expenditure of 0.13 for human capital and 0.2 for non-durable consumption. I also find evidence that, for shocks of higher monetary amounts, the effects are observed the year after the shock.

This study contributes to the literature that examines how consumption and human capi-

[1] For an overview of the literature see (Becker and Tomes, 1986; Souleles, 1999; Banerjee, 2004; Frankenberg and Thomas, 2017). The source of income shocks studied in the literature include: economic conditions, weather changes, conflict, and assistance programs.

[2] An obvious concern on the use of tax data to infer expenditure is its reliability. The data section provides evidence indicating that the tax-information used in this study represents objective and real expenditures.

tal respond to temporary changes in income. Souleles (1999) analyzes the consumption of U.S. households after receiving a tax refund and finds excess sensitivity to shocks, particularly among liquidity constraint households. Parker et al. (2013) look at consumption following the 2008 stimulus package in the United States, and find that households spend up to a third of their additional income on non-durables. Haushofer and Shapiro (2016) show that, following an increase in income from an unconditional cash transfer, household consumption increased by 23%, medical expenses increased by 38%, and expenditures in education by 19%.

The main contribution of this paper to the literature is that it examines an income shock that is unexpected, positive and temporary. In this particular setting, the shock comes from an increase in labor supplied by the household head, as opposed to tax rebates or cash handouts. Furthermore, the unique dataset allows me to provide estimates for both non-durable consumption and human capital, areas which have traditionally been studied separately. One of the limitations of the data is that, due to administrative data restrictions, I can only measure expenditures at the aggregate household level. As a result, I cannot study how the shock is allocated within the family. Nonetheless, the results provide further evidence that non-durable consumption and human capital investment respond strongly to transitory changes in household income.

The rest of the paper is divided as follows: section 2.2 discusses a theoretical framework to analyze the role of income shocks on household expenditures. Section 2.3 describes the institutional context. Section 2.4 describes the data. Section 2.5 discusses the empirical strategy. Section 2.6 presents the results and section 2.7 concludes.

2.2 Theoretical framework

In this section, I present a simple dynamic model based on Cunha and Heckman (2007) and Carneiro and Ginja (2016) that illustrates the theoretical implications of income shocks on household consumption and human capital investment. Consider a household made-up of one parent and one child. The parent is the sole income earner and decides how to allocate her income between household consumption and child-specific goods. The parent supplies labor inelastically, is always employed and receives an exogenous wage, w_t. Parents are altruistic and leave no bequest to their children. Children are born with a level of ability, h_c. This ability does not depreciate and can increase by investing in child specific goods, g_t.

For a given level of assets a_{it}, wage w_{it}, and human capital, h_{it-1}, the parent maximizes household consumption, c_t, and child investment, g_t, to solve:

$$\max_{c_t, g_t}(w_t, a_t, h_{t-1}) = \sum_{t=1}^{T} \beta^t u(c_t, h_t) \tag{1}$$

subject to the budget constraint $\frac{a_{t+1}}{1+r} = a_t + w_t - c_t - g_t$ and the human capital production function of the child $h_t = f(h_{t-1}, g_t)$. If credit constraints are binding, an additional constraint is that $a_t \geq 0$

In general, there is no analytical solution for equation 1. Carneiro and Ginja (2016) show that the Euler equation for this problem can be expressed as:

$$\beta(1+r)\mathbf{E_t}\Big\{\frac{U_c c_t}{U_c(c_{t+1})}\Big\} = 1 \tag{2}$$

$$\beta(1+r)\mathbf{E_t}\Big\{\frac{U_h h_t}{U_h(h_{t+1})}\Big\} = 1 \tag{3}$$

Where U_c and U_h denote the marginal utility of consumption and human capital, respectively. Equation 2 is the familiar Euler equation for consumption. Equation 3 suggests that parents equate the ratio of investment between periods. This, in turn depends on the degree of substitutability (inter-temporal elasticity of substitution) between periods. If investments are substitutes, then parents can save one period and invest in the other without affecting the human capital of the child. If they are complements, then late investments might not compensate for missing past investments. This set-up illustrates that investments in children depend, among other things, on past investments and the level of human capital of the child.

Expression 2 can only be obtained by assuming no credit constraints, perfect foresight, and parental knowledge of the human capital production function. Heckman and Mosso (2014) highlight additional complications in models that consider credit imperfections and stochastic income. Consequently, the role of income shocks on changes in human capital investment and consumption is not conceptually straightforward to identify.

2.3 Institutional Setting

In this section, I first provide a brief overview of *menor cuantia*, a procurement process that randomly selects winning bidders for public tenders. This process is discussed in depth in the previous chapter; for the sake of brevity, I only discuss its main features. I then describe the tax deduction process in Ecuador, which I use as the data source to capture household expenditures.

2.3.1 Menor cuantia

Ecuador is a developing country with a dollarized economy since the year 2001 and a 2016 GDP per capita of $6,205. Between the years 2005-2014 a high international price of oil financed a wave of public spending in the country. In 2008, a reform to the public procurement law was enacted, whereby all government purchases were centralized. As part of this reform, and of essential importance for this paper, was the creation of the so-called *menor cuantia* public procurement mechanism.

Menor cuantia is a process designed for public works whose value is below .0007% of the government budget.[3] For the years 2009-2012, the threshold to use the process was approximately $150,000 (2012 nominal USD). The process works through an online portal that connects suppliers with public institutions. To start the process, a public institution must create a new entry in the online platform which includes a description of the project and a set of requirements. Once an entry is created, potential suppliers that are registered in the system can submit their bids for the project. They do so by expressing their interest and uploading legal documents that verify they satisfy the requirements.

A public committee then evaluates all of the potential suppliers that submitted bids. The goal of the committee is to identify those providers that meet the minimum requirements stated in the project. Those that do so enter into a pool of qualified candidates. In the final phase of the process, the system automatically and randomly selects a winner from the pool of qualified candidates identified by the committee. This candidate is the winner of the contest (hereafter provider) and is assigned the public contract.

A priori, the design of the process suggests that, conditionally on qualifying to enter the random draw, the observed and unobserved characteristics of providers are orthogonal to the outcome of the lottery. This is corroborated by the fact that contracts are not awarded based on individual characteristics and that there is no negotiation between institutions and bidders, as the price for a given public work is fixed. Additionally, the requirements that are set for each contract are defined in terms of objective criteria, and are certified by legal documents. The random allocation of contracts, however, is ultimately an empirical matter tested in section 2.5.

2.3.2 Tax Deductions

The Servicio de Rentas Internas (SRI) is the government agency responsible for collecting taxes in Ecuador. The SRI collects three types of taxes: value added taxes for certain goods and services, personal income taxes, and special taxes on international transfer fees, estates, and lotteries (Bohne and Nimczik, 2016). The data for this project comes from personal income taxes which all income earners must file. Taxes are progressive and based on a tax-schedule that varies from year to year (see Table 2.1). Joint tax filing is not allowed; if a household has two or more income-earners, each of them must file their taxes separately.

[3]This process consists mostly of new construction or remodeling projects. Before procuring a new public work, it must be approved in the budgetary process which occurs at least one year before the public work is expected to begin.

Table 2.1: Tax Schedule in Ecuador for the year 2016

Minimum	Maximum	Tax Amount	Tax Rate
0	11,170	0	0%
11,170	14,240	0	5%
14,240	17,800	153	10%
17,800	21,370	509	12%
21,370	42,740	938	15%
42,740	64,090	4,143	20%
64,090	85,470	8,413	25%
85,470	113,940	13,758	30%
113,940	113,940+	22,299	35%

The following table describes the tax schedule for 2016. The first and second column show the minimum and maximum values for a given tax bracket. The fourth column shows the tax rate for a given bracket. The values shown are in U.S. dollars (the official currency of Ecuador). Source-Tax Authority of Ecuador.

Individuals can deduct from their taxable income expenses incurred in the following five categories: education, health, food, clothing, and housing. The total deductions can reach up to 50% of the gross income amount or up to 1.35 the tax-exempt value, whichever is the lowest.[4] Common deductions include: payments for school tuition, school transportation, uniforms, school books, purchase of groceries, alimony payment, purchase of clothes and shoes, remodeling of a house, payment of housing utilities, medicine, and health services. To claim a deduction, an individual must have a corresponding receipt assigned to their unique tax identification number, a process usually done at the time of purchase. Deductions for a given receipt can be claimed only once. The information from tax deductions provide a reliable measure of spending that overcomes some of the limitations of survey data. The advantages of using tax deductions is that they are based on actual purchases. In addition, households have an incentive to report the expenses, as it lowers their tax burden. In contrast to surveys, however, tax deductions do not capture informal and/or small purchases.

2.4 Data

I use a unique dataset that combines detailed level data on all procurement contracts done between 2009-2012 under *menor cuantia* with individual tax-level data for the years 2006-2013. Data for

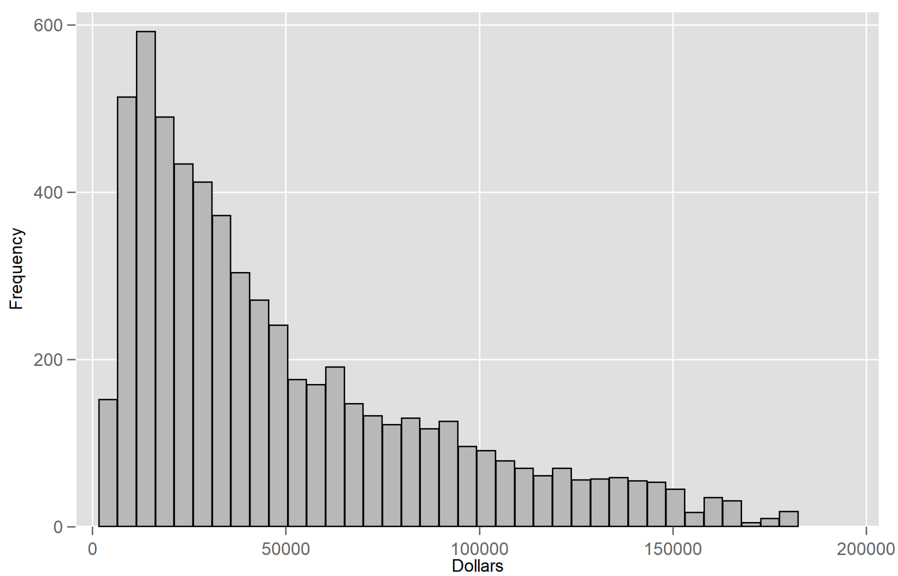
[4] The maximum amount individuals can claim on health expenditures is 135% of the tax-exempt values. For food, clothing, housing, and education, this value is 32.5% of the tax-exempt value. For example, using the tax schedule for 2016 presented in Table 2.1, an individual making $15,000 during 2016, could claim total deductions of up to $7,500. The maximum amount deducted from each area, except for medical expenditures, is $4,875.

menor cuantia was constructed by scraping the information from the National Procurement Agency (SERCOP).[5] Data for tax deductions comes from the National Tax Authority of Ecuador (SRI). Additional regional data used to control for economic variables comes from the national statistical institute of Ecuador (INEC).

The dataset allows me to match data on the amount received from *menor cuantia* to household expenditures. I only examine households with one-income earner during the year of the contest that participated and qualified in the *menor cuantia* process.[6]

Due to administrative limitations, demographic information was not available from the SRI. I supplemented this data with proprietary information that includes: household composition, age of children, and marital status from a large Ecuadorian financial institution. Due to confidentiality reasons this information is only used to control for household characteristics in the empirical estimations.

Figure 2.1: Distribution of Contracts (2010-2012)



The figure above provides the contract amount of the 14,589 public works in the sample performed between the years 2010-2012. The values for public works are presented in U.S. dollars.

The dataset contains information on 2,902 heads of household that participated in 14,589 public works for the years 2009-2012. Figure 2.1 provides the distribution of contract amounts for the period 2009-2012. Public works done under *menor cuantia* have an average value of $45,414 and approximately 85% of the contracts last less than three months. The number of contracts

[5] See appendix in the previous chapter for description of the data gathering process.

[6] I only consider individuals that participated as individual contractors and not as a representative of a firm. Individual contractors bid for projects as natural citizens. For tax purposes, they report this income on their personal income tax forms. Individuals that are also representatives of firms follow other reporting procedures.

grew from 1,077 in 2009 to 4,256 in 2010, declining slightly in 2011 and 2012. On average, each contract had 13 qualified providers, the minimum being 2 and the maximum 156. The breakdown of participants per year is as follows: 2010 had 2,305 providers that participated (1349 won); 2011 had 2,103 providers that participated (1231 won); 2012 had 1,695 providers that participated (963 won). The average contract consists of a set of 6 requirements that providers need to satisfy to qualify for the draw. Common requirements include: previous professional experience in public works, registry of machinery, and educational certificates.

