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PhD Thesis

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Essays on Development Economics

Information Technology, Human Capital, and Conflict

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Contents

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Summary

This PhD thesis consists of an introductory chapter and four self-contained chapters.

Chapters 2 and 3 analyse the determinants and consequences of the rapid expansion of information technology in rural Viet Nam. In **Chapter 2, Can Internet Improve Agricultural Production? Evidence from Viet Nam**, which is co-authored with Finn Tarp, we investigate whether the arrival of the first internet access point in rural Vietnamese communes increased the value of agricultural production through better access to information. During the time-span of the study (2008-12) a number of online platforms on agriculture, both public and private, started operating in the country. Our findings suggest that internet access is associated with a higher value of total agricultural output, though not in the case of rice. This is in line with strong government involvement in rice production.

In **Chapter 3, Adoption of Mobile Phones in Viet Nam – The Role of Social Status** I study which demographic and social groups are leading and which are lagging behind in mobile phone ownership. Between 2006 and 2014, mobile phone ownership increased from 18 to 89 per cent in rural Viet Nam. By using panel data from this period, I find that households with political connections are early adopters of the technology. A Blinder-Oaxaca decomposition reveals that their higher adoption rates are not fully explained by observable characteristics. At the same time, ethnic minorities are lagging behind in phone adoption. However, if the ethnic minorities had similar observable characteristics than non-minority households, they would adopt even more phones than non-minority households. Other demographic characteristics such as young age, having a male household head, and migrant status are associated with higher phone own-

ership. These differences are however fully explained by observable characteristics, such as income.

In **Chapter 4, Early life Determinants of Cognitive Ability -A Comparative Analysis on Madagascar and Senegal**, joint work with David Sahn and Naveen Sunder, we use comparable long term panel data sets from both countries and find that Malagasy children had higher test scores in second grade, but the difference converges in early adulthood. In both countries cognitive skills, measured using test scores in the second grade, and health, proxied by adult height, are strong predictors of school attainment in young adulthood. Cognition in second grade is a stronger predictor of cognitive skills in young adulthood in Senegal than Madagascar. In Madagascar school inputs and health matter more for cognitive skills in early adulthood than in Senegal. Early life family conditions have an enduring impact on test scores of young adults in both countries.

In **Chapter 5, Do Fences Make Good Neighbors? Evidence from an Insurgency in India**, joint work with Saurabh Singhal and Divya Tuteja, we seek explanations for the reduced violence levels in the ongoing insurgency in the Indian state of Jammu & Kashmir. We use a variety of tests to detect structural breaks in the time series for violence over the period 1998-2014. We identify a transition from a high violence regime to a low violence regime that coincides with (i) the fencing of the border with Pakistan (ii) the implementation of a large-scale development program, and (iii) the phasing in of the Indian National Rural Employment Guarantee Scheme (NREGS). Our results highlight the complementary roles of development programs and security in reducing violence.

Resumé (Danish summary)

Denne ph.d.-afhandling består af et introduktionskapitel, samt fire selvstændige kapitler.

Kapitel 2 og 3 analyserer årsagerne til og konsekvenserne af den hurtigtvoksende informations- og kommunikationsteknologi i Vietnams landområder. I **Kapitel 2: Can Internet Improve Agricultural Production? Evidence from Viet Nam**, som er skrevet sammen med Finn Tarp, undersøger vi hvorvidt indførelsen af de første internetopkoblinger i landlige vietnamesiske kommuner har medvirket til værditilvækst i landbrugsproduktionen igennem bedre adgang til landbrugsrelateret information. I tidsrummet hvor data blev indsamlet (2008-12) begyndte flere offentlige og private online platforme med landbrugsinformation at operere i landet. Vores resultater viser, at adgang til internettet er relateret til merværdi af landbrugsproduktion, bortset fra produktionen af ris. Dette er i overensstemmelse med en stærk statslig indblanding i produktionen af ris.

I **Kapitel 3: Adoption of Mobile Phones in Viet Nam – The Role of Social Status** analyserer jeg hvilke demografiske grupper og samfundslag der er først på markedet, samt hvilke grupper der sakker bagud, når det kommer til ejerskab af mobiltelefoner. Mellem 2006 og 2014 steg andelen af befolkningen som ejer en mobiltelefon fra 18 til 89 procent i Vietnams landområder. Ved at anvende paneldata fra denne periode finder jeg, at husholdninger med politiske forbindelser er de første til at adoptere den nye teknologi. En Blinder-Oaxaca dekomponering afslører at den større sandsynlighed for at eje en mobiltelefon ikke er fuldt ud forklaret af observerbare karakteristika. På samme tid ser vi at etniske minoriteter sakker bagud i optagelsen af mobiltelefoner. Under antagelse af at etniske minoriteter har samme observerbare karakteristika som husholdninger der

ikke tilhører en etnisk minoritet, vil det derimod forventes at de har flere mobiltelefoner. Øvrige demografiske karakteristika som alder, hvorvidt husholdningen har en mand som familiens overhoved, og hvorvidt man har en migrant i familien er alle positivt korreleret med ejerskab af en mobiltelefon. Effekten forsvinder dog når andre variable tages i betragtning.

I **Kapitel 4: Early life Determinants of Cognitive Ability - A Comparative Analysis on Madagascar and Senegal**, der er skrevet sammen med David Sahn og Naveen Sunder, anvender vi sammenlignelige langsigtede paneldatasæt fra begge lande, og finder at børn fra Madagaskar havde højere testresultater i anden klasse, men at forskellen mindskes i tidlig voksenalder. I begge lande er kognitive færdigheder og sundhed, målt som henholdsvis testresultater og voksenhøjde, stærke indikatorer for skolegang i tidlig voksenalder. Kognition i anden klasse er en stærkere indikator for kognitive færdigheder i tidlig voksenalder i Senegal i forhold til i Madagaskar. I Madagaskar betyder inputs til skolen og sundhed mere for kognitive færdigheder i tidlig voksenalder sammenlignet med Senegal. Familieforhold i starten af livet har en vedvarende effekt på testresultater for unge voksne i begge lande.

I **Kapitel 5: Do Fences Make Good Neighbors? Evidence from an Insurgency in India**, som er fælles arbejde med Saurabh Singhal og Divya Tuteja, søger vi forklaringer på den mindskede grad af vold i det eksisterende oprør i den indiske stat, Jammu & Kashmir. Vi bruger flere forskellige slags tests til at opspore strukturelle brud i tidsserien for vold i perioden 1998-2014. Vi identificerer en transition fra høj grad af vold til lav grad af vold som falder sammen med (i) opsætning af hegn på grænsen til Pakistand, (ii) implementeringen af et storstilet udviklingsprogram, samt (iii) indfasningen af den Indiske Nationale Landlige Beskæftigelsesgaranti (Indian National Rural Employment Guanrantee Scheme, NREGS). Vores resultater fremhæver de komplementære roller af udviklingsprogrammer og sikkerhed i forbindelse med faldende grad af vold.

Chapter 1

Introduction

1 Introduction

At the core of development economics lies the distinction between "developed" and "developing" countries. Therefore any given topic in this field can be motivated by its importance to improving welfare, reducing poverty or fostering economic growth. This motivation for studying "developing economies" thus links any given topic to a broader macroeconomic framework. The combination of macro and micro is what Rodrik and Rosenzweig (2010) in the introduction chapter of the Handbook of Development Economics mention as being a unique aspect of development economics, relative to other sub-fields in economics.

The four chapters of this thesis aim to unravel microeconomic mechanisms behind macro-level phenomena: new technology, the formation of human capital, as well as conflict and counter-conflict policies. The motivation for all these three topics arise from their importance to economic growth. Information and communication technology and human capital are drivers of growth, whereas conflict is a tremendous obstacle to growth and well-being.

This thesis uses observational data from predominantly rural settings, covering time-periods ranging from four years to almost two decades. All the chapters first provide descriptive evidence of a national level phenomenon over time, and then move towards identifying either some of its causes or consequences by using econometric methods for observational data.

In chapters 2 and 3, the macro-level phenomenon studied is the information and communication technology (ICT) revolution in the context of rural Viet Nam. Chapter 2 studies the potential benefits of ICT, and Chapter 3 the obstacles to ICT adoption. Chapter 4 moves to discussing human capital formation in Sub-Saharan Africa, where low levels of schooling and skills are a pressing policy concern. Chapter 5 deals with the ongoing insurgency in the Indian state of Jammu & Kashmir, that has hindered economic development since the beginning of the conflict in the late 1980's.

Another distinct feature of development economics according to Rodrik and Rosenzweig (2010) is the importance of institutions: *Scratch any economic issue of consequence, and you are likely to find politics lurking underneath.* This phrase applies very well to all of the chapters of this thesis. In none of the thesis chapters have I analyzed institutions or governance as a topic in of itself, but it is clear that the quality of institutions plays a role as an underlying determinant in all of the results. As Rodrik and Rosenzweig (2010) point out, context matters, for how and why development policy works. This is important, as differences in economic institutions are a fundamental cause of differences in economic development (Acemoglu et al. 2005).

In this introductory chapter, I discuss my thesis chapters on issues in development microeconomics through the lens of these two cross-cutting themes, economic growth, and the role of institutions.

2 Information and communication technology

Chapters 2 and 3 discuss the determinants and consequences of information and communication technology in rural Viet Nam. The obvious question regarding the motivation of this topic is: when developing countries are still struggling with problems such as malnutrition, poor drinking water an basic healthcare, why should we care about the internet?

Research shows that ICT has had an impact on growth (Andersen et al. 2012; Choi and Yi 2009; Jalava and Pohjola 2008), like any other general purpose technology before it. It is therefore important that also developing countries are able to exploit the vast opportunities brought by the ICT revolution. The World Development Report 2016 (World Bank 2016), a flagship publication by the World Bank, is devoted to ICT for these reasons. This publication outlines various reasons why ICT should be included as an integral part of development policy.

2.1 Consequences of ICT

Unravelling the microeconomic mechanisms of how ICT contributes to economic development is a notoriously complicated task. The World Development Report 2016 outlines potential pathways, of which an important one is productivity gains to old existing sectors. This is also what Chapter 2, which is joint work with Finn Tarp, discusses. In a rural economy, where almost all households are engaged in agriculture, the potential benefits of ICT on agriculture are crucial. Chapter 2 contributes to this literature by showing that access to internet has improved the value of agricultural production, relative to areas without internet access.

The role of institutions in Chapter 2 relates to the variable of interest: availability of the internet. First of all, even though internet is a market good, the availability of the infrastructure is a necessary condition for anyone to purchase the good in the market. Second, institutions and the government can influence the prices and hence adoption. Third, the chapter discusses mechanisms of how agricultural information reaches households through the internet. In a one party state such as Viet Nam, where the government overlooks online *content*, institutions play a crucial role also in this regard.

Chapter 2 is under review for *Economic Development and Cultural Change*.

2.2 Determinants of ICT adoption

The benefits of ICT are evident. When a large fraction of the developing world still lacks access to mobile phones and the internet, another relevant question brought up in the World Development Report 2016 is, what are the barriers to ICT adoption? In resource scarce environments, removing barriers to ICT adoption is essential, if policy makers want to promote adoption.

Chapter 3 of this thesis discusses potential barriers to mobile phone adoption during the time span of 2006-14, when this technology started to spread, and reached almost full coverage in terms of all households having at least one phone.[1] As discussed in the previous section, barriers to adoption are strongly related to institutions and governance, the most obvious barrier being the lack of infrastructure. In the case of mobile phones, this means not having an adequate signal for 2G (GSM) or 3G.

In Chapter 3, I find no evidence for infrastructure barriers affecting phone adoption.

[1] More descriptive evidence on the ICT revolution during 2006-14 in rural Viet Nam, see Kaila (2017).

Households residing in communes that have 100 per cent coverage of 2G did not differ in their adoption patterns from households in areas with less than full coverage during 2012-14. This is in line with official information on GSM coverage, that states that GSM is in fact available throughout the country.

Other barriers to adoption that I study, are demographic and social observable characteristics, that are potentially related to cultural and psychological unobservable characteristics. I find that households with political connections are leading in phone adoption, and that the difference is not fully explained by observable factors, such as income and education. This result should be understood in the light of the value of what political connections can have in such a one party state as Viet Nam, where the Communist Party has a strong influence in the everyday lives of the citizens.

A surprising result in Chapter 3 is that even though ethnic minorities are lagging behind in phone adoption, they would adopt even more phones than a non-minority household, if they had their observable characteristics. This might be due to the ethnic minorities residing in remote areas, where phones are perhaps very valuable for acquiring information about markets and services. Given that ethnic minorities are much poorer than the average rural households, this result is indicative of them actually understanding the benefits of phones. Therefore, Chapter 3 does not provide suggestive evidence of any potential psychological or cultural barriers related to the demographic characteristics studied.

Finally, in all the analysis I have taken factors related to demand for goods with network benefits into account. These are income and the evolution of prices, which have been decreasing over the time period of the study. The analysis shows that these factors matter a great deal for phone adoption. Hence, as mobile phones and internet are goods that can be purchased in the markets, a barrier that has existed is the income constraint. Guaranteeing a competitive market for ICT services and goods is a way to keep prices low, and lift barriers to ICT adoption.

3 Education and cognitive skills

The relationship between human capital and growth has long been established. A more recent literature has found a link between cognitive skills and economic growth (Hanushek and Woessmann 2008; 2012; Hanushek 2013). This underscores the importance of measuring learning, not only the level of education, when quantifying human capital.

In Chapter 4, which is joint with David Sahn and Naveen Sunder, we compare the early life determinants of cognitive skills in early adulthood between two Francophone African countries. Cross-country studies using micro data from developing countries are still scarce, but becoming more common as comparable micro-level datasets are becoming available. This poses new challenges for conducting micro-level analysis, while being aware of the underlying macro-level developments of each country, such as institutions and the level of economic development.

This is also a challenge in Chapter 4, where we observe partly similar, and partly different determinants of cognitive skill formation in Madagascar and Senegal. We find that in the case of Senegal, early life cognitive skills have a strong effect to later life cognitive skills. The effect is robust to the inclusion of background characteristics (school and family inputs) and health, and of tests of omitted variable bias. In Madagascar this relationship is weaker. We find school inputs and health, as measured by adult height, to matter more for early adulthood cognitive skills.

The role of the underlying institutions is particularly important for the results of this chapter. The educational systems in these otherwise vastly different countries are both modeled after that of the old colonial power, France. This important institutional characteristic has led to the language of instruction being French in both countries. A contribution we make in this study, the comparison of the long term development of not just math but also language skills between two countries, is possible due to this similar institutional background.

During the time period of our study, the Malagasy children were living in an isolated island economy and experienced two periods of political conflict between the two rounds of data, 1998 and 2012. Economic growth averaged zero per cent during this time.

Meanwhile, Senegal has been an important dynamic economy in West Africa, with strong connections in the region and to France, and positive economic growth. The differences in the living conditions and the economic context might explain some of the differences in our results, especially given the similarity in the educational systems. Understanding the role of institutions, context, and economic growth for our results remains a challenge.

4 Conflict

Conflict and civil war are robustly linked to low per capita incomes and slow economic growth (Blattman and Miguel 2010). On a micro-level there are already a number of studies documenting the magnitudes of the adverse impacts of conflict on various outcomes of wellbeing, such as health (Akresh et al. 2012a;b) and education (Ichino and Winter-Ebmer 2004).

The evidence of what works in reducing conflict and violence is less studied (Blattman and Miguel 2010). Chapter 5, which is joint work with Saurabh Singhal and Divya Tuteja, contributes to this literature by analysing the evolution of violence levels in the ongoing insurgency in Jammu & Kashmir. We find that the reduction in violence levels coincided with three policies. The first policy that coincides with the early phase of the decrease in violence levels is a security policy, the completion of the fencing of the border with Pakistan. The fencing was followed by a large scale development program, the Prime Minister's Reconstruction Plan, which entailed construction of schools, the electrification of villages, and other infrastructure and social improvements. Finally, the third policy that took place was the NREGS, the National Rural Employment Guarantee Scheme, that was phased in throughout India. The program guarantees one hundred days of employment per year to rural households on a minimum wage.

It is plausible that the security policies and development policies were complementary to each other in reducing violence levels. Further research would be needed to disentangle the relative importance of these policies in the reduction of the conflict. Given that Chapter 5 discusses the policies undertaken by the Indian government in tackling the insurgency, the institutions and the political situation are not just *"lurking underneath"* the analysis, but an important determinant of first, the insurgency itself, and second, of the policies implemented to overcome it.

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Chapter 2

Can Internet Improve Agricultural Production? Evidence from Viet Nam

Can Internet Improve Agricultural Production? Evidence from Viet Nam*

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Abstract

This paper aims to contribute to the growing literature on the potential benefits of the internet on rural livelihoods. We estimate the effect of internet access on agricultural production in rural Viet Nam, using a panel dataset from 2008–12. This is a time span during which internet access increased tremendously and both government-run and private online outlets providing information about agriculture started operating. Our findings suggest that internet access is associated with a higher value of total agricultural output, though not in the case of rice. This is in line with strong government involvement in rice production.

JEL Classification: O33, O12, Q12
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1 Introduction

Information and communication technology (ICT) is spreading rapidly over the world and becoming available and affordable to an increasing share of the world population. ICT has reached areas where industrialization is still in its infancy and livelihoods rely on subsistence farming. This paper contributes to the literature that explores the question of how the new information economy can help the rural economy. Understanding how ICT can be used for development is considered one of the most important development challenges of today; the World Bank's World Development Report 2016 is devoted to this issue. Our results provide evidence of how the rural population in Viet Nam has been able to benefit from the ICT revolution.

Like many countries both in the developed and developing world, Viet Nam has experienced a tremendous increase in the number of internet users in the 2000's. The share of the Vietnamese population using the internet has increased from 17 per cent in 2006 to 40 per cent in 2012 (ITU 2013). Within the rural provinces studied, the share of households residing in communes with at least one internet access point has increased from 30.7 to 70.6 per cent between 2008–12.

In 2012, the population was still very dependent on agriculture as the main source of income as 76 per cent of all income earned came from agricultural activities in the rural provinces covered in our dataset. As poverty is more persistent in the rural areas (Markussen et al. 2013), new technologies could potentially provide the means to improve the livelihoods of the rural population. These opportunities have not been left unnoticed by the Vietnamese officials, who have started providing agricultural information online since 2006 (Hoa et al. 2008). Currently there are a number of websites, run both by the authorities as well as by private companies, that provide information about agriculture. The heavy reliance on agriculture coupled with the fact that the most important online activity among the Vietnamese internet users is "information gathering" (Cimigo 2011; BBG 2013), it is easy to see that there is demand for these kind of online platforms.

It is clear that the introduction of information technology, mobile phones, computers and the internet, has had tremendous effects on the economy at the macro-level.[1] Lio and Liu (2006) present macroeconomic evidence on the positive relationship between ICT and agricultural productivity. However, evidence on the precise transmission channels and the micro-foundations on how information technology – or any general purpose technology – affects growth, are still ambiguous (Foster and Rosenzweig 2010). More micro-level evidence on technology adoption is required to understand the linkages between technology and growth.

In a developing country context, the literature closest to our research question has explored how mobile phones can increase information in the market and potentially lead to improved market efficiency (Jensen 2007; Aker 2010; 2011; Fafchamps and Minten 2012; Aker and Fafchamps 2015; Muto and Yamano 2009; Shimamoto et al. 2015; Tadesse and Bahiigwa 2015; Mitra et al. 2016).[2] Jensen (2007) Aker (2010),and Aker and Fafchamps (2015) find mobile phones reduce price dispersion both spatially and over time with respect to both consumer and producer prices. Muto and Yamano (2009) find that mobile phone coverage has increased market participation. As summarized in Nakasone et al. (2014) and Jensen (2010), the literature on ICT and agriculture is mostly concentrated on agricultural markets, and most of the interventions are based on mobile phone technology. Even though there are a number of findings related to increased market efficiency, heterogenous effects – for instance between crops – dominate the results.

There are fewer studies related to the effect of ICT on agricultural practices. Fafchamps and Minten (2012), find little or no effect of a commercial market and weather information system using mobile phone technology on prices or agricultural practices in a controlled randomised experiment in the Indian state of Maharashtra. Aker and Ksoll (2016) find that households that received a mobile phone and education related to its use planted a more diverse basket of crops. To our knowledge there is only one study that examines the effects of the internet, instead of some mobile phone technology. Goyal (2010) finds

[1] See for instance Jalava and Pohjola (2008), and Choi and Yi (2009) on how information technology fosters economic growth building on the theories of endogenous growth.

[2] In the developed country context, another strand of the market efficiency literature looks at labor market matching efficiency (Autor 2001; Bagues and Labini 2009; Kroft and Pope 2012).

that as a result of internet kiosks providing information about soy prices and marketing opportunities the area under soy cultivation increased. Also, Goyal (2010) to our knowledge is the only one to find causal impacts on the level of prices received; not just price dispersion, as the new in information the farmers have access to allows them to avoid intermediaries.[3]

The internet being an information technology, it can be used as a means to acquire information that would not be available otherwise. The internet can therefore increase productivity both by providing information on other technologies, that is by improving a specific production process, or as a source of market information such as prices.

Our work presents new microeconomic evidence on the benefits of internet access on agricultural production;[4] and the findings suggest that having access to agricultural information online can increase the value of output produced. Our result does not hold for rice production, which is in line with there being more government involvement in rice production practices (Markussen et al. 2011) and price regulations in both sales and input prices (Thang and Linh 2015). Moreover, our findings suggest that the internet does not change significantly the input mix of the most important inputs used in production. This implies that the productivity gains arise from either having learned better to use the existing inputs, or obtaining higher prices for the output, as in Goyal (2010). Finally, even though the education level is positively associated with internet availability (Kaila 2017) we do not find evidence of a skill-bias related to the benefits of internet.[5]

Our research is unique in the sense that instead of evaluating a specific technology intervention (Fafchamps and Minten 2012; Goyal 2010; Bagues and Labini 2009; Kroft and Pope 2012), we study whether the mere access to a new general purpose technology translates into benefits to the farming household, such as in (Aker 2010). Therefore instead of studying whether a predetermined way of using a technology renders some

[3]Shimamoto et al. (2015) find mobile phones to have an effect on the level of prices as well, but they recognize that the effect is not necessarily causal.

[4]The effects of internet on productivity has been studied outside the agriculture framework by Akerman et al. (2015), who find that broadband adoption favors skilled labor by increasing its relative productivity and relative wages in Norwegian firms.

[5]Results are presented in Appendix C.

desired effect, we aim at answering what is the effect of the availability of the internet on agricultural output. Due to the observational nature of the data, the caveat of the analysis is that there remains several possible mechanisms of how the information online reaches the farming household, and how they eventually employ this information in their everyday lives at the farm. The benefit of the observational nature of the data is that we demonstrate the benefits of the ICT revolution that have taken place.

It is likely that internet access is correlated with a number of commune level or household level characteristics that also affect agricultural output, such as how urban or rural a commune is. Therefore our main identification strategy relies on the parallel trends assumption. We test this by running placebo tests in a household fixed effects framework, which confirms that we cannot reject the null of parallel trends. Our second approach to addressing the endogeneity issue is to construct bounds on the effects of the internet on agricultural output based on the correlation between observable controls and the internet following the test proposed by Oster (2017) that builds on Altonji et al. (2005). We find that the proposed lower bound for OLS is very close to our OLS estimate with controls.

This paper proceeds as follows. Section 2 presents information on the internet in Viet Nam and the data used, section 3 discusses the production function approach and estimation method; section 4 discusses the identification strategies, section 5 presents the results, and section 6 concludes.

2 Background and data

In parallel to the vast expansion of ICT, a number of online platforms spreading information about agriculture have emerged. The Vietnamese government has several such online outlets; government operated AgroInfo (agro.gov.vn) being a prominent one. The site was established before 2008, when it operated under the name PMARD (Hoa et al. 2008). AgroInfo names farmers as one of the target groups of the website; and it covers news related to agriculture, information about production, as well as information about regional prices of various inputs and crops. In addition to AgroInfo, the website of the

Ministry of Agriculture and Rural Development (MARD, <http://www.mard.gov.vn>) contains information about crop prices and news related to agriculture. Also some of the regional Departments of Agriculture and Rural Development (DARD) have their own websites, which are less educative in nature and with more focus on regional agricultural news among other things.[6] In addition to government maintained websites, we are aware of three privately run websites that provide information on agriculture in Vietnamese, that have been in operation during the period of our study. Altogether we are aware of six other online platforms. The list of all known online platforms is given in Appendix B.

The hypothesis that Vietnamese farmers are learning through information provided online is in line with the way the Vietnamese report using the internet. The most important activity on the internet in Viet Nam is "information gathering" (Cimigo 2011; BBG 2013); most importantly reading the news (93.6% of users according to the nationally representative gallup conducted by BBG). Some 78.3% went online to find out information about a specific topic (BBG 2013), and Google is the most visited website (Cimigo 2011; VNNIC 2014).

In order to get closer to the question of whether the Vietnamese are gathering information about agricultural practices online, we have collected information on the Google searches of the most important purchased inputs of production – fertilizers and pesticides from Google Trends (<https://www.google.com/trends/>). Figure B-1 in Appendix B shows that there has been an increase in the searches of both of these terms over the period covered in our analysis. This information shows that inputs are being googled, and increasingly so.[7] The details of the Google trends data are explained in Appendix B.

There are as many as eleven enterprises in Viet Nam that have been granted licenses to build network infrastructure. Of these three have built telecommunications network infrastructure on a national scale (Viettel, VTN (VNPT) and EVN Telecom). Therefore the arrival rate of the internet to the rural areas in our dataset is subject to decisions

[6] For example the Department of Agriculture and Rural Development of Lao Cai, one of the provinces in our sample, has a regional website <http://snnptnt.laocai.gov.vn>

[7] However, we do not know the absolute number of searches nor the regional composition within Viet Nam.

taken by a large number of companies and their coordination with respect to building the infrastructure (Tuan 2011). Maps of the VARHS communes and internet access in the proximity of Hanoi and Ho Chi Minh City are presented in in Appendix A Figures A-1 and A-2, respectively. Figure A-2 shows that the internet has spread first to the rural areas close to urban centers, Hanoi and Ho Chi Minh City, from where it has expanded to more remote rural areas over time. In the provinces further away from urban areas the arrival of the internet has been less systematic, plausibly resulting from the fragmented internet provider market.

For our analysis, we use the Viet Nam Access to Resources Household Survey (VARHS), a panel dataset of 12 rural provinces in Viet Nam.[8] In this paper we use three waves of data: 2008, 2010 and 2012, implemented between July and September 2008, June and August 2010, and June and August 2012. In addition to a large set of data on household characteristics as well as land and agriculture related variables, VARHS contains a commune level questionnaire answered by decision makers at the municipal level. Description of the variables used is given in Appendix A Table A-1.

Our variable of interest is internet access in the communes studied, collected as a recall question in a commune level questionnaire conducted in 2014. The question asked is whether the commune had at least one internet access point in a specific year. Table 1 illustrates how the internet has become available in the areas studied on a household level.

We have restricted the sample to a balanced panel of households that report having agricultural output larger than zero at every survey round. The data used consists of 478 communes with a sample size of 2,477 households, the attrition rate being very low, 2.2 per cent. Our dataset also includes information on the output value of rice, and input use and land use in rice production, which makes it possible to estimate a production function for rice only. In the analysis of rice production, the sample is restricted to households producing rice at every survey round, a total of 2,029 households. Table 2 shows summary

[8]The survey is a collaboration between the Development Economics Research Group (DERG) at the Department of Economics at the University of Copenhagen, and the Central Institute of Economic Management (CIEM), the Institute for Labor Studies and Social Affairs (ILSSA), and the Institute of Policy and Strategy for Agriculture and Rural Development (IPSARD) in Hanoi, Viet Nam.

Table 1: Internet Access

Internet in commune	**2008**	**2010**	**2012**
No internet, number of households	1,717	1,146	728
No internet, % of households	69.3	46.3	29.4
Internet, number of households	760	1,331	1,749
Internet, % of households	30.7	53.7	70.6
Total, number of households	2,477	2,477	2,477
Total, % of households	100	100	100

Notes: Description of the variables given in Appendix A Table A-1.

statistics for the balanced panel, as well as by year. A detailed description on how we arrived to the panel used, as well as a detailed description of the variables used in the analysis are presented in Appendix A.

Panel A of Table 2 presents characteristics of households that are engaged in agriculture during the entire four-year period, Panel B shows descriptive statistics related to agricultural output and input –the key variables in the production function. We have adjusted the value of agricultural output as well as the costs of inputs in agriculture with the land size of the land operated by the household for the sake of illustration. In the analysis we use the log values of the variables and include land size as an input in the production function. Panel C presents summary statistics for rice production variables for the subsample that produces rice in every year. We note that almost all farmers (82 per cent) produce rice every period. The input variables for rice are only inputs used in rice production.

The households in our sample have on average five members and the household heads are on average 50 years of age. Over half of the sample belong to the ethnic majority (Kinh), which we include as a dummy variable. The education level of the farmer takes values from 1 "cannot read and write" to 6 "has third level education". The average education level index of the farmers is 2.9, where value 3 indicates that they have finished primary school (and can read and write); 76% of the household heads have an education level index above 1, which means that they can read or write. The maximum education level of a household member is above 1 in 96.3 percent of the sample, which is in line with

Table 2: Summary statistics

	All years		2008		2010		2012	
	mean	sd	mean	sd	mean	sd	mean	sd
PANEL A: Household								
Number of HH members	4.9	1.9	5.1	2	4.9	1.9	4.8	1.9
Education, hh head	2.9	1.3	2.8	1.2	2.9	1.3	2.9	1.3
Female head HH	.14	.35	.14	.35	.14	.35	.15	.36
Age of head HH	49	13	47	13	49	13	51	13
Average age of adult household members	40	9.8	39	9.3	40	9.8	41	10
household is of kinh ethnicity	.56	.5	.56	.5	.56	.5	.56	.5
Real non-agricultural income	35747	80439	27762	77251	38465	94869	41018	65976
Radio	.16	.37	.2	.4	.16	.37	.13	.33
Television	.83	.38	.77	.42	.83	.38	.89	.31
Phone	.57	.5	.36	.48	.58	.49	.75	.43
PANEL B: Agriculture								
Output / hectare	41706	58214	41315	43510	41417	72688	42386	54698
Labour / hectare	992	9632	1381	14683	957	7816	638	1203
Capital / hectare	450	2943	569	4451	399	1359	381	2077
Fertilizers / hectare	547	1221	788	1785	402	657	452	876
Pesticides / hectare	111	220	151	288	92	172	91	173
Land operated (sqm)	11453	19910	11492	22183	11151	14300	11716	22200
Number of plots operated	5.4	2.7	5.5	2.9	5.4	2.7	5.3	2.6
Share of high quality land	.041	.17	.052	.19	.04	.17	.032	.16
Share of low quality land	.11	.28	.11	.26	.15	.31	.091	.25
Share of land with red book	.57	.44	.59	.42	.53	.45	.6	.43
Observations	7431		2477		2477		2477	
PANEL C: Rice								
Rice / hectare	51268	449286	61791	683669	51456	368693	40557	46619
Labour / hectare (rice)	519	7359	774	12315	437	3236	347	548
Seeds / hectare (rice)	248	3009	383	5116	191	950	170	264
Fertilizers / hectare (rice)	856	21632	1646	37302	502	3404	419	530
Pesticides / hectare (rice)	143	708	216	1131	114	427	99	186
Rice land operated (sqm)	3954	11978	4200	17978	3800	7027	3863	7606
Number of rice plots	2.7	2.5	2.8	2.6	2.7	2.5	2.7	2.4
Observations	6087		2029		2029		2029	

Notes: All values in '000 VND. Description of the variables given in Appendix A Table A-1.

almost universal primary school completion rates in Viet Nam today. It is therefore likely that the 2.7 per cent of our sample where the households are entirely illiterate cannot benefit from information online.[9] We keep this subsample in our analysis, since a third of the sample does reside in communes that have internet access, and we want to be able to capture the "intent-to-treat" (ITT) effect of the availability of the internet, hence allowing for spillovers.

Almost all of the households engage in other activities than agriculture, mainly wage labor and household enterprises, which we control for in our regressions. Agriculture is nevertheless still the most important source of livelihood, the value of agricultural output exceeding the total non-agricultural income in each period. Both agricultural and non-agricultural income have steadily risen in real terms.

In terms of information technology, we are controlling for the ownership of radio, television and phones. The variables are dummies indicating if a household has at least one of each of these assets. Radios are owned by only 16 per cent of the households with a steady decline over the years, whereas the ownership of televisions and phones (both fixed line and mobile combined) has increased significantly. We include these as controls in our regressions.

Panel B and C describe the agriculture-related variables. The output value and cost of inputs used in production are in monetary terms: 1000 Dong adjusted with province level CPI indexes to take into account differential inflation in different regions. The values are all for the last 12 month period, hence encompassing all agricultural seasons. Labor is measured by the number of days spent in agriculture. All input variables are for all the plots operated by the household, including all crops except those used for forestry. The inputs selected for the production function are those used by almost all farmers, so that they jointly yield a production function that has close to constant returns to scale. Capital consists of the value of machinery and tools used in the set of plots described.

By comparing panels B and C we can see that the value of output per hectare is higher for rice than for production on average; and rice is also more intensive in the use of

[9]The maximum education level variable is not displayed in the summary statistics.

pesticides and fertilizers. Other crops that are planted in these regions include for instance maize, potato, sweet potato, cassava, peanuts, soy beans and fruits and vegetables. Coffee farming is common in the region of Central Highlands, where three of the twelve provinces of VARHS are situated.

Panel B also includes information about how large a share of the land has a property right (a "red book"), which we control for. Over half of the land is under a formal property right and this figure changes little over time. We also control for self-reported measures of land quality as categorical variables, with the base category being "average quality" and the categories included in the regressions are higher and lower quality than average. Most of the land is perceived to be average quality. We also control for the number of plots.

In our production function analysis presented in section 5 we control for the household and land characteristics presented in Table 2.

3 Production function framework

In this section we present the production function framework and its empirical counterpart used in estimating the model.

3.1 Conceptual framework

The effects of internet access on agricultural output is studied using a Cobb-Douglas production function.[10] In our main specification, the internet enters the production function through the "unexplained" total factor productivity (TFP) component.

The production function used in our main analysis is

$$Y_{it} = e^{\gamma_0 + \gamma_1 D_{jt}} A_{it}^{\beta_{a0}} \boldsymbol{M}_{it}^{\boldsymbol{\beta}_{m0}} \tag{1}$$

where Y_{it} is value of agricultural production of household i at time t, D_{jt} is a dummy for internet access in commune j at time t and M_{it} is a vector of inputs in household production on farm, and A_{it} is land. Average TFP is denoted by $e^{\gamma_0 + \gamma_1 D_{jt}}$.