Table 2.2: Descriptive statistics of providers

	Avg.	SD.	Obs.	Min	Max
Age (Years)	45	11	9,202	22	83
Expenditure on clothing (USD)	1,299	825	652	4	4,308
Expenditure on food (USD)	2,153	1,076	652	45	7,140
Expenditure on education (USD)	1,667	1,115	652	3	6,318
Expenditure on health (USD)	1,393	1,111	652	12	7,152

[1] Descriptive statistics of 2,902 heads of household participating in the *menor cuantia* process for the years in the sample. Values are arithmetic averages. Age is presented in years while expenditure is in USD.

The heads of household that participated in the contracts consists of mostly adult males (92%). The average individual won 1.4 contracts during the sample period. Out of the 2,902 heads of household, 966 of them did not win a contract during the time period. The average winner of the bid is 45 years old, 70% of which are married, 22% single, and 8% divorced. The majority (93%) have a high school education. The average household head reported a monthly income of $1,534 before taxes. The highest deduction for tax purposes is on food ($2,153), followed by education ($1,667), health ($1,393) and clothing ($1,299). For households that won a contract, the reported average monthly income (after deductions) is $408 more than those that did not win a contract.

2.5 Empirical Strategy

The identification strategy relies on the assumption that, under the *menor cuantia* process, the allocation of contracts is exogenous to any individual characteristics that also affect expenditures on non-durable consumption and human capital. To test this proposition, I do a difference in means test between winners and runners-up of the contracts for each year between 2010 and 2012, presented in Table 2.3. There are no significant differences between both groups in total income, age, civil status, and deductions on housing, and health at the 10% level. For education, the runner-ups show higher expenditures for the years 2011 and 2012. This result, however, is due

Table 2.3: Difference in means Student t-test results by year

Variable	Runners-up	Winner	P-value
2010			
Expenditure on clothing (\$)	1010.32	907.05	0.54
Expenditure on education (\$)	1615.54	2049.30	0.24
Expenditure on health (\$)	875.22	934.95	0.72
Expenditure on food (\$)	2697.07	2973.24	0.54
Age (Years)	45.04	44.89	0.73
Gross income (\$)	27039.24	27389.39	0.75
2011			
Expenditure on clothing (\$)	983.05	1130.74	0.44
Expenditure on education (\$)	2312.14	1542.96	0.04
Expenditure on health (\$)	1169.24	1101.63	0.76
Expenditure on food (\$)	2112.51	2242.39	0.72
Age (Years)	45.43	45.00	0.35
Gross income (\$)	22223.24	23488.69	0.27
2012			
Expenditure on clothing (\$)	1139.80	1302.90	0.40
Expenditure on education (\$)	1819.35	1352.54	0.08
Expenditure on health (\$)	1165.07	1666.53	0.10
Expenditure on food (\$)	1750.28	1841.53	0.69
Age (Years)	45.00	45.40	0.47
Gross income (\$)	23579.57	23556.32	0.98

[1] Difference in means for individuals participating in the *menor cuantia* contest. The variables are the lags of the log values.

to a few households that reported high amount during those years.[7] Further tests based on the actual and theoretical distributions of winners provide additional evidence that the assignment of contracts is in fact random.[8]

The sample for this study consists only of one-income households that participated in *menor cuantia*. By focusing on this sample, I avoid instances with endogenous changes in the total labor supplied by the household that would occur if, for instance, winning a contract changes the hours worked by a spouse. Given that the amount received from *menor cuantia* is exogenous, one could estimate its effects on non-durable consumption and human capital expenditures separately using the following reduced form equations:

$$consumption_{it} = \beta_0 + \beta_1 income_{it} + X_{it}\beta_2 + W_t\beta_3 + \delta_{1i} + \epsilon_{1it} \tag{4}$$

$$human\_capital_{it} = \rho_0 + \rho_1 income_{it} + X_{it}\rho_2 + W_t\rho_3 + \delta_{2i} + \epsilon_{2it} \tag{5}$$

[7] Although there is a limit on the amount of tax deductions that household can claim in each area, the tax data show certain households that exceeded this threshold. The results of the paper remain unchanged if I exclude these households.

[8] This question is discussed in more detail in the previous chapter.

where $consumption_{it}$ and $human\_capital_{it}$ denote the log expenditures of household i during year t in non-durable consumption and human capital, respectively. The variables X_i are household specific observables, W_t, is a vector of economic conditions, and δ_i is a time fixed effect. To estimate the effects of income shocks at the extensive margin, I set the variable *income* to be a dummy variable equal to 1 if the head of household i won a contract during the year t and 0 otherwise. The extensive margin analysis shows the average differences in expenditure between winners and runners-up during time t. To measure the intensive margin, I set *income* to be equal to the log amount that the household obtained from the *menor cuantia*, thereby providing a measure of sensitivity of expenditures.

Equations 4 and 5 could be estimated separately using ordinary least squares; however, doing so does not take into account the potential correlation between human capital and consumption and does not allow to estimate how income shocks affect both variables jointly (Wooldridge, 2010). As a result, I estimate equations 4 and 5 jointly using seemingly unrelated regression (SURE).[9] A limitation of this specification is that it provides a measure of expenditure and not actual consumption. This implies that I cannot distinguish between expenditures due to changes in quantity and those due to a change in quality. Nonetheless, under the mild assumption that both human capital and non-durable consumption are normal goods, the coefficient, β_1, is unbiased and can provide an appropriate, though imprecise, measure of the effects of household income on actual consumption and human capital investment.

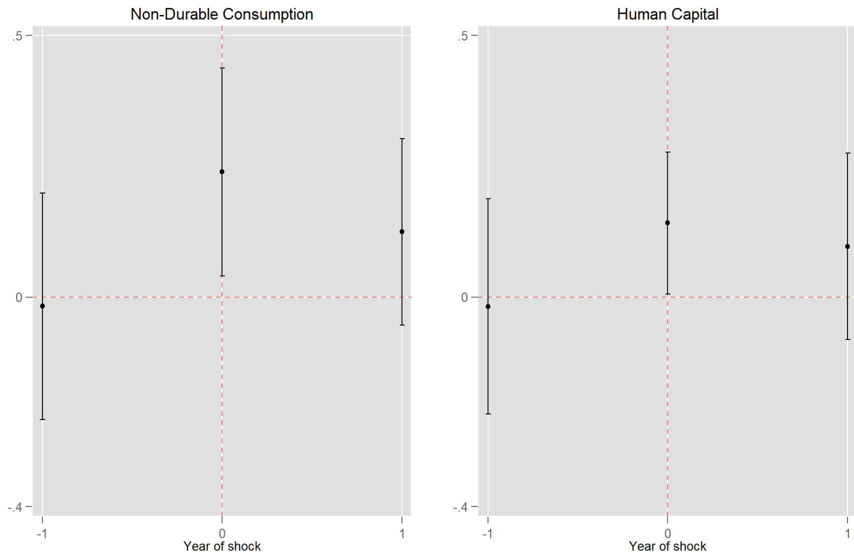
A possible problem that comes with using tax deductions to measure expenditure, is the misreporting of receipts. Businesses have an incentive to avoid issuing receipts to reduce their tax burden. They could, in principle, offer discounts to buyers if they do not request them. A parallel concern is that households close to the threshold of permitted deductions do not have an incentive to declare expenditures beyond this limit. While it is not possible to empirically test these concerns, they would, most likely, bias the results towards zero. Households that benefited from the lottery have, on average, a higher household income during the year of the shock. Taking into account that there is a correlation between household income and tax deductions, this suggests underreporting will be more likely in those households that benefited from the lottery.

2.6 Results

In this section, I present the results of the effect of income shocks on household expenditure at the intensive and extensive margin. For brevity of presentation, I combine expenditures on education and health labeling them as "human capital" and expenditures on clothing and food labeling them

[9] Note that a second possible estimation strategy would be to use the value from the *menor cuantia* as an instrument for household income. In this set-up, the estimation would be done using a system of equations via generalized methods of moments (GMM). For the sake of simplicity, I present the results using SURE. However, the results are quantitatively similar if I estimate it using the system GMM.

Figure 2.2: Differences in log expenditures between winners and runners-up



The figure above shows the differences in log expenditures between winners and runners-up of the *menor cuantia* process for the years leading (-1), the year during (0), and the year after (1) the contest. Non-durable consumption refers to clothing and food expenditures while human capital refers to health and education. The lines represent the 95% confidence interval.

as "non-durable consumption".

I first compare graphically the change in expenditures in human capital and non-durable consumption between the winners and runners-up of the *menor cuantia* process, shown in Figure 2.2. The point estimates and confidence intervals are obtained from a two-tailed Student-t test. I do the comparison for the years leading to, the year of, and the year after the shock. The left panel shows the differences in non-durable consumption while the right panel shows differences in human capital. As expected, there are no significant differences the year before the shock. During the year of the shock, the differences between runners-up and winners are significant. The year after the shock, these differences are positive but, due to the larger standard error, are not statistically different from zero.

Table 2.4 presents the results formally. The dependent variables are the log expenditures in human capital (upper panel) and non-durable consumption (lower panel). The independent variable is a dummy variable equal to 1 if the household won a contract during the year. The results show that non-durable consumption expenditure increased by approximately 11% during the year of the shock. The results are statistically significant at the 1% level and robust to the inclusion of region, time and household fixed effects. In pecuniary terms, this implies that, on average, winners of the contracts increase their expenditure in non-durable consumption by $400. For human capital, the results show an increase of 8%, implying an average increase in expenditures

Table 2.4: Effects of income shocks on household expenditure, extensive margin

	Year of shock				Year after shock			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-durable consumption								
Winner	0.11***	0.11***	0.11***	0.09***	0.07**	0.07**	0.07**	0.08***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Human Capital								
Winner	0.08**	0.09**	0.08**	0.04	-0.04	-0.03	-0.04	-0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Time Fixed Effect	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Regional Controls	No	No	No	Yes	No	No	No	Yes
Household Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	3520	3520	3520	3178	3616	3616	3616	3271
R^2	0.012	0.014	0.018	0.018	0.003	0.009	0.017	0.018

[1] Seemingly unrelated regression of the effects of winning a procurement contract on human capital expenditures and non-durable consumption. The variable winner is a dummy variable taking the value 1 if a head of household won a contest at time t. Standard errors (in parentheses) are clustered at the individual level. P-values $*p < .1, **p < .05, ***p < .01$.

of \$260. The results for human capital are statistically significant after including household fixed effect but become insignificant once I add regional controls. This, however, is due to the loss of 10% of the observations when including such controls.

Winning a contract during the year has an impact both on non-durable consumption and human capital.[10] Next, in columns 5 to 8 of Table 2.4, I check to see if the effects of income shocks persist the year after the shock. The year after the shock, non-durable consumption expenditures of winners are still higher than those for non-winners, suggesting an 8% difference. The coefficients for human capital are not statistically significantly different from zero.

Overall Table 2.4 suggests that a change in household income affects non-durable consumption and human capital. The extensive margin allows to estimate average responses but does not allow to examine the sensitivity of the results. To do this, I look at the intensive margin, presented in Table 2.4. The dependent variables are the log expenditures of human capital and non-durable consumption for the year of the shock. The independent variable is the log of the total value received from *menor cuantia*. The joint estimation suggest that, during the year of the shock, an increase in 10% in the value of *menor cuantia* increases total household expenditure in human capital and non-durable consumption by 1.3 and 2%, respectively. The results are robust to the inclusion of household characteristics and regional controls. In columns 5-8, I examine the results for the year after the shock. The results are similar in magnitude and statistical significance.

[10] The Wald test rejects the null hypothesis that non-durable consumption and human capital are equal to zero at level α=0.001

Table 2.5: Effects of income shocks on household expenditure, intensive margin

	Year of shock				Year after shock			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long Term								
Log menor cuantia	0.12***	0.13***	0.13***	0.13***	0.11**	0.12**	0.11**	0.11**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)
Short Term								
Log menor cuantia	0.20***	0.20***	0.20***	0.20***	0.22***	0.23***	0.22***	0.22***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
Time Fixed Effect	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Regional Controls	No	No	No	Yes	No	No	No	Yes
Household Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	1442	1442	1442	1442	1496	1496	1496	1496
R^2	0.009	0.021	0.022	0.024	0.003	0.006	0.010	0.008

[1] Seemingly unrelated regression of the effects of winning a procurement contract on human capital expenditures and non-durable consumption. Standard errors (in parentheses) are clustered at the individual level. P-values $*p < .1, **p < .05, ***p < .01$.

Comparing the results with the extensive margin, a possible explanation to this finding is that with increases in income, households can distribute the additional income in other years, thereby smoothing expenditures.