[10] This follows the approach used by Lio and Liu (2006) as well as Akerman et al. (2015).

Taking logs and rearranging we get

$$y_{it} = \gamma_0 + +\gamma_1 D_{jt} + \beta_{a0} a_{it} + \boldsymbol{\beta}_{m0} \boldsymbol{m}_{it} \tag{2}$$

which is our baseline formulation used in estimating the model, where low-case letters denote log-variables.

3.2 Empirical specification

Our baseline specification is the production function in equation 2.

To ensure that the production function is well specified, we first estimate using OLS a production function with the input vector $\boldsymbol{M}_{it}$, which includes labor, capital, pesticides and fertilizers; and land A_{it}, so that we can see that the production function yields close to constant returns to scale. The first model to be estimated is

$$y_{it} = \gamma_0 + \gamma_1 D_{jt} + \beta_a a_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_f f_{it} + \beta_p p_{it} + \lambda_t + \varepsilon_{it} \tag{3}$$

which is the empirical counterpart of equation 2. Now y_{it} is the log value of agricultural production for household i at year t, D_{jt} is a dummy denoting internet access in a commune j at year t. The log size of land operated by the household is denoted by a_{it}, k_{it} is the log value of capital, l_{it} is the log amount of household labor supplied on farm, f_{it} is the log value of fertilizers used by the household on farm, and p_{it} is the log value of pesticides used on farm. Time dummies are denoted by λ_t. In the second specification we impose the constant returns to scale –assumption, that is $\beta_a + \beta_k + \beta_l + \beta_f + \beta_p = 1$ on our input vector to ensure that the theoretical assumption is satisfied without causing major changes to the coefficient estimates of the unrestricted model.

As our treatment variable is a dummy denoting whether the commune has at least one internet access point, the coefficient estimate captures the ITT-effect of the availability of the internet on the value of agricultural production. Hence, we do not have self-selection into treatment at the household level.

The ITT estimate allows us to capture not just the effects of the internet use in the commune, but also the positive externalities of that use, if production related information obtained online spreads in the commune to non-users. Literature on technology adoption in developing countries (Conley and Udry 2010; Foster and Rosenzweig 2010; Munshi 2004; BenYishay and Mobarak 2014) suggest that farmers learn about new technologies through their social networks, such as neighbors. Hence it is not crucial to know how much internet use is devoted to looking up production related information – as long as someone acquires the information and the information spreads.

4 Identification

4.1 Parallel trends

The model in equation 3 gives us a well specified model in both a theoretical and a statistical sense, which serves as a good benchmark to start investigating the impact of the internet on agricultural output. Our identification strategy relies on the assumption of parallel trends. This means that the value of agricultural output would have evolved similarly in areas that received the internet and in areas that never did, had internet not been introduced. Since we have two time periods when the internet has arrived (either between 2008 and 2010, or between 2010 and 2012), first we estimate a fixed effects model, which is essentially a generalization of the difference-in-difference approach, in the case of more than 2 periods and more than 2 groups.

The model that we estimate takes the form

$$y_{it} = \gamma_1 D_{jt} + \beta_a a_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_f f_{it} + \beta_p p_{it} + \lambda_t + \delta_i + \boldsymbol{\theta}_{it} \boldsymbol{x}_{it} + \varepsilon_{it} \tag{4}$$

We introduce fixed effects on the level of the commune, i.e. on the level of the treatment, to account for commune level time-invariant characteristics, as well as on the level of observation, i.e. the household, denoted as δ_i in equation 4.[11] In addition to this, we also control for a large number of household specific time-varying controls denoted as $\boldsymbol{x}_{it}$.

[11] This specification will thus capture the effect of the change in the internet access (that is, the once occurring take-up of internet by the commune) to the change in the value of agricultural production.

The controls include controls for land, household characteristics, and other technology used in household described in Table 2.

A way to test the validity of the parallel trends assumption in our case is to run a placebo-test. We run a placebo test where we regress the*lead* of the internet variable D_{jt+1} to the value of agricultural output y_{it}. We would expect the coefficient estimate of this regression to be statistically significant 1) if the households in the commune can anticipate the information that the internet brings, which does not seem plausible; or 2) if the parallel trends assumption does not hold. Our results are robust to this placebo test: the coefficient estimates are very close to zero and not significant.

Our identification strategy does not require the treatment and control communes to be similar at baseline. Nevertheless it is noteworthy to point out that the commune and household fixed effects absorb the information about the time invariant characteristics of the communes, such as the distance to Hanoi or Ho Chi Minh City.

In all of the specifications, we use heteroscedasticity-robust standard errors that are clustered at the commune level, that is, at the level of the treatment (Bertrand et al. 2004).

4.2 Bounds based on OLS

To address the issue of possible omitted variable bias in our OLS estimates of the effects of the internet on agricultural output, we follow Altonji et al. (2005) and Oster (2017). Specifically, since unobserved commune characteristics related to internet access may also be correlated with agricultural output, as more remote communities get the internet later, the OLS estimate of the coefficient of the internet is likely to be biased upward. It can therefore be considered an upper bound of the effect.

Oster (2017) shows that, if selection on unobservables is perfectly proportional to selection on observables, the lower bound of the true effect equals

$$\beta^* = \widetilde{\beta} - \left[\dot{\beta} - \widetilde{\beta} \right] \frac{R_{max} - \tilde{R}}{\tilde{R} - \dot{R}} \tag{5}$$

Where $\widetilde{\beta}$ is the coefficient estimate of the internet coefficient in an OLS model with full controls, and $\tilde{R}$ correspond to the R^2 of that model. Similarly $\dot{\beta}$ and $\dot{R}$ are from an OLS regression with no controls; and R_{max} is the maximum value of the R^2 of our OLS model. As noted by Oster (2017), it is hard to come up with a realistic upper bound to R_{max}, a theoretical upper bound, which is empirically unfeasible and hence gives lowest possible result for β^* is to set the R_{max}, equal to 1.[12] We adopt this approach in order to have as rigorous results as possible.

Furthermore, based on Oster (2017) and Altonji et al. (2005) we calculate another test statistic to analyze the coefficient stability of our model. Assume a regression model of the form

$$y = \beta D + \boldsymbol{\gamma}_1 \boldsymbol{W}_1 + \boldsymbol{\gamma}_2 \boldsymbol{W}_2 + \epsilon \tag{6}$$

Where D is the treatment variable, $\boldsymbol{W}_1$ are the (observable) control variables, and $\boldsymbol{W}_2$ are the unobservables. The importance of the observables relative to the unobservables can be formulated as $\delta \frac{\sigma_{1D}}{\sigma_{11}} = \frac{\sigma_{2D}}{\sigma_{22}}$, where $\sigma_{iD} = Cov(\boldsymbol{W}_i,\ D)$ and $\sigma_{ii} = Var(\boldsymbol{W}_i)$, $i = 1,\ 2$. Now δ defines the proportionality between observables and unobservables. The R^2 of equation 6 is the R_{max} introduced previously, and we set it to 1.

As suggested by Oster (2017) we run a robustness check calculating the value for δ for which $\beta^* = 0$. Here also we set $R_{max} = 1$. This can be interpreted as the degree of selection on unobservables relative to observables which would be necessary to explain away the result.

5 Results

5.1 Production function results

Table 3 presents the results of estimating equations 3 and 4. The results suggest that internet access has had an impact on the value of agricultural production. In column 1 the

[12] For comparison, Oster (2017) considers R_{max} values between 0.5-0.6 in an empirical example using observational data.

production function is estimated with the internet variable, controlling only for year fixed effects. The second column is similar, except with the restriction of constant returns to scale for all the inputs, hence excluding the internet. This inflates slightly the coefficient estimate of the internet variable, but overall we can see that the coefficient estimates barely change from column 1 to column 2 suggesting that our model has indeed close to constant returns to scale without the explicit restriction.

In column 3 we add controls to the model as well as commune dummies.[13] These results suggest that internet access increases the value of agricultural output by 7 per cent.

In colums 4 and 5 of Table 3 we have included household fixed effects, in column 5 together with controls. From these results we infer that the arrival of the internet increases the average change in agricultural output by 6.6 per cent. All of the results are significant at the 5 per cent level. The standard errors are heteroscedasticity-robust and clustered at the commune level in all of the specifications.

It is furthermore important to comment on the controls, especially other information sources, television, radio and phones. In the specification with households fixed effects none of these are significant at the 5 per cent level.[14]

As shown in Table 4, the results do not carry over to restricting the sample to rice production. We can see that the coefficient estimates are between 1-3 per cent, but not statistically significant in any of the specifications.

We have also investigated whether there is a skill-bias in internet access, that is whether more educated farmers are able to derive more benefits from the arrival of the internet. We do not find evidence for this. Results are presented and discussed in Appendix C Table C-1.

As discussed in section 4.2, the OLS estimate of the coefficient of internet should be considered an upper bound for the true effect. We use the regression in column 3 of Table 3 as the full model with controls, and to get the lower bound β^* we set $\widetilde{\beta}= 0.070$ and

[13] Controls include the variables presented in Table 2.

[14] Results showing the coefficient estimates of the control variables are available from the authors on request.

Table 3: Production function of all crops

VARIABLES	(1)	(2)	(3)	(4)	(5)
Internet	0.073**	0.082***	0.070**	0.078**	0.066**
	(0.029)	(0.030)	(0.034)	(0.035)	(0.032)
Labour	0.198***	0.231***	0.176***	0.144***	0.128***
	(0.019)	(0.018)	(0.020)	(0.017)	(0.016)
Land	0.392***	0.408***	0.358***	0.262***	0.200***
	(0.021)	(0.021)	(0.031)	(0.042)	(0.040)
Fertilizers	0.130***	0.130***	0.135***	0.106***	0.104***
	(0.013)	(0.013)	(0.016)	(0.013)	(0.013)
Pesticides	0.174***	0.180***	0.118***	0.094***	0.088***
	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)
Capital	0.051***	0.050***	0.041***	0.028***	0.025***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Observations	7,431	7,431	7,431	7,431	7,431
R-squared	0.744		0.805	0.273	0.294
YEAR FE	YES	YES	YES	YES	YES
Controls	NO	NO	YES	NO	YES
Commune FE	NO	NO	YES	NO	NO
HH FE	NO	NO	NO	YES	YES
CRS	NO	YES	NO	NO	NO
Number of households				2,477	2,477

Notes: Dependent variable is the log value of agricultural output. Description of the explanatory variables given in Appendix A Table A-1. CRS denotes that the constant returns to scale –restriction is imposed on the coefficient estimates of the inputs. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the commune level. Significance: *** p<0.01, ** p<0.05, * p<0.10

Table 4: Production function for rice

VARIABLES	(1)	(2)	(3)	(4)	(5)
Internet	0.027	0.029	0.010	0.036	0.023
	(0.030)	(0.030)	(0.039)	(0.035)	(0.036)
Labour (rice)	0.238***	0.283***	0.189***	0.139***	0.110***
	(0.020)	(0.018)	(0.015)	(0.013)	(0.013)
Land (rice)	0.088***	0.089***	0.047**	0.042***	0.011
	(0.021)	(0.021)	(0.020)	(0.014)	(0.012)
Pesticides (rice)	0.152***	0.156***	0.065***	0.052***	0.041***
	(0.014)	(0.013)	(0.009)	(0.009)	(0.009)
Fertilizers (rice)	0.090***	0.095***	0.073***	0.060***	0.053***
	(0.011)	(0.011)	(0.009)	(0.008)	(0.008)
Seeds (rice)	0.361***	0.378***	0.327***	0.245***	0.218***
	(0.023)	(0.023)	(0.019)	(0.017)	(0.016)
Observations	6,087	6,087	6,087	6,087	6,087
R-squared	0.702		0.783	0.286	0.336
YEAR FE	YES	YES	YES	YES	YES
Controls	NO	NO	YES	NO	YES
Commune FE	NO	NO	YES	NO	NO
HH FE	NO	NO	NO	YES	YES
CRS	NO	YES	NO	NO	NO
Number of households				2,029	2,029

Notes: Dependent variable is the log value of rice output. Description of the explanatory variables given in Appendix A Table A-1. CRS denotes that the constant returns to scale −restriction is imposed on the coefficient estimates of the inputs. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the commune level. Significance: *** p<0.01, ** p<0.05, * p<0.10

$\tilde{R}$= 0.805. Similarly $\dot{\beta}$ and $\dot{R}$ are from an OLS regression with no controls (not reported in the results), with $\dot{\beta}$ = 0.108 and $\dot{R}$= 0.0025. This yields a β^*= 0. 061.[15] On this basis we conclude from the OLS specification that the effect of the internet on agricultural output likely lies between 6.1 and 7.0 percent, which under the assumption δ= 1, suggests that selection on unobservables is also low.

Next, using the same models as previously, we get a value for δ that would be needed to produce a treatment effect $\beta^* = 0$. We find this value to be $\delta = 7.48$, which suggests that the unobservables would need to be 7.48 times as important as the observables to produce a treatment effect of zero. Given that Altonji et al. (2005) and Oster (2017) regard the value $\delta = 1$ as a good benchmark, we conclude that it is very unlikely that our results are driven by unobservables.

5.2 The effect of internet on inputs

In order to explore the mechanisms driving our results, we investigate whether the results are driven by the change of the input mix: whether internet availability has actually had an effect on the value of inputs used on farm. The results are presented in Tables 5 and 6. The analysis is run with household and year fixed effects and the dependent variables are in logs. Standard errors are clustered at the commune level as previously.

We can see that in the production function of all crops, the internet has had little impact on the value of inputs used when time-invariant household characteristics are controlled for. However the internet has increased the use of seeds in rice production and this result is statistically significant.

The overall result of the rice analysis suggests that we cannot argue that the internet has had a positive effect on the value of rice production.[16] As discussed in Markussen et al. (2011) and also thoroughly documented in Vasavakul (2006), rice production is operated under significant constraints: authorities monitor that certain plots are reserved for rice only and quantities of rice produced are also monitored. In 2010 floor prices for rice

[15] Setting $R_{max} = 1$ and $\delta = 1$.

[16] In fact, also when we change the explanatory variable to the quantity of rice produced as well as the real sales value of rice, we cannot find an effect. The results are not provided in this version.

Table 5: The effect of internet on inputs

VARIABLES	(1) Labour	(2) Land	(3) Fertilizers	(4) Pesticides	(5) Capital
Internet	-0.020	0.001	0.027	0.146*	-0.029
	(0.067)	(0.025)	(0.089)	(0.088)	(0.133)
Observations	7,431	7,431	7,431	7,431	7,431
R-squared	0.043	0.001	0.036	0.056	0.011
Number of households	2,477	2,477	2,477	2,477	2,477
YEAR FE	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES

Notes: Description of the outcome variables given in Appendix A Table A-1. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the commune level. Significance: *** p<0.01, ** p<0.05, * p<0.10

Table 6: The effect of internet on rice inputs

VARIABLES	(1) Labour (rice)	(2) Land (rice)	(3) Pesticides (rice)	(4) Fertilizers (rice)	(5) Seeds (rice)
Internet	-0.020	0.006	0.067	-0.147	0.234***
	(0.080)	(0.250)	(0.083)	(0.126)	(0.073)
Observations	6,087	6,087	6,087	6,087	6,087
R-squared	0.029	0.005	0.084	0.016	0.145
Number of households	2,029	2,029	2,029	2,029	2,029
YEAR FE	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES

Notes: Description of the outcome variables given in Appendix A Table A-1. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the commune level. Significance: *** p<0.01, ** p<0.05, * p<0.10

purchased by enterprises from producers were introduced (Thang and Linh 2015). Prices being regulated implies that there is less arbitrage opportunities via price information that is available online. The government also regulates rice input prices and has policies to support the input costs in rice farming. These policies have taken place to guarantee a certain level of food security in the country.

As Markussen et al. (2011) show, the constraints set by the government are binding and thus households could have chosen their crops differently had they been able to decide freely. However, when taking into account that the households are subsidised, the net effect of interventions to the agricultural income of the household is not statistically significant from zero.

It is possible that due to the above mentioned reasons and rice being the main staple, farmers have sufficient information about its production practices from more traditional information sources.

5.3 Placebo tests

In Tables 7, 8, 9, 10 we run the placebo tests of the effect of the internet in period $t+1$ (that is 2010 for 2008 and 2012 for 2010), to our outcome variables of interest in period t. We have assumed that the value in the last period is the same as in the previous period, hence the same sample size as in the main specification.[17] Table 7 presents the placebo tests of the results in Table 3. We can see that all of the coefficient estimates are close to zero, and not even borderline significant.

Table 8 does the same placebo-test for the production function for rice presented in Table 4. The results in Table 4 are insignificant, so the placebo-results merely go to show that we cannot reject the assumption of parallel trends even in this case.

Tables 9 and 10 investigate the placebo tests for the regressions presented in Tables 5 and 6, respectively. We can see that the statistically significant results are not reproduced, and the rest of the coefficients are also close to zero and none of them are statistically

[17]The results do not change if we drop the last period out of the analysis, since we have assumed in the placebo tests that there is no movement in the treatment variable from the second last period to the last period.

Table 7: Placebo test: Production function of all crops

VARIABLES	(1)	(2)	(3)	(4)	(5)
Internet (t+1)	0.018	0.024	0.031	0.040	0.022
	(0.034)	(0.036)	(0.078)	(0.078)	(0.071)
Labour	0.197***	0.232***	0.176***	0.143***	0.128***
	(0.019)	(0.017)	(0.020)	(0.017)	(0.016)
Land	0.386***	0.402***	0.358***	0.262***	0.199***
	(0.021)	(0.021)	(0.031)	(0.042)	(0.040)
Fertilizers	0.134***	0.134***	0.135***	0.106***	0.104***
	(0.013)	(0.013)	(0.016)	(0.013)	(0.013)
Pesticides	0.175***	0.182***	0.119***	0.095***	0.089***
	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)
Capital	0.050***	0.050***	0.041***	0.028***	0.025***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Observations	7,431	7,431	7,431	7,431	7,431
R-squared	0.743		0.805	0.271	0.292
YEAR FE	YES	YES	YES	YES	YES
Controls	NO	NO	YES	NO	YES
Commune FE	NO	NO	YES	NO	NO
HH FE	NO	NO	NO	YES	YES
CRS	NO	YES	NO	NO	NO
Number of households				2,477	2,477

Notes: Dependent variable is the log value of agricultural output. Description of the explanatory variables given in Appendix A Table A-1. CRS denotes that the constant returns to scale –restriction is imposed on the coefficient estimates of the inputs. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the commune level. Significance: *** p<0.01, ** p<0.05, * p<0.10

significant.

Therefore we conclude that one cannot reject the hypothesis of parallel trends based on this placebo-test analysis.

Table 8: Placebo test: Production function of rice

VARIABLES	(1)	(2)	(3)	(4)	(5)
Internet (t+1)	0.032	0.033	0.099	0.115	0.072
	(0.038)	(0.037)	(0.093)	(0.084)	(0.079)
Labour (rice)	0.238***	0.283***	0.188***	0.138***	0.109***
	(0.020)	(0.018)	(0.015)	(0.013)	(0.012)
Land (rice)	0.089***	0.090***	0.048**	0.043***	0.012
	(0.021)	(0.021)	(0.020)	(0.014)	(0.012)
Pesticides (rice)	0.152***	0.156***	0.065***	0.052***	0.041***
	(0.014)	(0.013)	(0.009)	(0.010)	(0.009)
Seeds (rice)	0.361***	0.378***	0.327***	0.246***	0.219***
	(0.024)	(0.024)	(0.019)	(0.017)	(0.016)
Fertilizers (rice)	0.089***	0.094***	0.073***	0.060***	0.053***
	(0.012)	(0.012)	(0.009)	(0.008)	(0.008)
Observations	6,087	6,087	6,087	6,087	6,087
R-squared	0.702		0.784	0.288	0.337
YEAR FE	YES	YES	YES	YES	YES
Controls	NO	NO	YES	NO	YES
Commune FE	NO	NO	YES	NO	NO
HH FE	NO	NO	NO	YES	YES
CRS	NO	YES	NO	NO	NO
Number of households				2,029	2,029

Notes: Dependent variable is the log value of rice output. Description of the explanatory variables given in Appendix A Table A-1. CRS denotes that the constant returns to scale −restriction is imposed on the coefficient estimates of the inputs. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the commune level. Significance: *** p<0.01, ** p<0.05, * p<0.10

Table 9: Placebo test: The effect of internet on inputs

VARIABLES	(1) Labour	(2) Land	(3) Fertilizers	(4) Pesticides	(5) Capital
Internet (t+1)	0.056	0.019	-0.034	-0.037	-0.065
	(0.103)	(0.038)	(0.116)	(0.190)	(0.212)
Observations	7,431	7,431	7,431	7,431	7,431
R-squared	0.043	0.001	0.036	0.054	0.011
Number of households	2,477	2,477	2,477	2,477	2,477
YEAR FE	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES

Notes: Description of the outcome variables given in Appendix A Table A-1. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the commune level. Significance: *** p<0.01, ** p<0.05, * p<0.10

Table 10: Placebo test: The effect of internet on rice inputs

VARIABLES	(1) Labour (rice)	(2) Land (rice)	(3) Pesticides (rice)	(4) Fertilizers (rice)	(5) Seeds (rice)
Internet (t+1)	0.029	-0.242	-0.101	-0.143	-0.006
	(0.140)	(0.355)	(0.148)	(0.163)	(0.145)
Observations	6,087	6,087	6,087	6,087	6,087
R-squared	0.029	0.007	0.084	0.015	0.135
Number of households	2,029	2,029	2,029	2,029	2,029
YEAR FE	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES

Notes: Description of the outcome variables given in Appendix A Table A-1. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the commune level. Significance: *** p<0.01, ** p<0.05, * p<0.10

6 Concluding remarks

Our results suggest that internet access is associated with higher value of agricultural output by 6-7 per cent. We find that this effect is not the result of changing the input mix used on farm. Therefore, the effect we observe is due to either more efficient use of inputs, better practices; or a result of the farmers being able to obtain higher prices though the help of the internet by exploiting an information asymmetry in the markets (Goyal 2010). We do not find this result to hold for rice production, which is in line with the rice market being operated under restrictions on both production and prices. Given that there exists a number of both government and privately run online outlets supplying information on agricultural production, and the fact that information gathering is the most popular online activity in Viet Nam, the overall result suggests that farmers have indeed been able to use this information to their benefit. Since we look at the effect of the arrival of the first internet access point – the "intent-to-treat" effect – our results include possible spillovers: farmers that have benefitted from the new information might have been exposed to it through their social connections or otherwise.

Our identification strategy relies on the parallel trends assumption holding, which our placebo test results strongly support. Second, following the method proposed by Oster (2017) and Altonji et al. (2005) we derive a lower bound of the coefficient estimate of interest finding that it is very close to our most rigorous OLS specification; and that it is very unlikely that our results are driven by unobservables.

In our study we have been able to shed light on whether the introduction of such a general purpose technology as the internet can serve as a means of improving practices in the traditional sectors of the economy. This question is timely since after a period of rapid growth in the 2000s, some of the poorest rural provinces in Viet Nam are lagging behind overall economic development (Markussen et al. 2013). Moreover, since Viet Nam has recently obtained lower middle income country status by World Bank standards, foreign aid is gradually being withdrawn from the country. It is therefore crucial that poor households are not left behind in their capacity to use new technologies in their everyday lives. Furthermore, our results should be of interest for developing countries that are considering the costs and benefits of building national internet networks.

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Appendix

A Data

In 2008 the survey covered 3,269 households. Dropping missing observations leaves us with 3,065 households and restricting the sample to households with agricultural output greater than zero every year gives us a sample of 2,805 households. Balancing the sample at this stage yields a sample of 2,523 households. Furthermore, we drop 46 households for whom the internet access variable is missing or inconsistent, such that there is movement in and out of having internet in a commune. We are left with a balanced panel of 2,477 households.

If we balanced the panel before restricting the sample to households with agricultural production in each period, we would get a sample of 2,999 households in the balanced panel, hence with 66 attrited households and an attrition rate of 2.2 per cent. Balancing after restricting the sample to households with agricultural production results in dropping 282 households that were surveyed in 2008, 10 per cent of the sample, leaving out households who had agricultural production in 2008, but didn't have any in 2010 or 2012. This might be due to them being very small subsistence producers in the first place, or households that have moved out of agriculture. Hence the final attrition rate of our panel being 10 per cent is partly due to true attrition (2.2%) and for the remainder, it is due to moving away from, or in and out of agriculture. Restricting the sample to households with rice output in a similar way leaves us with a balanced panel of 2,029 households.

Table A-1: Description of variables

Variable	**Description**
Panel A: Household	
Internet	A dummy that takes value 1 if at a certain year a commune had at least one internet access point (from a questionnaire to commune administration collected in 2014). The question is formulated as following for year 2012, then similarly for 2010 and 2008: "The commune had at least one internet access point in 2012? (ANSWER YES IF THERE IS AT LEAST ONE INTERNET ACCESS POINT IN THE COMMUNE AND NO IF THERE IS NO INTERNET ACCESS IN THE COMMUNE), 1 = YES 2 = NO"
Number of HH members	Number of household members
Education hh head	Education level of household head: 1. Cannot read and write 2. Can read and write but did not finish primary school 3. Finished Primary School 4. Finished Lower Secondary School 5. Finished Upper Secondary School 6. Third Level.
Female head HH	Dummy that takes value 1 if household head is female
Age of head HH	Age of household head
Avg. age of adult HH members	Average age of household members over the age of 16
Household is of kinh ethnicity	Dummy that takes value 1 is household is of kinh ethnicity (the largest ethnic group)
Real non-agricultural income	Income from all sources excluding agriculture adjusted with province level CPI
Radio	Dummy that takes value 1 if household has at least one radio
Television	Dummy that takes value 1 if household has at least one television
Phone	Dummy that takes value 1 if household has at least one phone

Panel B: Agriculture	**Agricultural questions asked about the last 12 months**
Agricultural output	Log value of agricultural output adjusted with province level CPI (all crops on plots operated by the household excluding forestry production)
Labor	Log number of days spent in agriculture (all crops on plots operated by the household excluding forestry production)
Capital	Log value of agricultural machinery and tools owned by the household adjusted with province level CPI
Fertilizers	Log value of chemical fertilizers used adjusted with province level CPI (all crops on plots operated by the household excluding forestry production)
Pesticides	Log value of pesticides and herbicides used adjusted with province level CPI (all crops on plots operated by the household excluding forestry production)
Land operated (sqm)	The area of land operated by the household in sqm (including own land and rented land)
Number of plots operated	Number of plots operated by household (including own land and rented land)
Share of high quality /low quality land	Dummies for categories 1 and 3 in: "Compared to the average land fertility in the village, is the quality of this plot 1. Less than average 2. Average 3. Better than average", multiplied by the size of the plot(s) and divided by the land size operated
Share of land with red book	A dummy if the plot has a "red book", that is, there is a property right to the land multiplied by the size of the plot(s) and divided by the land size operated
Panel C: Rice	
Rice output	Log value of rice output adjusted with province level CPI (on plots operated by the household)
Labor (rice)	Log number of days spent in rice farming (on plots operated by the household)
Seeds (rice)	Log value of seeds used adjusted with province level CPI (on plots operated by the household)
Fertilizers (rice)	Log value of chemical fertilizers used adjusted with province level CPI (on plots operated by the household)
Pesticides (rice)	Log value of pesticides and herbicides used adjusted with province level CPI (on plots operated by the household)
Rice land operated (sqm)	The area of land operated by the household for rice production in sqm (including own land and rented land)
Number of rice plots	Number of plots operated by household used for rice production (including own land and rented land)

Figure A-1: Distribution of VARHS Communes

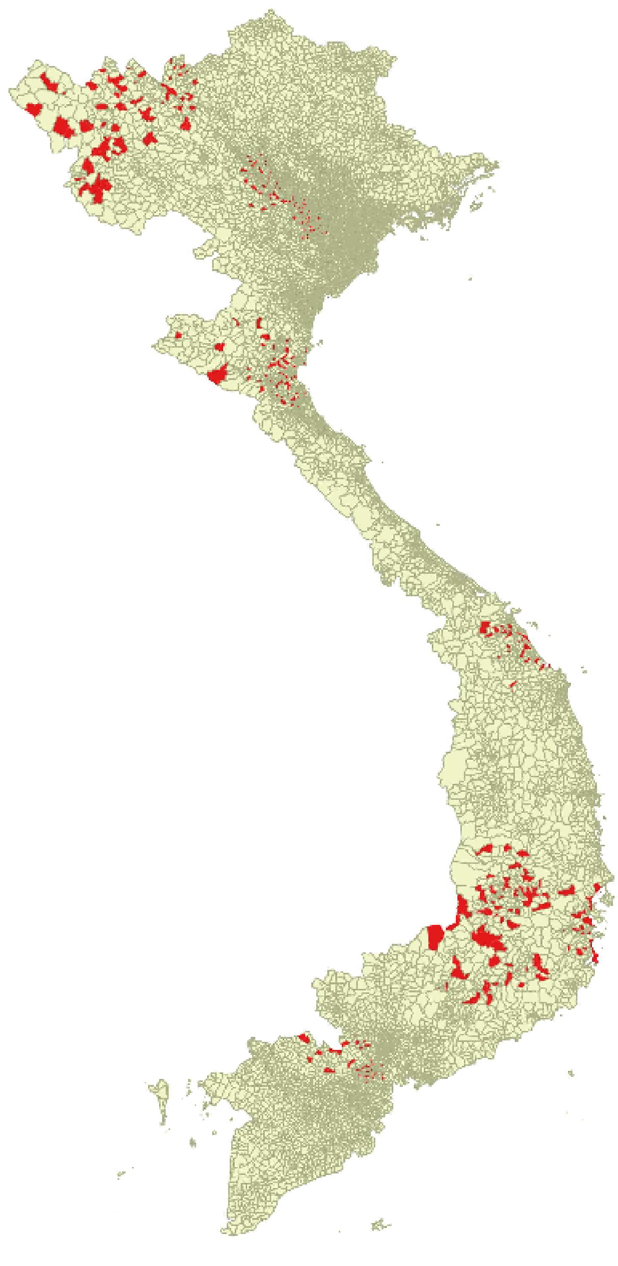
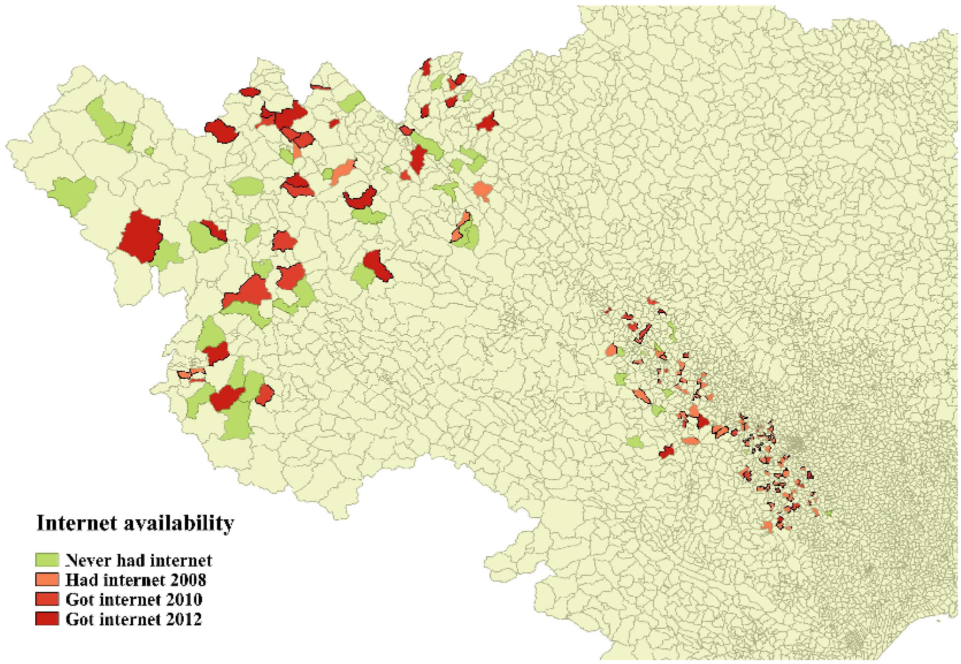
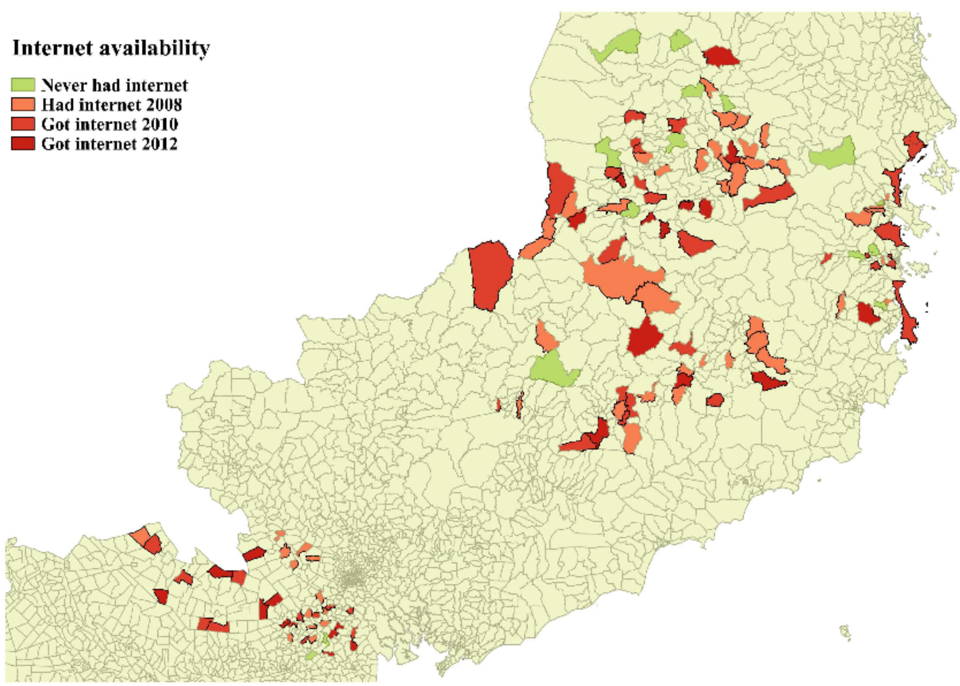


Figure A-2: Internet Availability



(a) Northern Viet Nam (Hanoi)



(b) Southern Viet Nam (Ho Chi Minh City)

B Internet sources

B-0.1 Government sources (covered also in the main text)

1. **AgroInfo** `<agro.gov.vn>` in operation since 2008, previously under the name PMARD (Hoa et al. 2008). Introduction on the website: *"Farmers need quality information for choices of high yield crops. To become a reliable address for rural and agricultural information, the Information Center (AGROINFO) - Agriculture and Rural Development applies modern research, analysis and multimedia communication tools to serve as a bridge linking analysis with practice, and provides consistent, useful and timely information as well as in-depth analyses to support different stakeholders such as farmers, leaders, experts, and businessmen."*

2. **Ministry of Agriculture and Rural Development (MARD)** <http://www.mard.gov.vn> provides information about crop prices and news related to agriculture

3. **Regional Departments of Agriculture and Rural Development DARD** have their own websites. For example of Lao Cai, one of the provinces in our sample, has a regional website <http://snnptnt.laocai.gov.vn>

B-0.2 Privately Run Vietnamese internet platforms on agriculture

1. ***Non-profit websites***

   (a) **Vinagrinews** <http://www.tintucnongnghiep.com/>, a non-profit that aims at "Connecting useful agricultural information to farmers". Their front page displays experts giving advice on various topics. In addition to this, they have market information and news on different crops and inputs, and of prices. One can also follow them on and Facebook (<https://www.facebook.com/vinagrinews>). Facebook being the most common social media in Viet Nam (Cimigo 2011), it can be considered a good channel to engage people interested in following their website. It is unclear how long the website has been functional, but the Facebook account has been in operation since 2011.

2. ***Newspapers online***

   (a) **Rural today newspaper** <www.danviet.vn> A rural newspaper that has specific section devoted to agriculture related news and encouraging agriculture. Domain license dates to 2009.

   (b) **Rural Economic Newspaper** http://www.kinhtenongthon.com.vn/> Domain license dates to 2011. Has a section devoted to "encouraging agriculture".

   (c) **An agriculture focused newspaper** <http://nongnghiep.vn/>, also supplies information about farming techniques. Newspaper has been in operation for 70 years, unclear how long content has been online.

3. ***Private companies***

   (a) **Viettuan Import - Export Co., ltd – VAGRIMEX** <http://nongsanviettuan.com/vi/news/thi-truong-nong-san/> provides a variety of information on agricultural products that their company has an interest. Company has been in operation since 1998, unclear how long the website has been functional. The only website we found reporting the number of visits, a total of 3.2 million on August 24, 2016.

   (b) **Agriviet.com** <http://agriviet.com/> "Contributing to the development of Viet Nam Agriculture initiated by the state". Has a forum for discussing agricultural problems, and a forum for buying and selling all kinds of agriculture related goods. Also gives information about prices. Unclear how long has been in operation.

Google trends data[18]

Google trends <https://www.google.com/trends/> website provides information about the relative number of Google searches of search terms in specific geographical areas. This

[18] Accessed 24 August 2016

appendix illustrates the development of the Google searches of some of the main inputs of our production function, fertilizers and pesticides.

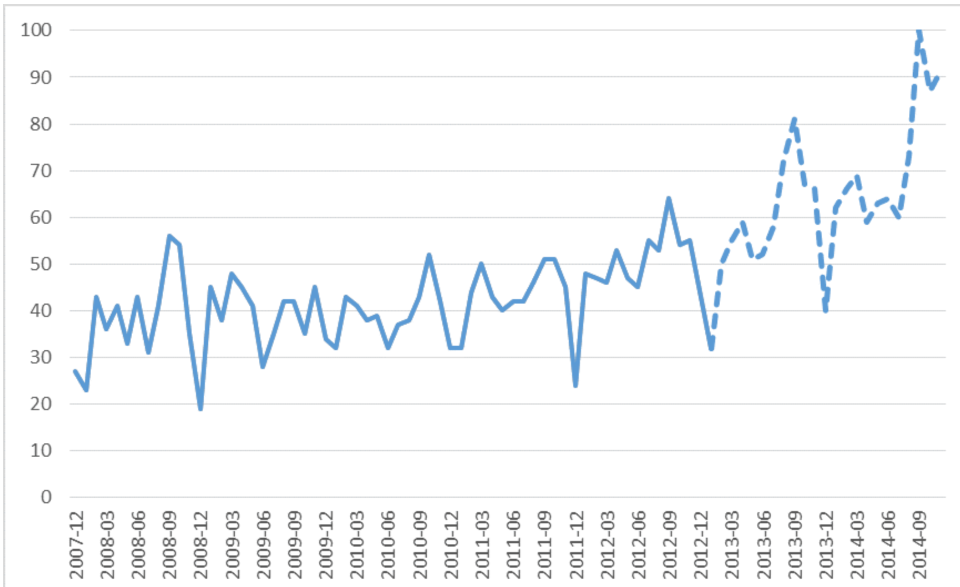
The numbers in Figure B-1 "represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. Likewise a score of 0 means the term was less than 1% as popular as the peak."

Figure B-1 shows the evolution of the popularity in Google searches in Viet Nam for fertilizers and pesticides, in Figures B-1a and B-1b, respectively.[19] Both figures tell us that the relative popularity of the words fertilizer and pesticides have increased over the period studied. The sample period is denoted by the solid line, and the following years are denoted by the dashed line for the sake of illustration. The optimal timing of fertilizer and pesticide use varies over regions and crops, so there is not one single period, where we would expect to find extreme peaks. However, in both of the series we do see some seasonality. Since the south of Viet Nam has the highest volumes of rice production, this might be driving the overall trend. For fertilizers the month with the highest relative Google searches are in September or October, there are also peaks during the spring. These peaks correspond to just before and at the beginning of the period of fertilizer application in rice farming in the South (Lundestad and Viswanadham 2001). The low values during winter months might be driven by the fact that there is no production during the cold winters in the North.

[19] Google trends does not allow investigating smaller geographical areas than the entire country.

Figure B-1: Google trends data

(a) Google search for fertilizers (phân bón)



(b) Google search for pesticides (thuc tr sâu)

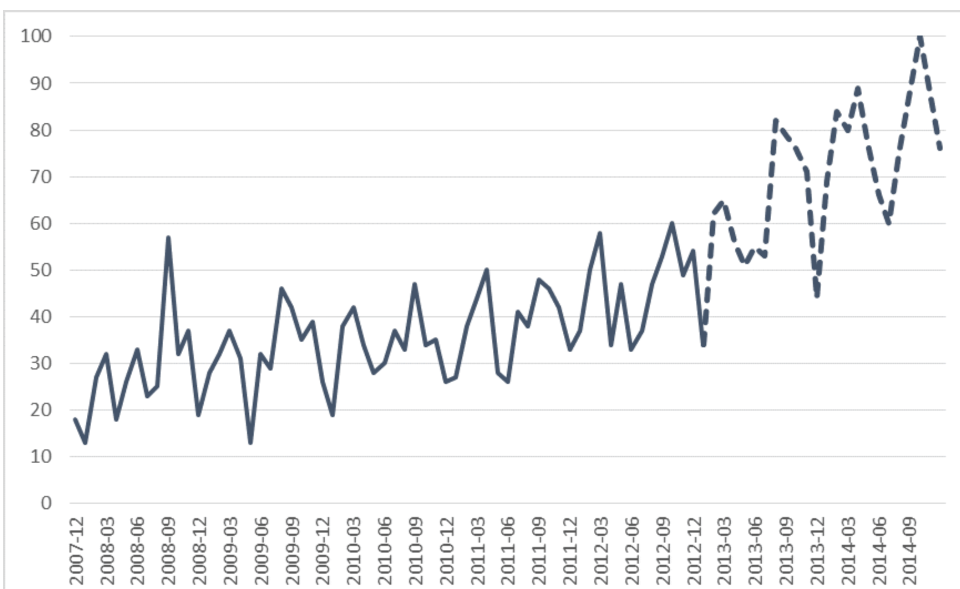


Figure B-2: Google searches of inputs

C Additional results: Is there a skill-bias?

The ability to use the internet might be higher for more educated households, and therefore they might be also benefiting the most on the new technology (Akerman et al. 2015; Aker and Ksoll 2016; Lio and Liu 2006). For studying skill-bias we also introduce the education level of the household head to the regression and interact it with internet access. We thus assume that the household heads are in charge of making decisions related to agriculture.[20]

As one of the largest differences in households in communes with internet access as well as the households that report using internet is the education level of the household head (Kaila 2017), it is plausible to assume that more educated households are able to benefit more from the internet.

As a measure of the education level we use the education level of the household head in 2008, on the first year that we have data. There is very little variation over time in the education level of household head and these changes might be due to the household head having changed, rather than him or her acquiring more education. We thus use the education level at the baseline in order not to capture in our measure of education the change of the household head, which might be due to shocks such as death or divorce.

Education level of the household head is a control in all of the regressions that include controls and is statistically insignificant in those specifications, so we do not find evidence on the direct effect of education on agricultural output. To test whether there is a skill-bias we have to interact education level of the household head with internet access. We hence modify equation 1 with the addition of the education variable

$$Y_{it} = e^{\gamma_0+\gamma_1 D_{jt}} E_i^{\beta_{e0}+D_{jt}\beta_{e1}} A_{it}^{\beta_{a0}} M_{it}^{\beta_{m0}} \tag{C-1}$$

Where E_i is the time-invariant education level. Internet access is skill-biased if $\beta_{e1} \neq 1$.

[20] We use as an input the total amount of labor supplied in agricultural activities by all of the household members irrespective of their education level. This input can be understood as "raw labor". The skill-bias is studied by interacting the education level of the household head with the internet-variable, assuming that the household heads are in charge of making decisions related to agriculture. The test for the skill-bias is hence not related to working hours, since we can assume that the skill level required for performing the actual tasks is the same in all agricultural activities and unrelated to the education level of the person taking part in agricultural activities.

Table C-1 shows that we cannot find evidence of a skill-bias in internet access in any of the specifications. Education level also is no longer significant after we control for other household characteristics. Due to household fixed effects the coefficient estimate of education is absorbed in columns 4 and 5. In these models the coefficient estimate of the interaction term is either not significant, or even negative and significant. The results are qualitatively similar when looking at rice production separately.[21]

[21] The results not provided in this version of the paper.

Table C-1: Production function of all crops augmented with education

VARIABLES	(1)	(2)	(3)	(4)	(5)
Internet	0.067**	0.075**	0.069**	0.072**	0.064**
	(0.029)	(0.030)	(0.033)	(0.034)	(0.032)
Labour	0.200***	0.232***	0.176***	0.143***	0.128***
	(0.018)	(0.017)	(0.020)	(0.017)	(0.016)
Land	0.396***	0.412***	0.358***	0.262***	0.198***
	(0.021)	(0.021)	(0.031)	(0.042)	(0.040)
Fertilizers	0.129***	0.128***	0.135***	0.106***	0.104***
	(0.013)	(0.013)	(0.016)	(0.013)	(0.012)
Pesticides	0.172***	0.178***	0.118***	0.094***	0.088***
	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)
Capital	0.051***	0.050***	0.041***	0.028***	0.025***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Education hh head 2008	0.009	0.012	0.010		
	(0.013)	(0.014)	(0.014)		
internet*education hh head	0.021	0.022	-0.002	-0.028*	-0.019
	(0.017)	(0.017)	(0.016)	(0.017)	(0.016)
Observations	7,431	7,431	7,431	7,431	7,431
R-squared	0.744		0.805	0.273	0.294
YEAR FE	YES	YES	YES	YES	YES
Controls	NO	NO	YES	NO	YES
Commune FE	NO	NO	YES	NO	NO
HH FE	NO	NO	NO	YES	YES
CRS	NO	YES	NO	NO	NO
Number of households				2,477	2,477

Notes: Dependent variable is the log value of agricultural output. Description of the explanatory variables given in Appendix Table A-1. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the commune level. Significance: *** p<0.01, ** p<0.05, * p<0.10

Chapter 3

Adoption of Mobile Phones in Viet Nam - The Role of Social Status

Adoption of Mobile Phones in Viet Nam –The Role of Social Status*

Heidi Kaila†

April 2017

Abstract

This paper studies the determinants of mobile phone adoption by building on a framework of demand for goods with network benefits. Between 2006 and 2014, mobile phone ownership increased from 18 to 89 per cent in rural Viet Nam. I use a panel dataset from this period to study the "digital divide", who are leading and who are lagging behind in mobile phone ownership. I find that households with political connections are early adopters of the technology. A Blinder-Oaxaca decomposition reveals that their higher adoption rates are not fully explained by observable characteristics. At the same time, ethnic minorities are lagging behind in phone adoption. However, if the ethnic minorities had similar observable characteristics than non-minority households, they would adopt more phones than non-minority households. Other demographic characteristics such as young age, having a male household head, and migrant status are associated with higher phone ownership. These differences are however fully explained by observable characteristics, such as income. I also find that lack of GSM coverage does not appear to be a barrier to phone adoption, even in remote regions of Viet Nam. Full GSM coverage is available for 86 per cent of households in this study, and there is some GSM coverage in all the areas studied.

JEL Classification: O12, O33, L96
Keywords: Information technology, digital divide, political connections, ethnicity.

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1 Introduction and motivation

One of the most rapid economic developments during the 21st century has been the spread of information and communication technology (ICT), especially that of mobile phones. The ICT revolution has not only created a new large industry, but ICT also affects our everyday lives in many various ways. Even though the availability of the ICT infrastructure is determined by cooperation between the private and the public sector, the government granting companies building permits –the decision about using new technology is in the hands of individuals and firms.

Studying adoption decisions in detail is interesting since literature shows that ICT can have large positive impacts on the economy (Choi and Yi 2009; Jalava and Pohjola 2008; Aker and Mbiti 2010). ICT allows us to communicate and exchange information faster and more efficiently than ever before. The importance of the benefits of the ICT revolution has been highlighted in the World Development Report 2016 (World Bank 2016). The World Bank considers closing the "digital divide", the gap between those with and without access to ICT, an important policy goal.

In this paper, I explore whether such digital divides have existed during the ICT revolution in Viet Nam. I study whether these gaps have emerged due to standard factors explaining demand in the market of phones, or whether demographic and social characteristics have also played a role.

The World Development Report 2016 is focused on the digital divide, since there is an understanding that ICT can bring about great benefits, which still remain largely unharnessed. The literature on the evidence of the benefits of ICT is growing. In the developing country setting a number of studies focus on the effects of information technology on agricultural markets, showing impacts of reduced price dispersion and increased market efficiency, particularly for perishable goods (Aker and Ksoll 2016; Aker and Fafchamps 2015; Fafchamps and Minten 2012; Aker 2010; Goyal 2010; Muto and Yamano 2009; Jensen 2007).

It is inherent to general purpose technologies that agents *ex ante* have incomplete information about the benefits of a new technology. A first time user of a mobile phone clearly cannot understand all the possible ways in which it can be used –or discount the value of the future benefits. This might lead to procrastination in the adoption choice (Duflo et al. 2011). When it comes to any new technology, even if the user does understand the benefits, the learning cost related to adoption might hinder adoption (Hall 2005). Due to these often unobservable factors, lack of knowledge about the benefits and learning costs, different social groups might differ in their adoption patterns.

This paper studies the question: What makes households decide to buy a phone? Are adoption choices purely a function of classical demand factors of goods with network benefits, or do social roles, such as gender, ethnicity, or social status play a role?

By using panel data on rural Viet Nam over the period 2006–2014 I can track the spread of mobile phone ownership over time. Studying the adoption choices of ICT will allow us to better understand which kind of households are likely to adopt new technologies and benefit from them. The other side of the coin is to reveal which groups are lagging behind.

A priori, one might expect that household with connections to power also value these connections, and therefore have a higher propensity to adopt phones. One might also think that households that have a high social status also want to signal about this status.[1] In Viet Nam, a Communist Party membership is a strong indicator of a high social status. One might also worry that some demographic characteristics are related to a lower propensity to adopt. This might be the case if learning about new technologies becomes more challenging with age, or if taking interest in ICT is perceived a male activity in the social context. Hence, we might expect older and female-headed households to lag behind. This might also be the case with ethnic minorities, where the overall cultural context can be very different. The "digital divide" with respect to race and ethnicity has also been a policy debate in the U.S. (Anderson 2017; West and Karsten 2016). There is a racial and ethnic "digital divide" minority groups having lower access to computers and

[1] This paper does not discuss different qualities of phones, but anecdotal evidence suggests that quality smart phones carry a special luxury status in Viet Nam. Apple has a very strong position in the market, compared to China, where cheaper brands are much more common (Fortune Magazine 2014). Therefore being a leader in phone adoption when mobile phones became available, could also have been important for signalling social status.

the internet in the U.S. This difference is not fully explained by observable characteristics (Fairlie 2004).

Finally, by using GSM coverage maps, I also analyze whether constraints in infrastructure have been present. Understanding these differences is important if closing the "digital divide" is considered an important policy target in developing countries.

The closest to this study comes Björkegren (2016), who analyses demand for phone services in Rwanda, and simulates policy experiments using data from a mobile phone provider. This study differs from Björkegren (2016) in the sense that with rich demographic information, I can assess these group differences outlined earlier. To assess who is leading and who is lagging behind, I only look at the margin of the adoption choice, whereas Björkegren (2016) studies the entire consumer behaviour.

This paper uses data on mobile phones, due to the vast increases in adoption that have taken place. Given that all ICT goods have similar characteristics such as network benefits, the evidence presented here will be interesting for the study of other ICT goods as well. Indeed in an earlier work (Kaila 2017) I show that similar characteristics, such as income and asset wealth, predict both internet and mobile phone adoption in Viet Nam. Rainie (2016) shows similar descriptive evidence for the U.S.

A phone is a good with network benefits. Theoretically, this implies that the utility a consumer derives from such a good increases in the amount of other users. This can be understood in two ways. A network benefit requires that "(a) one agent's adoption increases others' incentive to adopt, and that (b) one agent's adoption of a good benefits other adopters" (Farrell and Klemperer 2007). In other words, the size of the network affects one's propensity to adopt, and also increases utility of the network good after adoption. Clearly, the empirical framework employed here captures the former.

From the point of view of technology adoption, this paper is tangentially related to a growing literature on the role of social networks in spreading new technologies in developing countries (Munshi 2004; Conley and Udry 2010; BenYishay and Mobarak 2014; Bandiera and Rasul 2006; Oster and Thornton 2012). Whether successful households are instrumental in spreading a new technology has been studied in the literature with varying results. Conley and Udry (2010) find that farmers who are successful in using a new farming technology are more likely to influence their neighbours' adoption decisions. However, it could also be that people compare themselves with those with the same socioeconomic status. BenYishay and Mobarak (2014) find that a new agricultural technology was more likely to spread through farmers whose socioeconomic status was close to the average than through village leaders.

This literature is related to our study in the following way. Given that a phone has network benefits, it is important to understand who adopts first. If a successful household became a phoneowner in period t, that will enter the utility function of the people in her network, and hence, increase their propensity to adopt. In this study, I do not explicitly study whether successful households indeed spread the technology. Instead, I show who are early adopters over this long period when this technology started to spread.

I find large group differences in phone adoption across different demographic and social characteristics. Households with a party member or connection to someone in a position of power are early adopters. Also migrant households have higher adoption rates. Ethnic minorities, older households, and female-headed households lag behind. However, a Blinder-Oaxaca decomposition analysis reveals, that a part of these descriptive findings are fully explained by differences in factors determining phone demand, as well as other observable characteristics. The group differences not explained by other observable characteristics are political connections (Party membership and connections to power), as well as ethnic minority status. Interestingly, the unexplained component in both of these characteristics suggest a *higher* propensity to adopt phones. This is the case also with ethnic minorities that are lagging behind. Therefore it seems unlikely that these households that lag behind are in fact procrastinating in the adoption choice, any more than non-minority households with otherwise similar characteristics. For households that are connected to power, a phone seems to be an important asset.

This paper proceeds as follows. In Section 2 I discuss the ICT revolution that has taken place in Viet Nam. In Section 3 I set up a model to analyze the adoption of network goods, and in Section 4 I explain how I estimate it. In Section 5 I present the data and descriptive analysis on group-specific adoption patterns. Finally Section 6 presents the results, and Section 7 concludes.

2 Context

During the 2000's Viet Nam has experienced not just high economic growth and a transformation to a middle-income country, but also a true ICT revolution. Viet Nam has one of the most fastest growing telecommunications sectors in the world, and the Vietnamese government is aiming at "Shifting Viet Nam to the level of strong countries in the world's ICT industry" (Global Investment Center 2015).

Figure 1 shows the development of phone ownership in Viet Nam using national statistics from General Statistics Office of Viet Nam (GSO 2015) with a comparison to the rural provinces in this study (the VARHS). National level subscription rates of mobile phones have increased tremendously, albeit with a recent slowdown. According to GSO (2015) the total number of all telephone subscriptions has increased nearly fivefold between the years 2006-2014, from 28.5 to 141.2 million. During the same period, the number of mobile phone subscriptions has gone up more than sixfold (from 19.7 to 131.7 million). In contrast, the number of fixed-line connections has increased only by 9 per cent between 2006 and 2012 and the share of fixed-line subscriptions of all subscriptions has decreased from 30.7 per cent to 6.7 per cent on a national level.

In the rural provinces studied, the average number of phones owned by households rose from being close to zero in 2006 to two phones in 2014, with almost universal phone ownership, as the share of household with at least one phone was close to 90 per cent in 2014.

We can see that during the period 2002-2014 the spread of the technology looks like an "S-curve". This shape is typical to diffusion patterns of new technology visible in national level statistics (Rogers 2003; Hall 2005).[2] Typically, the stabilizing of the curve over time

[2]Important detail to keep in mind that the S-curve is not specific to new technology that has network benefits, but to the diffusion of any kind of innovation. Hall (2005) illustrates that the diffusion of the telephone, as well as the diffusion of other goods, such as refrigerator, both display quite similar patterns of adoption over time.

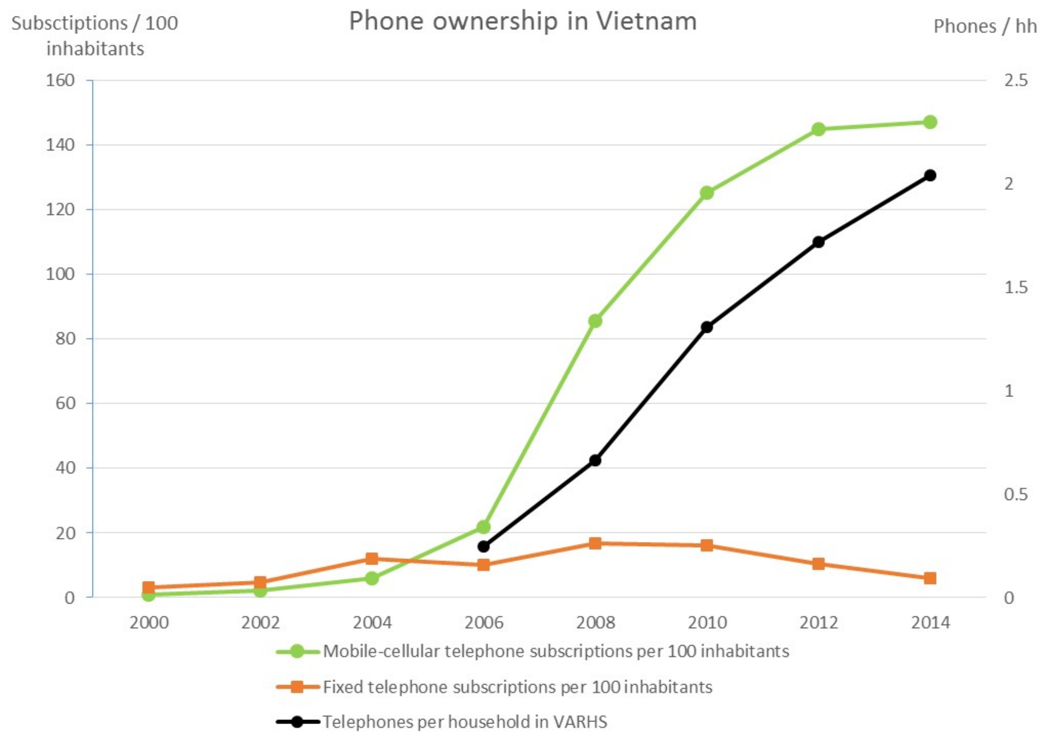


Figure 1: Phones in Viet Nam

is associated with a *saturation point*: everyone who needs this technology has purchased it. In Figure 1, the decrease in the adoption rate might be indicative of this. In the rural provinces represented by VARHS, one doesn't see the same decline in the growth rates in the number of phones per household. However, an average of two phones per household suggests that almost all adults have their own phone, therefore it is plausible that the saturation point is not far in the future among the rural households.

When it comes to adoption decisions of phones, infrastructure is a necessary condition. J. Hwang and Long (2009) find that the opening of the Vietnamese service provider market before 2006 led to a decrease in prices, which enhanced the diffusion of the technology. Figure 2 shows the coverage of the GSM i.e. 2G network in 2014 in Viet Nam.[3] The red areas are communes that are in our dataset. We can see from zoomed maps of the northern and southern parts of Viet Nam, that some of the communes in our analysis lie fully inside the coverage area of GSM, while some of the communes have incomplete coverage.

[3]The GSM coverage is the same in 2012 and 2014, hence only the 2014 map is shown.

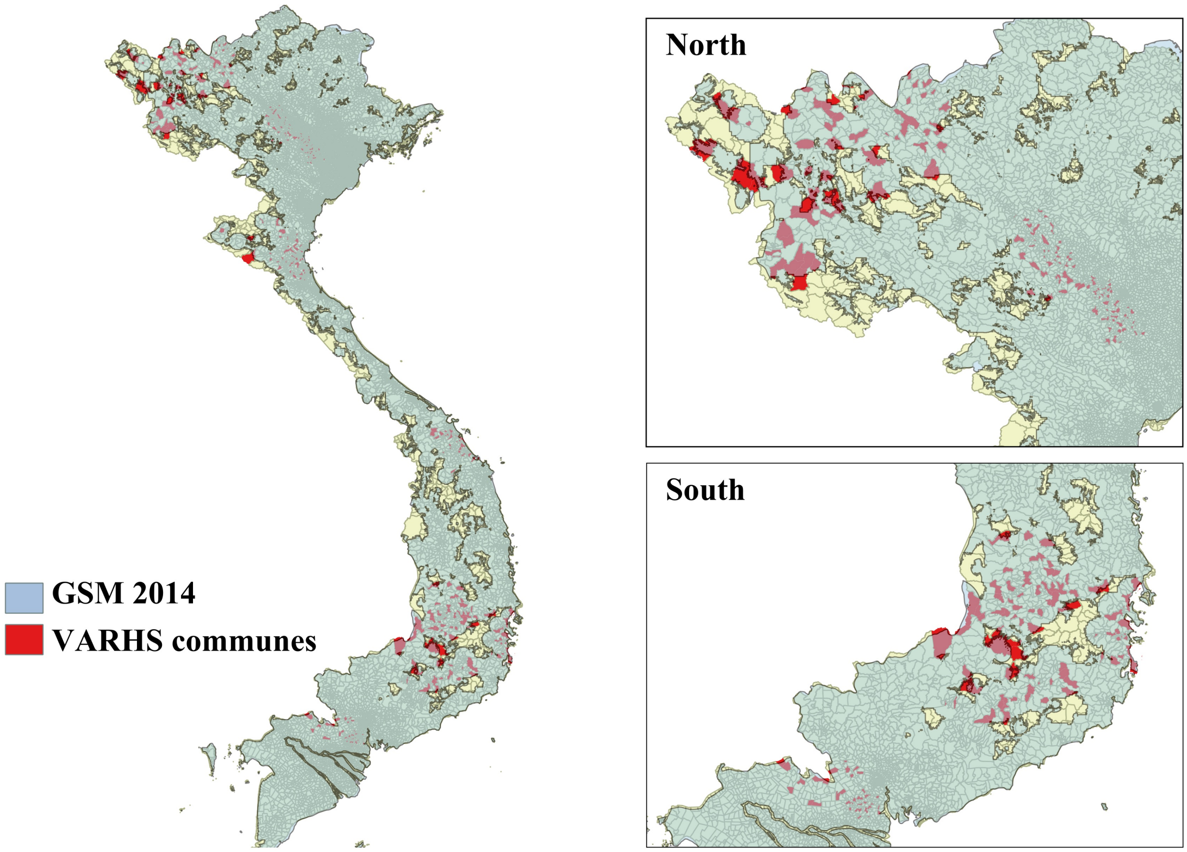


Figure 2: GSM Coverage and VARHS communes 2014

According to official sources, the country has full coverage of both GSM and 3G (Vietnam Post and Telecommunication Group 2015). Our coverage area is determined by some threshold level of signal set by the GSMA -the umbrella organization of GSM providers in the world.[4] Relying on information provided by Vietnam Post and Telecommunication Group (2015), infrastructure constraints should have no longer played a large role in the purchasing decision of a phone in 2014. The quality of the signal might be weaker in more remote areas.

[4] Operators have submitted strong (>= -92dBm) and variable (< -92dBm and >= -100dBm) signal strengths as part of their submissions. The data includes both types but does not make a distinction between the two (Collins Bartholomew 2014).

3 Theoretical framework

I set up a standard model of demand, where households choose between a durable, a phone, and consumption. The durable good exhibits network benefits for which I use the share of household in the proximity (district) having a phone. This is exogenous to the household.

3.1 Household's choice of adopting a phone

Households can choose between two goods: a discrete durable good $d \in 0, 1$ (i.e. a phone), and consumption c.[5] The choice is also affected by the reference level of the phone ownership, D, the network effect through some increasing function $f(D)$.

The utility function takes the Cobb-Douglas form

$$U(c, d, D) = c^{\alpha}(d - f(D))^{1-\alpha} \tag{1}$$

where the network benefit is additive.[6]

One can see that the phone itself can yield some utility to the household even when no-one else has a phone. One could for instance assume that $f(0) = 0$ and $f(1) = 1$, such that the network benefit is zero if no-one else has a phone, and its full value is realized in the case that everyone else has a phone.

The budget constraint of the household is

$$c + p_d d = y \tag{2}$$

Where p_d is the price of phone relative to the price of consumption, which is set to 1, and y is household income. We assume $c \leq y$ and $d = 0, 1$. That is, a discrete choice between buying a phone or not buying one.

Solving the model yields the demand function for phones with network benefits

[5] In this kind of a static setting the durable good and consumption good cannot be said to differ, but the distinction would become important in a dynamic setting.

[6] We could also define a utility function with multiplicative network externalities $U(c, d, D) = c^{\alpha}(df(D))^{1-\alpha}$, which yields similar implications for demand.

$$d^{*} = (1-\alpha)\,\frac{y}{p_d} + f(D) \tag{3}$$

Keeping constant the utility function parametrization $(1-\alpha)$, the model has the standard implications: demand is increasing in income y and decreasing in the relative price of phones p_d.

A simple extension is to consider the above problem from the perspective of an individual instead of a household, to understand why would a household purchase more than one phone. Denote household size as h and the number of phones again as d. Then the probability for being able to use a phone when needed for an individual household member is $\frac{d}{h}$.[7]

In the empirical specification I will study both the adoption choice of the first phone, as well as the number of phones per capita in household. In addition to capturing the individual's propensity of being able to use a phone, on a household level this dependent variable can be considered as the *intensive margin* for the household. Therefore the dummy of whether household has a phone or not is the *extensive margin* of the adoption choice.

3.2 Network benefits

A functional form to describe the way in which utility of a network good increases in the amount of other users is often described by Metcalfe's law. Metcalfe's law states that the value of the network increases exponentially in its size

$$f_M(n) = n^2 - n \tag{4}$$

where n is the number of other users (Shapiro and Varian 1998).

Networks that are large in size, the Zipf's Law (Zipf 1935; 1949), which incorporates the idea that the links in a network are of different values, might be an accurate description

[7]Plugging this formulation in the demand function yields an individual's demand for phones (now for additive formulation): $d^{\star} = \left((1-\alpha)\,\frac{y}{p_d} + f(D)\right) h$.

of the value of the network (Briscoe et al. 2006). According to Zipf's law, the k^{th} most important link is $\frac{1}{k}$ times as valuable that the most important link. It can be shown, that the value of the network is then close to

$$f_Z(n) = n \log(n). \tag{5}$$

The value of the network according to this formulation increases much slower in n, than suggested by Metcalfe's law.

In the above model, the relationship of how someone's adoption choice depends on the network is denoted by the function $f(n)$. By using the equality $n = DN$, where D is the share of the reference group having a phone and N is the number of people in that group, I can derive the the marginal utilities as a function of the share of users in the network. This is presented in Appendix E.

The network benefits are exponential in both cases, but less so in the case of Zipf's law, which implies that as the size of the network grows, the network benefits approach a linear case N.

These laws are illustrative of network benefits, but there remains ambiguity about the kind of network goods these relationships are relevant to.[8] To study the issue we set $f(D) = D + D^2$, and estimate the parameters freely to study what kind of linear or non-linear relationship is in question.

4 Empirical specification

4.1 Baseline model

I estimate a reduced form specification of the demand for phones d, for household i in district k.[9] I assume $f(D) = D + D^2$, where D is defined as the share of households in a

[8] For instance language can be considered a network good, and this is the network good that Zipf's law initially refers to.

[9] In order to fully account for the fact that a phone is a durable, estimating a structural dynamic model of discrete choice would be ideal. The results for this paper are those of a static model using reduced form.

district that have a phone, excluding the household herself. This function thus captures the network benefits. The empirical counterpart of D is

$$D_{ik} = \frac{\sum_{j=1}^{n_k-1} d_{j\neq i}}{n_k - 1} \tag{6}$$

where n_k is the number of households in district k, and d is again a dummy denoting phone ownership. The estimated model is

$$d_{it} = \alpha_0 + \alpha_1 D_{ikt} + \alpha_2 D_{ikt}^2 + \alpha_3 ln(y_{it}) + \alpha_4 ln(p_{d,t}) + \alpha_5 ln(p_{c,it}) + \boldsymbol{\beta_1 x_{it}} + \varepsilon_{it} \tag{7}$$

where notations are as previously. Now $\boldsymbol{\beta_1 x_{it}}$ is a vector of household specific controls (described in Table D-1). In some specifications household fixed effects are used.

The way in which the adoption choice depends on the network benefits is given by $\alpha_1 D_{ikt} + \alpha_2 D_{ikt}^2$. I consider three possibilities:

- Linear network benefits: $\alpha_1 > 0$ and $\alpha_2 \approx 0$
- Increasing (exponential) in the share of people being in the network: $\alpha_1 > 0$ and $\alpha_2 > 0$
- Marginally decreasing in the share of people being in the network: $\alpha_1 > 0$ and $\alpha_2 < 0$.