I perform several specification tests, shown in the appendix, to analyze the sensitivity of the results. The results are robust to performing the analysis year by year, using household fixed effects, the use of other estimation techniques, and different definitions of growth.

Overall, the results show that households have a high propensity to consume out of temporary and positive income shocks. Compared to the literature, the elasticities found in this study are consistent with other findings, albeit smaller in magnitude. How generalizable are these results? One limitation of the study is that it relies on single-income households. Due to the nature of the contests, these households are also in the construction sector and are formed by self-employed and small firm owners. As such, this particular sample might have more experience with financial planning that the entire population.

2.7 Conclusion

In this paper, I study the effects that income shocks have on household expenditures on human capital and non-durable consumption. Using a unique quasi-experimental setting as an exogenous source of household income, I compare how different single-income earner households respond to a positive and temporary shock. I find that households affected by an income shock increase their spending in education and health and food and clothing during the year of the shock. This increase in expenditure is also observed the year after the year following the shock. The results suggest an elasticity of non-durable consumption and human of 0.13 and 0.2, respectively.

The results of this study contribute to the mounting evidence that suggest that, contrary to the predictions of life-cycle models and the Permanent Income Hypothesis, households respond strongly to temporary shocks. Further research should explore how different conditions, particularly credit-constraints and the composition of the household, affect how temporary shocks are allocated.

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A Robustness

In this section, I present the sensitivity of the results to several specification tests.

In Table 2.6, I present the results for non-durable consumption. Columns 1-5 present the extensive margin results. Column 1 reports the results using household fixed effects. In columns 2-4, I report the results, running each year individually. In column 5, I use an alternative definition of growth $\dot{y} = \frac{y_t - y_{t-1}}{.5 * y_t + y_{t-1}}$. Columns 6-10 present the intensive margin results. Column 6 reports the results using household fixed effects. In columns 7-9, I report the results running each year individually. In column 10 I estimate the effects using an alternative definition of growth.

Table 2.6: Effects of income shocks on non-durable consumption expenditure, year of shock

	Extensive Margin					Intensive Margin				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Winner	0.68***	0.14**	0.11**	0.08	0.21***					
	(0.12)	(0.06)	(0.05)	(0.06)	(0.05)					
Log menor cuantia						0.07	0.18***	0.17***	0.02	0.03
						(0.08)	(0.04)	(0.05)	(0.04)	(0.03)
Observations	6826	1158	1105	982	6419	4322	553	512	508	4144
R^2	0.018	0.005	0.004	0.002	0.379	0.010	0.031	0.024	0.000	0.397

[1] Least squares estimation of the effects of winning a procurement contract on non-durable consumption expenditures. The variable winner is a dummy variable taking the value 1 if a head of household won a contest at time t. The variable *menor cuantia* is the log total amount received from *menor cuantia*. Standard errors (in parentheses) are clustered at the individual level. P-values $*p < .1, **p < .05, ***p < .01$.

In Table 2.7, I present the results on human capital expenditure. Columns 1-6 present the extensive margin results. Column 1 reports the results using household fixed effects. In columns

2-4, I report the results running each year individually (2010-2012). Column 5 uses an alternative definition of growth $\dot{y} = \frac{y_t - y_{t-1}}{.5 * y_t + y_{t-1}}$. Columns 6 uses the alternative definition of growth with household fixed effects. Columns 7-11 present the intensive margin results. Column 7 reports the results using household fixed effects. In columns 8-10, I report the results running each year individually. sFinally column 11 uses the alternative definition of growth.

Table 2.7: Effects of income shocks on household expenditure on human capital,

	Extensive Margin						Intensive Margin				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Winner	0.66***	0.14**	0.04	0.06	0.15***	0.22***					
	(0.12)	(0.07)	(0.07)	(0.08)	(0.03)	(0.05)					
Log menor cuantia							0.03	0.14***	0.16***	0.04	0.01
							(0.08)	(0.05)	(0.06)	(0.06)	(0.03)
Observations	6826	1153	1115	976	6419	6419	4322	557	512	507	4144
R^2	0.016	0.004	0.000	0.001	0.009	0.380	0.008	0.013	0.013	0.001	0.384

[1] Least squares estimation of the effects of winning a procurement contract on human capital expenditures. The variable winner is a dummy variable taking the value 1 if a head of household won a contest at time t. The variable *menor cuantia* is the log total amount received from *menor cuantia*. Standard errors (in parentheses) are clustered at the individual level. P-values $*p < .1, **p < .05, ***p < .01$.

Chapter 3
Income Shocks and Children's Educational Development: The Case of Uganda

Abstract

The economics literature has documented that income shocks have an enduring and persistent effect on children's educational development. We study this in the context of Uganda, where we measure how income shocks, stemming from unanticipated weather variation, impact children in four key areas of education: school attendance, educational expenditures, child labor, and competency levels in mathematics. We proxy the variations in income with deviations in sub-county-level rainfall from the long-term average. To interpret the results, we propose a simple theoretical framework which allows us to decompose income shocks into two opposing forces: an income effect and a substitution effect. We show that the interaction of these two forces can lead to heterogeneous effects across households.

Overall, we find that an increase in household income, in the form of a one standard deviation increase in rainfall from the long-term average, increases the odds of children attending school by 25%, increases school expenditures by 13%, decreases the odds of child labor by 19% and increases the odds for children to reach a higher level of proficiency in mathematics by 3%. When we distinguish across household types, we find that income shocks have almost no effect on school attendance and child labor for children from subsistence-farming households. The main contribution of this paper is that it shows that even within the same country, income shocks have heterogeneous effects. By disaggregating across households, our results help reconcile some of the seemingly conflicting results previously found in the literature.

Keywords: Income shocks, education, child labor

J.E.L. Codes: D13, N37

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3.1 Introduction

> "*By the year 2030, ensure that all girls and boys complete free, equitable and quality primary and secondary education...*"
>
> Sustainable Development Goal 4, target 1

In many developing countries, poor economic conditions and child labor often stand in the way of children's education, particularly in the absence of adequate social protections (Fitzsimons, 2007; Banerjee, 2004; Doran, 2013). Due to its importance and relation to education, the impact that income shocks have on children's schooling and labor is a question that has been studied extensively in the literature (see for instance, Carneiro and Ginja, 2016; Haushofer and Shapiro, 2016; Shah and Steinberg, 2015).

Notwithstanding the numerous studies on the topic, there is still not an unequivocal answer to this question. On one hand, some studies have found a positive link between income shocks and children educational development. Haushofer and Shapiro (2016) examine an unconditional cash transfer program in Kenya and suggest that educational expenditures are highly sensible to income changes. Edmonds et al. (2011) conclude that increases in schooling rates in India were mainly due to a reduced cost of schooling (see also: Bourguignon, 2003; Beegle et al., 2006; De Janvry et al., 2006). On the other hand, some studies have documented evidence of increased occurrence of child labor during periods of economic growth (Kruger, 2007; Rogers and Swinnerton, 2004). For instance, Duryea and Arends-Kuenning (2003) show that employment rates increase in boys 14-16 as local labor market opportunities improve.

A potential reason for such diverse findings in the literature is that households develop mitigating strategies to deal with income shocks but their effectiveness "var[ies] with the context in ways that are not straightforward to measure or model" (Frankenberg and Thomas, 2017). Soares et al. (2012) argue that these seemingly conflicting empirical findings can be reconciled under a simple theoretical framework, which decomposes income shocks into two forces: an income effect and a substitution effect. Positive income shocks increase household revenue, making schooling more affordable. Concurrently, income shocks, in the form of higher expected wage rates, also increase the opportunity cost of schooling.

In this paper we estimate the effects that income shocks, stemming from unanticipated weather variation, have on children's educational development. We address this question for the case of Uganda for four key areas of education: school attendance, educational expenditures, child labor, and proficiency in grade-2 level mathematics. Uganda provides a good setting to implement this study, as agriculture employs about 70% of the population and crops are mostly rain-fed (Hausmann et al., 2014). To guide the empirical analysis, we build on Soares et al. (2012) and adapt a theoretical framework to the Ugandan context. We show how the relative magnitude of the income and substitution effects can have heterogeneous implications for different households.

Our data come from two separate sources that measure complementary outcomes. While both datasets are representative at the national level, they are based on different samples, making it unfeasible to merge them together. To capture child-specific school attendance, educational expenditures, and child labor, we use longitudinal household survey data from the Uganda National Panel Survey (UNPS) for the years 2010 to 2012. To capture child proficiency in mathematics, we use data from the Uwezo project for the years 2010 to 2015.[1]

Our identification strategy relies on using standardized rainfall deviations from the long-term average, as a direct proxy of income shocks (Björkman-Nyqvist, 2013). Due to data limitations, we use rainfall deviation as a direct proxy for income shocks, instead of using it as an instrumental variable.[2] We argue that this direct proxy captures the income channel, rather than other channels, by controlling for other rain-related outcomes identified in the literature. We match this deviation at the sub-county level, the second lowest administrative level in Uganda. Using rainfall deviations, rather than the total yearly rainfall, allow us to account for sub-county-specific climate and provides a source of unanticipated variation (Frankenberg and Thomas, 2017).[3]

We find two sets of results. Overall, we find that an income shock, in the form of a one standard deviation increase in rainfall from the long-term average, increases the odds of children attending school by 25% and increases child-specific school expenditures by 13%. Similarly, they decrease the odds that children work by 19% and increase the odds of a child reaching a higher level of competency level in mathematics by 3%. When we distinguish between subsistence farmers and other types of households, we find that the effect on school attendance and child labor is almost null for subsistence farmers. Interpreting these results in light of our theoretical framework, we argue that subsistence farmers are more sensitive to the substitution effect. Our results are robust to non-linear effects due to excessive rainfall deviation, alternative definitions of rainfall deviation, and unobservable selection tests.

The main contribution of this paper is that it shows the heterogeneous effects of income shocks by differentiating across different types of households. Our results are in line with Edmonds (2006), in that we find a positive relationship between income shocks and child educational development. Concurrently, they corroborate Duryea and Arends-Kuenning (2003), in that we find a quasi-null effect for subsistence farmers. Our findings highlight the need to account for varying household conditions when addressing similar areas of research. From a policy perspective, our results emphasize the need for governments in developing countries to take measures ensuring that all children

[1] Uwezo is a non-profit organization that aims to measure the learning proficiency of children in Uganda. It is funded in part by the World Bank, the UK Department for International Development, and Swedish International.

[2] We define standardized rainfall deviations as the normalized difference between yearly total rainfall and the 1983-2015 average.

[3] For instance, in the case of a negative anticipated income shock, parents might take preemptive steps to smooth investments in children's education, making it more difficult to identify the relationship between income and educational inputs and outcomes.

benefit equally from periods of increased economic opportunity. In the Ugandan context, public policy should target subsistence farming households to provide incentives to counteract the increased opportunity cost of schooling when agricultural conditions improve.

The rest of this paper is divided as follows: section 3.2 provides a simple theoretical framework to drive the analysis. Section 3.3 introduces the data. Section 3.4 details our identification strategy and empirical methodology. In section 3.5, we present and discuss our results. We conclude in section 3.6.

3.2 Theoretical Framework

In this section, we present a simple theoretical framework to discuss the expected effects of a weather-induced income shock on children's educational development, based on the models developed by Soares et al. (2012) and Basu and Van (1998). We present it in the context of Uganda, where a significant part of the workforce is employed in agriculture. We start by showing how income shocks can be decomposed into an income and a substitution effect. We then suggest that the theoretical predictions can be heterogeneous across households.

3.2.1 Household consumption and child labor

Consider a household with one parent and one child. The parent decides how much of the child's time, t_c, is devoted to schooling, s_c, and to work, l_c, such that $t_c = s_c + l_c$. The utility function $U(c_h, s_c)$ of the household depends on total household consumption, c_h, and child schooling, s_c. In addition to satisfying the Inada conditions, we assume that the utility function is separable on c_h and s_c.

Employment, $l_i \forall i \in c, p$, takes the form of working on the household farm. The parent supplies their labor inelastically ($t_p = l_p$). The production function of the farm takes the form $f(l_c, l_p) = \alpha f(l_c) + \alpha f(l_p)$, where α denotes an exogenous augmenting factor on labor. This can be interpreted as the yield of crops due to varying weather conditions- the same labor input will yield a different crop production under different weather conditions.[4] We assume that all the production from the farm is sold for a market price and spent on consumption, c_h, given a unitary price p_c, which we set equal to 1. Under these conditions, the household's revenue can be written as:

$$R = f(l_c, l_p) = \alpha f(l_c) + \alpha f(l_p) \tag{1}$$

We assume that there are no direct costs to schooling.[5] Additionally, we assume that $f(l_i) =$

[4]In case of improved weather conditions and assuming a partial equilibrium framework, this will imply a higher household income.

[5] Uganda has implemented universal primary and secondary education, thereby reducing, and sometimes eliminating, direct costs to schooling. If we assume that the remaining schooling costs are unaffected by weather-related income shocks, their addition would not contribute to the intuition presented in this framework.

$\beta_i l_i, \forall i \in c, p$. The parameter β_i captures the different productivity between children and their parents. In cases where $\beta_c = \beta_p$, child labor is a perfect substitute for adult labor. Expressing child and adult labor (l_c, l_p) as a function of their available time (t_c, t_p), the household budget constraint can then be written as:

$$p_c c_h + \alpha\beta_c s_c \leq \alpha\beta_c t_c + \alpha\beta_p t_p \tag{2}$$

The household thus faces the following maximization problem:

$$\begin{aligned} &\max_{c_h, s_c} U(c_h, s_c) \\ &s.t.\ p_c c_h + \alpha\beta_c s_c \leq \alpha\beta_c t_c + \alpha\beta_p t_p \end{aligned} \tag{3}$$

Taking the first order conditions, the solution to (3) is given by:

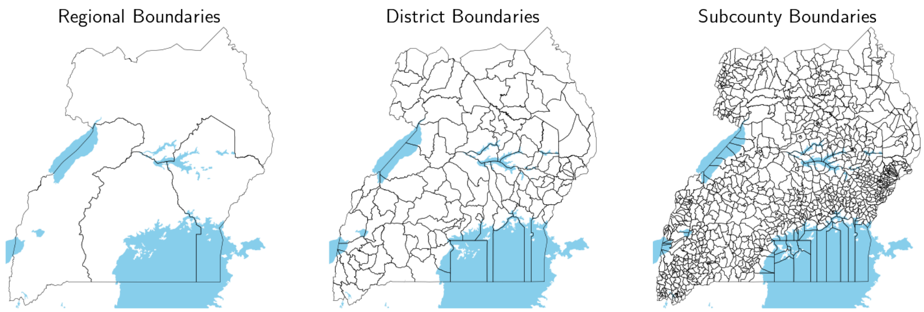
$$\frac{U_c}{p_c} = \frac{U_s}{\alpha\beta_c} \tag{4}$$

Where U_c and U_s are the respective marginal utilities of consumption and schooling. Equations (3) and (4) help characterize the impact of an exogenous income shock. In this setup, the exogenous shock comes from a change in α, such as a change in crop yield following a rainfall shock.[6] The term $\alpha\beta_c s_c$ captures the opportunity cost of schooling. We see from equation (2) that an increase in α, ceteris paribus, increases the total revenue of the household, thus creating an income effect. Assuming that consumption and schooling time are normal goods, this increase in revenue will lead to an increase in consumption and schooling, thus reducing child labor. Concurrently, however, an increase in α also increases the opportunity cost of schooling, $\alpha\beta_c s_c$, hence a substitution effect which increases the time the child spends working. The magnitude of the substitution effect, depends on the difference between U_c and U_s.

Assume that utility $U(c, s)$ is concave on consumption c, and linear on schooling, s, such that $U_{cc} < U_{ss}$, where U_{cc} and U_{ss} are the second derivatives of utility with respect to consumption and schooling respectively. This implies that $\lim_{c \to 0} U_c \to \infty$ and $\lim_{s \to 0} U_s = a$, where a is a positive constant. The marginal utility of consumption is thus much larger than that of schooling at low levels of consumption and schooling. As consumption increases, however, the marginal utility of consumption approaches zero. As such, as the level of consumption and education increases, the difference between U_c and U_s decreases. Consequently, an increase in the opportunity cost of schooling following a positive rain shock leads to a stronger substitution effect at low levels of consumption and schooling, leading to heterogeneous effects across household types.

[6]Note that we assume a monotonic relation between rainfall and crop yield. In the robustness section we check for non-linear effects of rainfall on crop yields.

Figure 3.1: Administrative Boundaries of Uganda



This figure shows the administrative boundaries of Uganda for the year 2010. The left pane shows the region (highest administrative division). The center pane shows the districts (third highest administrative division). The third pane shows the sub-counties (second lowest administrative division). The blue area denotes water. *Source*: Ugandan Bureau of Statistics, own computation.

3.3 Data

We use two separate but complementary data sources to investigate four key areas of child educational development. To evaluate child-specific school attendance, school expenditure, and child labor, we use survey data from the Uganda National Panel Survey (UNPS). We use UNPS data for waves 2009-2010, 2010-2011 and 2011-2012 (2010, 2011 and 2012 henceforth).[7] To address child competency in mathematics we use all available data from the Uwezo project, spanning each year between 2010 and 2015. UNPS and Uwezo are both representative at the national level, but it is not possible to match individual or household observations between the two sources, since they come from different samples.

We match, separately, UNPS and Uwezo data with rainfall data at the sub-county level. Sub-counties are the second lowest administrative level in Uganda. In 2010, our year of reference for administrative divisions in Uganda, there were 964 sub-counties in the country (see Figure 3.1).[8] Geo-localized data on rainfall come from the Tropical Applications of Meteorology using Satellite (TAMSAT). We deflate all prices using the consumer price index (CPI) information, with 2005 being the reference year. We use CPI information from Uganda Bureau of Statistics (UBOS) for 6 Ugandan cities and deflate using the CPI of the reference city closest to the sub-county.

[7]At the time of this writing, there were a total of 4 waves available. Starting from wave IV (2012-2013), the UNPS sampling framework changed and most of the households from waves 2010-2011-2012 were not sampled in UNPS 2012-2013. As a result we only use waves I, II, and III in our study.

[8]In Uganda, the administration divisions are: regions, sub-regions, districts, counties, sub-counties, and parishes. Uganda has undergone significant changes in its administrative structure since the 1990s, going from 38 districts in 1991 to 112 in 2014.

3.3.1 School attendance, school expenditures and child labor

UNPS is a longitudinal survey implemented by the Uganda Bureau of Statistics. In addition to its panel dimension, UNPS provides a wealth of information on household and child characteristics.[9]

We select all children aged 6 to 16 years-old for which we were able to match rainfall data. The selection of the age range 6-16 was done to ensure consistency with Uwezo data. In total, our UNPS sample includes 7170 children from 2111 different households.

Table 3.1 presents descriptive statistics for the households and children included in our UNPS sample. The left panel displays statistics for all the households and children. It shows that about 80% of households are located in rural areas. The average household has about 9 members, including 1.5 infants (0-to-5 years old) and slightly more than 3 children (6-to-16 years old). Excluding infants, between 35 to 40% of the members of the average household work on the family farm. This proportion drops to 31 to 34% when focusing specifically on children. The average household owns assets worth between 6600 and 9500 USD (in 2005 PPP). About half of the children in our UNPS data are girls. The average child is slightly under 11 years old, and has 2.6 siblings.[10] The central panel of Table 3.1 details statistics for subsistence-farming households. Subsistence farming households are defined as households whose main source of income is subsistence farming. The right panel displays the same statistics for households with other main sources of income. In terms of sample size, roughly half of the households and children in our UNPS data come from subsistence-farming households. Over 90% of subsistence-farming households are rural. This proportion drops to 66-77% for other households. Both are similar in terms of household composition, but subsistence-farming households typically have a higher share of their non-infant members (45 to 52%) working on the family farm. In the average subsistence-farming household, 38 to 43% of children worked on the family farm the week before the UNPS interview, compared to only 21 to 32% of children from other types of households. The average subsistence-farming household owns assets worth only half of what the average other household owns. Child level characteristics are almost identical in terms of gender, age, relationship to the household head and number of siblings.

Table 3.2 displays descriptive statistics across survey waves for the outcomes we measure, for the full sample, and by type of household. 86 to 88% of children in our sample declared to be attending school at the time of the interview. This proportion is similar across household types.

[9] The sample was constructed as follows: in 2005 the Uganda National Household Survey (UNHS) interviewed 7,400 households. For the UNPS, 3,123 out of the 7000 households were selected to be part of the panel surveys (Waves I-III). The same sample was maintained for the three waves. Households or individuals that had permanently left the original households were also interviewed. Out of the 3,123 households that were originally sampled for the UNPS, a total of 2,607, 2,564, and 2,356 households were successfully interviewed in waves I-III, respectively Uganda Bureau of Statistics (2011)

[10] We define siblings as any other children (not infants) present in the household at the time of interview, regardless of who is the biological parent.

Table 3.1: UNPS Household and Child Characteristics

	Full Sample			Subsistence Farmers			Others		
	2010	2011	2012	2010	2011	2012	2010	2011	2012
N Households	2,151	2,110	2,101	1,068	980	1124	813	1068	941
% Rural Households	78.24	79.05	80.53	92.88	94.59	93.24	76.63	65.92	65.67
% Urban Households	21.76	20.95	19.47	7.12	5.41	6.76	23.37	34.08	34.33
$\overline{N}$ Individuals in h.h.	8.60	8.87	9.22	8.64	8.96	9.03	8.99	8.82	9.51
$\overline{N}$ Infants (0-to-5)	1.53	1.57	1.42	1.60	1.55	1.45	1.57	1.58	1.42
$\overline{N}$ Children (6-to-16)	3.20	3.15	3.13	3.29	3.24	3.13	3.27	3.08	3.14
$\overline{\%}$ Members farm work	40.85	37.84	35.46	52.20	49.05	45.45	37.53	27.02	22.84
$\overline{\%}$ Children farm work	34.47	33.97	31.01	42.91	42.97	37.81	32.13	24.63	21.18
$\overline{X}$ h.h. Assets (2005 \$)	9,557	6,713	6,613	6,907	4,973	4,994	1,2178	8,639	8,698
N Children	5,941	5,985	6,011	3,047	2,867	3,284	2,243	2,948	2,632
% Female Children	49.98	50.89	51.49	49.32	51.00	51.63	49.51	50.83	51.47
$\overline{X}$ Age	10.92	10.89	10.90	10.96	10.97	10.86	10.93	10.79	10.93
% Children Head	69.24	69.28	69.29	71.20	69.24	70.28	66.59	69.31	68.64
$\overline{N}$ Siblings	2.60	2.58	2.56	2.68	2.66	2.59	2.65	2.51	2.53

[1] This table presents descriptive statistics for households (h.h.) and children in the Ugandan National Panel Survey, by wave. N refers to the number, % refers to the percentage (in levels), $\overline{N}$ denotes the mean of individuals, and $\overline{X}$ denotes the sample mean. In the case of h.h. statistics (upper panel), "Full sample" refers to all households with at least one child (6-to-16 y.o.) and for whom we were able to match rainfall data. In the case of child-specific statistics (lower panel), it includes only the children from those households. "Subsistence-farmers" refers to households that rely on subsistence farming as their main source of income. "Others" refers to households which are not subsistence farmers. Note that due to missing values, the number of households and children may not add up perfectly across columns. Averaged statistics computed with the UNPS sampling weight.

Most children attending school do so at the primary level of education (80 to 86%), followed by pre-primary (10 to 13%) and secondary education (2 to 8%). These proportions differ significantly for subsistence-farmers and other types of households. In particular, children from subsistence farming households are statistically more likely to be enrolled in primary school, but also less likely to be enrolled in secondary school, in spite of having the same average age as their counterparts. Regarding school expenditures, households spend, on average, about 40 USD a year per child. This value drops to 20 USD for children from subsistence-farming households, but reaches up to 67 USD for other households. 35 to 39% of children in the UNPS sample worked the week before the interview. We define child labor as having engaged in any of the following activities the week preceding the UNPS interview: working on the household farm, running a business, working for pay (including on domestic tasks) or working for free in the household business. The vast majority of child labor takes the form of work on the household farm (92 to 96%), followed by unpaid work in the household business (4 to 7%), paid work (2 to 6%), and running a business (1 to 2%). Child labor is more prevalent among children from subsistence-farming households than for other households.