Metcalfe's law is closest to the first option. Zipf's law would be approximated best by the first option with small network sizes, and by the second option with large network sizes.[10]

I use two dependent variables to study the adoption choice at both the extensive and at the intensive margin. For the extensive margin, I use a dummy denoting whether the household has at least one phone. For the intensive margin, I use the number of phones

[10] I do not consider it possible that the utility of the network is decreasing in the share of users $\alpha_1 < 0$, since it would be contradictory to the idea of network benefits altogether.

per capita in a household, assuming that a household maximizes the probability for an individual to able to use a phone.

4.2 Estimating group differences

In order to estimate the contribution of being a member of a specific group to the ownership of phones, I resort to the Blinder-Oaxaca decomposition (Blinder 1973; Oaxaca 1973). To illustrate how the methodology works, imagine two groups A and B. The expected difference in the mean outcomes can be derived from a simple linear model

$$Y_l = X_l' \beta_l + \epsilon_l, \quad E(\epsilon_l) = 0 \quad l \in (A, B) \tag{8}$$

where X contains the predictors and a constant. The differences in the mean outcomes can be written as

$$R = E(Y_A) - E(Y_B) = E(X_A)' \beta_A - E(X_B)' \beta_B. \tag{9}$$

I use the so-called "twofold" decomposition to decompose the differences into the explained and unexplained components. This relies on the definition of a nondiscriminatory coefficient vector β^*.

The outcome difference can be written as

$$R = \{E(X_A) - E(X_B)\}' \beta^* + \{E(X_A)'(\beta_A - \beta^*) + E(X_B)'(\beta^* - \beta_B)\}. \tag{10}$$

Now the decomposition is in two components $R = Q + U$, where

$$Q = \{E(X_A) - E(X_B)\}' \beta^*. \tag{11}$$

and

$$U = E(X_A)'(\beta_A - \beta^*) + E(X_B)'(\beta^* - \beta_B) \tag{12}$$

The explained part Q is capturing the outcome differential that is explained by group differences. The unexplained part U is the part that cannot be attributed to observable group differences. Hence it consists of the unexplained components of the differences in the group specific means.

Kline (2011) shows that the Blinder-Oaxaca decomposition is equivalent to a reweighting estimator for studying treatment effects, where the propensity of treatment is a linear function of the control variables (in contrast to propensity score estimators, that use a logit or a probit functional form). Blinder-Oaxaca also performs well in cases where one of the groups is small compared to the other one.

There are issues that need to be addressed to argue that the Blider-Oaxaca procedure yields a causal estimate. First, Kline (2011) shows that the estimator is consistent and unbiased if the linear model is correctly specified. Further, the results are sensitive to observable characteristics chosen.

I have assessed these concerns by setting up a formal model of phone demand on which the analysis is based, thus the crucial observable characteristics are taken into account with a functional form derived from theory. Further, a large number of controls is added to take into account any characteristics that might drive phone adoption.

A concern that remains is the interpretation of the coefficient estimate for prices. Now the prices used are province level means of the self-reported resale prices. Ideally the best price information would be the minimum price for a phone, in order to capture the willingness to pay at the margin of the adoption choice, since this analysis abstracts away from product differentiation.[11]

Another concern is the fact that the self-reported price is an equilibrium price of demand and supply. Supply side factors should be taken into account to get the causal effect. To address the concern of self-reported prices, I conduct a robustness check using an external survey data. This price information is also an equilibrium price, but as it is exogenous to the survey, it provides a valid robustness check, which confirms our results.

[11]The minimum price can be either a bundled good that has airtime and a phone for a specified period of time, or those two goods separately, depending on which option at each year was the cheapest option.

5 Data

5.1 Household data

For the analysis I employ the Vietnam Access to Resources Household Survey (VARHS), a panel dataset of 12 rural provinces in Viet Nam.[12] This analysis uses five waves of the panel: 2006, 2008, 2010, 2012 and 2014. The dataset contains a large set of variables on household characteristics as well as land and agriculture related information, and extensive information on durables including phones.

Figure 3 shows the development of phone ownership in VARHS households: the fraction of households with at least one phone, number of phones per household, and the average value of all phones owned in a household. One can see that all of the indicators have increased significantly. In VARHS, one cannot differentiate between a fixed-line phone and a mobile phone, but the vast majority of the increase in phone ownership is attributable to the increase in mobile phones, not fixed-line connections, which is supported by the evidence provided in Figure 1. The share of fixed line subscriptions per capita has even decreased since 2008. One can see that the number and value of phones has a very long right tale. The mean resale value of the phones owned by the household was 707 000 VND, that is around 31 USD.[13]

Table 1 outlines the summary statistics for the key variables of interest, pooled and per round. I use three different panels depending on which group is studied. The 2006-14 panel consists of five rounds of 2155 households, adding up to 10775 observations. This panel is available for studying the differences between female-headed and male-headed households, households with young or old household head (where the cut-off is the mean age, 40.2 years), and whether the household is of an ethnic minority, what I call the group "Non-Kinh", the Kinh being the majority ethnic group in Viet Nam. The 2006-14 panel is also used to study differences between households with and without a Communist Party

[12]The survey is a collaboration between the Development Economics Research Group (DERG) at the Department of Economics at the University of Copenhagen, and the Central Institute of Economic Management (CIEM), the Institute for Labour Studies and Social Affairs (ILSSA), and the Institute of Policy and Strategy for Agriculture and Rural Development (IPSARD) in Hanoi, Viet Nam.

[13]Using Google exchange rate April 15, 2017.

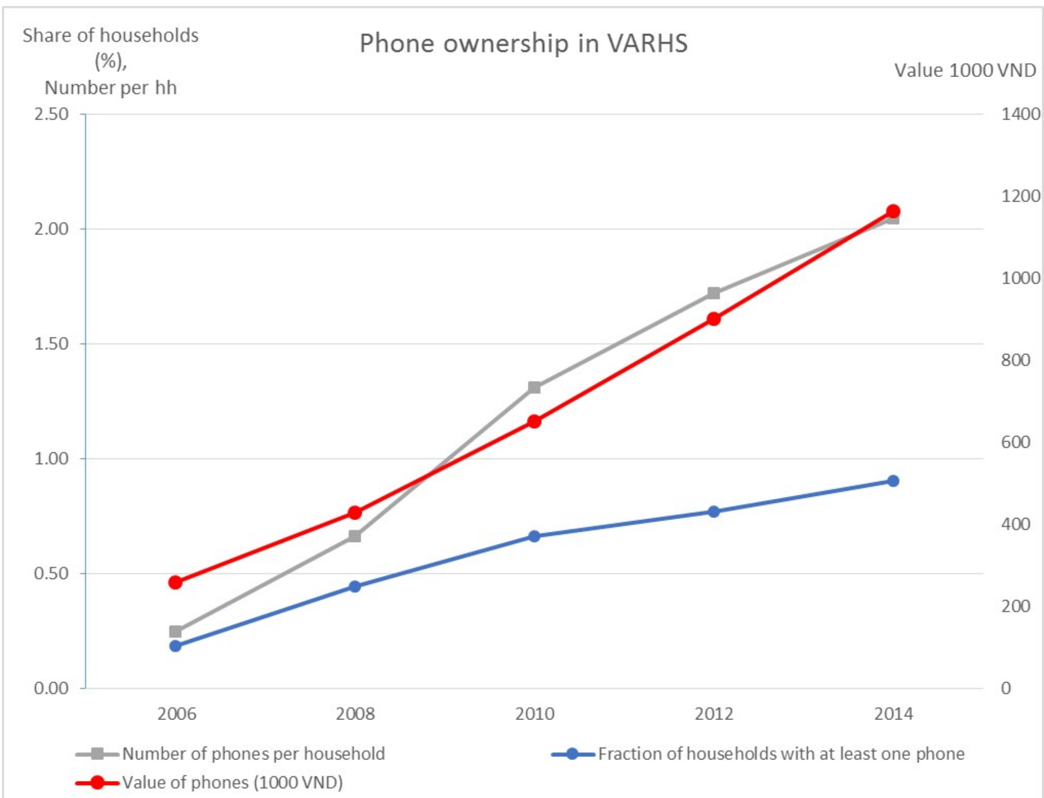


Figure 3: Phones in VARHS

member.

The 2008-14 panel has a larger cross-sectional dimension: 3091 households amounting to 12364 observations. This panel is used to study the group differences between those households that have a relationship to someone in a position of power (a family member, relative or friend), and those who do not.

Finally, a shorter panel 2012-14 is used to study group differences in households that have a migrant member living outside of the household, and the GSM coverage. These variables are not available for earlier rounds. In merging the GSM coverage data with VARHS, not all VARHS communes could be merged with the GSM data: 749 of the 3091 households were dropped.[14]

The attrition in VARHS is very low, the rates between waves being between 1.1 per cent and 2.5 per cent. The overall attrition rate over the five waves 2006 -14 is only 7 per cent (Brandt and Tarp 2017). Thus I am not concerned that the analysis is impacted by attrition in any significant way.

From Table 1 we can see that two distinct income measures are used for the analysis, one for the long panel 2006-14, and one for the shorter 2008-14. I take this approach, since the 2008-14 measure is more comprehensive, it includes several different income sources, whereas the 2006-14 measure is more crude.[15] I use the share of households in a district owning a phone as a measure of network benefits. The network benefits are now captured by the variables user intensity and user intensity squared, denoted by D and D^2 in the theory.[16]

[14]In the analysis where I use the 2012-14 panel, this leaves me with 4684 observations across two rounds.

[15]MacKay and Tarp (2017) provide a detailed description of these variables and an analysis of their evolution over time.

[16]Actual network data is not available in our survey, hence a geographical measure is used. There are three geographical areas that could have been used to calculate the user intensity variable in the empirical specification: provinces, districts and communes. There are 12 provinces in the dataset (from a total of 58 provinces in Viet Nam) and these areas as very large, most have over a million inhabitants. In our data there are 136 districts, which is a large enough number to conduct this analysis rigorously. The smallest level is the commune (the municipality). In most instances there are less than 10 households per commune, so constructing the user intensity variable by using communes would have given us very noisy measures. Using the district as a the geographical unit for calculating network benefits also makes sense from the point of view that in rural communities people do interact with neighbouring and nearby communes for trade, non-farm labour, education etc.

Table 1: Summary statistics

	All years		2006		2008		2010		2012		2014	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
HH has a phone	.58	.49	.18	.39	.39	.49	.6	.49	.74	.44	.89	.31
Number of telephones per capita	.28	.32	.058	.15	.13	.21	.27	.31	.39	.34	.47	.32
Number of phones in HH	1.2	1.3	.24	.62	.55	.86	1.1	1.3	1.6	1.4	1.9	1.3
Income 06-14	84048	125122	55459	80724	64726	103259	108917	164362	85338	108723	97145	133341
Income 08-14	73852	71224	.	.	59799	61831	68848	69937	79889	71395	86870	77822
User intensity	-.0082	.31	-.41	.16	-.21	.23	.0014	.27	.16	.16	.3	.093
User intensity sq	.097	.097	.19	.11	.099	.12	.073	.091	.051	.047	.099	.046
Phone price (province avg.)	968	639	2335	411	1003	312	782	155	586	94	548	82
HH size	4.6	1.8	4.6	1.7	4.9	1.9	4.7	1.8	4.6	1.9	4.5	1.9
Female HH head	.18	.39	.19	.39	.17	.38	.17	.38	.18	.39	.2	.4
Young HH head	.61	.49	.64	.48	.68	.47	.62	.48	.58	.49	.51	.5
Non-Kinh	.35	.48	.19	.4	.38	.48	.37	.48	.37	.48	.37	.48
Migrant	.14	.35	.	.	.	.	.	.	.14	.34	.15	.36
Party member	.088	.28	.11	.31	.069	.25	.084	.28	.077	.27	.11	.31
Power	.27	.44	.	.	.28	.45	.32	.47	.26	.44	.41	.49
Incomplete GSM	.14	.34	.	.	.	.	.	.	.14	.34	.14	.34
Observations	14519		2155		3091		3091		3091		3091	

5.2 Mobile phone coverage data

The mobile phone coverage data used[17] comprises of spatial coverage maps for 2012 and 2014 for all companies operating in Viet Nam with the exception of Mobifone.[18] Figure 2 illustrates the GSM coverage and the survey areas. As the coverage does not change over time, the map of only 2014 is shown. The area definition is a dummy in the sense that the GSM operators have reported whether a specific area is covered or not. Therefore it doesn't take into account different signal qualities. From this measure, I calculate the share of area in a commune that has been covered 100 per cent by the GSM network, and those that have less, that is, incomplete coverage.[19] In the analysis I use the dummy whether the coverage is incomplete. Table 1 shows that 14 per cent of households reside in communes with incomplete coverage. The incomplete coverage ranges from 12 to 99 per cent of the area of the commune being covered. Among the areas of incomplete coverage, the mean coverage is rather high, 76 per cent. This goes to show tha most areas indeed have a high availability of GSM coverage.

5.3 Descriptive statistics on group differences

Through descriptive analysis we can understand what kind of groups are early adopters, and who are lagging behind. Figures 4 and 5 present predicted probabilities of having a phone, and the predicted number of phones per capita as a quadratic function of time, respectively. That is, there are no controls in these Figures, but these are pure differences.[20]

We can see from Figure 4 that there are some large differences between groups. Households that are of the major ethnic group Kinh have had a much higher probability of

[17]The data is the Mobile Coverage Explorer provided by Collins Bartholomew (Collins Bartholomew 2014).

[18]However, according to OpenSignal.com (accessed 14 August 2016) the signal of Mobifone is very much centered in the urban areas and province capitals, areas that are covered by the other operators.

[19]I use the commune for this, since it is the smallest geographical area to which we can link the household, and therefore provides the most accurate information about GSM available to the household, as we do not know the GPS-coordinates of the household herself.

[20]The quadratic formulation is used due to the possibly non-linear nature of adoption patters as a function of time, as discussed in Section 2.

purchasing the first phone. By 2014 the ethic minorities (Non-Kinh) had caught up. This pattern is opposite for the female-headed and male-headed households, where in contrast the adoption probabilities were very similar during 2006-08, but after that, female-headed households started to lag behind.

Differences are striking also in the relationship to power. Households that have a member in the Communist Party, and household with a connection to someone in a position of power have been much more likely to be phone owners that those who do not have these connections. These differences have narrowed over time.

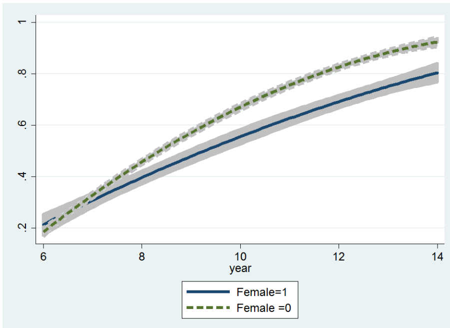
During 2012-14, the time period which is available to study households that have a member that has migrated, we can see that the predicted probabilities of having a phone were much higher for the households with a migrant. This time period is also the period for which the GSM coverage data is available. We can see that areas that had incomplete coverage in 2014 were not statistically different in their adoption patterns of the first phone.

In Figure 5 the predicted number of phones per household member are displayed over time. This is the intensive margin. We can see that female and male headed households no longer differ from each other. There are also no differences between young and old household heads, and across different availabilities of GSM.

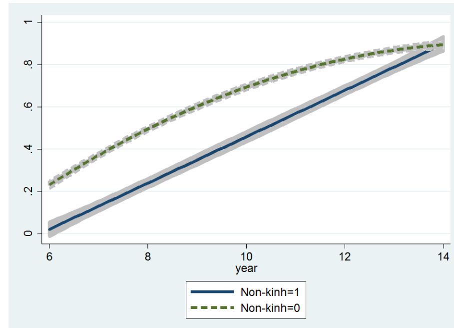
Rest of the differences do hold also at the intensive margin (Figure 5). Non-Kinh households have less phones per capita, and the difference does not become narrower over time. Also the households with a party member and with connections to position of power have more phones per capita over the whole time period. The same goes for households that have a migrant member.

This goes to show that in fact, the extensive and intensive margin are not very different, and most of the differences observed are present at both margins. Most of the differences persist over time, but there is some "catching up": at the extensive margin ethnic minority households and households without Party members or political connections do catch up. However, this happens at very high adoption rates: In 2014 the probabilities in these groups of having the first phone are no longer that different, but then again, this is the

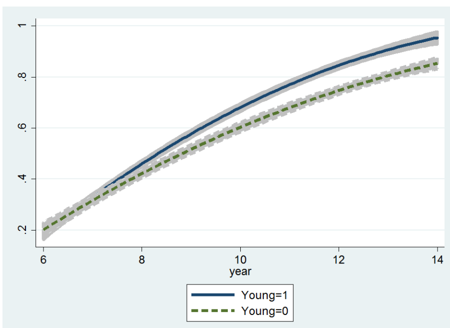
Figure 4: First phone over time



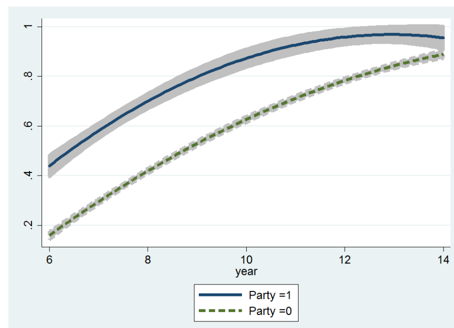
(a) Female



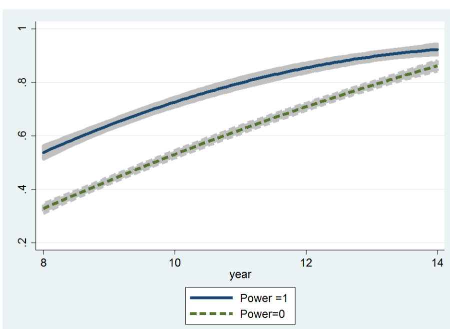
(b) Non-Kinh



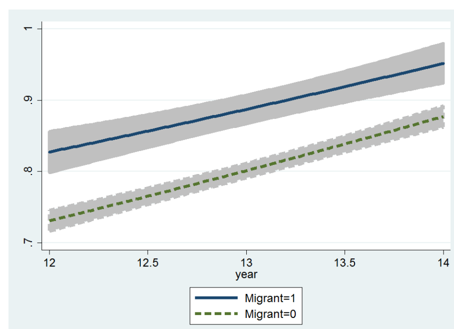
(c) Young



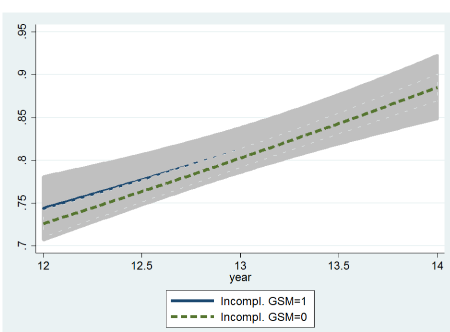
(d) Party



(e) Power



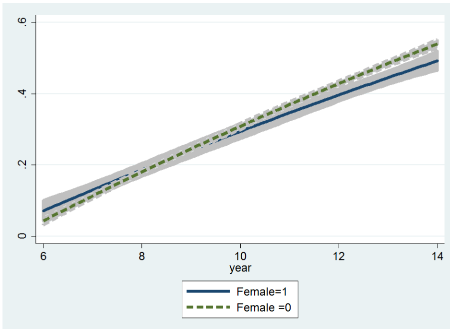
(f) Migrant



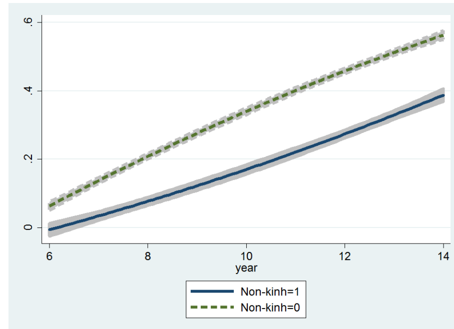
(g) Incomplete GSM

Note: Quadratic prediction with no controls. Grey bounds denote 95% confidence intervals.

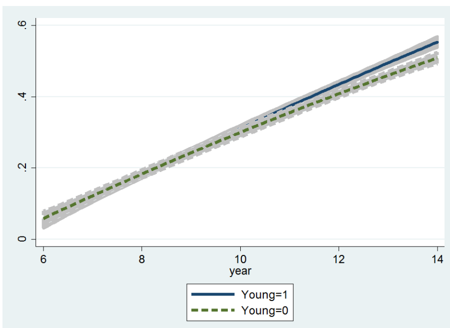
Figure 5: Phones per capita over time



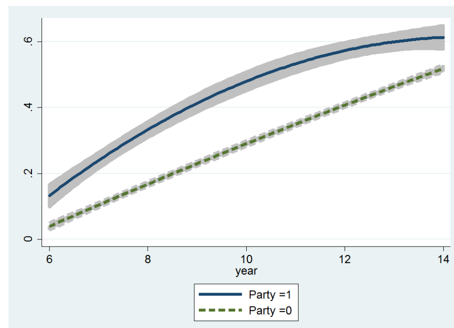
(a) Female



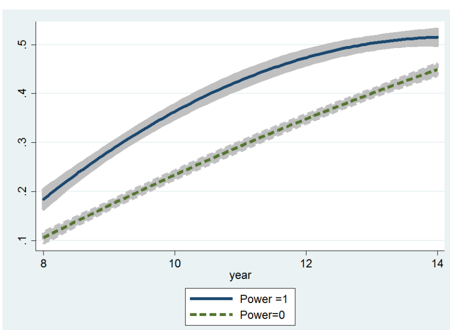
(b) Non-Kinh



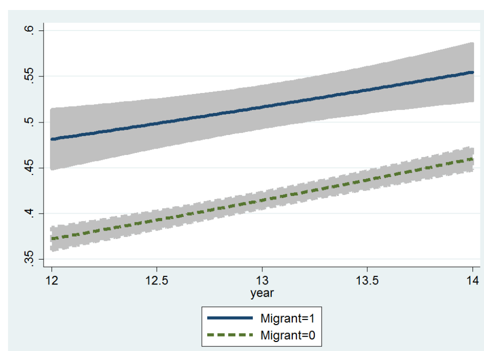
(c) Young



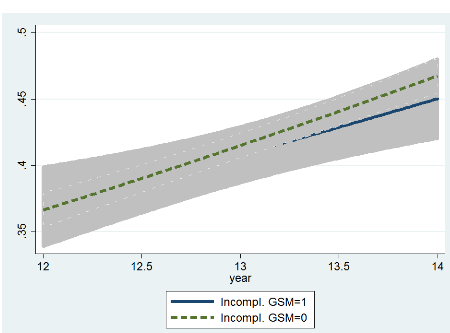
(d) Party



(e) Power



(f) Migrant



(g) Incomplete GSM

Note: Quadratic prediction with no controls. Grey bounds denote 95% confidence intervals.

time when almost all households already had at least one phone.

Similar group comparisons are also displayed over the variable user intensity, in Figure B-1 for the extensive and in Figure B-2 for the intensive margin. They tell a similar story regarding adoption patterns as Figures 4 and 5. At any given size of the network (the share of users in the district), the households connected to power have a larger propensity to adopt a phone. The same holds for migrant and the majority ethnic group Kinh households. There are no differences at different levels of GSM coverage. Overall the differences seem to be smaller at the intensive than at the extensive margin. The fact that these differences are similar to those observed over time (Figures 4 and 5) makes sense, as the user intensity grows tremendously over time.

Further, we study group differences by running t-test of all the variables of interest, including the controls used in the analysis. The results are reported in Tables B-2, B-3 and B-4 for the groups of variables we call demographic characteristics (gender, age and ethnicity in Table B-2) and to connections to power (Party membership and being connected to someone a position of power in Table B-4), GSM coverage, and migrant status (Table B-3). We can see that there are large differences in observable characteristics across these groups.

Female headed households heads make up 18 per cent of the sample (Table 1). From Table B-2 we can see that male-headed households are wealthier and more highly educated than female-headed households. They are equally likely to have wage income, but male-headed households are more likely to also have other income sources, such as income from household enterprises and agriculture. This might partly be an artefact of having more adults in the household, as the majority of female household heads are widows.[21]

There are fifty-four officially recognized ethnic groups in Viet Nam. Ethnic minorities (Non-Kinh) make up 35 per cent of the sample (Table 1). We can see from Table B-2 that they are less wealthy than the Kinh, and this has been the case historically (Singhal and Beck 2017). A large majority of them live in the sparsely populated provinces of the Northern and Central highlands with longer distances to public services. Almost all of

[21]To be precise, 68 per cent in the 2008-14 panel. See Newman (2017) for details and for descriptive evidence on female-headed households.

them have income from agricultural sources, and they are less likely to operate household enterprises or have a wage employment than the Kinh (see Table B-2). Singhal and Beck (2017) show that the wealth disparities between the Kinh and Non-Kinh have stayed close to constant over 2006-14 as measured by income and food expenditures. Further, they find that non-Kinh are more likely to diversify into non-farm activities, particularly to common property resources.

Households with young household heads, below the mean age 40.2, make up 61 per cent of the sample. From Table B-2 we can see that they are wealthier than older households, be more educated and have more children. Also on average they are more likely to have income of any of the sources listed, pointing towards a more diverse income. However, they are less dependent on transfers.

Households with a migrant are also wealthier than households without a migrant (Table B-3). They make up around 15 per cent of the sample (Table 1). They are also more centrally located, and more educated. A typical migrant in our sample would have moved to the urban centers, Hanoi or Ho Chi Minh City for employment, or for education.[22]

Table B-4 shows how different households with connections to power are from those without. We can see that being connected to power is related to higher income and assets including land, higher education level, and also to being more centrally located. Connected households are not more likely to have crop income, but are more likely to have income from wages, livestock, aquaculture, and land rentals. This holds for both Party members and those households that have a connection to someone in a position of power. Markussen (2017) discusses membership of the Communist Party, and indeed shows that in this one-party regime, Party membership is a privilege reserved to the few. Markussen (2017) shows that Party membership is related to social status: Party members are much wealthier than the rest of the population, and this disparity has stayed stable over the VARHS study period.

Finally, it is interesting to see how these groups are related. Table B-1 displays the

[22] See Narciso (2017), who also provides more descriptive analysis between households with and without a migrant member.

correlations across these groups. We can see that none of the group memberships are over 20 per cent correlated. So even though there are some statistically significant relationships, for instance from Table B-2 we can see that even though male-headed households are more likely to be connected to be someone in power, and to be of ethnic minority, there is no great overlap between these groups. Also the correlation between party membership and knowing someone in a position of power is only 18 per cent. This makes sense as these groups are very different in size: from the summary statistics (Table 1) we can see that only about 9 per cent of households have a Party member whereas 27 per cent of the sample have a connection to someone in a position of power. Therefore it can be said that each of the groups capture something unique to that specific group.

6 Results

In this section I first estimate a model of phone adoption and study how the adoption patterns differ across extensive and intensive margin in terms of income, user intensity, and prices. This is done in Section 6.1. In this framework I also study what is the contribution of a group membership over and above these typical demand factors of network goods.

Second, in Section 6.2 I study how the group differences in adoption on phones can be explained by observables, and to what degree they are due to unobservable factors. This is done by using the Blinder-Oaxaca decomposition (Blinder 1973; Oaxaca 1973).

6.1 Phone adoption

In Tables 2, 3 and 4 the OLS models for phone adoption is estimated. The coefficient estimates of user intensity, income and prices as well as group membership are displayed.

Columns 1 and 2 show the regressions for phones per capita in household, the extensive margin. Column 2 is estimated with household fixed effects. The dependent variable is standardized.[23] The coefficient estimates can therefore be interpreted in terms of standard

[23]The dependent variable takes the form: $\frac{\text{phones per capita} - mean(\text{phones per capita})}{sd(\text{phones per capita})}$

deviations. For instance, column 2 in Table 2 shows that a one per cent increase in income is associated with a 0.09 standard deviations increase in the number of phones per capita.

In columns 3 and 4 the dependent variable is a dummy denoting whether the household has a phone or not. In column 4 household fixed effects are included. We can see that the coefficients of interest are of the right signs in all three tables across specifications and dependent variables: adoption choice is increasing in income and decreasing in prices. In Table 2 where the sample using the longest panel is employed, all these coefficient estimates are statistically significant at the one per cent level (except column 4 prices is only at the 5 per cent level).

User intensity, the variable denoting the share of people in the district having at least one phone, is exponentially increasing at the intensive margin (phones per capita), but marginally decreasing at the extensive margin (the first phone). The signs are similar in all the sub-samples in Tables 2, 3 and 4.

The theoretical frameworks of Metcalfe's and Zipf's laws do not provide a straightforward explanation for this, as they only describe a relationship between the utility of belonging to a network as a function of the network size. The explanation might be that for the adoption choice of the first phone, the fact that there is some critical mass that has a phone is important, but the $(n+1)^{th}$ connection at large network sizes is no longer as important as the n^{th}. This makes sense if a phone is initially purchased for some specific purpose requiring only a small network, and the fact that it can be used for a variety of communication is not yet evident to the household. However, in looking at the purchasing choice of phones per capita (columns 1 and 2 in Tables 2, 3 and 4), the squared term of user intensity is positive and in all but one case, statistically significant at the one per cent level. It might be that the utility for an individual to be able to use a phone at any given moment is in fact increasing in the size of the network. A household who already has one phone has better information about all the possible uses of a phone, and becomes informed about these as the network grows.

In these Tables 2, 3 and 4 describing phone demand, I have a also added the variables denoting group membership. Due to there being very little time variation in these variables, they are not included in the specifications of columns 2 and 4 that have household fixed effects. We can see that being from a Non-Kinh household actually has a statistically significant *positive* relationship with the purchasing decision. This holds both at the extensive and at the intensive margin. This is interesting as the ethnic minorities are buying less phones than the Kinh ethnicity. Also being a member of the Communist Party increases the probability of phone ownership both at the extensive and intensive margin. So does having a connection to power (Table 3). In contrast, being a female-headed household is related to around 2.7 per cent smaller probability of buying the first phone, but there is no statistically significant difference at the intensive margin. The age of the household head does not have a statistically significant relationship with phone ownership.

From Table 4 we can see that even though migrant households have more phones than households with no migrant members, the difference is no longer statistically significant after adding controls. The coverage area of the GSM is also not statistically significant.

In all of the Tables 2, 3 and 4, a number of controls that could be correlated with the probability of a household having a phone are used. These are the same variables that are presented in the t-tests in tables B-2, B-3 and B-4. These variables include other demographic characteristics, measures of owning other technology, variables related to how remotely the household is located, shocks, and characteristics of the living conditions such as access to good water, electricity, and total area of land owned, as well as dummies for sources of income. Also year dummies are controlled for. All standard errors are clustered at the district level.

6.2 Differences across groups

In Tables 5, 6a and 6b the Blinder-Oaxaca decomposition results are presented. The first two rows in each table are the group specific predicted probabilities for phone adoption. "Group=1" is for the group variable in the column that gets value one, for instance the dummy Non-Kinh getting the value one. That is, "Group=0" denotes the predicted probability of phone adoption for the Kinh ethnicity. The row "difference" denotes the

Table 2: Phone adoption 2006-14 sample

	Phones per capita		First phone	
	(1)	(2)	(3)	(4)
User intensity	0.5790***	0.7528***	0.3945***	0.4815***
	(0.0777)	(0.0850)	(0.0345)	(0.0444)
User intensity sq	0.5886***	0.7734***	-0.1953***	-0.1735***
	(0.1528)	(0.1381)	(0.0640)	(0.0613)
Income (ln) 06-14	0.0915***	0.0453***	0.0430***	0.0213***
	(0.0143)	(0.0129)	(0.0052)	(0.0044)
Phone price, ln (province avg.)	-0.1747***	-0.1580***	-0.0492***	-0.0437**
	(0.0448)	(0.0444)	(0.0173)	(0.0172)
Female HH head	-0.0266		-0.0274**	
	(0.0300)		(0.0120)	
Young HH head	0.0201		0.0046	
	(0.0176)		(0.0082)	
Non-Kinh	0.0759**		0.0365**	
	(0.0374)		(0.0151)	
Party member	0.0600**		0.0578***	
	(0.0290)		(0.0149)	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
HH FE	No	Yes	No	Yes
Observations	10775	10775	10775	10775

Notes: OLS-estimates of phone adoption. Phones per capita is transformed to a z-score. Description of controls is given in Table D-1. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the district level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 3: Phone adoption 2008-14 sample

	Phones per capita		First phone	
	(1)	(2)	(3)	(4)
User intensity	0.5770***	0.7615***	0.4430***	0.5481***
	(0.0722)	(0.0952)	(0.0316)	(0.0430)
User intensity sq	0.6244***	0.8621***	-0.2723***	-0.2379***
	(0.1516)	(0.1247)	(0.0602)	(0.0604)
Income (ln) 08-14	0.0285***	0.0089	0.0064*	-0.0009
	(0.0072)	(0.0070)	(0.0033)	(0.0030)
Phone price, ln (province avg.)	-0.1654***	-0.1273***	-0.0350**	-0.0226*
	(0.0527)	(0.0457)	(0.0169)	(0.0135)
Power	0.0957***		0.0516***	
	(0.0167)		(0.0079)	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
HH FE	No	Yes	No	Yes
Observations	12364	12364	12364	12364

Notes: OLS-estimates of phone adoption. Phones per capita is transformed to a z-score. Description of controls is given in Table D-1. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the district level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 4: Phone adoption 2012-14 sample

	Phones per capita		First phone	
	(1)	(2)	(3)	(4)
User intensity	0.6849***	0.8965***	0.5439***	0.7719***
	(0.1451)	(0.2087)	(0.0832)	(0.0683)
User intensity sq	0.1948	1.6566***	-0.2146	0.0707
	(0.3786)	(0.5200)	(0.1964)	(0.1981)
Income (ln) 08-14	0.0366***	0.0154	0.0072	0.0059
	(0.0130)	(0.0151)	(0.0044)	(0.0059)
Phone price, ln (province avg.)	-0.1955*	-0.1827	-0.0773**	-0.0822**
	(0.1008)	(0.1217)	(0.0352)	(0.0336)
Migrant	0.0136		0.0236	
	(0.0431)		(0.0143)	
Incomplete GSM	0.0015		0.0152	
	(0.0342)		(0.0148)	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
HH FE	No	Yes	No	Yes
Observations	4684	4684	4684	4684

Notes: OLS-estimates of phone adoption. Phones per capita is transformed to a z-score. Description of controls is given in Table D-1. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the district level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

difference in the predicted probabilities. "Explained" denotes the difference that is explained by covariates, and "Unexplained" denotes the difference that cannot be explained by the covariates. Thus it captures the unobservable differences between the groups, that arise because of the causal effect of being a member of the group, or the unobservable characteristics related to being in that group.