Table 3.2: UNPS School Attendance, School Expenditures and Child Labor

	Full Sample			Subsistence Farmers			Others		
	2010	2011	2012	2010	2011	2012	2010	2011	2012
% Attending School	86.85	86.25	88.61	87.23	86.23	88.26	85.91	86.06	88.80
% Pre-Primary	10.61	12.45	12.82	11.14	11.67	14.20	10.17	13.21	11.36
% Primary	84.27	83.18	81.84	85.66	85.94	82.86	84.11	80.47	80.85
% Secondary and Above	5.12	4.37	5.34	3.20	2.39	2.94	5.72	6.32	7.79
$\overline{X}$ School Expenditures	41.41	39.99	42.33	24.32	19.66	23.46	52.07	62.34	67.45
% Children Working	38.55	39.86	35.02	46.54	47.70	41.54	36.67	31.70	25.59
% Working on h.h. Farm	93.91	91.97	95.57	97.48	97.27	98.66	91.63	83.63	88.99
% Running a Business	2.24	1.75	0.97	1.48	0.80	0.92	3.53	3.32	1.17
% Working for Pay	6.09	5.50	2.40	4.34	4.76	1.46	7.70	6.72	4.51
% Working in h.h. Business	6.61	6.61	3.77	3.91	2.00	1.32	9.14	13.81	8.87
% Children Sick	33.42	26.18	25.44	24.05	27.17	27.02	34.66	26.20	24.27

[1] This table presents descriptive statistics for school attendance and school expenditures, and details the occurrence of child labor the week preceding the UNPS interview, by wave. Working for pay includes paid domestic work. Full sample refers to all children (6-to-16 y.o.) for whom we were able to match rainfall data. N refers to the number, % refers to the percentage (in levels), $\overline{N}$ denotes the mean of individuals, and $\overline{X}$ denotes the sample mean. A child can engage in several forms of labor at the same time, which is why percentages do not necessarily add up. "Subsistence-farmers" refers to households that rely on subsistence farming as their main source of income. "Others" refers to households which are not subsistence farmers. Averaged statistics computed with the UNPS sampling weight.

3.3.2 Math proficiency

The data for children competency comes from the Uwezo project. Uwezo is civil-society driven initiative, inspired from the successes of Pratham's Annual Status of Education Reports (ASER) in India. Uwezo measures the learning proficiency of children in Uganda and are funded, in part, by the World Bank, the UK Department for International Development, and Swedish International Development Agency.[11] Their findings have been used as a benchmark to monitor performance between and within countries (Banerjee et al., 2016; Mbiti, 2016; Jones et al., 2014). Uwezo provides a nationally representative sample of children aged 6 to 16 and includes information on household and child characteristics.

[11] They also operate in Kenya and Tanzania. For more information visit http://www.uwezo.net.

Uwezo tests children on grade-two-level competency tests in mathematics, English, and local languages. All children take the same test, regardless of age or grade. Uganda is a multilingual country, with English and Swahili as the official languages and a set of regional languages derived from Bantu, Nilotic, and Central Sudanic. Due to this variety in spoken languages, we restrict our analysis to mathematics. In mathematics, children are graded on a scale that ranges from innumeracy to the ability to perform divisions. The levels are as follows: 1) innumeracy, 2) ability to count from zero to nine, 3) from ten to ninety-nine, 4) being able to do additions, 5) subtractions, 6) multiplications and 7) divisions.

Our sample on child competency consists of all children in the Uwezo sample attending school at the time of the interview, and for whom we matched localized rain data. It includes 382 145 children from 129 272 households.

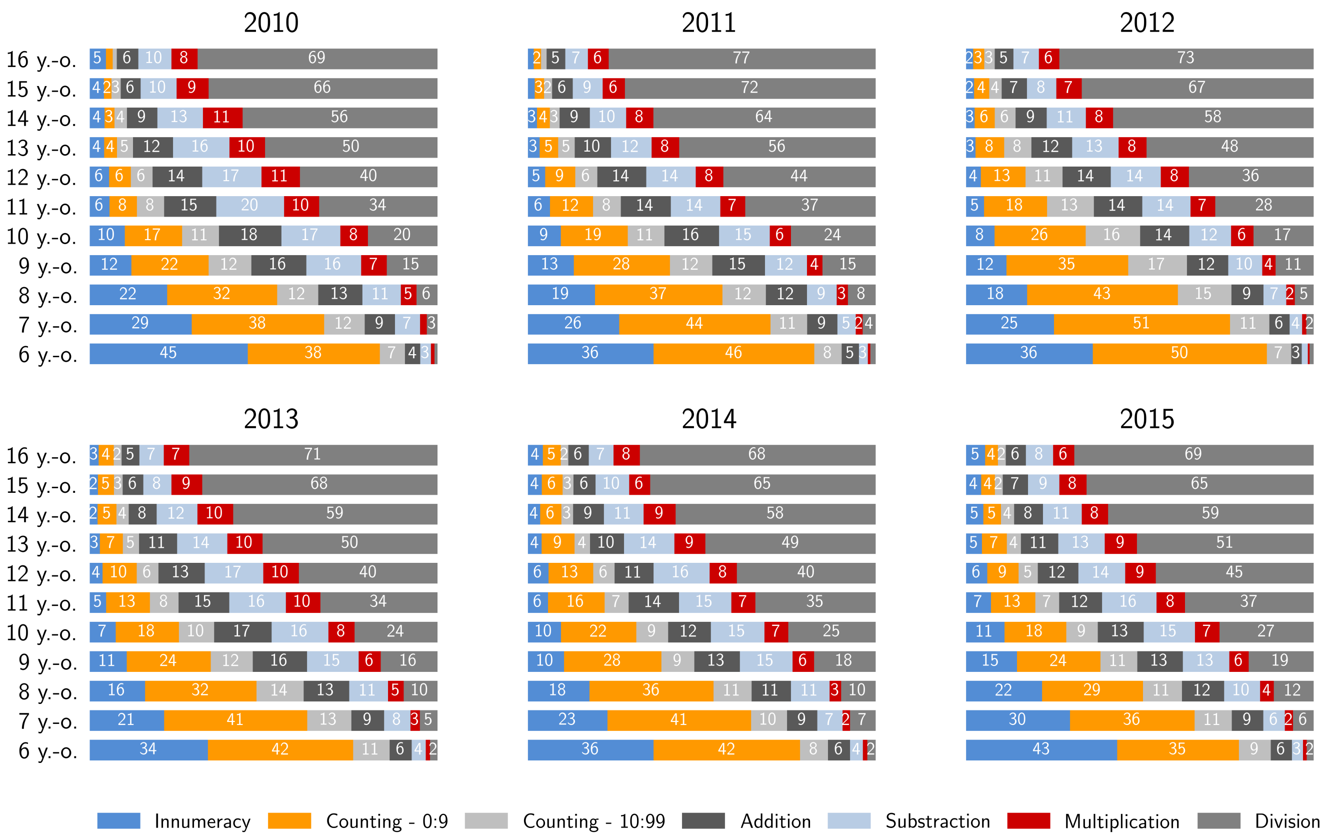
Table 3.3: Uwezo Child Characteristics

	2010	2011	2012	2013	2014	2015
N Households	12,366	35,350	34,643	33,853	10,629	35,395
N Children	32,725	100,688	92,130	86,898	25,708	84,003
N Attending School	29,299	92,308	85,605	79,398	22,614	72,921
% Primary	93.18	93.62	94.01	98.01	97.63	94.98
% Secondary	6.82	6.38	5.99	1.99	2.37	5.02
% Female Children	49.21	49.35	49.38	49.44	50.03	50.50
$\overline{X}$ Age	10.84	10.77	10.69	10.57	10.48	10.42
$\overline{N}$ Siblings	2.34	3.68	2.44	2.94	2.79	3.34
% Mother educ. – None	23.80	18.12	14.92	27.59	22.54	23.09
% Mother educ. – Primary	59.21	64.47	68.27	65.94	64.97	56.99
% Mother educ. – Secondary	14.15	13.23	13.33	5.00	9.74	17.83
% Mother educ. – > Secondary	2.84	4.17	3.47	1.46	2.75	2.09

[1] This table shows descriptive statistics for children sampled in the Uwezo projects during waves 2010 to 2015. N refers to the number, % refers to the percentage (in levels), $\overline{N}$ denotes the mean of individuals, and $\overline{X}$ denotes the sample mean. Averaged statistics are computed only for children attending school, using the Uwezo data sampling weight.

Table 3.3 displays descriptive statistics on sample size and child characteristics. Uwezo's geographical coverage varies across survey waves, which is why the number of households and children changes significantly across waves. About 89 to 93% of children attend school. Similarly to UNPS, most of the children in the Uwezo sample are attending primary school. The sample is balanced across gender, with an average age of slightly less than 11 years-old. Figure 3.2 shows the share of children by competency levels in mathematics and shows that a quarter of 16 year olds cannot do divisions.

Figure 3.2: Share of Children by Competency Level in Uwezo Tests

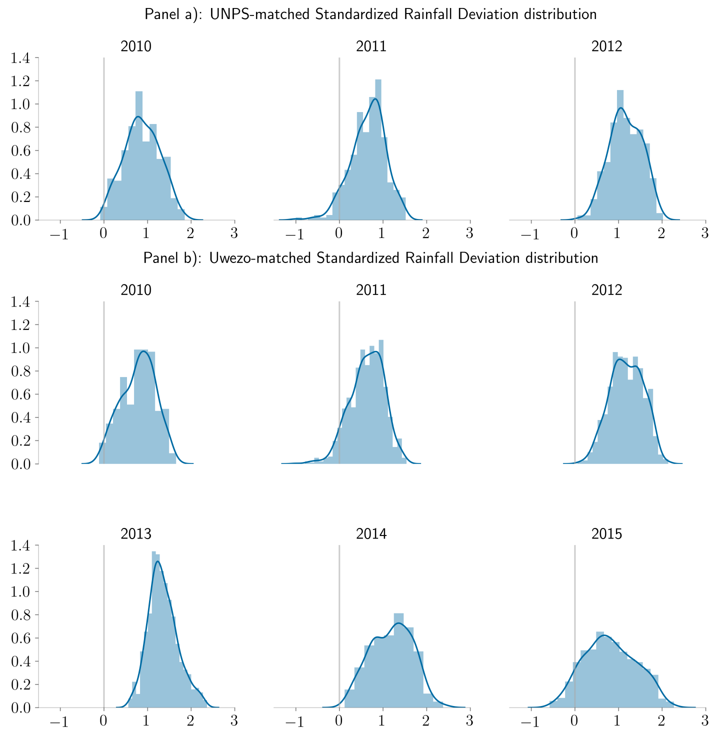


Note: This figure breaks down mathematics competency for children aged 6-16, by wave year, as reported by Uwezo. The same test is administered to all children regardless of age or grade. The competency levels are 1) innumeracy, 2) ability to count between 0-9, 3) 10-99, 4) ability to perform additions, 5) subtractions, 6) multiplication, and 7) divisions.

3.3.3 Rainfall

Uganda is considerably affected by the Inter-Tropical (ITCZ) Convergence Zone, a belt of converging trade winds and rising air (Mubiru et al., 2012; Lazzaroni, Lazzaroni). There are two agricultural seasons in Uganda: December to May and June to November (Asiimwe and Mpuga, 2007). Rainfall data come from the Tropical Applications of Meteorology using Satellite (TAMSAT) data. TAMSAT was established by the University of Reading in the late 1970s and has benefited in part from collaborations with the Climate Division of the National Centre for Atmospheric Science (NCAS) and the National Centre for Earth Observation (NCEO) Maidment et al. (2014). TAMSAT precipitation estimates are available at a resolution of .035 degrees (around 4 km.) for all of Uganda between the years of 1983-2015. We define long-term average based on this time frame. We match precipitation data with each sub-county using the latitude and longitude

Figure 3.3: Density Distribution of Rainfall Deviation across UNPS Waves



This figure shows the distribution of the standardized rainfall deviation from the long-term average (1983-2015) of all sub-counties present in the Uganda National Panel Survey and Uwezo, by year. Standardized Rainfall Deviation (SRD) is defined as $\frac{(R_{st_1} - \overline{R_s})}{\sigma_s}$, where $\overline{R_s}$ is the average total yearly rainfall, R_{st_1} is the measure of total yearly rainfall at time $t-1$, and σ_s is the standard deviation of total yearly rainfall for the period. *Source*: TAMSAT.

of its centroid (Maidment et al., 2017; Funk et al., 2015; Maidment et al., 2014).[12]

For the years 2010 to 2015 the average total rainfall in the country was 1,121 millimeters per year. The highest rainfall occurred in the sub-counties of Kayonza and Bugaya (over 2500 mm. per year) while the lowest in Tapac, Kalapata, and Kaabong (less than 600 mm. per year). Throughout this period, most sub-counties experienced a positive deviation from their long-term average. Figure 3.3 displays a density distribution of standardized rainfall deviations across UNPS and Uwezo sub-counties. Matched rainfall deviation are normally distributed and are almost exclusively positive. This suggests that for our sample, most sub-counties experienced rainfall higher than the long-term average. To check for instances of excessive rainfall or drought, we used the Standardized Precipitation Index. Only 0.5% of sub-counties in our sample experienced excessive rainfall and none experienced a drought in the period we study.

[12] We use the reprojected coordinates from TAMSAT data and match them with the centroid of each sub-county. The matching is done based on the smallest euclidean distance. The average sub-county has an approximate area of 200 square kilometers, about twice the area of the city of Paris, France. In the robustness section we control for sub-county area and assign the district average to those sub-counties with missing information.

3.4 Empirical Strategy

The main identification issue in estimating a causal impact of income shocks on our variables of interest is to find a measure of income shocks which is exogenous to within-household resource allocation. Their joint variation can indeed be associated with unobserved factors such as health shocks (Björkman-Nyqvist, 2013).

To overcome this issue, we follow a well-established literature (Björkman-Nyqvist, 2013; Nordman et al., 2017; Maccini and Yang, 2009) and use lagged, sub-county-specific, standardized rainfall deviations from the long-term average. We define the long-term average as the period ranging from 1983 to 2015, the period for which TAMSAT data is available. Formally our measure is defined as: $\frac{(R_{st-1}-\overline{R_s})}{\sigma_s}$ where R_{st-1} denotes the total rainfall for year $t-1$, $\overline{R_s}$ and σ_s are the average and the standard deviation of total yearly rainfall for the period 1983-2015, respectively.[13] Note that we use rainfall shocks as a direct proxy of income shocks instead of using it as an instrumental variable. We choose to do so for two main reasons. First, the majority of respondents in the UNPS are not wage earners. Questions pertaining to income ask for their total income received during varying spells of time. As a result, the responses differ in terms of income received for time worked. For example, a response might show earnings per week, per hour or per month. Consequently, imputing a consistent measure across households is problematic and requires us to use strict assumptions. Second, Uwezo data does not include information on income.

Assume that the relation can be represented by the following reduced form model:

$$Y_{ihst} = \alpha + \beta SRD_{st} + \epsilon_{ihst} \tag{5}$$

Where Y is the outcome of interest (school attendance, school expenditures, child labor, and competency in mathematics) for child i from household h, residing in sub-county s, during year t. β is a parameter to be estimated, and ϵ is an error term.

The majority of individuals in Uganda work in agriculture and rely on rain as their main source of irrigation (Hausmann et al., 2014). As such, meteorological variations in rainfall can reasonably be expected to affect household income.[14] An obvious concern in claiming that income is the mechanism through which rainfall deviations affects child educational development is the existence of other rain-sensitive factors which are related to educational development. For example, abnormally high rainfall might impact the disease vectors which could in turn affect school attendance. Controlling for these channels is crucial to interpret rainfall deviations as income shocks. To address this concern, we compiled a list of the channels identified in the literature, and used

[13] We choose to normalize our rainfall data directly rather than fitting it to a gamma distribution as it is done in computing the standardized precipitation index (SPI) defined in McKee et al. (1993). We do so to improve the interpretation of our results, but using the SPI does not change our results, see appendix.

[14] We find that standardized rainfall deviation (SRD) is positively and significantly related to the natural logarithm of household assets.

them as controls or tested for their relation with rainfall deviations in the years of our sample (see appendix).

We found the following channels, other than income, through which rainfall could affect our measures of child educational development: health of children, fertility, food prices, land ownership, access to credit, migration, civil conflict, floods and droughts. In our regressions we control for health, fertility, and land ownership of the household. To test for conflicts, we use Uppsala Conflict Data Program (UCDP) data from the University of Uppsala. During the years of the sample, we find no correlation between rainfall deviation and civil conflicts.

An implicit assumption of equation 5 is that rain positively affects income. This might not be the case for excessive rainfall. In this situation, schools, household assets, or the roads connecting them might be damaged by floods, making school attendance no longer possible or too costly. We would then expect a downward bias for the estimated impact of rainfall deviation on school attendance, and learning outcomes, and an upward bias for child labor. The direction of the bias resulting from excessive rainfall is unclear. If household assets need maintenance, they may reduce school expenditures. On the other hand, households with children attending school may have to contribute to school repairs following excessive rainfall, thereby increasing school expenditures.

To test for the occurrence of the above scenarios in our sample, we use the Standardized Precipitation Index (SPI) (McKee et al., 1993). The SPI provides a measure which classifies instances of droughts and flooding. Based on this measure, no sub-county in our sample shows values for drought and only about 0.5% of sub-counties show flooding conditions.[15] In the robustness section, we also examine the sensitivity of our results to excessive rainfall by looking at non-linear effects, and controlling for instances of flooding conditions.

Since we use the deviation from the long-term average to measure rainfall, our β parameter is safe from the influence of unobserved, sub-county-specific, time-invariant characteristics. Sub-counties with access to more abundant average rainfalls (large $\overline{R_s}$) may indeed differ from their counterparts in dimensions which are relevant for the relationship between income and children's educational development (Björkman-Nyqvist, 2013). For instance, since sub-counties with abundant rainfall can sustain more population and more urbanization, their residents could have access to more diversified income sources, as well as different schooling facilities, such as closer but more expensive schools. We further condition our estimates on individual and household characteristics, as measured in UNPS and Uwezo, and take advantage of their time dimension and various levels of aggregation to add fixed effects. The reduced-form model can be thus written as:

$$Y_{ihst} = \alpha + \beta_R SRD_{st} + \beta_I I_{ihst} + \beta_H H_{hst} + \delta_t + \delta_s + \epsilon_{ihst} \tag{6}$$

Where I is a set of individual characteristics for child i, and H a set of household's features. δ_t

[15] The SPI measure is categorized as follows: Values between -1 and 1 suggest near normal conditions. Values between 1 and 1.49 show moderately wet conditions. Values between 1.5 and 1.99 correspond to very wet conditions. Any values higher than 2 are considered indicative of extremely wet conditions.

and δ_s are year and sub-county fixed effects respectively. The coefficient of interest is β_R.

We use different estimation techniques to estimate the parameters of equation (6) depending on the nature of our dependent variable. School attendance is measured as a binary variable and takes value 1 if the child was attending school during the time of the interview and 0 otherwise. Similarly, child labor is a binary variable recording whether a given child engaged in any form of labor during the week before the interview. We therefore estimate the parameters of equation (6) via logistic regression when considering school attendance and child labor. School expenditures is a continuous variable defined as the natural logarithm of real total expenditures per child in the previous year.[16] We estimate the coefficients of equation (6) using ordinary least squares when focusing on school expenditures. Finally, since child competency in mathematics is measured on an ordinal scale ranging from 1 to 7, we use an ordered logistic regression to estimate the parameters of equation (6) when the dependent variable is competency levels.

3.5 Results

In this section, we present the results of the impact of income shocks on four key areas of child development. First, we look at child-specific school attendance, school expenditures, and child labor. We then test for heterogeneous effects by disaggregating between households that rely on subsistence farming as their main source of income and those that do not. Next, we look at the effects on mathematics competency. We conclude by discussing the robustness of our results. For simplicity, we will refer to a one standard deviation increase in rainfall from the long-term average as a unitary increase in standardized rainfall deviation (SRD). All results are weighted using the survey sampling weights. When using UNPS data, we cluster standard errors at the household-by-wave level and use the following set of controls: gender, age, child relation to the household head, number of siblings, a binary variable for subsistence farmers, and the natural logarithm of household assets. When using Uwezo data, we cluster standard errors at the household level and use the following controls: gender, age, number of siblings, and mother's education. We present the results using SRD for the years $t-1$ and $t-2$ ($t-2$ and $t-3$ for educational expenditures). For brevity, we focus only on $t-1$, and discuss the results for $t-2$ if they are quantitatively different than the ones for $t-1$.

[16] Since this question refers to the period in $t-1$ w.r.t. the interview, we use the corresponding lagged period for our measure of rainfall shock, that is $t-2$.

3.5.1 School Attendance, School Expenditures and Child Labor

3.5.1.1 Baseline Results

Table 3.4 presents the results for school attendance. Column 1 presents the unconditional effects. Column 2 adds a set of controls. Column 3 includes year fixed effects, and columns 4 to 6 control for regional, district and sub-county fixed effects, respectively. Our unconditional estimate is significant at the 1 percent level and indicates that a unitary increase in standardized rainfall increments the odds of a child being in school by approximately 34%. As we add controls and fixed effects, our estimates lose magnitude, although they remain statistically significant. Our preferred estimate (column 6), indicates that a unitary increase in standardized rainfall increases the odds of a child attending school by about 27%.

Next, we discuss our results on school expenditures, presented in Table 3.5. Column 1 presents the unconditional effects. Columns 2 to 7 add controls, including grade and a binary variable for scholarship recipients. Columns 3 to 7 add year fixed effects and regional, district, sub-county and household fixed effects, respectively. Column 1 suggests that, on average, a unitary increase in SRD increases school expenditures by approximately 65%. This estimate is significant at the 1 percent level, as are those of columns 2 to 7. Once we control for child and household observables, the inclusion of fixed effects does not significantly alter the magnitude or statistical significance of the rainfall coefficients. Our preferred estimate (column 7), suggests that a unitary increase in SRD causes school expenditures to increase by 17%.

Table 3.6 presents the results for child labor. Column 1 displays the unconditional effects. We find that a unitary increase in SRD decreases the odds of child labor by approximately 35%. As we control for fixed effects, the coefficient progressively loses magnitude and statistical significance. Overall, using our preferred estimate, we find that a unitary increase in SRD decreases the odds of child labor by 28%.

Table 3.4: Regression Results, School Attendance

	(1)	(2)	(3)	(4)	(5)	(6)
SRD $t-1$	0.292***	0.143*	0.343***	0.235**	0.158	0.240**
	[0.077]	[0.086]	[0.097]	[0.099]	[0.099]	[0.109]
SRD $t-2$	0.509***	0.522***	0.562***	0.461***	0.278***	0.364***
	[0.087]	[0.092]	[0.096]	[0.095]	[0.106]	[0.109]
Female		0.159**	0.164**	0.170**	0.140**	0.150**
		[0.070]	[0.070]	[0.070]	[0.071]	[0.073]
Age in Complete Years		0.139***	0.139***	0.141***	0.155***	0.170***
		[0.015]	[0.015]	[0.015]	[0.016]	[0.016]
Child of Household Head		0.123	0.139	0.156*	0.159*	0.283***
		[0.086]	[0.085]	[0.084]	[0.085]	[0.089]
Number of Siblings in h.h.		-0.032	-0.030	-0.040*	-0.009	-0.005
		[0.022]	[0.022]	[0.023]	[0.023]	[0.025]
Number of Adults in h.h.		0.039	0.039	0.029	0.053*	0.037
		[0.026]	[0.025]	[0.025]	[0.027]	[0.027]
Number of Infants in h.h.		-0.046	-0.048	-0.063*	-0.013	0.006
		[0.033]	[0.033]	[0.034]	[0.035]	[0.033]
Sick in past 30 days		-0.032	-0.049	-0.056	-0.040	-0.026
		[0.083]	[0.084]	[0.086]	[0.085]	[0.081]
Subsistence Farmer		0.090	0.113	0.131	0.054	0.127
		[0.078]	[0.079]	[0.080]	[0.081]	[0.078]
ln(Owned Land in Km)		-0.017	-0.050**	-0.037	-0.026	-0.003
		[0.011]	[0.025]	[0.024]	[0.023]	[0.021]
ln(Household Assets)		0.197***	0.206***	0.192***	0.101***	0.050*
		[0.026]	[0.027]	[0.027]	[0.028]	[0.027]
Observations	16241	13839	13839	13839	13838	13030
Time Trends	No	No	Yes	Yes	Yes	Yes
Fixed Effects	No	No	No	Region	District	Sub-county

[1] This table presents the results from estimating equation 6 via logistic regression, where the dependent variable is school attendance, taking value 1 if the child attended school the week preceding the interview and zero otherwise. Standardized Rainfall Deviation (SRD) is defined as $\frac{(R_{st_1}-\overline{R_s})}{\sigma_s}$, where $\overline{R_s}$ is the average total yearly rainfall for the period 1983-2015, R_{st-1} is the measure of total yearly rainfall at time $t-1$, and σ_s is the standard deviation of total yearly rainfall for the period 1983-2015. Female, Child of Household Head and Subsistence Farmer are binary variables. They denote being a female child, being the biological child of the household (h.h). head, and living in a subsistence-farming household, respectively. The estimates are weighted using UNPS sampling weights. Robust standard error in squared brackets, clustered at household-by-wave level. * 10% significance level, ** 5% significance level, *** 1% significance level.