Table 5 presents the results of both the extensive and intensive margin across Party membership as well as connections to power. We can see that the unexplained component in Communist Party membership is significant at the extensive but not at the intensive margin. Having a connection to power is significant at the one per cent level in both. Thus being connected to someone in power is strongly related to buying more phones, and this is not explained by typical demand factors, and not by other observables. This result could be explained by the fact that well connected households also have a tendency to maintain these connections by acquiring more phones.

Tables 6a and 6b show similar results for demographic characteristics. We can see that the only statistically significant results that are not explained by the observables are related to ethnicity. Both at the extensive and intensive margin the Kinh have a higher predicted probability of acquiring phones (denoted by the row "group=0") than the non-Kinh ("group=1"). However, the analysis suggest that if the Non-Kinh had similar observable characteristics as the Kinh, they would in fact own more phones than the Kinh. This unexplained difference corresponds to 32 per cent of the difference in phones per capita, and to 25 per cent in first phone.

The fact that ethnic minorities are adopting more phones might be due to the fact that a lot of these minorities are more remotely located that the average Kinh household, and therefore a phone might be a necessity, and the income elasticity of demand lower.[24] It thus seems unlikely that the Non-Kinh are lagging behind in phone adoption due to insufficient knowledge about the benefits, learning costs, or other similar factors. The analysis points towards the opposite: an ethnic minority household is likely to purchase

[24] Fairlie (2004) finds that in the U.S. minority groups were less likely to have internet or computers, even when observable characteristics are taken into account. However, Fairlie (2004) shows that minority groups in the U.S. are less likely to live in remote rural areas.

more phones given income and other observable characteristics, than a Kinh household with similar characteristics.

Albeit the large differences in predicted probabilities in other demographic characteristics, particularly in migrant status, the unexplained components are small and statistically insignificant. Therefore these differences are fully explained by the observables. Also households residing in areas with incomplete GSM coverage do not differ in their adoption patterns. This goes to show that the coverage, albeit imperfect, is adequate such that there are no infrastructure constraints hindering adoption.

Table 5: Blinder-Oaxaca decomposition, relations to power and party

	Phones per capita		First phone	
	(1)	(2)	(3)	(4)
	Party	Power	Party	Power
group=0	0.0035	-0.0230	0.5767***	0.5966***
	(0.0288)	(0.0574)	(0.0130)	(0.0274)
group=1	0.4135***	0.3506***	0.7713***	0.7758***
	(0.0505)	(0.0600)	(0.0204)	(0.0196)
difference	-0.4100***	-0.3736***	-0.1945***	-0.1792***
	(0.0470)	(0.0282)	(0.0198)	(0.0144)
explained	-0.3841***	-0.2885***	-0.1410***	-0.1278***
	(0.0413)	(0.0252)	(0.0166)	(0.0118)
unexplained	-0.0259	-0.0851***	-0.0536***	-0.0514***
	(0.0329)	(0.0190)	(0.0160)	(0.0085)
Observations	10775	12364	10775	12364

Notes: Blinder-Oaxaca decomposition. Phones per capita is transformed to a z-score. Description of controls is given in Table D-1. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the district level. Significance: *** p<0.01, ** p<0.05, * p<0.10

6.3 Alternative price information

Here we present the results using VHLSS price data. Tables C-1, C-2 and C-3 present results of the OLS estimation using regional price indices constructed using the VHLSS

Table 6: Blinder-Oaxaca decomposition by demographic groups

(a) Phones per capita

	(1) Non-Kinh	(2) Female	(3) Young	(4) Migrant	(5) Incomplete GSM
group=0	0.1318***	0.0395	0.1092***	0.4121***	0.4029***
	(0.0294)	(0.0311)	(0.0324)	(0.0651)	(0.0813)
group=1	-0.3252***	0.0444	-0.0161	0.7367***	0.4244***
	(0.0426)	(0.0431)	(0.0324)	(0.0537)	(0.1458)
difference	0.4570***	-0.0049	0.1253***	-0.3246***	-0.0215
	(0.0509)	(0.0445)	(0.0316)	(0.0529)	(0.1615)
explained	0.6006***	-0.0168	0.1185***	-0.3211***	-0.0254
	(0.0659)	(0.0338)	(0.0287)	(0.0400)	(0.1630)
unexplained	-0.1436***	0.0119	0.0068	-0.0035	0.0038
	(0.0412)	(0.0290)	(0.0192)	(0.0375)	(0.0377)
Observations	10775	10775	10775	6182	4684

(b) First phone

	Non-Kinh	Female	Young	Migrant	Incomplete GSM
group=0	0.6280***	0.6076***	0.6040***	0.8036***	0.7929***
	(0.0132)	(0.0136)	(0.0155)	(0.0183)	(0.0219)
group=1	0.4596***	0.5460***	0.5864***	0.8922***	0.8025***
	(0.0235)	(0.0194)	(0.0148)	(0.0137)	(0.0425)
difference	0.1684***	0.0616***	0.0176	-0.0885***	-0.0096
	(0.0266)	(0.0191)	(0.0158)	(0.0172)	(0.0467)
explained	0.2113***	0.0394**	0.0163	-0.0753***	-0.0047
	(0.0285)	(0.0155)	(0.0143)	(0.0110)	(0.0470)
unexplained	-0.0429***	0.0221*	0.0014	-0.0132	-0.0050
	(0.0153)	(0.0118)	(0.0087)	(0.0129)	(0.0155)
Observations	10775	10775	10775	6182	4684

Notes: Blinder-Oaxaca decomposition. Phones per capita is transformed to a z-score. Description of controls is given in Table D-1. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the district level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

2006, 2008, 2010 and 2012 rounds.[25] They correspond to Tables 2, 3 and 4.

The benefit of using this data is that the price information is external to our survey, and that it measures the current value of the phone owned, instead of the estimated resale value. Hence the formulation of the question is different, and the prices reported are also slightly higher due to this.[26]

We can see that the sign of prices is negative as expected in all the specifications. Also the rest of the coefficient estimates are similar to the previous specification. Phone ownership is related to being connected to someone in a position of power or a member of the Party, and being of ethnic minority. Female-headed households are slightly less likely to have phones. Migrant status and GSM coverage are not statistically significant determinants of phone ownership. To conclude, the estimates of the main analysis are robust to a different price data.

7 Conclusions

In this paper I have studied the adoption choices of mobile phones in rural Viet Nam. By setting up a formal model of demand for network goods, a standard demand model for this type of good is estimated, resulting in coefficient estimates that are consistent with theoretical predictions. My analysis reveals that the marginal propensity to buy a phone is decreasing in the number of users at the extensive margin, and increasing at the intensive margin.

This paper sheds light to an important policy concern, the "digital divide" (World Bank 2016). I find that there exists large group differences in who is leading and who is lagging behind in phone adoption in rural Viet Nam. Households that have a Communist Party member or who have a connection to someone in power, are early adopters and have

[25] The mean regional price is computed for five regions. The VHLSS is the living standards measurement survey for Viet Nam conducted by the General Statistics Office of Viet Nam and the World Bank. For details see for instance: <http://microdata.worldbank.org/index.php/catalog/2350/get_microdata>.

[26] 1082 000 Vietnamese Dong, that is around 47 USD, compared to 31 USD in VARHS (Using Google exchange rate April 15, 2017).

higher adoption rates throughout most of the study period. A similar pattern is present with households that have a migrant member. The other side of the coin is that ethnic minorities are lagging behind, as well as female-headed households, to a lesser degree.

By conducting a Blinder-Oaxaca decomposition (Blinder 1973; Oaxaca 1973), I find that only some of these differences are impacted by being a member of any of the groups studied. The differences that persist when observable characteristics are taken into account are those related to households connected to power and ethnic minorities. However, interestingly not only connected households but also ethnic minorities would have even higher adoption rates, if they had the characteristics of the opposite group.

This might be a result of the fact that ethnic minorities are remotely located and in these circumstances being connected might be very valuable. For people with connections to someone in power, there might also be an additional advantage to having a new means of communication relative to similar households with no connections to power.

Finally, I find that areas that had less than 100 per cent GSM coverage in 2012-14, adoption patterns of phones were similar to areas with full coverage. This is in line with the official information that GSM is available through the entire country (Vietnam Post and Telecommunication Group 2015).

Therefore I conclude that I have not found evidence that some groups would be in a risk of lagging behind, due to differential learning costs, procrastination or some similar unobservable reason. On the contrary, it seems plausible that marginalized ethnic groups have understood the value of phones. Given that adoption patters do vary across different groups, when not controlling for income, it is obvious that income constraints have played a role in phone adoption.

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Appendix

A Phone price data

I construct a measure of phone prices by using the reported resale value of phones in the VARHS. For each household I have the average resale price per phone. To construct a measure of prices, which takes into account reasonable geographical differences, I then construct a the mean price of a phone per province.

The value of phones is adjusted with regional CPI index. Figure A-1 illustrates the development of province level phone prices. One can see that the prices are decreasing consistently over time. Even though this measure does not perfectly capture the phone prices at the time of the purchase, the decreasing trend nevertheless illustrates the decreasing prices of the cheapest models in the market and is hence informative of the phone value.

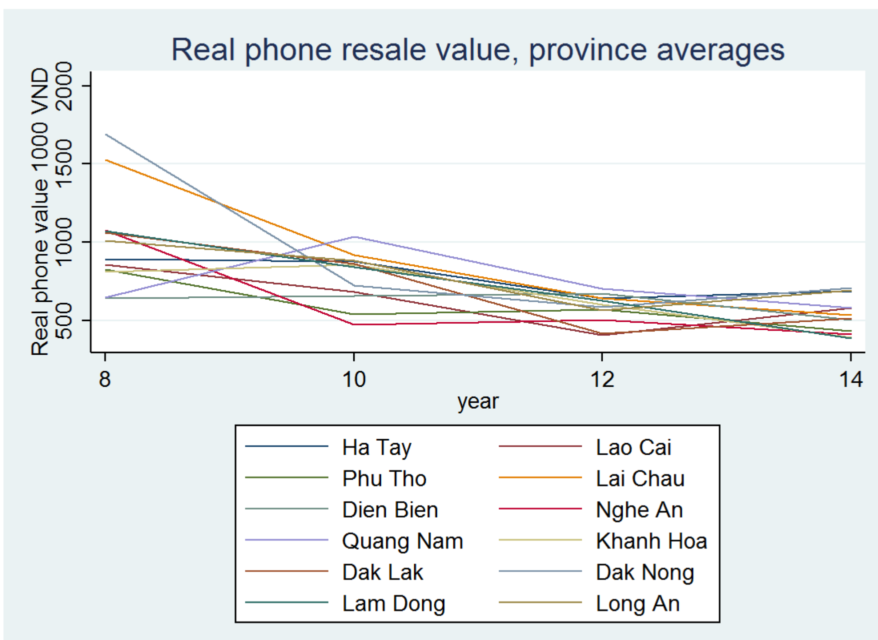


Figure A-1: Phones prices VARHS

B Additional descriptive statistics

Table B-1: Correlation matrix of subgroups

	Female	Young	Non-Kinh	Migrant	Party	Power	Incomplete GSM
Female	1.00						
Young	-0.15	1.00					
Non-Kinh	-0.17	0.17	1.00				
Migrant	-0.01	0.02	-0.07	1.00			
Party	-0.02	-0.06	-0.01	0.01	1.00		
Power	-0.06	-0.01	0.02	0.04	0.18	1.00	
Incomplete GSM	-0.02	0.03	0.01	0.01	0.02	0.02	1.00

Table B-2: T-test of group differences: demographic characteristics

	Female		Young		Non-Kinh	
	=0	=1	=0	=1	=0	=1
HH has a phone	0.61	0.55***	0.60	0.59*	0.63	0.46***
Number of telephones per capita	0.30	0.30	0.32	0.28***	0.33	0.18***
Number of phones in HH	1.24	1.02***	1.11	1.26***	1.28	0.87***
Income 06-14	93179.41	74748.14***	82549.02	94733.13***	96371.14	60562.93***
Income 08-14	84078.28	68823.63***	73349.15	87398.10***	86767.36	56649.76***
Asset index w/o phones	0.22	-0.32***	-0.05	0.24***	0.17	-0.14***
Food expenditures	1120.07	963.40***	1035.75	1128.28***	1156.28	806.44***
Female HH head	0.00	1.00	0.28	0.16***	0.24	0.10***
Non-Kinh	0.23	0.09***	0.14	0.25***	0.00	1.00
Young HH head	0.59	0.41***	0.00	1.00	0.52	0.67***
Migrant	0.17	0.13***	0.13	0.20***	0.17	0.13***
Incomplete GSM	0.17	0.15*	0.14	0.18***	0.15	0.22***
Female HH head	0.00	1.00	0.28	0.16***	0.24	0.10***
Non-Kinh	0.23	0.09***	0.14	0.25***	0.00	1.00
Party member	0.09	0.08	0.11	0.07***	0.09	0.09
Power	0.33	0.26***	0.32	0.31	0.32	0.32
HH size	4.58	3.55***	3.76	4.86***	4.11	5.36***
Education per capita	7.50	6.91***	6.86	7.80***	8.00	4.88***
Number of children <15	0.94	0.67***	0.70	1.03***	0.76	1.36***
Total area owned	8208.97	4234.63***	6188.85	8319.07***	6126.47	12278.11***
HH speaks Vietnamese	0.98	0.99***	0.99	0.98***	1.00	0.92***
Electricity	0.98	0.99*	0.99	0.97***	0.99	0.93***
Toilet	0.84	0.84	0.88	0.81***	0.91	0.55***
Good water	0.81	0.87***	0.84	0.81***	0.88	0.58***
Number of motorcycles	1.10	0.83***	0.93	1.14***	1.09	0.85***
Number of color tv's	0.97	0.93***	0.98	0.95**	1.00	0.80***
Number of computers	0.08	0.08	0.06	0.10***	0.10	0.02***
Internet	0.23	0.21***	0.18	0.26***	0.26	0.10***
Natural shock	0.17	0.13***	0.15	0.18***	0.15	0.23***
Pest shock	0.24	0.16***	0.19	0.25***	0.17	0.42***
Economic shock	0.04	0.03**	0.03	0.05***	0.04	0.05***
Economic shock (agriculture)	0.03	0.02**	0.03	0.03***	0.03	0.03
Health shock	0.10	0.15***	0.13	0.10***	0.12	0.09***
Distance all weather road	2.20	2.04	2.02	2.28***	1.90	3.21***
Distance peoples committee	2.16	1.96***	1.98	2.22***	1.92	2.91***
Distance public health care	2.11	1.92***	1.96	2.17***	1.89	2.75***
Distance private health care	14.70	10.48***	10.51	16.73***	9.31	31.52***
Distance primary school	1.64	1.59	1.62	1.64	1.57	1.87***
Crop income (dummy)	0.88	0.78***	0.83	0.88***	0.83	0.98***
Forest income (dummy)	0.04	0.03***	0.03	0.04**	0.04	0.04
Livestock income (dummy)	0.73	0.58***	0.66	0.73***	0.65	0.88***
Aguaculture income (dummy)	0.13	0.06***	0.10	0.13***	0.10	0.19***
Common property income (dummy)	0.37	0.26***	0.29	0.40***	0.24	0.79***
Wage income (dummy)	0.61	0.62	0.52	0.69***	0.62	0.56***
HH enterprise income (dummy)	0.28	0.21***	0.23	0.29***	0.29	0.16***
Private transfer income (dummy)	0.53	0.61***	0.63	0.48***	0.57	0.46***
Public transfer income (dummy)	0.40	0.50***	0.54	0.33***	0.36	0.69***
Land rent income (dummy)	0.25	0.26	0.23	0.27***	0.26	0.20***
Phone price, ln (province avg.)	6.10	6.07***	6.05	6.13***	6.09	6.08*
User intensity	-0.01	0.04***	0.05	-0.04***	0.03	-0.11***
User intensity sq	0.10	0.08***	0.09	0.10***	0.08	0.14***
Observations	10775		10775		10775	

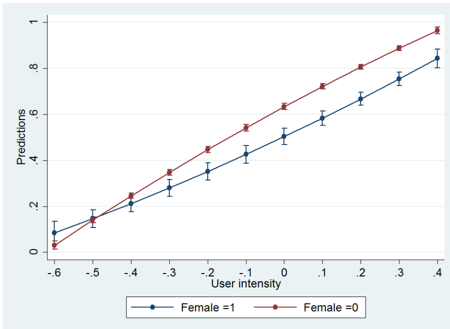
Table B-3: T-test of group differences: Migrant and GSM

	Migrant		Incomplete GSM	
	=0	=1	=0	=1
HH has a phone	0.80	0.89***	0.79	0.80
Number of telephones per capita	0.42	0.52***	0.41	0.42
Number of phones in HH	1.73	2.12***	1.69	1.75
Income 06-14	88066.82	110344.26***	82784.44	75241.79**
Income 08-14	81120.62	96971.38***	75934.14	73620.37
Asset index w/o phones	-0.01	0.38***	0.04	0.11
Food expenditures	1384.62	1667.72***	1359.07	1329.26
Female HH head	0.20	0.18	0.19	0.19
Non-Kinh	0.39	0.26***	0.40	0.39
Young HH head	0.54	0.60***	0.52	0.55
Migrant	0.00	1.00	0.14	0.17
Incomplete GSM	0.13	0.15	0.00	1.00
Female HH head	0.20	0.18	0.19	0.19
Non-Kinh	0.39	0.26***	0.40	0.39
Party member	0.09	0.10	0.09	0.10
Power	0.33	0.39***	0.34	0.35
HH size	4.55	4.39***	4.53	4.49
Education per capita	6.91	8.71***	7.10	7.22
Number of children <15	1.10	0.66***	1.06	0.98
Total area owned	9423.09	9286.06	7166.65	6470.56*
HH speaks Vietnamese	0.95	0.99***	0.96	0.87***
Electricity	0.96	0.98**	0.95	0.99***
Toilet	0.75	0.85***	0.74	0.75
Good water	0.72	0.81***	0.67	0.70*
Number of motorcycles	1.22	1.40***	1.12	1.19*
Number of color tv's	0.98	1.04***	0.97	0.95
Number of computers	0.09	0.20***	0.10	0.08
Internet	0.22	0.37***	0.22	0.22
Natural shock	0.19	0.18	0.22	0.21
Pest shock	0.31	0.26***	0.35	0.32
Economic shock	0.06	0.05	0.06	0.10***
Economic shock (agriculture)	0.04	0.04	0.04	0.04
Health shock	0.11	0.10	0.11	0.10
Distance all weather road	3.04	2.63*	3.30	1.37***
Distance peoples committee	2.82	2.41***	2.97	1.95***
Distance public health care	2.74	2.38***	2.88	1.91***
Distance private health care	13.06	10.34***	13.47	10.79***
Distance primary school	1.91	1.69***	1.79	1.48***
Crop income (dummy)	0.87	0.88	0.87	0.87
Forest income (dummy)	0.00	0.00	0.00	0.00**
Livestock income (dummy)	0.67	0.69	0.71	0.78***
Aguaculture income (dummy)	0.08	0.09	0.08	0.10
Common property income (dummy)	0.50	0.38***	0.49	0.53**
Wage income (dummy)	0.62	0.68***	0.61	0.69***
HH enterprise income (dummy)	0.23	0.26**	0.26	0.25
Private transfer income (dummy)	0.55	0.61***	0.60	0.52***
Public transfer income (dummy)	0.58	0.47***	0.63	0.60
Land rent income (dummy)	0.06	0.05	0.06	0.06
Phone price, ln (province avg.)	5.95	5.94***	5.94	5.93*
User intensity	0.23	0.25***	0.21	0.20**
User intensity sq	0.07	0.08***	0.07	0.06***
Observations	6182		4684	

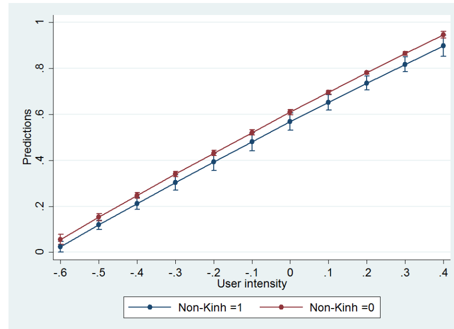
Table B-4: T-test of group differences: relations to power and the Party

	Power		Party	
	=0	=1	=0	=1
HH has a phone	0.60	0.78***	0.58	0.77***
Number of telephones per capita	0.28	0.40***	0.29	0.42***
Number of phones in HH	1.15	1.67***	1.14	1.79***
Income 06-14	79349.30	109810.09***	84859.06	133047.12***
Income 08-14	66852.90	88870.94***	76567.62	124954.66***
Asset index w/o phones	-0.19	0.29***	-0.00	1.22***
Food expenditures	1023.95	1322.45***	1046.77	1484.84***
Young hh head	0.60	0.59	0.56	0.45***
Migrant	0.13	0.16***	0.16	0.15
Female HH head	0.20	0.15***	0.22	0.20
Non-Kinh	0.38	0.36	0.20	0.20
Party member	0.05	0.17***	0.00	1.00
Power	0.00	1.00	0.24	0.45***
HH size	4.63	4.67	4.34	4.63***
Education per capita	6.44	7.71***	7.13	9.81***
Number of children <15	1.14	1.02***	0.89	0.75***
Total area owned	8774.03	10721.35***	7200.52	8908.62***
HH speaks Vietnamese	0.93	0.97***	0.98	0.99***
Electricity	0.93	0.96***	0.98	0.99**
Toilet	0.70	0.78***	0.83	0.93***
Good water	0.73	0.76***	0.82	0.83
Number of motorcycles	1.00	1.23***	1.01	1.43***
Number of color tv's	0.88	0.99***	0.95	1.12***
Number of computers	0.06	0.12***	0.07	0.24***
Internet	0.17	0.26***	0.21	0.42***
Natural shock	0.21	0.24***	0.17	0.12***
Pest shock	0.30	0.34***	0.23	0.20*
Economic shock	0.05	0.07**	0.04	0.03***
Economic shock (agriculture)	0.04	0.05*	0.03	0.02***
Health shock	0.09	0.12***	0.11	0.13
Distance all weather road	3.99	3.17***	2.20	1.82**
Distance peoples committee	2.90	2.47***	2.17	1.56***
Distance public health care	2.84	2.44***	2.10	1.70***
Distance private health care	22.36	15.84***	13.86	12.84
Distance primary school	1.85	1.60***	1.66	1.36***
Crop income (dummy)	0.88	0.89	0.86	0.83***
Forest income (dummy)	0.03	0.04***	0.04	0.04
Livestock income (dummy)	0.67	0.74***	0.69	0.75***
Aguaculture income (dummy)	0.08	0.13***	0.11	0.17***
Common property income (dummy)	0.48	0.45***	0.36	0.25***
Wage income (dummy)	0.56	0.64***	0.60	0.76***
HH enterprise income (dummy)	0.23	0.26**	0.27	0.25
Private transfer income (dummy)	0.47	0.55***	0.54	0.57*
Public transfer income (dummy)	0.54	0.54	0.41	0.56***
Land rent income (dummy)	0.05	0.07***	0.24	0.33***
Phone price, ln (province avg.)	5.96	5.93***	6.09	6.10
User intensity	0.04	0.11***	0.00	0.01
User intensity sq	0.08	0.08*	0.10	0.10*
Incomplete GSM	0.13	0.15**	0.16	0.19*
Observations	12364		10775	

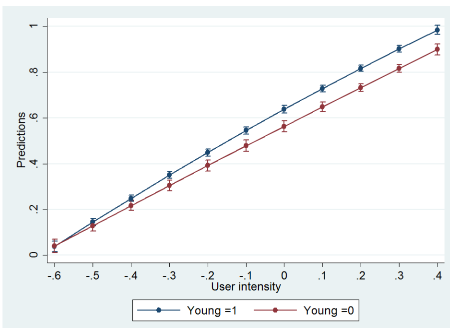
Figure B-1: First phone over user intensity



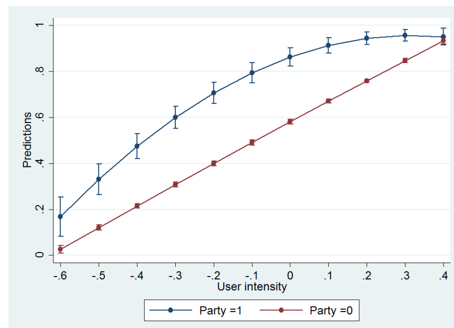
(a) Female



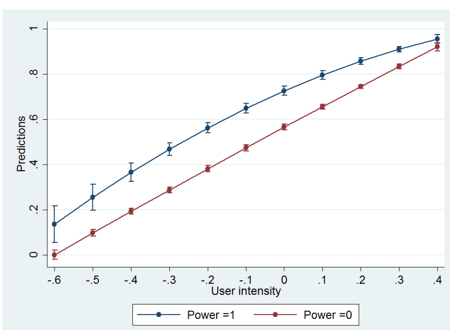
(b) Non-Kinh



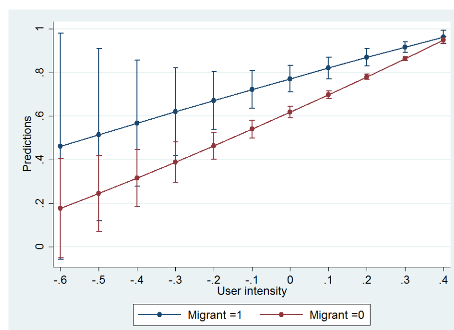
(c) Young



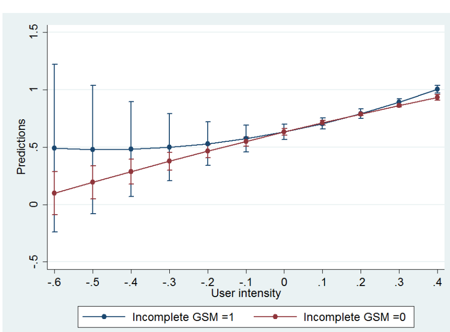
(d) Party



(e) Power



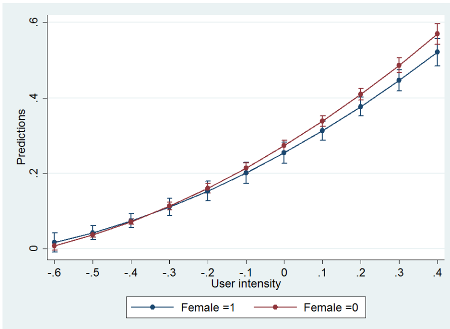
(f) Migrant



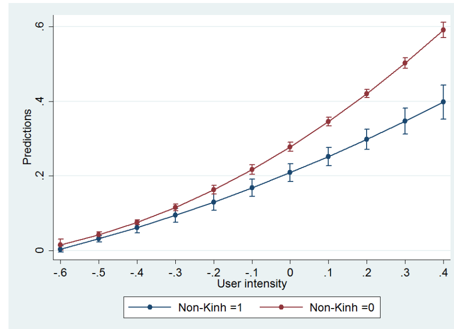
(g) Incomplete GSM

Notes: Quadratic prediction with no controls. Grey bounds denote 95% confidence intervals. Vertical axis has Phones per capita in household (not the z-score transformation). Horizontal axis denotes user intensity, which is demeaned.

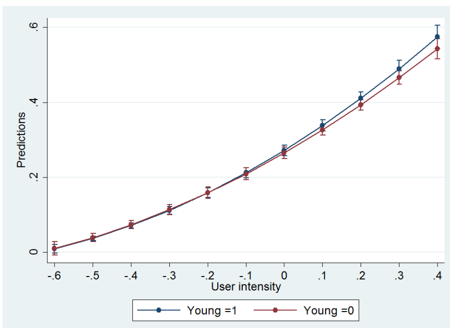
Figure B-2: Phones per capita over user intensity



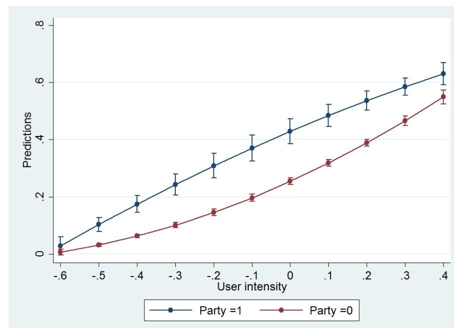
(a) Female



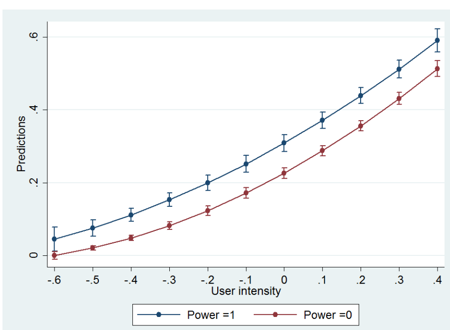
(b) Non-Kinh



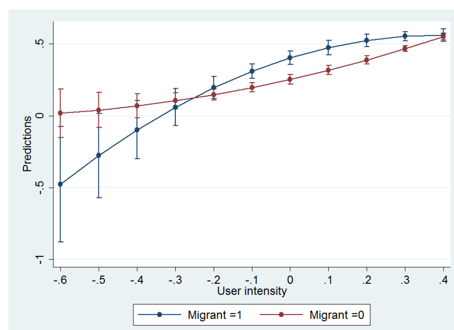
(c) Young



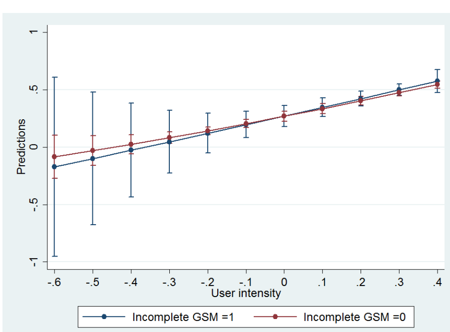
(d) Party



(e) Power



(f) Migrant



(g) Incomplete GSM

Note: Quadratic prediction with no controls. Grey bounds denote 95% confidence intervals. User intensity variable is demeaned.

C Additional results

Table C-1: Phone adoption (2006-12), alternative prices

	Phones per capita		First phone	
	(1)	(2)	(3)	(4)
User intensity	0.6873***	0.8876***	0.4305***	0.5303***
	(0.0817)	(0.0879)	(0.0327)	(0.0403)
User intensity sq	0.5891***	0.6868***	-0.1891***	-0.1821***
	(0.1467)	(0.1420)	(0.0663)	(0.0641)
Income (ln) 06-14	0.0897***	0.0412**	0.0492***	0.0249***
	(0.0169)	(0.0161)	(0.0066)	(0.0057)
Mobile price (region)	-0.1062*	-0.1808***	-0.0860***	-0.0844***
	(0.0557)	(0.0543)	(0.0267)	(0.0270)
Female HH head	-0.0056		-0.0257**	
	(0.0303)		(0.0124)	
Young HH head	0.0067		0.0004	
	(0.0181)		(0.0092)	
Non-Kinh	0.1072***		0.0346**	
	(0.0366)		(0.0164)	
Party member	0.1047***		0.0771***	
	(0.0332)		(0.0164)	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
HH FE	No	Yes	No	Yes
Observations	8620	8620	8620	8620

Notes: OLS-estimates of phone adoption. Phones per capita is transformed to a z-score. Description of controls is given in Table D-1. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the district level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table C-2: Phone adoption 2008-12, alternative prices

	Phones per capita		First phone	
	(1)	(2)	(3)	(4)
User intensity	0.6822***	0.8149***	0.4289***	0.5293***
	(0.0816)	(0.1070)	(0.0353)	(0.0487)
User intensity sq	0.6509***	0.9702***	-0.2340***	-0.1929***
	(0.1587)	(0.1440)	(0.0720)	(0.0735)
Income (ln) 08-14	0.0260***	0.0054	0.0064	-0.0023
	(0.0083)	(0.0083)	(0.0041)	(0.0036)
Mobile price (region)	-0.1836*	-0.0939	-0.0211	-0.0155
	(0.0949)	(0.1118)	(0.0372)	(0.0370)
Power	0.1095***		0.0638***	
	(0.0217)		(0.0100)	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
HH FE	No	Yes	No	Yes
Observations	9273	9273	9273	9273

Notes: OLS-estimates of phone adoption. Phones per capita is transformed to a z-score. Description of controls is given in Table D-1. Heteroscedasticity-robust Wonder Woman standard errors in parentheses. Standard errors clustered at the district level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table C-3: Phone adoption 2012, alternative prices

	(1) telephone per capita	(2) HH has a phone
User intensity	0.5956***	0.3335***
	(0.1854)	(0.1015)
User intensity sq	0.1991	-0.0885
	(0.5522)	(0.2978)
Income (ln) 08-14	0.0328	0.0096*
	(0.0258)	(0.0055)
Mobile price (region)	-0.1279	-0.1672
	(0.3151)	(0.1070)
Migrant	0.0431	0.0253
	(0.0569)	(0.0222)
Incomplete GSM	-0.0196	-0.0030
	(0.0516)	(0.0230)
Controls	Yes	Yes
Observations	2342	2342

Notes: OLS-estimates of phone adoption. Phones per capita is transformed to a z-score. Description of controls is given in Table D-1. Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the district level. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

D Description of variables

Table D-1: Description of variables

Variable	**Description**	**Rounds**
HH has a phone	Household owns at least one phone	2006-14
Number of telephones per capita	Number of phones in household / household size	2006-14
Number of phones in HH	Number of phones in household	2006-14
User intensity	Share of households in district that have at least one phone (demeaned)	2006-14
User intensity sq	Share of households in district that have at least one phone (squared)	2006-14
Phone price, ln (province avg.)	Province level mean of resale price of phones (log, adjusted with province level CPI)	2006-14
Mobile price (region)	Regional (5 regions) level mean of resale price of phones (log, adjusted with province level CPI)	2006-12
Income 06-14	Log income for main sources of income adjusted with province CPI	2006-14
Income 08-14	Log income for a large set of income sources adjusted with province CPI	2008-14
Asset index w/o phones	Asset Index for durables excluding phones (see MacKay & Tarp 2017)	2006-14
Food expenditures	Log food expenditures adjusted with province level food price index	2006-14
Young HH head	Household head younger than mean age (<40.2 years)	2006-14
Migrant	Household has a migrant member living outside the household	2012-14
Incomplete GSM	Dummy if GSM coverage less than 100 per cent in a commune	2012-14
Female HH head	Household head is female	2006-14
Non-Kinh	Dummy if household is not of Kinh ethnicity, i.e. is a minority	2006-14
Party member	Someone in the household is a member of the Communist Party	2006-14
Power	Dummy for yes in any of these questions: Does any member of your household hold any office or other positions of public responsibility in the Commune, or higher levels of government? Same question for relatives outside this household, and personal friends.	2008-14
HH size	Household size	2006-14
Education per capita	Years of education per capita in household	2006-14
Number of children <15	Number of children less than 15 years of age	2006-14
Total area owned	Total area owned (log)	2006-14

Variable	**Description**	**Rounds**
HH speaks Vietnamese	Household speaks Vietnamese	2006-14
Electricity	Dummy for household having access to electricity	2006-14
Toilet	Dummy for household having a toilet	2006-14
Good water	Dummy for household having a good water source	2006-14
Number of motorcycles	Number of motorcycles in household	2006-14
Number of color tv's	Number of color tv's in household	2006-14
Number of computers	Number of computers in household	2006-14
Internet	Dummy if household has access to internet	2006-14
Natural shock	Household has experienced a natural shock in the last 2 years	2006-14
Pest shock	Household has experienced a pest shock in the last 2 years	2006-14
Economic shock	Household has experienced an economic shock in the last 2 years	2006-14
Economic shock (agriculture)	Household has experienced an agriculture-related economic shock in the last 2 years	2006-14
Health shock	Household has experienced a health shock in the last 2 years	2006-14
Distance all weather road	Distance (in km) to an all weather road	2006-14
Distance peoples committee	Distance (in km) to peoples committee	2006-14
Distance public health care	Distance (in km) to public health care	2008-14
Distance private health care	Distance (in km) to private health care	2008-14
Distance primary school	Distance (in km) to primary school	2008-14
Crop income (dummy)	Dummy if household has any income from crops	2006-14
Forest income (dummy)	Dummy if household has any income from forestry	2006-14
Livestock income (dummy)	Dummy if household has any income from livestock	2006-14
Aguaculture income (dummy)	Dummy if household has any income from aquaculture	2006-14
Common property income (dummy)	Dummy if household has any income from common property resources	2008-14
Wage income (dummy)	Dummy if household has any wage income	2008-14
HH enterprise income (dummy)	Dummy if household has any income from a household enterprise	2008-14
Private transfer income (dummy)	Dummy if household has any income from private transfers	2006-14
Public transfer income (dummy)	Dummy if household has any income from public transfers	2006-14
Land rent income (dummy)	Dummy if household has any income from land rentals	2006-14

E Network benefits: comparative statics

This Appendix derives the marginal utilities of the network benefits of Metcalfe's law and Zipf's law, equations 4 and 5 in Section 3.2, respectively.