Table 3.5: Regression Results, School Expenditures per Children

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SRD $t-2$	0.508***	0.130***	0.143***	0.118***	0.256***	0.220***	0.164***
	[0.058]	[0.045]	[0.048]	[0.046]	[0.048]	[0.043]	[0.035]
SRD $t-3$	0.188***	-0.035	-0.016	0.017	0.170***	0.172***	0.116***
	[0.068]	[0.052]	[0.051]	[0.051]	[0.055]	[0.047]	[0.039]
Female		-0.100***	-0.097***	-0.098***	-0.080***	-0.062***	-0.033
		[0.023]	[0.023]	[0.022]	[0.020]	[0.019]	[0.020]
Age in Complete Years		0.004	0.006	0.001	0.003	0.017***	0.035***
		[0.008]	[0.008]	[0.008]	[0.007]	[0.006]	[0.007]
Child of Household Head		0.143***	0.150***	0.163***	0.167***	0.198***	0.294***
		[0.037]	[0.037]	[0.035]	[0.032]	[0.030]	[0.042]
Receives a Scholarship		-1.418***	-1.419***	-1.292***	-1.238***	-1.182***	-0.950***
		[0.039]	[0.039]	[0.040]	[0.038]	[0.036]	[0.045]
Grade		0.238***	0.235***	0.241***	0.232***	0.210***	0.182***
		[0.011]	[0.011]	[0.010]	[0.010]	[0.009]	[0.011]
Number of Siblings in h.h.		-0.005	-0.006	-0.010	-0.014	-0.021**	-0.012
		[0.011]	[0.011]	[0.010]	[0.009]	[0.009]	[0.018]
Number of Adults in h.h.		0.058***	0.059***	0.055***	0.047***	0.034***	-0.003
		[0.011]	[0.011]	[0.010]	[0.009]	[0.009]	[0.020]
Number of Infants in h.h.		-0.050***	-0.051***	-0.035**	-0.037***	-0.019	-0.008
		[0.016]	[0.016]	[0.014]	[0.012]	[0.012]	[0.024]
Sick in past 30 days		0.099**	0.089**	0.067*	0.071**	0.064***	0.039*
		[0.040]	[0.041]	[0.039]	[0.032]	[0.024]	[0.024]
Subsistence Farmer		-0.290***	-0.277***	-0.232***	-0.189***	-0.064**	0.077*
		[0.036]	[0.036]	[0.034]	[0.030]	[0.030]	[0.041]
ln(Owned Land in Km)		-0.003	-0.024***	-0.018**	-0.020***	0.002	0.006
		[0.005]	[0.009]	[0.008]	[0.007]	[0.008]	[0.009]
ln(Household Assets)		0.172***	0.180***	0.172***	0.148***	0.120***	0.050***
		[0.013]	[0.014]	[0.013]	[0.012]	[0.011]	[0.015]
Observations	12392	9534	9534	9534	9534	9534	9534
Adjusted R^2	0.025	0.555	0.556	0.582	0.626	0.668	0.758
Time Trends	No	No	Yes	Yes	Yes	Yes	Yes
Fixed Effects	No	No	No	Region	District	Sub-county	Household

[1] This table presents the results from estimating equation 6 via OLS, where the dependent variable is the natural logarithm of child-specific real school expenditures. Standardized Rainfall Deviation (SRD) is defined as $\frac{(R_{st_1}-\overline{R_s})}{\sigma_s}$, where $\overline{R_s}$ is the average total yearly rainfall for the period 1983-2015, R_{st_1} is the measure of total yearly rainfall at time $t-1$, and σ_s is the standard deviation of total yearly rainfall for the period. Female, Child of Household Head, Receives a Scholarship and Subsistence Farmer are binary variables. They denote being a female child, being the biological child of the household (h.h.) head, receiving a scholarship and living in a subsistence-farming h.h., respectively. The estimates are weighted using UNPS sampling weights. Robust standard error in squared brackets, clustered at household-by-wave level. * 10% significance level, ** 5% significance level, *** 1% significance level.

Table 3.6: Regression Results, Child labor

	(1)	(2)	(3)	(4)	(5)	(6)
SRD $t-1$	-0.302***	-0.308***	-0.282***	-0.218**	-0.277***	-0.258**
	[0.063]	[0.071]	[0.088]	[0.091]	[0.098]	[0.102]
SRD $t-2$	-0.160**	-0.130*	-0.043	-0.132	-0.230**	-0.264***
	[0.065]	[0.075]	[0.081]	[0.083]	[0.091]	[0.095]
Female		-0.343***	-0.347***	-0.336***	-0.344***	-0.310***
		[0.048]	[0.048]	[0.048]	[0.048]	[0.049]
Age in Complete Years		0.242***	0.243***	0.245***	0.250***	0.272***
		[0.008]	[0.008]	[0.008]	[0.008]	[0.009]
Child of Household Head		0.052	0.047	0.103	0.080	0.051
		[0.068]	[0.069]	[0.069]	[0.068]	[0.071]
Number of Siblings in h.h.		0.085***	0.083***	0.065***	0.059**	0.073***
		[0.021]	[0.021]	[0.022]	[0.023]	[0.023]
Number of Adults in h.h.		-0.118***	-0.121***	-0.114***	-0.113***	-0.110***
		[0.022]	[0.022]	[0.022]	[0.023]	[0.024]
Number of Infants in h.h.		0.009	0.007	-0.005	-0.009	-0.005
		[0.030]	[0.030]	[0.030]	[0.030]	[0.030]
Sick in past 30 days		-0.352***	-0.352***	-0.386***	-0.398***	-0.426***
		[0.062]	[0.062]	[0.062]	[0.063]	[0.063]
Subsistence Farmer		0.394***	0.368***	0.390***	0.365***	0.269***
		[0.066]	[0.066]	[0.067]	[0.068]	[0.071]
ln(Owned Land in Km)		0.002	0.060***	0.062***	0.057***	0.053**
		[0.009]	[0.021]	[0.021]	[0.020]	[0.021]
ln(Household Assets)		-0.039*	-0.055**	-0.041*	-0.056**	-0.022
		[0.023]	[0.024]	[0.024]	[0.026]	[0.026]
Observations	17937	15092	15092	15092	15091	14931
Time Trends	No	No	Yes	Yes	Yes	Yes
Fixed Effects	No	No	No	Region	District	Sub-county

[1] This table presents the results from estimating the equation 6 via logistic regression, where the dependent variable is child labor, taking value 1 if the child worked the week preceding the interview and zero otherwise. Standardized Rainfall Deviation (SRD) is defined as $\frac{(R_{st_1}-\overline{R_s})}{\sigma_s}$, where $\overline{R_s}$ is the average total yearly rainfall for the period 1983-2015, R_{st_1} is the measure of total yearly rainfall at time $t-1$, and σ_s is the standard deviation of total yearly rainfall for the period. Female, Child of Household Head and Subsistence Farmer are binary variables. They denote being a female child, being the biological child of the h.h. head, and living in a subsistence-farming h.h., respectively. The estimates are weighted using UNPS sampling weights. Robust standard error in squared brackets, clustered at household-by-wave level. * 10% significance level, ** 5% significance level, *** 1% significance level.

Interpreting the findings through our theoretical framework, the results provide evidence that the income effect, following an unanticipated and positive income shock, compensates for the substitution effect stemming from the change in the opportunity cost of schooling. Concurrently, however, we see that the effects on school attendance and child labor are weakened once we control for lower units of aggregation, suggesting possible heterogeneous effects. In the next sub-section, we explore this heterogeneity for households that rely on subsistence farming as their main source of income.

3.5.1.2 Subsistence Farming Households

In this section we test for heterogeneous effects by interacting SRD with a binary variable recording whether a household's main source of income is subsistence farming.

Table 3.7: Regression Results, School Attendance - Interaction with Subsistence Farming

	(1)	(2)	(3)	(4)	(5)	(6)
SRD $t-1$	0.503***	0.379***	0.548***	0.437***	0.321***	0.438***
	[0.093]	[0.104]	[0.107]	[0.106]	[0.115]	[0.129]
SRD $t-1$ × Sub. Farmer	-0.455***	-0.442***	-0.412**	-0.409***	-0.313**	-0.373**
	[0.153]	[0.157]	[0.160]	[0.156]	[0.146]	[0.149]
SRD $t-2$	0.630***	0.641***	0.647***	0.513***	0.203	0.290**
	[0.129]	[0.132]	[0.131]	[0.131]	[0.135]	[0.145]
SRD $t-2$ × Sub. Farmer	-0.252	-0.226	-0.171	-0.110	0.128	0.122
	[0.169]	[0.172]	[0.171]	[0.168]	[0.154]	[0.160]
Subsistence Farmer	0.707***	0.714***	0.662***	0.629***	0.271	0.414**
	[0.199]	[0.200]	[0.200]	[0.197]	[0.194]	[0.203]
Observations	15519	13839	13839	13839	13838	13030
Time Trends	No	No	Yes	Yes	Yes	Yes
Fixed Effects	No	No	No	Region	District	Sub-county

[1] This table presents the results from estimating equation 6 via logistic regression, where the dependent variable is school attendance, taking value 1 if the child attended school the week preceding the interview and zero otherwise. Standardized Rainfall Deviation (SRD) is defined as $\frac{(R_{st_1}-\overline{R_s})}{\sigma_s}$, where $\overline{R_s}$ is the average total yearly rainfall for the period 1983-2015, R_{st_1} is the measure of total yearly rainfall at time $t-1$, and σ_s is the standard deviation of total yearly rainfall for the period. Female, Child of Household Head and Subsistence Farmer are binary variables. They denote being a female child, being the biological child of the h.h. head, and living in a subsistence-farming h.h., respectively. SRD × Subsistence Farmer is an interaction term between Standardized Rainfall Deviation and the Subsistence-Farming h.h. binary variable. The estimates are weighted using UNPS sampling weights. Robust standard error in squared brackets, clustered at household-by-wave level. * 10% significance level, ** 5% significance level, *** 1% significance level.

Table 3.7 displays the results for school attendance. We find that the effect of income shocks is almost null for subsistence farmers. We also find a positive effect for households that do not rely on subsistence farming as their main source of income. This pattern remains unchanged as we add controls, although the magnitude of the coefficients decreases as we control for fixed effects. Nonetheless, linear and interacted rainfall coefficients are statistically significant across all columns. Taking our preferred estimate (column 6), we find that a unitary increase in SRD increases the odds of a child attending school by 47% for non-subsistence farming household, but only by 5%, on average, for children from subsistence-farming households.

Table 3.8: Regression Results, Child Labor - Interaction with Subsistence Farming

	(1)	(2)	(3)	(4)	(5)	(6)
SRD $t-1$	-0.248**	-0.172	-0.142	-0.073	-0.136	-0.159
	[0.106]	[0.108]	[0.118]	[0.119]	[0.125]	[0.127]
SRD $t-1$ × Sub. Farmer	-0.084	-0.243*	-0.244*	-0.252*	-0.246*	-0.160
	[0.133]	[0.139]	[0.141]	[0.141]	[0.140]	[0.138]
SRD $t-2$	-0.368***	-0.365***	-0.269**	-0.407***	-0.503***	-0.539***
	[0.097]	[0.114]	[0.118]	[0.123]	[0.129]	[0.135]
SRD $t-2$ × Sub. Farmer	0.425***	0.404***	0.386***	0.460***	0.449***	0.440***
	[0.126]	[0.141]	[0.142]	[0.145]	[0.148]	[0.150]
Subsistence Farmer	0.314**	0.305*	0.297*	0.266	0.244	0.069
	[0.156]	[0.174]	[0.176]	[0.178]	[0.182]	[0.186]
Observations	17021	15092	15092	15092	15091	14931
Time Trends	No	No	Yes	Yes	Yes	Yes
Fixed Effects	No	No	No	Region	District	Sub-county

[1] This table presents the results from estimating the equation 6 via logistic regression, where the dependent variable is child labor, taking value 1 if the child worked the week preceding the interview and zero otherwise. Standardized Rainfall Deviation is defined as $\frac{(R_{st_1}-\overline{R_s})}{\sigma_s}$, where $\overline{R_s}$ is the average total yearly rainfall for the period 1983-2016, R_{st_1} is the measure of total yearly rainfall at time $t-1$, and σ_s is the standard deviation of total yearly rainfall for the period 1983-2015. Female, Child of Household Head and Subsistence Farmer are binary variables. They denote being a female child, being the biological child of the h.h. head, and living in a subsistence-farming h.h., respectively. SRD × Subsistence Farmer is an interaction term between Standardized Rainfall Deviation and the Subsistence-Farming h.h. binary variable. The estimates are weighted using UNPS sampling weights. Robust standard error in squared brackets, clustered at household-by-wave level. * 10% significance level, ** 5% significance level, *** 1% significance level.

Table 3.8 shows the interacted results for child labor. We do not find any significant results when lagging SRD by one year. However, when using two lags, we find that a unitary increase in SRD decreases the odds of child labor for non-subsistence farmers while having a quasi-null or even negative effect in the case of children from subsistence farming households. This pattern is statistically significant in all columns and varies only slightly in magnitude when adding fixed effects. According to column 6, a unitary increase in SRD decreases the odds of child labor, on average, by 3-5% (about 5 times less than for non-subsistence farming households).

School attendance and labor appear to be less sensitive to income shocks for children living in subsistence farming house. Interpreting these findings through our theoretical framework, they suggest that the income effect following an income shock does not compensate for the related substitution effect in the case of children from subsistence farming households. Nevertheless, the literature stresses the importance of skill acquisition, as opposed to mere schooling, in determining economic development (Hanushek and Woessmann, 2008). In the next sub-section we test if the changes in educational inputs correlate to actual changes in math competency.