For Metcalfe the utility is exponentially increasing in the share of people having phones (keeping size of the reference group constant):

$$\frac{\partial f_M(DN)}{\partial D} = 2DN^2 - DN > 0, \quad \text{when} \quad N \geq \frac{1}{2}$$

$$\frac{\partial^2 f_M(DN)}{\partial^2 D} = 2N^2 - N > 0, \quad \text{when} \quad N \geq 1$$

For Zipf's law

$$\frac{\partial f_Z(DN)}{\partial D} = N \log(D) + N + Nlog(N) > 0$$

$$\frac{\partial^2 f_Z(DN)}{\partial^2 D} = \frac{N}{D} > 0.$$

We can see that the network benefits are exponential in both cases. However, the second derivative in Zipf's law approaches N as D increases. Hence as the size of the network grows, the network benefits approach a linear case N.

Chapter 4

Early Life Determinants of Cognitive Ability: A Comparative Study on Madagascar and Senegal

Early Life Determinants of Cognitive Ability: A Comparative Study on Madagascar and Senegal*

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Naveen Sunder§

April 2017

Abstract

We study the determinants of educational and human capital outcomes of young adults in Madagascar and Senegal using a model of school attainment and a production function for cognitive skills. We use unique and comparable long term panel data sets from both countries and find that Malagasy children had higher test scores in second grade, but the difference converges in early adulthood. In both countries cognitive skills, measured using test scores in the second grade, and health, proxied by adult height, are strong predictors of school attainment in young adulthood. Cognition in second grade is a stronger predictor of cognitive skills in young adulthood in Senegal than Madagascar. In both countries, second grade math scores are a stronger predictor of adult cognitive skills than French scores. In Madagascar school inputs and health matter more for cognitive skills in early adulthood than in Senegal. Early life family conditions have an enduring impact on test scores of young adults in both countries.

JEL Classification Codes: I21, O12
Keywords: Education, cognitive ability, human capital, test scores

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1 Introduction

Cognitive ability has important implications not only for individual wellbeing, but also for economic growth (Hanushek and Woessmann 2008; 2012; Hanushek 2013). In this paper we study the determinants of cognitive ability and grade attainment of young adults. By using a cognitive ability production function, we examine the importance of early life inputs such as health and parental inputs, as well as cognitive ability in early life, to understand how the educational level and cognitive capacity of young adults are formed. To do so, we rely on two unique and very similar panel surveys from Madagascar and Senegal that follow children from the time they enter second grade in school until they are young adults. The cohort is thus followed over a period of 17 years in Senegal and 15 years in Madagascar, an unusually long period of time for survey data, especially in the African context where we are not aware of any other panel data that follow individuals from early childhood until adulthood.

The research on the effects of early life conditions and ability on success in later life is generally quite limited. The most rigorous studies in this area have been conducted in developed country settings, where research in economics and psychology has shown that children with high academic performance in elementary school are also much more likely to have higher academic performance later in life, as measured in terms of school attainment and test scores (Cunningham and Stanovich 1997; Feinstein 2003; Bourne et al. 2007; Duncan et al. 2007).[1]

In developing countries, the evidence on the impact of early ability on human capital accumulation is scarce due to the lack of long-term panel data and, in particular, the lack of data on academic performance that spans the period from early childhood to young adulthood. Among the relevant studies, two come from India where Helmers and Patnam (2011) found evidence of self-productivity of cognitive skills from the ages 5 to 12, and Singh and Mukherjee (2016) found that early primary school skills contribute to the likelihood of completing secondary education.[2] In the context of Guatemala, Behrman

[1]For a review article on effects of early life attributes to adult outcomes and their relation to social mobility, see Heckman and Mosso (2014).

[2]The two latter references related to the Young Lives project, which has followed a cohort of children

et al. (2014) found that schooling has a significant impact on adult reading comprehension. In none of these cases, however, was the impact of early ability on school attainment and human capital of young adult examined.

Another distinguishing characteristic of our work is that we are able to make comparisons between two countries. Studies on cross-country comparisons in human capital formation, especially from developing countries, are in general quite rare. To our knowledge, only Singh (2017) studies a similar issue across countries, albeit using a panel that only spans three years, instead of ours that covers more than 15 years. His results from Peru and Vietnam show that although pre-school differences in tests scores are low across the two countries, there are large differences in test scores at the age of 8 years. He finds that most of these differences are accounted for by differential productivity of schools across the two contexts. Our set-up also differs, and is thus also unique in the fact that we are able to compare not only math, but also language scores since the language of instruction, French, is the same across the countries in our study.

In the African context, there is an even a great paucity of evidence with respect to the impact of early cognitive ability on later life outcomes. Exceptions, albeit which cover a much more limited time span, are Glick and Sahn (2010) and Aubery and Sahn (2014). By using information from the 1995-96 and 2003-04 rounds of the same Senegal data set as ours, Glick and Sahn (2010) found that skills in early primary school (second grade) in 1995–6 are strongly positively associated with later school progression, as measured in 2003. Similarly, Aubery and Sahn (2014) found persistence in academic skills in Madagascar from teenage years to early adulthood.

As noted above, however, we are not only concerned with the role that early cognitive ability plays in later life outcomes, but also of health and the household context. In regard to health, there is a limited literature showing that health status early in life, using height measurements as proxy, has an important impact on outcomes, including cognitive ability, both as a child (Duc 2011; Spears 2012), but also as an adult (Case and Paxson 2008; Behrman et al. 2014; Vogl 2014; LaFave and Thomas 2016). Behrman et al. (2014) found

for 11 years as of the time of the writing of this paper. Details: <http://www.younglives-india.org/findings-and-data>.

that the effect of schooling on adult cognitive skills is overestimated if the health status as a child is not taken into account. This is supported by evidence of the positive relationship with childhood health status and cognitive ability in later life (Alderman et al. 2006). As implied by the cognitive production function (Todd and Wolpin 2003; 2007; Cunha and Heckman 2007; Cunha et al. 2010), and also documented in Case and Paxson (2008), we know that the effect of health in early life affects human capital in later life via the formation of cognitive skills early in life. This highlights the importance of improved health as a child in determining adult cognitive ability, potentially being mediated by better schooling outcomes. We therefore study explicitly whether early childhood health and cognition have independent impacts on adult cognitive skills.

Although our focus is on the role of early cognitive ability and health, in terms of their impact on human capital formation, we are also interested more broadly in the role of family background, particularly wealth and parental education in this regard. Here the literature clearly indicates that parents' education affects grade progression and cognitive skills of their children, both in developing and developed countries (Cunha and Heckman 2007; Todd and Wolpin 2007; Cunha et al. 2010; Glick et al. 2011; Behrman et al. 2014; Jones et al. 2014). Moreover, Fiorini and Keane (2014) find evidence that cognitive skill formation depends heavily on the amount of time spent in educational activities after school. This result highlights the importance of parental inputs.

In the context of Sub-Saharan Africa, Glick et al. (2011) and Jones et al. (2014) found that parental background plays a significant role in ability—children of educated and non-poor parents perform much better than their peers. In terms of wealth, or other money metric measures of income, there is considerable evidence that material well-being matters for education and cognition (Cunha and Heckman 2007; Todd and Wolpin 2007; Cunha and Heckman 2008; Behrman et al. 2014; Helmers and Patnam 2011). However, in the majority of studies from developing countries, income, expenditures, or wealth are measured contemporaneously with the cognitive indicator. In contrast, what we are interested in is early childhood conditions, where we measure wealth at the second school year.

We build upon a standard cognitive production function framework (Todd and Wolpin 2003; 2007; Cunha and Heckman 2007; Cunha et al. 2010), in which cognitive skills are developed over time as a function of inputs from the child's environment, such as parents' education, wealth, and the schooling environment. In turn, there is the possibility that parental and school inputs could also be a function of earlier test scores, if parents are willing to invest more in children that have performed better in school (Glick and Sahn 2010).

In this study, we examine the production of human capital among young adults in the vastly different contexts of two poor Sub-Saharan African countries, Madagascar and Senegal. Although the nature and role of schooling, the importance and value of skills, and the social context and related social norms differ across these two countries, there are many other similarities. Both are low-income countries that struggle with low primary school completion and education levels among their populations. This is the case despite the significant increase in primary school completion rates over the 1996–2012 period—from 40 to 59 percent in Senegal, and from 31 to 70 percent in Madagascar. Primary school gross enrolment rate in Senegal has also increased from 59 percent to 81 percent between 1996 and 2012, and in Madagascar from 86 per cent in 1996 to 145 percent in 2012 (World Bank 2016).[3]

One important consideration in interpreting the results in our paper is that the sample is limited to a cohort of children who we follow from the late 1990's to the 2010's, but also to children that at least initially enrolled in school as young children, even if they did not progress very far in primary school, as is the case among many of the children in this study. For those who attended school in Madagascar and Senegal in the 1990's, grade repetition and dropout rates were very high (Michaelowa 2001; Glick and Sahn 2010). In both Senegal and Madagascar, much of the instruction is in French, the primary language of instruction in both countries. This is a reflection of the fact that both countries follow similar educational systems, one, which is modeled after the French system. Nonetheless,

[3]Net enrolment rate is not available for Madagascar after 2003. The large disparity in the gross enrolment rates indicates that in Madagascar, there is potentially much more enrolment of overaged or underaged children, as well as rampant grade repetition.

there are some important differences in the educational system of the countries. Perhaps most important is that Senegal has a large network of Koranic schools that offer religious education and where there is a high proportion of preschool students, including even those who subsequently enrol in the secular government schools. The question of whether Koranic schools complement or substitute formal education is an open one. But, recent analyses shows that the opening of formal schools in Senegal reduced the enrolment and the amount of time spent in Koranic schools (André and Demonsant 2013), which points towards them being substitutes.

The Malagasy and Senegalese economies also differ in many important respects. Madagascar is an island economy that has experienced almost two decades of political turmoil since 1998, with average GDP per capita growth being zero during the period of our study (World Bank 2016). In contrast, Senegal is one of the more dynamic economies in West Africa, with GDP per capita growth averaging 1.2 percent between 1995–2012. Likewise, the poverty headcount ratio has increased slightly in Madagascar, to 75 percent in 2010. In Senegal, however, the headcount ratio stood at 47 percent in 2010 (World Bank 2016).

Madagascar has lower levels of intergenerational mobility of education and occupation than a number of other African countries (Bossuroy and Cogneau 2013; Azomahou and Yitbarek 2016). Further, Glick et al. (2011) find that parents' education and schools are important determinants of learning in the case of Madagascar. In the case of Senegal, Glick and Sahn (2009) show that conditional on a child's level of schooling at the age of 14-17 years, having better educated parents or a higher level of household resources have only modest benefits for academic performance. They find similar results for school-level variables.[4] Therefore, even though children in Madagascar and Senegal are exposed to similar schooling systems, the opportunities they might encounter later in life, and the extent to which their background matters for their achievements in later life, are very different.

In our analysis, we find that school attainment and cognitive skills of young adults are strongly related to cognition at the time of school entry, particularly in Senegal. This

[4]In the case of Senegal, Dumas and Lambert (2011) find that family characteristics do matter for enrolment and the level of education, but they do not have information on cognitive skills as we do.

relationship is stronger for math than for French skills. The lack of statistically significant effects in the case of Madagascar may in part be due to the smaller sample size. We also find that height plays an important role in grade attainment in both countries, but only in Madagascar does it matter for cognitive ability formation. This impact of child health is independent of the impact of early childhood cognitive ability. As indicators of early life inputs in the production of human capital, we also find that wealth of the household when children are entering school has an impact on schooling and cognitive skills of young adults, and that parents' education matters significantly for grade attainment. These findings are in line with those in the literature and generally support a production function approach to cognitive skill formation, where inputs from parents and the socio-economic environment play a significant role, one that persists over the life course of the children, independent of the effect of early cognitive ability which is also included in the model. Interestingly, however, parents' education level is only related to cognitive skill formation in Madagascar, but not in Senegal. In Madagascar mothers' education seems to matter more than father's education.

The paper is organized as follows. Section 2 presents the data and some descriptive statistics. In Sections 3 and 4 we discuss the theoretical and empirical frameworks, respectively. The results are presented in Section 5. Finally, Section 6 concludes.

2 Data

For our analysis we use long-term panel data sets from Madagascar and Senegal. The first round of the survey was conducted in 1995–6 in Senegal and 1997–8 in Madagascar, and in both cases involved administering math and French tests to children at the beginning and end of the second grade. The children at that time were in the age range of 7 to 10 years.[5] These school-based tests were administered as part of a multi-country study *Program on the Analysis of the Conference of Francophone Ministers of Education*, which

[5]Some children were older or younger because of early or delayed enrollment.

is referred to by its French acronym, PASEC.[6] Urban and rural communities with at least 20 students in a given grade level were included in our sample. From among these communities, some were chosen randomly and were part of the sample where the school-based testing took place. One important implication of this random sampling procedure was that rural PASEC clusters were larger than the average-sized rural communities, especially in Madagascar, since the cluster needed an elementary school with a sufficient number of children in a given grade for the survey. Another important element of the original PASEC sample is that since it was school-based, those children who did not attend school were excluded. Thus, the sample is not representative of the entire cohort of children in the age range in the PASEC clusters.

A subset of the children attending second grade in 1995–6 in Senegal and 1997–8 in Madagascar were re-surveyed in the early 2000s when they were adolescents,[7] and again in 2011–12. The children in this long-term cohort were randomly selected from slightly less than half the original clusters included in the mid-1990's PASEC surveys.[8] The 2011–12 data sets, referred to as the *Life Course Transition of Young Adults Surveys* in the two respective countries, consist of young adults who were 21 to 23 years old at the time of the survey.

Our final sample includes 333 and 405 children that were in second grade in the 1990's in Madagascar and Senegal, respectively.[9] Most of the attrition in the cohort occurred between the original PASEC surveys and a household survey conducted in the early 2000's. But the attrition between 2004 and 2012, in contrast, is much lower. Nonetheless, the overall attrition rate is around 50 per cent. We remain concerned about attrition and the bias it introduces, even though we feel that this rate of attrition is not surprising

[6] In French, the study name is *Programme d'analyse des systèmes éducatifs de la Confemen*. They were conducted under the authority of the *Conference of Education Ministers for Francophone Africa*, CONFEMEN. For more information on the PASEC, see PASEC (2016) and Michaelowa (2001).

[7] These surveys are referred to as the Progression Through School and Academic Performance in Madagascar Study (EPSPAM) and Senegal Household Education and Welfare Survey (EBMS) in Senegal.

[8] The limited number of clusters, or so-called PASEC communities, revisited was due to budgetary constraints in carrying out the survey, especially since the cost of finding the original children was quite high.

[9] The main reason for the smaller sample size in Madagascar is that we only attempted to find 15 randomly selected children from the original PASEC sample per community, compared to 20 in Senegal.

given the 15-17 year interval and challenges of keeping track of these remote populations with exceedingly low living standards in amongst the poorest communities in the world. To better understand the implications of this attrition rate, we compared the current sample of children in the cohort with those in the original PASEC samples, which were designed to be representative of school-aged children. Appendix Tables D-1a and D-1b show a comparison of means for key variables between the original PASEC sample and the cohort in our sample. We find that there are no statistically significant differences for most variables. In the case of Senegal, there are no statistically significant differences at the level of 5 or 1 per cent. In the case of Madagascar the children in the panel come from households with slightly less assets, and with slightly less educated teachers. They are also slightly younger. More importantly, we see no systematic differences in the test scores.

Despite there being relatively little difference in the characteristics of the samples, we want to emphasize that we are not making any claims that our cohort is representative of the entire population in this age group since, as noted above, this is a school-based sample and excludes children who had not completed at least one year of schooling at the time of the first survey. Furthermore, the sample is biased in that the smallest and most remote rural villages, particularly in Madagascar, are not represented, since their schools were too small to qualify for inclusion in the original sample. That being said, we would argue that we have a unique long-term panel from two African countries, spanning from second grade until young adulthood, which includes information on cognition and other socioeconomic characteristics of the children, their families, schools, and communities. There is much to be learned from this panel, despite the recognized limitations in terms of size and attrition.[10]

As indicated above, cognitive skills assessments, in the form of math and French tests, were administered in all survey rounds. It must be noted that the tests administered in the two countries though not identical, did have a lot of overlap owing to the fact that

[10]We should note that other unique panels of this type of duration and detail from developing countries, such as the Guatemalan studies ((Grajeda et al. 2005; Behrman et al. 2014)) and Young Lives studies (see <http://www.younglives.org.uk/content/sampling-and-attrition>), suffer from similar attrition problems. For a discussion see Alderman et al. (2001).

the same institution (PASEC) administered the tests across the two countries. In this analysis, the main method of construction of scores is based on the Item Response Theory (IRT), which yields a cardinal measure of test performance, whereas the more commonly used measure of percentage of correct answers yields a merely ordinal ranking of test takers. The method is explained in detail in Appendix B.

Additional information on school characteristics were collected in the original PASEC surveys conducted in the mid–90's, as well as a limited set of household characteristics, including household assets, that allow us to create an asset index by using factor analysis.[11] The PASEC survey also has a comprehensive module on school characteristics. We use this data to create a school infrastructure index that on classroom equipment, such as blackboard and furniture, as well as information on school level infrastructure such as whether the school has electricity, running water, infirmary, toilets, cafeteria, schoolyard, garden etc. We create the index by using factor analysis. We also use teacher's education as a school related input.

Tables C-1a and C-1b present summary statistics of the variables of interest for Senegal and Madagascar, respectively. In terms of education-related variables, in Senegal the sample on average has completed 9 grades of school, compared to 10 grades in Madagascar. The test score variables are the IRT transformations based on the full sample, which explains the mean being close to zero, both in the 1990's and in 2012. We can see that in Senegal, the sample has a slight majority of males, whereas in Madagascar, females have a slight majority. The Senegalese sample is on average 24 years of age in 2012, compared to 22 years in Madagascar. This is consistent with the second grade baseline data having been collected 2 years earlier in Senegal. The Malagasy sample is almost 10 centimeters shorter than the Senegalese sample. The teacher education variable is the number of years of education in Senegal and years completed starting from middle school in Madagascar, that is assuming that they have about four years of primary school education prior to middle school. We can see that the Senegalese teachers are more educated than the Malagasy teachers, the Malagasy teachers having on average nine years of education.

[11] These assets include armchairs, cooking pot, fridge, tap, bed, electricity, petrol lamp, car, bicycle, moped, cart, video cassette player, television, radio, stove, fireplace, toilet with running water, and plow.

Therefore the Senegalese teachers have on average three more years of education.

3 Theoretical framework

In this paper we analyze how early life endowments, particularly cognitive ability, but also the health and family background, affect later life outcomes, including grade attainment, and human capital, measured as test scores. Our theoretical framework builds on the prominent work of Todd and Wolpin (2003; 2007), which is also the analytical point of departure of Fiorini and Keane (2014); Aubery and Sahn (2014); Singh (2017).

A simple illustration of the 2-period mechanism in the case of grade attainment is the following:

$$Y_2 = f(\beta_1 A_1(\mu_0) + \beta_2 P_1 + \beta_3 H_1(\mu_0) + \beta_4 S_1) \tag{1}$$

where the grade attainment Y_2 in Period 2 is a function of cognitive ability A_1, and the health endowment, H_1 in Period 1, both of which are a function of a genetic component, μ_0, at the time of conception. In Period 1, P_1 denotes parental investments, including the household wealth level in Period 1 as well as the education of the parents, and S_1 are the school inputs.

In terms of cognitive skills, the model is,

$$A_2 = g(\gamma_1 A_1(\mu_0) + \gamma_2 P_1 + \gamma_3 H_1(\mu_o) + \gamma_4 S_1) \tag{2}$$

where we explain the stock of skills in Period 2, A_2, using cognition in Period 1, A_1 as an explanatory variable. Otherwise the function is similar to equation 1.

Equation 3 describes the cognitive ability production at the point of entry to the first grade, where notations are as previously. We can see that the equation is the same, except for the fact that school level inputs are not included prior to school entry

$$A_1 = h(\beta_1 A_0(\mu_o) + \beta_2 P_0 + \beta_3 H_0). \tag{3}$$

The time index 0 denotes all investments made prior to the first period, that is, from conception to the first grade. Since our test score data starts at the beginning of the second grade, we have the empirical counterparts for Y_2 and A_2, and inputs during period 2. This theoretical framework illustrates the dynamic process of skill formation. We could iterate this process forward, to get to the theoretical counterpart for the formation of skills in early adulthood.

The dynamic nature of this theoretical framework allows parents' investments in a given period during school to change as a function of the previous period's test score. Therefore this framework allows parents to invest more (less) in better performing children, which would then potentially lead them to perform even better (or not as well) in the next period, and so on (Glick and Sahn 2009; 2010). This is a relevant point to keep in mind in resource-constrained environments such as Madagascar and Senegal where in addition to the direct cost of schooling, parents' who are maximizing their lifetime utility are also faced with high opportunity cost of schooling, child labor. Therefore in families with several children, as is most often the case, the parents might be inclined to invest in the schooling of the best performing child, although, this is not necessarily the case.

4 Empirical framework

This framework allows us to analyze the relative importance of skills, acquired until the second grade vis-à-vis family background and health, in future schooling human capital accumulation.

In the simplest version, the empirical counterpart of equation 1 is a reduced form that can be estimated as an OLS model of the following form:

$$Y_{i,t+1} = \beta_0 + \beta_1 A_{i,t} + \beta_2 Height_{i,t+1} + \beta_3 HH_i + \beta_4 School_{j,t} + \beta_5 X_i + \varepsilon_i \tag{4}$$

In this regression, $Y_{i,t+1}$ stands for the highest grade completed in 2012, and $A_{i,t}$ stands for a measure of early life ability of the children. $Height_{i,t+1}$ refers to health in 2012, which is a function of health inputs received during the life-cycle as well as genetics. HH_i is household level (time-invariant) inputs, $School_{j,t}$ are school level inputs in school j, and X_i denotes time-invariant control variables.

Estimating equation 2 leads to a very similar reduced form regression

$$A_{i,t+1} = \beta_0 + \beta_1 A_{i,t} + \beta_2 Height_{i,t+1} + \beta_3 HH_i + \beta_4 School_{j,t} + \beta_5 X_i + \varepsilon_i \tag{5}$$

Our dependent variables $A_{i,t+1}$ are performance on French and math tests in 2012, both a composite score and separately.

This setup is analogous to a Value Added (VA) specification, where current outcomes are regressed on past realization of the outcomes and related inputs. These specifications have been mostly used in modeling production functions of achievement and in the estimation of teacher/school effects for school-aged children enrolled in school. Even though our model framework has these similarities, it differs conceptually because we are interested in explaining cognitive skills in early adulthood –a time during which the cohort is no longer in school. This is also the reason why including contemporaneous inputs in our estimations is not relevant.[12]

In our analysis, we measure the early life ability of the student using second grade math and French test scores. The richness of our data provides us with two alternate test scores that we can use here, a pre-test score and a post-test score. The pre-test was administered to students at the start of second grade and the post-test was administered at the end of second grade. In addition to capturing "ability endowment," the second grade scores also include any household and school inputs that the children have received from the point of conception up until the start of second grade. This can be thought of as a specification that includes lagged inputs and lagged achievement. Fiorini and Keane (2014) describe this as a "combination of cumulative and value added models". It generalizes the value added model and was preferred in Todd and Wolpin (2007) because it minimized the out of sample root mean squared error.[13]

[12]See Fiorini and Keane (2014) for an overview of different specifications of VA-models to explain cognitive skill formation for school-aged children with contamporaneus and lagged inputs.

[13]In addition, Fiorini and Keane (2014) also discuss data intensiveness of these procedures and the associated sample size issues in their analysis. We also face similar challenges but still end up with nearly

We also estimate a model with only lagged inputs and no lagged test score, which in Todd and Wolpin (2007) and Fiorini and Keane (2014) is referred as the "cumulative model", where the assumption is that the lagged inputs incorporate the innate ability and unobserved inputs. Our estimations clearly show that this is not the preferred specification. However, it is an interesting exercise revealing how the lagged inputs change when the lagged test score is added to the model.[14]

In the main specifications, we look at a composite score of the math and French tests which is created using Item Response Theory (IRT). In latter specifications, we use the French and math tests scores individually to see if math and French test scores during early childhood are equally strong predictors for adult skills, or if, as found in some literature from the US, math ability is a stronger predictor of skills in later life (Duncan et al. 2007; Duncan and Magnuson 2011).

4.1 Correcting for measurement error

Test scores typically suffer from measurement error, as they are based on a one-time spot performances of students which could be impacted by many factors in the test day environment. If these factors are idiosyncratic, then they would bias the results towards zero. We address these measurement error concerns using an instrumental variable approach. Since we have test score data at the beginning and the end of the second grade, we use the second grade pre-test scores to instrument for the post-test scores.[15]

We could implement this strategy in a couple of different ways—use either the French or math score of one round of tests to instrument for the respective score on the other

the same sample size as their specifications.

[14] Another potential specification for studying the effect of lagged inputs on cognitive ability in early adulthood is the fixed effects framework (Fiorini and Keane 2014). The underlying assumption being that the lagged coefficient of the test score is equal to one (Singh 2017). Our results show that this is not a valid assumption as the coefficient estimates are much lower (as in Singh (2017) and Fiorini and Keane (2014)), and also not feasible due to the fact that we do not have time-varying inputs in our regressions. We argue hence that omitting this specification is not a concern.

[15] Another potential empirical strategy would be to use the pre-test as the input variable and instrument it using the post-test score. Technically the exclusion restriction would not hold, as the post test is administered after the pre-test. We have estimated this model, and the second stage estimates are highly inflated. We do not go forward with this technique.

round, or use the average score of one round to instrument for the average of the other round. For our main specifications, we choose the latter strategy because we want to use a composite measure of ability that is provided by the combination of the French and math scores.

We can only control for the observed individual, household and school factors, thus the unobserved factors to be part of the error term. These unobserved factors might in turn be correlated with both our outcome of interest (like later life schooling), and the early life test scores, thus potentially leading to endogeneity bias. It is important to note that the above instrumental variable strategy does not solve the endogeneity bias and simply addresses systematic measurement errors. Thus like other literature that has looked at early childhood ability and how it affects outcomes in adult life, we rely on an extensive set of controls and thus there is the possibility of such endogeneity.

And while we thus acknowledge this concern, we also note that several recent papers have looked at the comparison between value added estimates of the type explored here and estimates from experimental or quasi-experimental analyses. They have all mostly concluded that the non-experimental estimates are unbiased based on the comparison with experiments (Kane et al. 2013; Angrist et al. 2013; Deming et al. 2014; Deming 2014). Also, the long duration of our panel also mitigates concerns related to endogeneity.

Our 2SLS model, therefore, takes the following form:

$$TS_i^{post} = \alpha_0 + \alpha_1 TS_i^{pre} + \alpha_2 Height_i + \alpha_3 HH_i + \alpha_4 School_j + \alpha_5 X_i + \tau_i \tag{6}$$

$$Y_i = \gamma_0 + \gamma_1 \hat{TS}_i^{post} + \gamma_2 Height_i + \gamma_3 HH_i + \gamma_4 School_j + \gamma_5 X_i + \epsilon_i \tag{7}$$

where post and pre-test scores are denoted by TS_i^{post} and TS_i^{pre}, respectively; $School_j$ denotes characteristics of the school attended in second grade; HH_i refers to household level inputs (parents' education and assets); and X_i denotes controls.

4.2 Omitted variable bias

In addition to correcting for measurement error, we also address the issue of omitted variable bias in the lagged test score, the main variable of interest, by conducting a test for coefficient stability proposed by Oster (2017), that builds on Altonji et al. (2005). This test derives a lower bound for the causal effect of any given variable in an OLS model, which is relevant, since in the presence of omitted variable bias, our OLS-coefficient would be biased upwards.[16] This is done by comparing the movement of R^2 and β when moving from a model with no controls to a model with full set of controls. This movement in R^2 and β provides insight on the extent to which observables impact the regression parameters.

Oster (2017) proposes, that if selection on unobservables is perfectly proportional to selection on observables, the lower bound of the true effect equals

$$\beta = \widetilde{\beta} - \delta[\acute{\beta} - \widetilde{\beta}]\frac{R_{max} - \tilde{R}}{\tilde{R} - \acute{R}} \tag{8}$$

Where $\widetilde{\beta}$ and $\tilde{R}$ correspond to the coefficient estimate of the variable of interest and the the R^2 of an OLS model with full controls. Similarly $\acute{\beta}$ and $\acute{R}$ are from an OLS regression with no controls. Parameters that need to be set to some value are R_{max}, the maximum R^2 that can be reached even if all of the unobservables were included in the regression, and δ, a parameter that denotes the importance of unobservables relative to observables. As discussed by Oster (2017) and Altonji et al. (2005), the knife-edge case of $\delta = 1$ can be considered a rigorous upper bound, which means that unobservables are as influential as observables, and hence, that the observables selected in our model are as good as random. We set $\delta = 1$ in our results using equation 8.

As pointed out by Oster (2017), it is difficult to come up with a realistic upper bound to R_{max}. We set $R_{max} = 1.5 \times \tilde{R}$. Given that analysis conducted using survey data from developing countries often have quite low levels of R^2, we consider this to be a rigorous

[16]The test proposed by Oster (2017), that builds on Altonji et al. (2005) is mostly used for studying the stability of a treatment effect when using observational data. Given that the test statistic is applicable to study coefficient stability in the presence of potential omitted variable bias of any variable of interest in an OLS-model, it is applicable for our study

upper bound for what can be attainable in our model. Coupled with the assumption of $\delta = 1$, we argue that this specification gives a conservative lower bound for β.

Second, to understand the rationale underlying the parameter δ, consider a regression model of the form

$$y = \beta D + \gamma_1 W_1 + \gamma_2 W_2 + \epsilon \tag{9}$$

Where D is the variable of interest, W_1 are the (observable) control variables, and W_2 are the unobservables. The importance of the observables relative to the unobservables is $\frac{\sigma_{1D}}{\sigma_{11}} = \frac{\sigma_{2D}}{\sigma_{22}}$, where $\sigma_{iD} = Cov(W_i, D)$ and $\sigma_{ii} = Var(W_i)$, $i = 1,2$. Now δ defines the proportionality between observables and unobservables. The R^2 of equation 9 is the R_{max} introduced previously.

As suggested by Oster (2017) we run a test calculating the value for δ for which $\beta = 0$, with the given R_{max}. This can be interpreted as the degree of selection on unobservables relative to observables, which would be necessary to explain away the result.

5 Results

5.1 Comparing the test scores between countries

We begin with some descriptive comparisons of math and French skills between Madagascar and Senegal, something we are able to do given that the questionnaires of the second grade post-test scores are the same for both of the countries, as well as the fact that questionnaires from the 2012 tests include a subset of same questions.

Figure 1 plots the cumulative density functions (CDF) of the test scores in both countries for the two periods.[17] The distribution of second grade composite scores for Madagascar first order stochastically dominates the distribution for Senegal. This pattern holds for both math (Figure 1b) and French (Figure 1c) scores separately. By 2012, there has been considerable convergence in the scores across the countries as the distribution

[17] A similar figure was presented in Singh (2017).