3.5.2 Tests scores

In this section we discuss the results we obtain when looking at learning outcomes as defined by Uwezo competency levels in mathematics.

Table 3.9: Regression Results, Mathematics Competency Levels

	(1)	(2)	(3)	(4)	(5)	(6)
SRD $t-1$	-0.080***	-0.153***	0.064***	0.003	0.029	0.019
	[0.012]	[0.015]	[0.017]	[0.017]	[0.019]	[0.018]
SRD $t-2$	0.094***	0.118***	0.110***	0.055***	0.041**	0.032**
	[0.011]	[0.013]	[0.015]	[0.015]	[0.017]	[0.016]
Female		-0.010	-0.012	-0.013	-0.010	-0.015
		[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Age in Complete Years		0.130***	0.129***	0.134***	0.140***	0.152***
		[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Grade		0.735***	0.748***	0.756***	0.761***	0.767***
		[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Number of siblings		-0.030***	-0.035***	-0.019***	-0.009**	-0.005
		[0.004]	[0.004]	[0.003]	[0.004]	[0.004]
Mother's education		0.381***	0.418***	0.359***	0.303***	0.266***
		[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Observations	350 507	321 650	321 650	321 650	321 650	321 650
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Geography Fixed Effects	No	No	No	Region	District	Sub-county

[1] This table presents the results from estimating the equation 6 via ordered logistic regression. The dependent variable is an ordinal variable ranging from 1 (innumeracy) to 7 (being able to do grade-2-level divisions), denoting competency in mathematics. SRD refers to Standardized Rainfall Deviation, which is defined as $\frac{(R_{st_1}-\overline{R_s})}{\sigma_s}$, where $\overline{R_s}$ is the average total yearly rainfall for the period 1983-2016, R_{st-1} is the measure of total yearly rainfall in $t-1$, and σ_s is the standard deviation of total yearly rainfall for the period 1983-2016. Mother's Education is a categorical variable ranging from 0 (no formal education) to 3 (> secondary education). The estimates are weighted using Uwezo sampling weights. Robust standard error in squared brackets, clustered at household level. * 10% significance level, ** 5% significance level, *** 1% significance level.

Our results are displayed in Table 3.9. Column 1 shows the unconditional effects of rainfall deviation, column 2 includes controls, column 3 adds year fixed effects, and columns 4 to 6 add regional, district and sub-county fixed effects, respectively. Rainfall deviation at $t-1$ has a negative and significant effect in columns 1 and 2, but switches sign in column 3 before becoming non-statistically different from zero in columns 4 to 6. On the contrary, coefficients for rain deviation at $t-2$ are positive and statistically significant in all columns. Our preferred estimate (column 6) shows that a unitary increase in SRD increases the odds of a child reaching a higher competency level in mathematics by 3%.

To test the robustness of our results, we examine their sensitivity to several specification tests. First, instead of using SRD, we use the standardized precipitation index (SPI). Second, for the sub-counties for which we were not able to match rainfall data, we assign the district specific average. Third, we test for non-linear effects of rain. Finally, we test for selection on unobservables (Oster selection). The results are presented in the appendix.

3.6 Conclusion

In this paper, we address the relationship between income shocks and child educational development, using rainfall deviation from the long-term average. We find that income shocks have a positive impact on school attendance, school expenditures and competency in mathematics, and a negative impact on child labor. We also find that the impact of income shocks is heterogeneous across household types in the case of school attendance and child labor. Specifically, income shocks have almost no effect on these outcomes for children from subsistence-farming households. We interpret these results through a theoretical framework which shows that a positive income shock, increases both household revenue and the opportunity cost of schooling. As such, while it makes schooling more affordable, it also reduces parents' incentives to send their children to school, making them more likely to send them to work.

Our findings have important policy implications. Times of better economic opportunities may create incentives for households to send their children to work, especially for households where child labor is critical to reach a subsistence level of consumption. In such instances, there is a need for government to provide incentives to keep children in school. Although we cannot directly link child schooling with educational outcomes, we believe the conflicting incentives following a positive income shocks may lead to heterogeneous effects in learning proficiency as well. Further research is needed to investigate whether income shocks translate differently into cognitive-skill acquisition for children from different types of households.

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A Sample selection

UNPS 2010 includes 2991 households and 18 750 individuals. In UNPS 2011, 2721 households and 19 194 individuals were sampled. Finally, UNPS 2012 covers 2907 households and 21 544 individuals. Out of these individuals, we select only children aged 6 to 16 years-old, so as to be consistent with Uwezo's age range. Furthermore, although we matched the majority of UNPS households with the corresponding rain data for their sub-county of residence, successive changes in administrative divisions in Uganda made it difficult to match rainfall data to some UNPS sub-counties, resulting in the loss of about 10% of children's observations.

Uwezo 2010 includes 12 380 households and 32 768 children. In the next wave – Uwezo 2011, the sample grew considerably to reach 35 359 households and 100 715 children. In 2012, Uwezo sampled 34 667 households and 92 188 children, and another 34 013 households and 87 339 children in 2013. In 2014, Uwezo's raw sample shrunk back to a level similar to 2010, with 11 670 sampled households and 28 147 children. Finally, in 2015, 51 835 households and 164 129 were sampled by Uwezo. In total, we matched 96% of all observations in our sample.

B Robustness

B.1 Mechanism

To check for the existence of other rain-sensitive factors which are related to educational development, we reviewed recent economic research that looks at the impact of rainfall shocks. We found the following channels, other than income, through which rainfall could affect our measures of child educational development: health of children, fertility, food prices, land ownership, access to credit, migration, civil conflict, floods and droughts.

The UNPS data allow us to test for health, fertility, migration, and land ownership, which we include in all our regressions. To test for civil conflicts, we use Uppsala Conflict Data Program (UCDP) data from the University of Uppsala.

To check for non-linearities in the effect of rain on educational outcomes, we interact SRD with a binary variable equal to 1 if standardized rainfall deviation is greater than 2 (flooding). The results are presented in Table 3.10. Our main results remain qualitatively similar.

Table 3.10: Regression Results, non-linearity

	In School		School Expenditures		Child Labor	
	(1)	(2)	(3)	(4)	(5)	(6)
SRD	0.353***	0.183	0.495***	0.131***	-0.342***	-0.216*
	[0.082]	[0.157]	[0.059]	[0.038]	[0.060]	[0.111]
Excess Rain$x$SRD	11.694*	1.653	0.506	1.965***	-2.171	-6.623*
	[6.347]	[8.958]	[1.053]	[0.688]	[3.449]	[3.831]
Excess Rain	-23.577*	-2.817	-0.880	-4.163***	4.750	13.202*
	[12.969]	[18.281]	[2.186]	[1.419]	[7.337]	[8.016]
Observations	16241	11744	12392	10436	17937	12686
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Household Controls	No	Yes	No	Yes	No	Yes
Individual Controls	No	Yes	No	Yes	No	Yes
Geography Fixed Effects	No	No	No	Region	District	Sub-county

[1] This table presents the results from estimating the equation 6. SRD refers to Standardized Rainfall Deviation, which is defined as $\frac{(R_{st_1} - \overline{R_s})}{\sigma_s}$, where $\overline{R_s}$ is the average total yearly rainfall for the period 1983-2016, R_{st-1} is the measure of total yearly rainfall in $t-1$, and σ_s is the standard deviation of total yearly rainfall for the period 1983-2016. Exess rain is a binary variable equal to 1 if standardized rainfall deviation suggest flooding conditions. The regression controls (omitted) include age of child, mother's education, number of siblings, number of adults in the household, a variable looking at the health of the child, sex of the child, the amount of land owned, and household assets. The estimates are weighted using Uwezo sampling weights. Robust standard error in squared brackets, clustered at household level. * 10% significance level, ** 5% significance level, *** 1% significance level.

Finally, we use a different measure of long-term rain deviation, called the standardized precipitation index (SPI). The results are presented in Tables 3.11 and 3.12.

Table 3.11: Regression Results, SPI

	In School		School Expenditures		Child Labor	
	(1)	(2)	(3)	(4)	(5)	(6)
SPI	0.613***	0.771***	0.542***	0.145***	-0.227***	-0.292***
	[0.092]	[0.157]	[0.062]	[0.040]	[0.067]	[0.113]
Observations	16241	11727	12392	10427	17937	12664
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Household Controls	No	Yes	No	Yes	No	Yes
Individual Controls	No	Yes	No	Yes	No	Yes
Geography Fixed Effects	No	Sub-county	No	Sub-county	No	Sub-county

[1] This table presents the results from estimating the equation 6 for various outcomes. SPI refers to Standardized Precipitation Index. SPI refers refers to the year $t-1$ for school and child labor and $t-2$ for school expenditures. The regression controls (omitted) include age of child, mother's education, number of siblings, number of adults in the household, a variable looking at the health of the child, sex of the child, the amount of land owned, and household assets. The estimates are weighted using Uwezo sampling weights. Robust standard error in squared brackets, clustered at household level. * 10% significance level, ** 5% significance level, *** 1% significance level.

Table 3.12: Regression Results, interacted SPI

	In School		School Expenditures		Child Labor	
	(1)	(2)	(3)	(4)	(5)	(6)
spi$x$subfarm	-0.364**	-0.387	0.070	0.036	0.435***	0.703***
	[0.177]	[0.254]	[0.066]	[0.072]	[0.130]	[0.185]
SPI	0.783***	1.032***	0.090*	0.122**	-0.438***	-0.744***
	[0.135]	[0.236]	[0.052]	[0.057]	[0.098]	[0.167]
Subsistence Farmer	0.322**	0.539**	-0.025	0.023	0.227*	-0.339*
	[0.160]	[0.259]	[0.069]	[0.074]	[0.124]	[0.177]
Observations	15519	11727	12003	10427	17021	12664
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Household Controls	No	Yes	No	Yes	No	Yes
Individual Controls	No	Yes	No	Yes	No	Yes
Geography Fixed Effects	No	Sub-county	No	Sub-county	No	Sub-county

[1] This table presents the results from estimating the equation 6 for various outcomes. SPI refers to Standardized Precipitation Index. SPI refers refers to the year $t-1$ for school and child labor and $t-2$ for school expenditures. spi$x$subfarm is an interaction term between SPI and the Subsistence-Farming h.h. binary variable. The regression controls (omitted) include age of child, mother's education, number of siblings, number of adults in the household, a variable looking at the health of the child, sex of the child, the amount of land owned, and household assets. The estimates are weighted using Uwezo sampling weights. Robust standard error in squared brackets, clustered at household level. * 10% significance level, ** 5% significance level, *** 1% significance level.

B.2 Unobservable Selection

A plausible concern to the study is that the results on children's educational development might be driven by unobservables. We follow Oster (2017) to calculate the level of proportionality between the unobservables and observables, thereby examining if unobservable omitted variables spuriously drive our results. We do this procedure using the STATA routine called *psacalc* only for school expenses, as its implementation is, at the time of this writing, only available for linear models.

The process allows to estimate the coefficient that would result if the researcher were able to control for unobservables (direct bias calculation) as well as calculating how important the unobservables would have to be relative to the observables to eliminate the estimated effect (bounding argument). The results of the exercise (presented in the following table), suggest that the unobserved variables would have explain more than twice the controls to eliminate the effect. Additionally the coefficient is relatively stable, suggesting that omitted variables are not creating a spurious relation.

Table 3.13: Oster unobservable selection test, School Expenditures

	(1)
SRD	0.238***
	[0.042]
δ R(.9)	2.37
δ R(.95)	1.70
δ R(1)	1.30
β R(.9)	.16
β R(.95)	.12
β R(1)	.08
Observations	7482
Observations	7482
Time Trends	Yes
Fixed Effects	Yes

[1] * 10% significance level, ** 5% significance level, *** 1% significance level.

C Concave Production Function

The purpose of this section is to show the effects of the model presented in the text, using a concave production function for child labor. Let the production function for the household be $f(l_c, l_p)$ where l_c and l_p are the labor by the child and the parent, respectively. Assume that the production function is separable such that $f(l_c, l_p) = \alpha f(l_c) + \alpha f(l_p)$. The first order conditions of the system are:

$$\frac{U_c}{p_c} = \frac{U_s}{\alpha f'(s_c)}$$

In this setup, the exogenous shock also comes from a change in α. The term $\alpha f'(s_c)$ captures the opportunity cost of schooling. Note that for a given α, the marginal productivity of child labor is higher at low levels of child labor than at higher levels of child labor. As a result, the substitution effect of an increase in α will be higher for households with low levels of child labor. As such, we see that using a concave production function may lead to heterogeneous effects of income shocks.