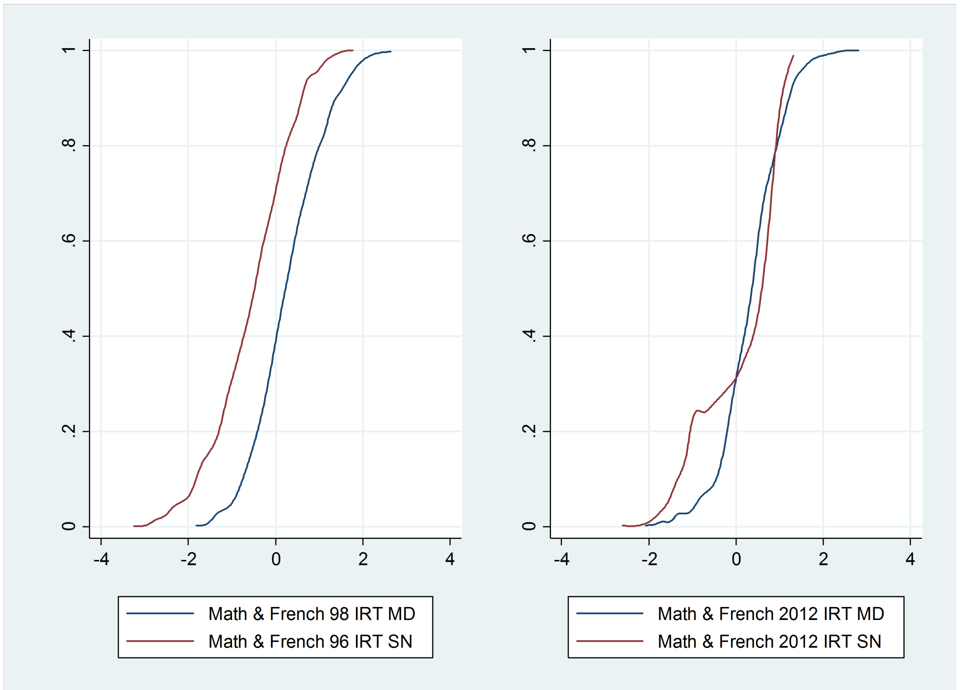
for Senegal is very close to that of Madagascar, albeit there is a different shape to the CDF that results from a bimodal distribution of test scores in Senegal.[18]

Figure 2 illustrates a similar converging pattern by showing the percentile-percentile plot of the test scores in second grade and in adult life. The 45-degree line represents a scenario where the percentiles across the two countries match up perfectly. The left panels depict the baseline scores for the composite (Figure 2a), math (Figure 2b) and French (Figure 2c). In each of these figures, the plot is below the 45-degree line at all points, which implies that a higher percentile in the Senegalese distribution corresponds to a lower percentile in the Malagasy distribution. In the right panels of the same figures, we can see that the plot of the 2012 test scores is partially below and partially above the 45-degree line. This again illustrates that the mean of the test-scores have converged over the 1995-2012 period. While Madagascar has a single-peaked distribution, that of Senegal is bimodal (discussed above). Figures 1 and 2 altogether point in the direction of Malagasy children performing better at baseline, but the Senegalese children catching up with them by their adult life.

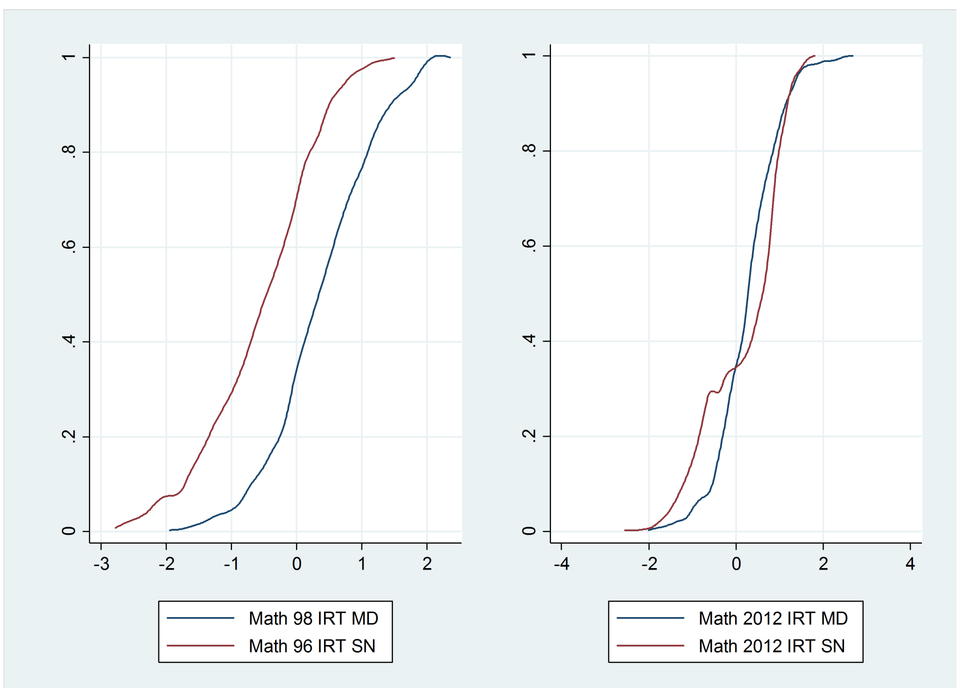
Finally, we also do a graphical analysis of the relationship between early life and later life test scores, and compare that relationship between the countries. In Figure 3, we have plotted the Kernel densities of the adult scores as a function of scores in second grade, where the levels of the test scores are comparable across countries. Figure 3a shows that conditional on early life score, the 2012 Madagascar conditional mean is higher at the lower end of the score distribution. The plot for conditional math score means across the countries (Figure 3b) exhibit a higher Senegalese conditional mean at the higher end of the distribution. French scores seem to be different, where the Malagasy seem to have a higher conditional mean across the whole distribution. A strong implication from the Figures 3 is that the relationship between the second grade and early adulthood scores is stronger in Senegal than in Madagascar, as the slopes of the curves are steeper.

[18] A bimodal distribution and a number of other non-normal distributions have been observed to be common in achievement and psychometric measures (Micceri 1989). The bimodality is also present if we look at the percentage of correct answers instead of the IRT scores as well as in the full 2012 sample of test scores. Hence, the shape of the distribution is not an artefact of the panel sample used nor of the IRT method.

Figure 1: Cumulative distribution functions of test scores



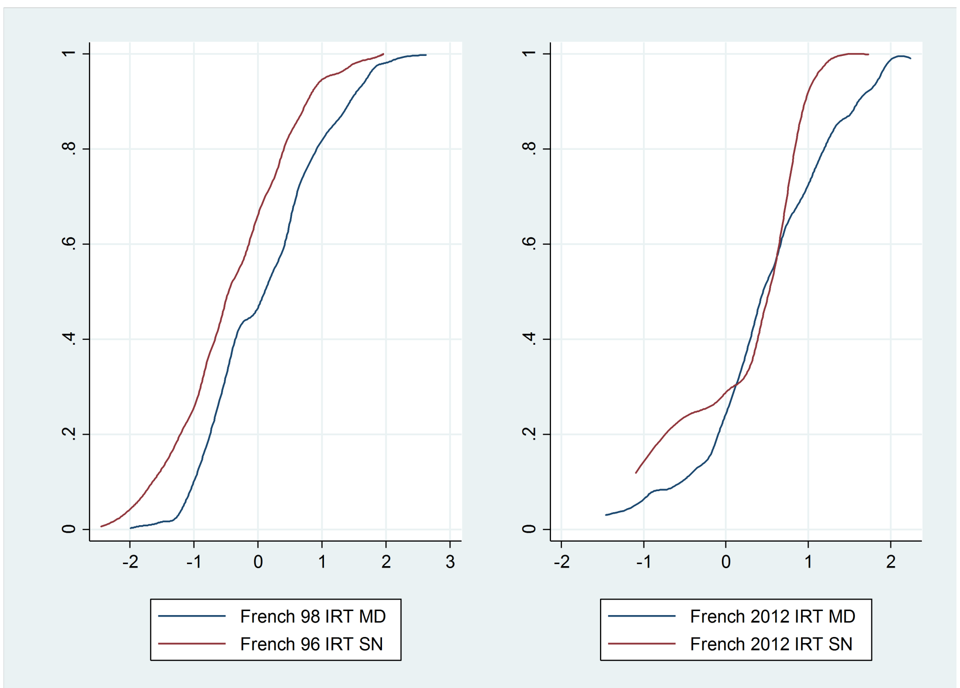
(a) Math and French



(b) Math

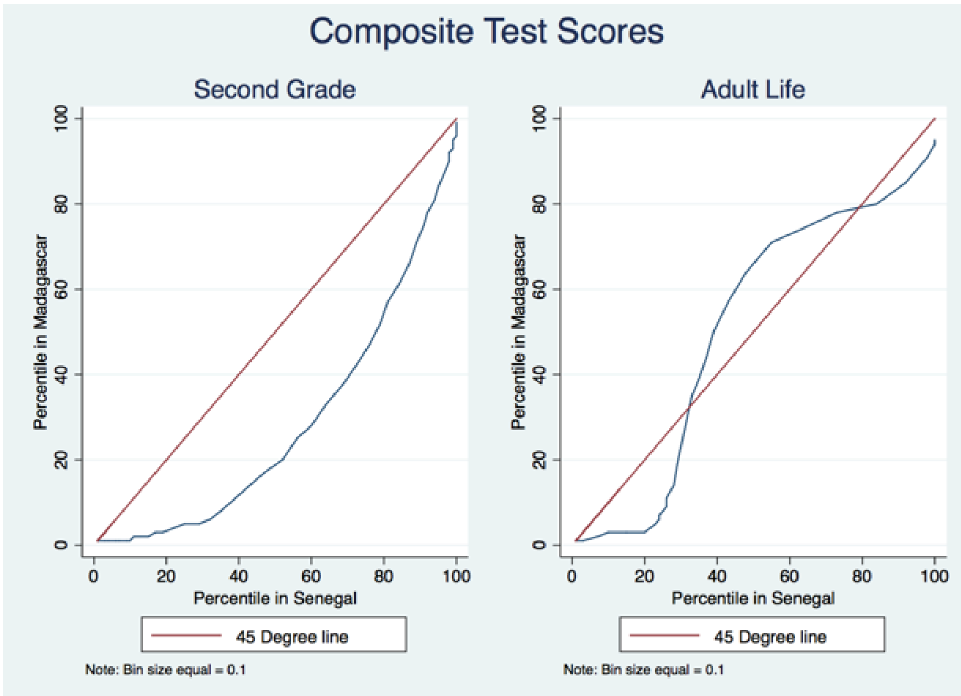
Figure 1: Cumulative distribution functions of test scores (cont.)

(c) French

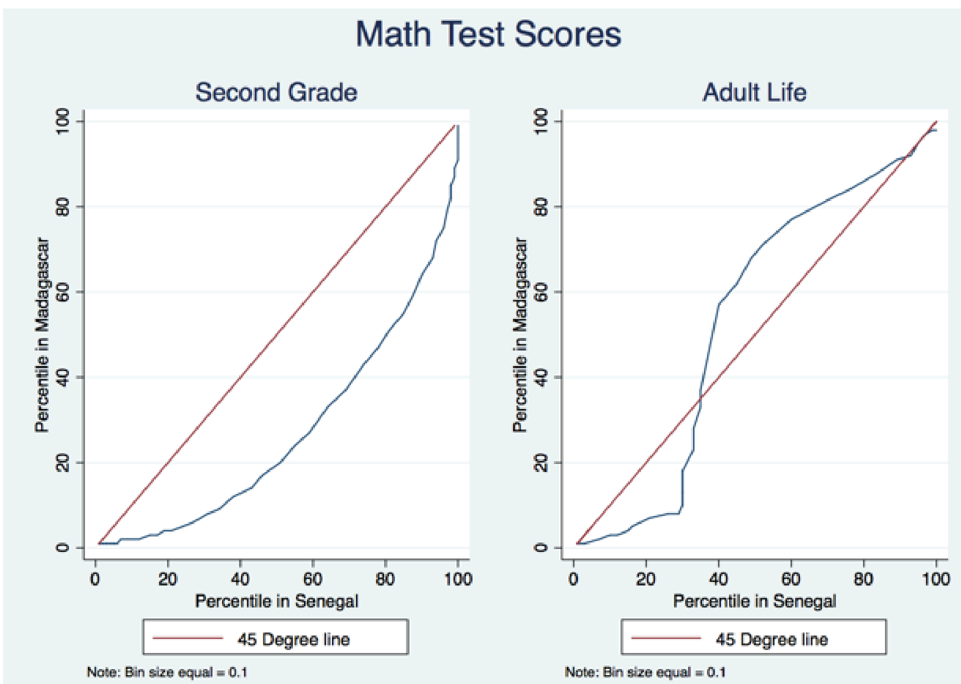


Note: Test scores used are jointly estimated for each round for both countries using IRT. They are comparable across countries within each round.

Figure 2: Percentile – percentile plots of test scores

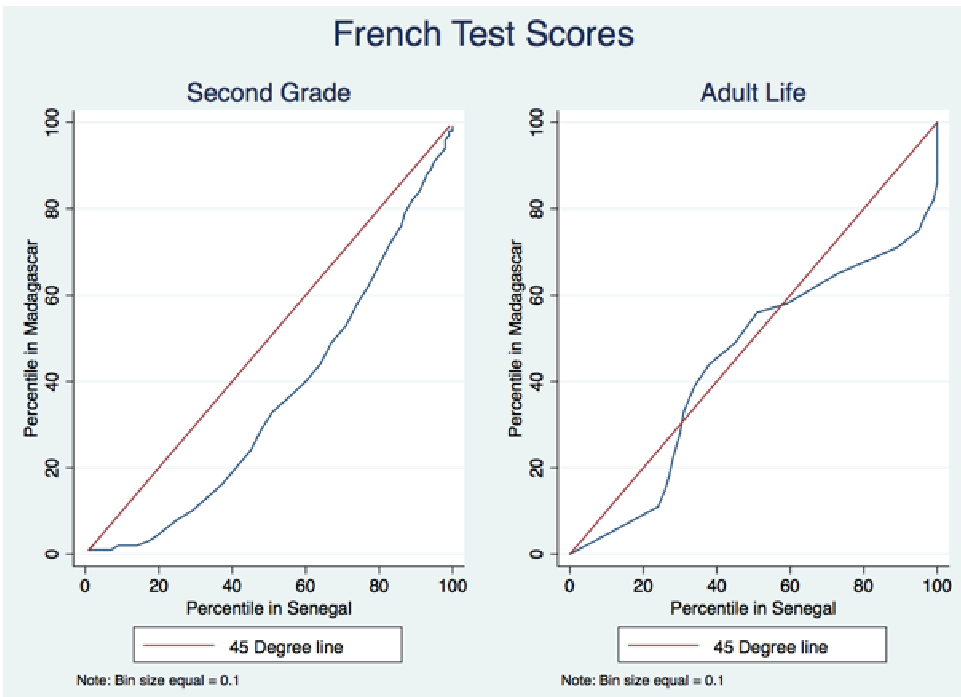


(a) Math and French



(b) Math

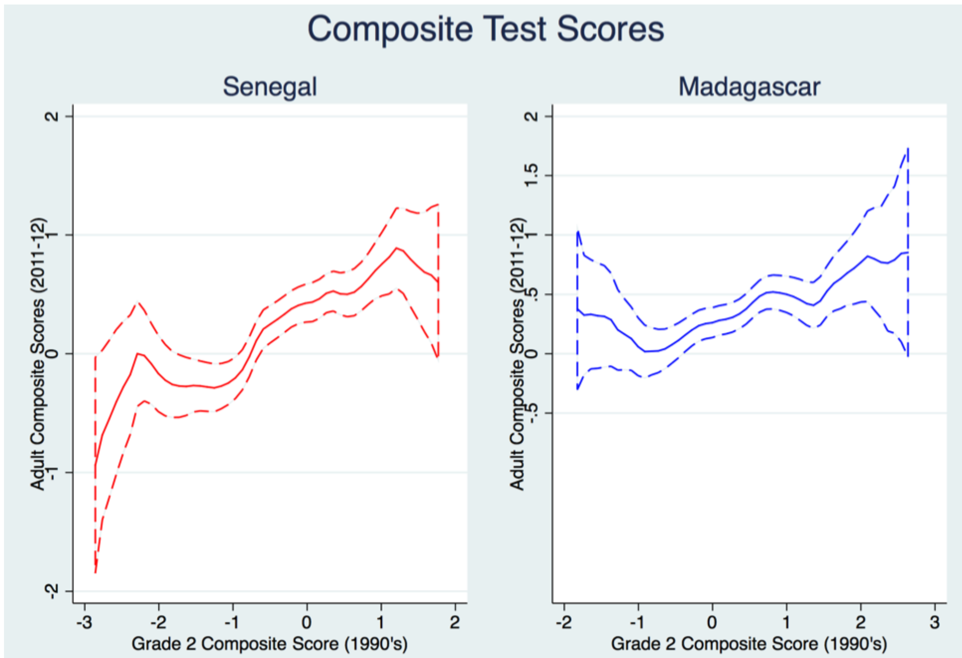
Figure 2: Percentile – percentile plots of test scores (cont.)



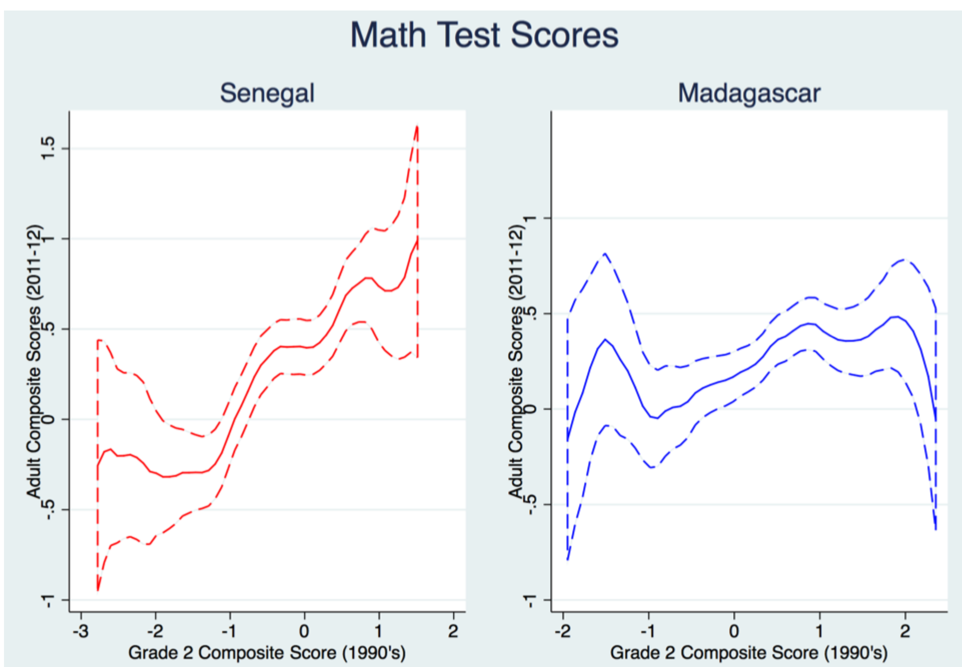
(c) French

Note: Test scores used are jointly estimated for each round for both countries using IRT. They are comparable across countries within each round.

Figure 3: Learning progress curves

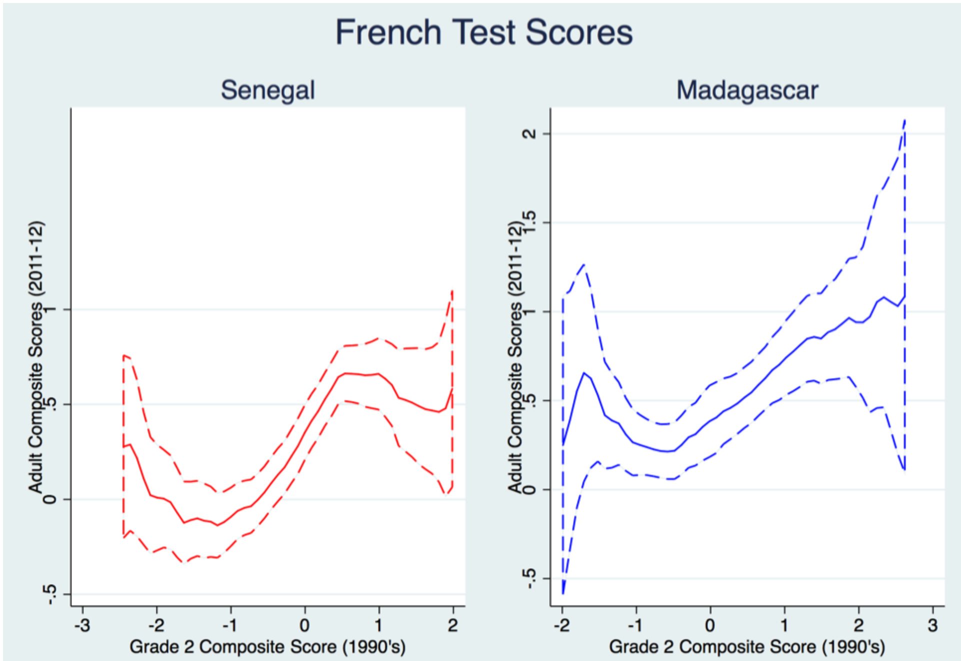


(a) Math and French



(b) Math

Figure 3: Learning progress curves (cont.)



(c) French

Note: Curves computed using Epanechikov kernel with of degree zero and bandwidth of 0.2 for both countries. Dashed lines are 95% confidence intervals. Test scores used are jointly estimated for each round for both countries using IRT. They are comparable across countries within each round.

5.2 Highest grade attained

Now we turn to the models in Tables 1a and 1b, where we show the relationship between cognitive ability in early life and the highest grade attained. It is important to note that the highest grade attained might be different from the number of years of schooling, since repeating grades is quite common in both countries, especially in this time period under consideration. This is something ubiquitous across all school systems in Africa that follow the French model.

The first column of Tables 1a and 1b display the results from simple OLS regressions with a single covariate, the composite post-test score from second grade. As pointed out earlier, the test score variables have been created using IRT with mean close to zero and standard deviation close to one. A score that is one standard deviation above the mean in the second grade implies that the highest grade attained will be around 1.6 years greater in Senegal and almost one year greater in Madagascar. Adding a series of household and individual covariates in column 2 leads to a slight fall in these coefficients to 1.49 in Senegal, and a larger decline to 0.49 in Madagascar, although they still remain significant at the 1 percent level.

In columns 3 and 4 of Tables 1a and 1b, we examine how the inclusion of adult height, a proxy measure of childhood health and nutritional status, affects this relationship. In column 3 of these tables, we see that when test scores are excluded, height has a positive and statistically significant impact on the highest grade attained in both countries. Being one centimeter taller is associated with an increase of 0.06 years and 0.04 years of schooling in Senegal and Madagascar, respectively. In column 4 we add back into the models the early childhood test scores. In comparison to column 3 (where early test score is excluded), the coefficient on height falls slightly in Senegal, while it rises slightly in Madagascar. The early childhood test score coefficient is virtually the same with and without including height.

These results indicate that the impact of early childhood human capital measured in terms of health and cognition operate largely independent of each other, although a small part of the impact of child health on adult cognition is potentially operating through early childhood cognitive ability in Senegal. Comparing columns 3 and 4, we find that the addition of the lagged test score leads to the height coefficient to fall by around 27 percent in Senegal and to rise by around 7 percent in Madagascar. To put the 27 and 7 percent decline in the height coefficient with the addition of the composite scores in context, Vogl (2014) conducted a similar analysis in Mexico and found that the inclusion of cognition scores in the estimation reduces the height premium in daily earnings by around 13 percent. Analogously, comparing columns 2 and 4 in Tables 1a and 1b, we find that the coefficient on the second grade composite score falls two percent (in Senegal) and rises by around one percent (in Madagascar) when the height variable is added to the model.[19]

[19]Additionally, we did try adding various interactions in these models, including between height and cognition, and between height and other variables of interest. None of these were significant. This may

As explained earlier, the second grade test score suffers from idiosyncratic measurement error problems, which could lead to a biased estimate of the coefficient. In column 5 of Tables 1a and 1b, we report the results from the IV strategy that corrects for this potential bias due to measurement error. In column 5 of Tables 1a and 1b, we include the pre-test composite score as an instrument for the post-test composite score. The F-statistic for the excluded instrument (labeled "widstat") is 237.6 in Senegal and 106.1 in Madagascar.

The second stage IV estimates in column 5 of Tables 1a and 1b suggest that scoring one standard deviation above the mean in the second grade on a composite math and French score leads to an increase of 0.9 years (Senegal) and around 0.5 years (Madagascar) on the highest grade attained. The coefficient is significant at the one percent level in Senegal, but is not statistically significant in Madagascar, despite that the value of the parameter estimate is the same as the OLS. The coefficient of height is still positive and significant in each country, and close in value to the OLS specification. This points towards a consistent narrative of the significant positive impact of health on cognitive achievement later in life.

Both the mother's and father's education have a positive impact on grade attainment in Madagascar. In Senegal, parents' have on average low levels of education, so instead of using a continuous measure of education, we use dummies for whether each parent has some education or not. Results show that parents education has a small positive impact on grade attainment, but this effect is not statistically significant.

Household assets have a large positive and significant impact on highest grade attained in Senegal. The corresponding effect in Madagascar is slightly smaller and is not statistically significant. We create the assets index using factor analysis on variables of household ownership of different assets in the second grade. We find that an increase of one unit in the asset index raises schooling by 0.75 years and 0.07 years in Senegal and Madagascar, respectively (column 4 in tables 1a and 1b). It is noteworthy to point out, that this coefficient estimate of the asset index is obtained while controlling for parental education. We also tried adding interaction terms of the early life scores separately with

in part be due to the small sample size in our models.

assets and parents' education to these models. These variables were not significant and were hence, omitted from the specifications reported here. Also, there does not seem to be a differential impact by gender, as indicated by the largely insignificant female dummy variable in both countries.

The variables denoting school inputs, teacher's education level and a school infrastructure index are not significant in the case of Senegal. In Madagascar, school infrastructure seems to have a statistically significant positive impact, while the education level of the teacher does not have a significant impact. This no longer holds, if we remove the infrastructure index from the specifications, then teacher's education is positive and significant, as expected. In Madagascar, an increase in one unit of the school infrastructure index is associated with 0.43 years of grades completed. A plausible explanation for these differential effects in the two countries is the fact that Madagascar was much poorer during the 90's, and hence had a minimal level of infrastructure and materials in school. Therefore, the presence of even small amount of infrastructure might have had a higher impact on outcomes. Whereas, although Senegal was also poor and underdeveloped, it's schools might have had a higher infrastructure level and hence had a smaller marginal impact on students' outcome.

5.3 Test scores

In the next set of tables we estimate the impact of early cognitive ability and early childhood health on composite test scores of French and math (Tables 2a and 2b), and math (Tables 3a and 3b) and French (Tables 4a and 4b) separately. The finding regarding the importance of early life ability is consistent with the results discussed earlier in terms of grade attainment.

In Table 2a, columns 1–4 show that there is a robust positive and significant relationship between early life cognitive ability and later life composite French and math scores in Senegal. In contrast, Table 2b indicates that this pattern exists in Madagascar as well, but the relationship is weaker. In contrast, there is a strong effect of height and school characteristics on composite test scores (discussed below). A one standard deviation increase in the second grade composite score leads to composite scores in 2012 that are 0.265 and 0.058 standard deviations higher Senegal and Madagascar, respectively (column 4 in Tables 2a & 2b).

As expected, Tables 2a and 2b show that adult height is positively associated with the composite scores in both countries, although the coefficient estimate is significant only in Madagascar. The stronger height parameter in Madagascar is perhaps due to the possibility that health inputs play a more significant role in human capital formation in Madagascar with its markedly worse health conditions. This is supported by the fact that in our sample, Malagasy young adults are on an average 10 centimeters shorter than their Senegalese counterparts.

Additionally, results in Table 2a suggest that in Senegal the coefficient associated with the assets of the household when the cohort member was in second grade is both positive and significant. A one-unit increase in the assets index is related to an increase in composite test scores by around 0.12–0.18 standard deviations.

In Madagascar mother's education has a positive and marginally significant relationship with the composite test score (column 2 of Table 2b). However, this effect disappears when the height variable is included in the regressions, indicating that the majority of the relationship may be operating through the positive health effects. One more year of education for the father is associated with an increase of the composite score by around 0.03 standard deviations in Madagascar. In contrast to the relationship of mother's education, this relationship is robust to the addition of height in these regressions. As was the case in Senegal, living in a household with more assets in second grade is associated with higher composite test scores later in life in Madagascar. This result is statistically significant in most specifications (columns 2-4 Table 2b) as opposed to the corresponding coefficient when the outcome was the highest grade attained (columns 2-4 Table 2a).

The IV specifications in column 5 in Tables 2a and 2b suggest a positive impact of second-grade composite scores on adult life composite scores. The effect sizes are comparable across the two countries, 0.13 in both Senegal and Madagascar. The Senegal results are statistically significant at the ten percent level, whereas the Madagascar t-statistic falls below standard levels of significance.

We observe similar patterns in the results in Tables 3a, 3b, 4a and 4b, where the individual 2012 math and French test scores, rather than the composite score, are the outcomes of interest. Early life cognitive ability seems to have a large and positive impact on both math and French scores in Senegal, whereas they have a positive, but smaller impact in Madagascar. The adult height coefficient is positive in the regressions of both math and French scores in both countries, but they are statistically significant only in the case of French test scores in Madagascar. Family assets has a robust positive and statistically significant relationship with both test scores in Senegal. In Madagascar, both the assets when in second grade and mother's education are positively associated with both adult math and French scores, but neither one of them is statistically significant.

The results in Tables 3a-4b are consistent with the results we found for the composite score in Tables 2a and 2b. Tables 2a, 3a and 4a suggest that in the Senegal IV specifications, the impacts of composite second grade-scores on adult life test scores are the following: composite score (0.13), math (0.33), and French (0.10). The analogous results for Madagascar are: composite score (0.13), math (0.15), and French (0.11). We see that the impact on the adult math scores is far stronger than French scores.[20]

The differences in both countries could be a result of the relative importance of family background and investment in children in these two countries. Our results showing that conditional on test scores in the second grade, family and school inputs matter less in Senegal than Madagascar is thus consistent with the results in Glick and Sahn (2009) and Glick et al. (2011).

[20] Using the z-scores of the percentage of correct answers as a dependent variable yields very similar in results to the ones presented above. This is due to the fact, that the z-scores and the IRT scores are very highly correlated. The results are available from the authors by request.

Table 1: Impact of early life composite French and math scores on grade completed

(a) Senegal

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV(1)
Math and French 2nd grade	1.629***	1.501***		1.473***	0.927***
	(0.20)	(0.20)		(0.20)	(0.31)
Height 2012			0.0518**	0.0369	0.0424*
			(0.025)	(0.023)	(0.023)
Female		-0.283	0.0603	0.0695	0.0661
		(0.35)	(0.46)	(0.42)	(0.42)
Age 2012		-0.516***	-0.500***	-0.522***	-0.514***
		(0.078)	(0.082)	(0.078)	(0.078)
Mother's education (Dummy)		0.869	0.637	0.707	0.681
		(0.60)	(0.64)	(0.61)	(0.60)
Father's education (Dummy)		0.292	0.295	0.263	0.275
		(0.46)	(0.51)	(0.46)	(0.47)
Assets 2nd grade		0.756***	1.076***	0.724***	0.854***
		(0.22)	(0.23)	(0.22)	(0.23)
School infrastructure 2nd grade		-0.159	-0.156	-0.147	-0.150
		(0.26)	(0.28)	(0.26)	(0.26)
Teacher's Education		0.0327	0.0447	0.0457	0.0453
		(0.070)	(0.076)	(0.071)	(0.071)
Constant	9.101***	20.97***	11.24**	14.46***	13.26***
	(0.18)	(2.12)	(4.83)	(4.59)	(4.60)
Observations	405	405	405	405	405
F	69.09	19.25	9.756	17.12	10.43
r2	0.139	0.241	0.142	0.246	0.232
widstat					237.8

Table 1: Impact of early life composite French and math scores on grade completed (cont.)

(b) Madagascar

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV
Math and French 2nd grade	0.993***	0.493***		0.499***	0.496
	(0.19)	(0.18)		(0.18)	(0.32)
Height 2012			0.0374*	0.0387*	0.0387*
			(0.021)	(0.020)	(0.020)
Female		-0.174	0.130	0.135	0.135
		(0.29)	(0.33)	(0.33)	(0.32)
Age 2012		-0.729***	-0.705***	-0.735***	-0.735***
		(0.11)	(0.11)	(0.11)	(0.11)
Mother's education		0.0824*	0.0894*	0.0746	0.0747
		(0.048)	(0.047)	(0.047)	(0.047)
Father's education		0.142***	0.146***	0.133***	0.133***
		(0.047)	(0.048)	(0.048)	(0.048)
Assets 2nd grade		0.0950	0.189	0.0736	0.0744
		(0.18)	(0.18)	(0.18)	(0.19)
School infrastructure 2nd grade		0.419**	0.443**	0.432**	0.432**
		(0.17)	(0.17)	(0.17)	(0.17)
Teacher's education		0.438***	0.520***	0.434***	0.435***
		(0.13)	(0.13)	(0.13)	(0.14)
Constant	10.08***	22.43***	15.27***	16.31***	16.31***
	(0.17)	(2.66)	(4.39)	(4.34)	(4.22)
Observations	333	333	333	333	333
F	26.51	42.13	38.79	38.39	37.52
r2	0.0848	0.359	0.348	0.365	0.365
widstat					106.1

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school. Household asset index and school infrastructure index are constructed using factor analysis. Heteroscedasticity-robust standard errors in paranthesis. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 2: Impact of early life composite French and math scores on adult composite French and math score

(a) Senegal

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV(1)
Math and French 2nd grade	0.301***	0.267***		0.265***	0.135*
	(0.046)	(0.047)		(0.048)	(0.072)
Height 2012			0.00617	0.00341	0.00476
			(0.0061)	(0.0059)	(0.0059)
Age 2012		-0.0780***	-0.0758***	-0.0785***	-0.0771***
		(0.021)	(0.022)	(0.021)	(0.021)
Female		-0.115	-0.0813	-0.0830	-0.0822
		(0.086)	(0.11)	(0.11)	(0.11)
Mother's education (Dummy)		-0.00576	-0.0300	-0.0203	-0.0250
		(0.16)	(0.17)	(0.16)	(0.16)
Father's education (Dummy)		0.00554	0.00340	0.00105	0.00220
		(0.12)	(0.13)	(0.12)	(0.12)
Assets 2nd grade		0.126**	0.184***	0.123**	0.153***
		(0.052)	(0.052)	(0.052)	(0.053)
School infrastructure 2nd grade		0.0688	0.0737	0.0690	0.0713
		(0.052)	(0.055)	(0.052)	(0.052)
Teacher's Education		0.0187	0.0207	0.0200	0.0204
		(0.017)	(0.018)	(0.018)	(0.017)
Constant	0.266***	1.928***	0.748	1.324	1.042
	(0.041)	(0.55)	(1.20)	(1.19)	(1.17)
Observations	349	349	349	349	349
F	43.40	9.263	4.699	8.316	4.878
r2	0.102	0.169	0.0976	0.170	0.153
widstat					208.2

Table 2: Impact of early life composite French and math scores on adult composite French and math score (cont.)

(b) Madagascar

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV
Math and French 2nd grade	0.205***	0.0541		0.0584	0.129
	(0.053)	(0.048)		(0.048)	(0.092)
Height 2012			0.0124**	0.0128**	0.0132**
			(0.0055)	(0.0056)	(0.0056)
Female		-0.0734	0.0285	0.0296	0.0308
		(0.080)	(0.087)	(0.087)	(0.086)
Age 2012		-0.118***	-0.116***	-0.121***	-0.127***
		(0.032)	(0.031)	(0.032)	(0.031)
Mother's education		0.0224*	0.0214	0.0198	0.0179
		(0.014)	(0.014)	(0.014)	(0.014)
Father's education		0.0335***	0.0322**	0.0303**	0.0280**
		(0.012)	(0.012)	(0.012)	(0.013)
Assets 2nd grade		0.106*	0.112**	0.0983*	0.0824
		(0.059)	(0.056)	(0.059)	(0.060)
School infrastructure 2nd grade		0.157***	0.160***	0.159***	0.157***
		(0.041)	(0.040)	(0.040)	(0.039)
Teacher's education		0.141***	0.149***	0.140***	0.128***
		(0.035)	(0.035)	(0.035)	(0.036)
Constant	0.306***	1.830**	-0.275	-0.153	-0.00554
	(0.046)	(0.78)	(1.12)	(1.11)	(1.08)
Observations	310	310	310	310	310
F	15.01	24.06	25.59	23.23	23.13
r2	0.0538	0.316	0.322	0.325	0.320
widstat					93.78

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school. Household asset index and school infrastructure index are constructed using factor analysis. Heteroscedasticity-robust standard errors in paranthesis. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 3: Impact of early life composite French and math scores on adult math score

(a) Senegal

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV(1)
Math and French 2nd grade	0.543***	0.493***		0.486***	0.339***
	(0.069)	(0.071)		(0.071)	(0.11)
Height 2012			0.0137	0.00883	0.0103
			(0.0090)	(0.0086)	(0.0086)
Age 2012		-0.136***	-0.130***	-0.137***	-0.135***
		(0.031)	(0.032)	(0.031)	(0.031)
Female		-0.336***	-0.255	-0.252*	-0.253*
		(0.12)	(0.16)	(0.15)	(0.15)
Mother's education (Dummy)		0.0528	-0.00927	0.0139	0.00694
		(0.22)	(0.26)	(0.23)	(0.23)
Father's education (Dummy)		0.0694	0.0731	0.0623	0.0655
		(0.16)	(0.18)	(0.16)	(0.16)
Assets 2nd grade		0.222***	0.330***	0.214***	0.249***
		(0.081)	(0.083)	(0.081)	(0.085)
School infrastructure 2nd grade		0.0973	0.0973	0.100	0.0993
		(0.089)	(0.098)	(0.089)	(0.089)
Teacher's Education		0.0234	0.0261	0.0265	0.0264
		(0.025)	(0.027)	(0.026)	(0.026)
Constant	0.448***	3.537***	0.916	1.979	1.658
	(0.062)	(0.81)	(1.78)	(1.73)	(1.72)
Observations	405	405	405	405	405
F	61.39	13.17	6.144	11.87	7.218
r2	0.125	0.202	0.112	0.204	0.196
widstat					237.8

Table 3: Impact of early life composite French and math scores on adult math score (cont.)

(b) Madagascar

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV
Math and French 2nd grade	0.175***	0.0637		0.0663	0.149
	(0.049)	(0.047)		(0.047)	(0.091)
Height 2012			0.00631	0.00672	0.00724
			(0.0054)	(0.0055)	(0.0055)
Female		-0.130	-0.0782	-0.0764	-0.0742
		(0.085)	(0.089)	(0.089)	(0.089)
Age 2012		-0.113***	-0.108***	-0.114***	-0.122***
		(0.033)	(0.033)	(0.033)	(0.033)
Mother's education		0.0196	0.0202	0.0185	0.0163
		(0.014)	(0.014)	(0.014)	(0.014)
Father's education		0.00791	0.00832	0.00611	0.00335
		(0.013)	(0.013)	(0.013)	(0.013)
Assets 2nd grade		0.105*	0.116**	0.101*	0.0817
		(0.054)	(0.053)	(0.054)	(0.056)
School infrastructure 2nd grade		0.120***	0.123***	0.122***	0.119***
		(0.043)	(0.043)	(0.042)	(0.042)
Teacher's education		0.116***	0.127***	0.115***	0.101***
		(0.036)	(0.036)	(0.036)	(0.039)
Constant	0.286***	2.047**	0.852	0.997	1.178
	(0.045)	(0.81)	(1.15)	(1.15)	(1.13)
Observations	318	318	318	318	318
F	12.80	13.73	14.11	12.79	12.94
r2	0.0406	0.212	0.210	0.215	0.207
widstat					98.86

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school. Household asset index and school infrastructure index are constructed using factor analysis. Heteroscedasticity-robust standard errors in paranthesis. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 4: Impact of early life composite French and math scores on adult French score

(a) Senegal

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV(1)
Math and French 2nd grade	0.278***	0.234***		0.232***	0.112
	(0.043)	(0.045)		(0.045)	(0.071)
Height 2012			0.00501	0.00259	0.00384
			(0.0059)	(0.0057)	(0.0057)
Age 2012		-0.0685***	-0.0665***	-0.0689***	-0.0676***
		(0.020)	(0.021)	(0.020)	(0.020)
Female		-0.0709	-0.0451	-0.0467	-0.0459
		(0.082)	(0.11)	(0.10)	(0.10)
Mother's education (Dummy)		0.0458	0.0262	0.0348	0.0303
		(0.14)	(0.16)	(0.15)	(0.15)
Father's education (Dummy)		0.0326	0.0313	0.0292	0.0303
		(0.11)	(0.12)	(0.11)	(0.12)
Assets 2nd grade		0.161***	0.212***	0.159***	0.187***
		(0.048)	(0.049)	(0.048)	(0.049)
School infrastructure 2nd grade		0.0539	0.0582	0.0541	0.0562
		(0.052)	(0.054)	(0.052)	(0.052)
Teacher's Education		0.0168	0.0184	0.0178	0.0181
		(0.016)	(0.017)	(0.017)	(0.017)
Constant	0.490***	1.928***	0.964	1.470	1.209
	(0.040)	(0.52)	(1.15)	(1.13)	(1.12)
Observations	349	349	349	349	349
F	41.20	10.09	5.852	9.106	5.797
r2	0.0952	0.170	0.109	0.170	0.154
widstat					208.2

Table 4: Impact of early life composite French and math scores on adult French score (cont.)

(b) Madagascar

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV
Math and French 2nd grade	0.237***	0.0503		0.0545	0.106
	(0.055)	(0.049)		(0.050)	(0.094)
Height 2012			0.0123*	0.0126*	0.0129**
			(0.0064)	(0.0065)	(0.0064)
Female		0.0339	0.135	0.136	0.136
		(0.080)	(0.100)	(0.100)	(0.098)
Age 2012		-0.0872**	-0.0862**	-0.0909***	-0.0953***
		(0.035)	(0.034)	(0.034)	(0.034)
Mother's education		0.0268*	0.0258*	0.0243*	0.0230
		(0.014)	(0.014)	(0.014)	(0.014)
Father's education		0.0526***	0.0513***	0.0495***	0.0478***
		(0.013)	(0.013)	(0.014)	(0.014)
Assets 2nd grade		0.101	0.106	0.0939	0.0821
		(0.069)	(0.067)	(0.069)	(0.070)
School infrastructure 2nd grade		0.156***	0.159***	0.158***	0.156***
		(0.042)	(0.041)	(0.040)	(0.040)
Teacher's education		0.175***	0.183***	0.174***	0.165***
		(0.035)	(0.035)	(0.035)	(0.035)
Constant	0.277***	0.764	-1.310	-1.193	-1.083
	(0.048)	(0.84)	(1.33)	(1.32)	(1.31)
Observations	312	312	312	312	312
F	18.39	30.66	32.18	28.85	28.68
r2	0.0644	0.358	0.364	0.367	0.365
widstat					95.43

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school. Household asset index and school infrastructure index are constructed using factor analysis. Heteroscedasticity-robust standard errors in paranthesis. Significance: *** p<0.01, ** p<0.05, * p<0.10.

5.4 Additional results

To add to our analysis, we replicate the regressions discussed above using a slightly modified empirical strategy. Instead of using the composite math and French scores as the measure of early childhood ability, we use the French and math scores separately as independent variables in the regression. We are motivated to do so to address the question of whether certain types of abilities are more important in affecting later life outcomes, a finding that has been reported elsewhere in the literature (Duncan et al. 2007; Duncan and Magnuson 2011).

We see that there is a strong and positive association of highest grade attained with second-grade French and math scores individually in Senegal, and only with respect to math in Madagascar. This effect persists even after the addition of childhood health inputs in these regressions. This is consistent with what we observed in our previous results (Tables 1a and 1b). In the IV regression, we use the second-grade French (math) pre-test as an instrument for the second-grade French (math) post-tests.

We find that the math scores have a strong and positive impact on highest grade attained in both countries. In Senegal, in the OLS specification, the impact of a one standard deviation rise in the second-grade math score leads to a rise in highest grade attained by about 1.32 years (column 4 in Table A-1a). The corresponding effect in Madagascar is 0.54 years (column 4 in Table A-1b). This effect size in each country is comparable to the impact of the composite score (Tables 1a and 1b) in both Senegal (1.47 years) and Madagascar (0.50 years). Similarly, the OLS specification in column 1 of Tables A-5a and A-5b tells us that the impact of the second-grade French test scores on highest grade attained are 1.22 (Senegal) and 0.26 (Madagascar), respectively. As compared to the math score results discussed above, these effects are much smaller and are not as close to the aforementioned composite test score results (Tables 1a and 1b). In fact, the impact of second grade French scores on highest grade is not statistically significant. In Tables A-2a-A-4a & A-2b-A-4b, we replicate the results for the other outcomes using math and French test scores in second grade as the main dependent variable of interest.

5.5 Addressing omitted variable bias

As an additional robustness check, we use the method by Oster (2017) to examine the issue of whether omitted variable bias affects our results regarding the the impact of lagged test score, our main variable of interest.

Tables 5a and 5b report the results for Senegal and Madagascar, respectively. Column 1 reports the β from the model with no controls (column 1 in Tables 1-4), and column 2 the the β in the model with full controls (column 4 in Tables 1-4) for the lagged test score. Columns 3 and 4 report the results from the Oster (2017) test: the lower bound of β and the the test statistic δ, respectively.[21]

We can see that particularly in the case of Senegal (Table 5a), the coefficients of the lagged test score are very stable, especially for grade completed and math. In the case of Madagascar (Table 5b), however, the coefficient estimates stay positive for grade completed, but are unstable for the test scores. For instance, the bias corrected coefficients for the highest grade obtained would be 1.24 and 0.09 in Senegal and Madagascar respectively.

Columns 4 reports how influential the unobservables would have to be to produce $\beta = 0$. In the case of Senegal, all the δ's are well above one, which confirms the story of the high importance of the early life test scores in all the regressions. As an illustration, for the impact of test scores on highest grade attained to become zero, the unobservables would have to be 3.6 times more influential than the observables. This seems highly unlikely. In the case of Madagascar, δ is larger than one in the regression on grade completed and less than one for the test score outcomes. This is in line with the findings from the regressions where these coefficient estimates are less statistically significant.

[21] In all the specifications we assume $R_{max} = 1.5 \times R^2$, where R^2 is the R^2 of the equation with full controls. For calculating β in column 3, we assume that $\delta = 1$.

Table 5: Results of Oster test

(a) Senegal

Dependent variable	Beta No Control (1)	Beta Full Controls (2)	Beta Oster-test (3)	Delta Oster-test (4)
Highest grade	1.629	1.473	1.269	3.843
Math and French score	0.301	0.265	0.147	1.612
Math score	0.543	0.486	0.374	2.492
French score	0.278	0.232	0.123	1.596

(b) Madagascar

Dependent variable	Beta No Control (1)	Beta Full Controls (2)	Beta Oster-test (3)	Delta Oster-test (4)
Highest grade	0.993	0.499	0.094	1.190
Math and French score	0.205	0.058	-0.046	0.585
Math score	0.175	0.066	-0.016	0.825
French score	0.237	0.054	-0.072	0.449

Notes: All test scores are constructed using country specific IRT. Column (1) is equivalent to the first row in column (1) in Tables 1-4. Column (2) is equivalent to the first row in column (4) in Tables 1-4. Column (3) and (4) report the β and δ from the Oster test using $R_{max} = 1.5 \times R^2$.

6 Conclusions

We find persuasive evidence of the impact of early life cognitive ability and health on educational outcomes and cognitive skills in early adult life across two Francophone Sub-Saharan African countries, Senegal and Madagascar. By using comparable panel datasets from these countries, we find that Malagasy children had higher skills in both math and language (French) while in second grade in school. But, these differences disappear in young adulthood.

Using different measures of early life cognitive skills in a human capital production function framework, we find that early life (second grade) composite math and French test scores have large and significant impacts on highest grade attained in both countries. Early life cognitive skills have an enduring effect on cognitive skills in young adulthood. This relationship is stronger in Senegal than in Madagascar. We find that in both countries, math scores are stronger predictors of later life outcomes than French scores. Additionally, child health, measured by using adult height as a proxy, also has a significant impact on adult human capital. These effects of early cognitive ability and health on later life outcomes are robust to the inclusion of each other in the specification, indicating they are operating through different pathways.

These results are robust to the addition of other childhood inputs, such as parental education and asset levels, as well as school inputs, teacher education and school infrastructure measured at the time of entry into second grade in primary school. Parental inputs have an independent effect on early adulthood outcomes in both countries, but school inputs only have an enduring effect in the case of Madagascar. Household asset levels seem to have a significant positive impact on young adulthood outcomes in Senegal. Furthermore, our results are robust to tests of omitted variable bias suggested in Oster (2017).

These results imply large and robust impacts of early life ability endowment and argue for policies that target preschool-aged children who are lagging behind other children in terms of their skills and health status. It is important to note that although the analysis argues for early childhood interventions, it does not provide insights into the exact nature of the interventions required.

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Appendix

A Results on math and French separately

A-1 Impact of early life math scores

Table A-1: Impact of early life math score on grade completed

(a) Senegal

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV(1)
Math 2nd grade	1.452***	1.343***		1.320***	1.248***
	(0.18)	(0.18)		(0.19)	(0.31)
Height 2012			0.0518**	0.0399*	0.0405*
			(0.025)	(0.024)	(0.024)
Female		-0.160	0.0603	0.219	0.211
		(0.35)	(0.46)	(0.42)	(0.42)
Age 2012		-0.511***	-0.500***	-0.518***	-0.517***
		(0.077)	(0.082)	(0.077)	(0.077)
Mother's education (Dummy)		1.032*	0.637	0.853	0.842
		(0.60)	(0.64)	(0.62)	(0.61)
Father's education (Dummy)		0.383	0.295	0.349	0.346
		(0.47)	(0.51)	(0.47)	(0.46)
Assets 2nd grade		0.804***	1.076***	0.768***	0.785***
		(0.22)	(0.23)	(0.22)	(0.23)
School infrastructure 2nd grade		-0.170	-0.156	-0.157	-0.157
		(0.26)	(0.28)	(0.26)	(0.26)
Teacher's Education		0.0336	0.0447	0.0476	0.0475
		(0.071)	(0.076)	(0.072)	(0.071)
Constant	9.038***	20.73***	11.24**	13.70***	13.57***
	(0.18)	(2.13)	(4.83)	(4.73)	(4.69)
Observations	405	405	405	405	405
F	64.77	19.24	9.756	17.36	11.28
r2	0.126	0.232	0.142	0.238	0.238
widstat					178.5

Table A-1: Impact of early life math score on grade completed (cont.)

(b) Madagascar

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV
Math 2nd grade	0.907***	0.547***		0.544***	0.663**
	(0.21)	(0.18)		(0.18)	(0.32)
Height 2012			0.0374*	0.0365*	0.0363*
			(0.021)	(0.020)	(0.020)
Female		-0.141	0.130	0.150	0.154
		(0.29)	(0.33)	(0.33)	(0.32)
Age 2012		-0.728***	-0.705***	-0.733***	-0.739***
		(0.11)	(0.11)	(0.11)	(0.10)
Mother's education		0.0827*	0.0894*	0.0757	0.0727
		(0.047)	(0.047)	(0.047)	(0.046)
Father's education		0.148***	0.146***	0.140***	0.138***
		(0.047)	(0.048)	(0.048)	(0.047)
Assets 2nd grade		0.171	0.189	0.152	0.144
		(0.18)	(0.18)	(0.18)	(0.18)
School infrastructure 2nd grade		0.386**	0.443**	0.399**	0.389**
		(0.17)	(0.17)	(0.17)	(0.17)
Teacher's education		0.455***	0.520***	0.453***	0.438***
		(0.13)	(0.13)	(0.13)	(0.13)
Constant	10.03***	22.25***	15.27***	16.46***	16.72***
	(0.17)	(2.62)	(4.39)	(4.32)	(4.22)
Observations	333	333	333	333	333
F	19.47	42.66	38.79	39.06	39.05
r2	0.0634	0.363	0.348	0.368	0.367
widstat					106.0

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school. Household asset index and school infrastructure index are constructed using factor analysis. Heteroscedasticity-robust standard errors in paranthesis. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table A-2: Impact of early life math score on adult composite French and math scores

(a) Senegal

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	IV(1)
Math 2nd grade	0.261***	0.227***		0.225***	0.205***
	(0.045)	(0.046)		(0.046)	(0.076)
Height 2012			0.00617	0.00437	0.00453
			(0.0061)	(0.0060)	(0.0059)
Age 2012		-0.0771***	-0.0758***	-0.0777***	-0.0775***
		(0.020)	(0.022)	(0.021)	(0.020)
Female		-0.0936	-0.0813	-0.0528	-0.0553
		(0.087)	(0.11)	(0.11)	(0.11)
Mother's education (Dummy)		0.0199	-0.0300	0.00110	-0.00165
		(0.16)	(0.17)	(0.16)	(0.16)
Father's education (Dummy)		0.0126	0.00340	0.00676	0.00646
		(0.12)	(0.13)	(0.12)	(0.12)
Assets 2nd grade		0.136***	0.184***	0.132**	0.136**
		(0.051)	(0.052)	(0.052)	(0.054)
School infrastructure 2nd grade		0.0663	0.0737	0.0666	0.0673
		(0.053)	(0.055)	(0.053)	(0.052)
Teacher's Education		0.0191	0.0207	0.0208	0.0208
		(0.017)	(0.018)	(0.018)	(0.018)
Constant	0.254***	1.880***	0.748	1.107	1.075
	(0.042)	(0.55)	(1.20)	(1.20)	(1.18)
Observations	349	349	349	349	349
F	33.30	7.986	4.699	7.277	5.562
r2	0.0867	0.156	0.0976	0.157	0.156
widstat					157.1

Table A-2: Impact of early life math score on adult composite French and math scores (cont.)

(b) Madagascar

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV
Math 2nd grade	0.170***	0.0667		0.0683	0.113
	(0.059)	(0.052)		(0.052)	(0.090)
Height 2012			0.0124**	0.0126**	0.0127**
			(0.0055)	(0.0055)	(0.0055)
Female		-0.0703	0.0285	0.0314	0.0333
		(0.080)	(0.087)	(0.087)	(0.085)
Age 2012		-0.118***	-0.116***	-0.122***	-0.125***
		(0.032)	(0.031)	(0.032)	(0.031)
Mother's education		0.0222	0.0214	0.0198	0.0187
		(0.013)	(0.014)	(0.014)	(0.014)
Father's education		0.0342***	0.0322**	0.0312**	0.0305**
		(0.012)	(0.012)	(0.012)	(0.012)
Assets 2nd grade		0.114**	0.112**	0.107*	0.105*
		(0.057)	(0.056)	(0.056)	(0.056)
School infrastructure 2nd grade		0.153***	0.160***	0.154***	0.151***
		(0.040)	(0.040)	(0.039)	(0.039)
Teacher's education		0.142***	0.149***	0.141***	0.136***
		(0.035)	(0.035)	(0.035)	(0.034)
Constant	0.298***	1.827**	-0.275	-0.135	-0.0428
	(0.046)	(0.79)	(1.12)	(1.11)	(1.08)
Observations	310	310	310	310	310
F	8.180	24.25	25.59	23.41	23.66
r2	0.0329	0.317	0.322	0.327	0.325
widstat					99.41

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school. Household asset index and school infrastructure index are constructed using factor analysis. Heteroscedasticity-robust standard errors in paranthesis. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table A-3: Impact of early life math score on adult math score

(a) Senegal

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV(1)
Math 2nd grade	0.498***	0.447***		0.441***	0.447***
	(0.067)	(0.066)		(0.067)	(0.11)
Height 2012			0.0137	0.00976	0.00970
			(0.0090)	(0.0086)	(0.0085)
Age 2012		-0.134***	-0.130***	-0.136***	-0.136***
		(0.030)	(0.032)	(0.030)	(0.030)
Female		-0.294**	-0.255	-0.202	-0.201
		(0.12)	(0.16)	(0.15)	(0.15)
Mother's education (Dummy)		0.107	-0.00927	0.0632	0.0643
		(0.22)	(0.26)	(0.23)	(0.23)
Father's education (Dummy)		0.0992	0.0731	0.0909	0.0912
		(0.16)	(0.18)	(0.16)	(0.16)
Assets 2nd grade		0.236***	0.330***	0.227***	0.226***
		(0.081)	(0.083)	(0.081)	(0.085)
School infrastructure 2nd grade		0.0938	0.0973	0.0970	0.0970
		(0.092)	(0.098)	(0.091)	(0.090)
Teacher's Education		0.0237	0.0261	0.0271	0.0271
		(0.026)	(0.027)	(0.026)	(0.026)
Constant	0.428***	3.460***	0.916	1.740	1.752
	(0.063)	(0.80)	(1.78)	(1.74)	(1.71)
Observations	405	405	405	405	405
F	55.88	12.58	6.144	11.55	8.101
r2	0.120	0.197	0.112	0.199	0.199
widstat					178.5

Table A-3: Impact of early life math score on adult math score (cont.)

(b) Madagascar

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV
Math 2nd grade	0.163***	0.0878*		0.0888*	0.129
	(0.054)	(0.050)		(0.050)	(0.092)
Height 2012			0.00631	0.00654	0.00664
			(0.0054)	(0.0054)	(0.0054)
Female		-0.126	-0.0782	-0.0739	-0.0719
		(0.085)	(0.089)	(0.089)	(0.088)
Age 2012		-0.114***	-0.108***	-0.116***	-0.119***
		(0.033)	(0.033)	(0.033)	(0.033)
Mother's education		0.0192	0.0202	0.0182	0.0173
		(0.014)	(0.014)	(0.014)	(0.014)
Father's education		0.00846	0.00832	0.00677	0.00606
		(0.013)	(0.013)	(0.013)	(0.013)
Assets 2nd grade		0.114**	0.116**	0.111**	0.108**
		(0.053)	(0.053)	(0.052)	(0.052)
School infrastructure 2nd grade		0.114***	0.123***	0.116***	0.112***
		(0.042)	(0.043)	(0.042)	(0.043)
Teacher's education		0.117***	0.127***	0.116***	0.111***
		(0.037)	(0.036)	(0.037)	(0.037)
Constant	0.277***	2.075**	0.852	1.049	1.138
	(0.045)	(0.82)	(1.15)	(1.15)	(1.13)
Observations	318	318	318	318	318
F	9.033	14.21	14.11	13.18	13.25
r2	0.0313	0.216	0.210	0.218	0.217
widstat					101.7

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school. Household asset index and school infrastructure index are constructed using factor analysis. Heteroscedasticity-robust standard errors in paranthesis. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A-4: Impact of early life math score on adult French score

(a) Senegal

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV(1)
Math 2nd grade	0.226***	0.185***		0.183***	0.177**
	(0.042)	(0.043)		(0.044)	(0.073)
Height 2012			0.00501	0.00354	0.00359
			(0.0059)	(0.0058)	(0.0057)
Age 2012		-0.0676***	-0.0665***	-0.0681***	-0.0680***
		(0.020)	(0.021)	(0.020)	(0.020)
Female		-0.0550	-0.0451	-0.0219	-0.0227
		(0.083)	(0.11)	(0.10)	(0.10)
Mother's education (Dummy)		0.0668	0.0262	0.0515	0.0507
		(0.15)	(0.16)	(0.15)	(0.15)
Father's education (Dummy)		0.0388	0.0313	0.0340	0.0339
		(0.12)	(0.12)	(0.12)	(0.12)
Assets 2nd grade		0.173***	0.212***	0.170***	0.171***
		(0.048)	(0.049)	(0.049)	(0.050)
School infrastructure 2nd grade		0.0522	0.0582	0.0525	0.0527
		(0.053)	(0.054)	(0.052)	(0.052)
Teacher's Education		0.0171	0.0184	0.0185	0.0185
		(0.017)	(0.017)	(0.017)	(0.017)
Constant	0.478***	1.883***	0.964	1.256	1.247
	(0.040)	(0.52)	(1.15)	(1.15)	(1.13)
Observations	349	349	349	349	349
F	28.66	8.572	5.852	7.917	6.405
r2	0.0716	0.151	0.109	0.152	0.152
widstat					157.1

Table A-4: Impact of early life math score on adult French score (cont.)

(b) Madagascar

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV
Math 2nd grade	0.177***	0.0499		0.0515	0.113
	(0.062)	(0.054)		(0.054)	(0.090)
Height 2012			0.0123*	0.0124*	0.0126**
			(0.0064)	(0.0065)	(0.0064)
Female		0.0368	0.135	0.137	0.139
		(0.081)	(0.100)	(0.10)	(0.098)
Age 2012		-0.0867**	-0.0862**	-0.0901***	-0.0947***
		(0.035)	(0.034)	(0.035)	(0.035)
Mother's education		0.0270*	0.0258*	0.0246*	0.0231*
		(0.014)	(0.014)	(0.014)	(0.014)
Father's education		0.0535***	0.0513***	0.0505***	0.0496***
		(0.013)	(0.013)	(0.013)	(0.013)
Assets 2nd grade		0.109	0.106	0.103	0.0994
		(0.068)	(0.067)	(0.067)	(0.067)
School infrastructure 2nd grade		0.153***	0.159***	0.155***	0.150***
		(0.042)	(0.041)	(0.040)	(0.040)
Teacher's education		0.177***	0.183***	0.176***	0.169***
		(0.035)	(0.035)	(0.035)	(0.034)
Constant	0.268***	0.731	-1.310	-1.203	-1.076
	(0.049)	(0.85)	(1.33)	(1.32)	(1.31)
Observations	312	312	312	312	312
F	8.187	30.71	32.18	28.89	28.90
r2	0.0318	0.358	0.364	0.367	0.363
widstat					100.5

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school. Household asset index and school infrastructure index are constructed using factor analysis. Heteroscedasticity-robust standard errors in paranthesis. Significance: *** p<0.01, ** p<0.05, * p<0.10.

A-2 Impact of early life French scores

Table A-5: Impact of early life French score on grade completed

(a) Senegal

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV(1)
French 2nd grade	1.387***	1.247***		1.220***	0.639
	(0.22)	(0.22)		(0.22)	(0.41)
Height 2012			0.0518**	0.0414*	0.0464*
			(0.025)	(0.024)	(0.024)
Female		-0.450	0.0603	-0.0506	0.00217
		(0.36)	(0.46)	(0.43)	(0.44)
Age 2012		-0.515***	-0.500***	-0.521***	-0.511***
		(0.080)	(0.082)	(0.080)	(0.080)
Mother's education (Dummy)		0.748	0.637	0.569	0.601
		(0.60)	(0.64)	(0.62)	(0.61)
Father's education (Dummy)		0.219	0.295	0.187	0.239
		(0.48)	(0.51)	(0.48)	(0.48)
Assets 2nd grade		0.845***	1.076***	0.808***	0.935***
		(0.22)	(0.23)	(0.22)	(0.24)
School infrastructure 2nd grade		-0.148	-0.156	-0.135	-0.145
		(0.26)	(0.28)	(0.26)	(0.27)
Teacher's Education		0.0261	0.0447	0.0408	0.0426
		(0.071)	(0.076)	(0.072)	(0.073)
Constant	9.090***	21.08***	11.24**	13.77***	12.56***
	(0.18)	(2.17)	(4.83)	(4.61)	(4.70)
Observations	405	405	405	405	405
F	39.86	15.18	9.756	13.58	9.308
r2	0.0961	0.205	0.142	0.211	0.195
widstat					126.6

Table A-5: Impact of early life French score on grade completed (cont.)

(b) Madagascar

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV
French 2nd grade	0.782***	0.248		0.264	0.359
	(0.18)	(0.17)		(0.17)	(0.41)
Height 2012			0.0374*	0.0393*	0.0401**
			(0.021)	(0.020)	(0.020)
Female		-0.182	0.130	0.131	0.131
		(0.30)	(0.33)	(0.33)	(0.33)
Age 2012		-0.709***	-0.705***	-0.716***	-0.719***
		(0.11)	(0.11)	(0.11)	(0.11)
Mother's education		0.0914*	0.0894*	0.0834*	0.0812*
		(0.048)	(0.047)	(0.047)	(0.047)
Father's education		0.146***	0.146***	0.137***	0.134***
		(0.047)	(0.048)	(0.048)	(0.050)
Assets 2nd grade		0.131	0.189	0.105	0.0749
		(0.19)	(0.18)	(0.19)	(0.22)
School infrastructure 2nd grade		0.445**	0.443**	0.460***	0.466***
		(0.17)	(0.17)	(0.17)	(0.17)
Teacher's education		0.481***	0.520***	0.475***	0.459***
		(0.13)	(0.13)	(0.13)	(0.14)
Constant	10.11***	21.71***	15.27***	15.51***	15.60***
	(0.17)	(2.70)	(4.39)	(4.37)	(4.26)
Observations	333	333	333	333	333
F	18.99	39.34	38.79	35.51	35.27
r2	0.0582	0.346	0.348	0.353	0.352
widstat					65.84

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school. Household asset index and school infrastructure index are constructed using factor analysis. Heteroscedasticity-robust standard errors in paranthesis. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A-6: Impact of early life French score on adult composite French and math scores

(a) Senegal

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV(1)
French 2nd grade	0.260***	0.230***		0.227***	0.0815
	(0.045)	(0.047)		(0.047)	(0.091)
Height 2012			0.00617	0.00388	0.00535
			(0.0061)	(0.0059)	(0.0060)
Age 2012		-0.0784***	-0.0758***	-0.0789***	-0.0769***
		(0.022)	(0.022)	(0.022)	(0.021)
Female		-0.141	-0.0813	-0.104	-0.0894
		(0.088)	(0.11)	(0.11)	(0.11)
Mother's education (Dummy)		-0.0295	-0.0300	-0.0457	-0.0356
		(0.16)	(0.17)	(0.16)	(0.17)
Father's education (Dummy)		0.000253	0.00340	-0.00478	0.000467
		(0.12)	(0.13)	(0.12)	(0.12)
Assets 2nd grade		0.140***	0.184***	0.137***	0.167***
		(0.052)	(0.052)	(0.052)	(0.054)
School infrastructure 2nd grade		0.0747	0.0737	0.0749	0.0741
		(0.053)	(0.055)	(0.052)	(0.053)
Teacher's Education		0.0174	0.0207	0.0189	0.0201
		(0.017)	(0.018)	(0.018)	(0.018)
Constant	0.264***	1.966***	0.748	1.278	0.938
	(0.042)	(0.57)	(1.20)	(1.18)	(1.19)
Observations	349	349	349	349	349
F	32.87	8.449	4.699	7.562	4.349
r2	0.0741	0.149	0.0976	0.150	0.129
widstat					111.9

Table A-6: Impact of early life French score on adult composite French and math scores (cont.)

(b) Madagascar

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV
French 2nd grade	0.167***	0.0154		0.0219	0.122
	(0.049)	(0.046)		(0.046)	(0.12)
Height 2012			0.0124**	0.0127**	0.0136**
			(0.0055)	(0.0056)	(0.0058)
Female		-0.0728	0.0285	0.0289	0.0304
		(0.080)	(0.087)	(0.087)	(0.087)
Age 2012		-0.114***	-0.116***	-0.118***	-0.123***
		(0.032)	(0.031)	(0.032)	(0.031)
Mother's education		0.0235*	0.0214	0.0210	0.0190
		(0.014)	(0.014)	(0.014)	(0.014)
Father's education		0.0346***	0.0322**	0.0313**	0.0271**
		(0.012)	(0.012)	(0.012)	(0.013)
Assets 2nd grade		0.113*	0.112**	0.105*	0.0731
		(0.062)	(0.056)	(0.061)	(0.067)
School infrastructure 2nd grade		0.159***	0.160***	0.162***	0.168***
		(0.041)	(0.040)	(0.040)	(0.041)
Teacher's education		0.148***	0.149***	0.146***	0.130***
		(0.035)	(0.035)	(0.035)	(0.039)
Constant	0.315***	1.706**	-0.275	-0.253	-0.156
	(0.046)	(0.77)	(1.12)	(1.11)	(1.09)
Observations	310	310	310	310	310
F	11.89	23.81	25.59	22.85	22.40
r2	0.0407	0.313	0.322	0.322	0.311
widstat					58.27

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school. Household asset index and school infrastructure index are constructed using factor analysis. Heteroscedasticity-robust standard errors in paranthesis. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table A-7: Impact of early life French score on adult math score

(a) Senegal

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV(1)
French 2nd grade	0.457***	0.413***		0.406***	0.278*
	(0.073)	(0.075)		(0.075)	(0.14)
Height 2012			0.0137	0.0103	0.0114
			(0.0090)	(0.0087)	(0.0088)
Age 2012		-0.136***	-0.130***	-0.137***	-0.135***
		(0.032)	(0.032)	(0.032)	(0.032)
Female		-0.391***	-0.255	-0.292*	-0.280*
		(0.13)	(0.16)	(0.15)	(0.15)
Mother's education (Dummy)		0.0127	-0.00927	-0.0319	-0.0248
		(0.23)	(0.26)	(0.24)	(0.24)
Father's education (Dummy)		0.0449	0.0731	0.0370	0.0483
		(0.17)	(0.18)	(0.17)	(0.17)
Assets 2nd grade		0.250***	0.330***	0.241***	0.269***
		(0.082)	(0.083)	(0.082)	(0.087)
School infrastructure 2nd grade		0.101	0.0973	0.104	0.102
		(0.091)	(0.098)	(0.089)	(0.090)
Teacher's Education		0.0212	0.0261	0.0248	0.0252
		(0.026)	(0.027)	(0.026)	(0.026)
Constant	0.444***	3.574***	0.916	1.759	1.494
	(0.064)	(0.84)	(1.78)	(1.73)	(1.76)
Observations	405	405	405	405	405
F	38.77	10.82	6.144	9.719	6.301
r2	0.0845	0.171	0.112	0.174	0.168
widstat					126.6

Table A-7: Impact of early life French score on adult math score (cont.)

(b) Madagascar

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV
French 2nd grade	0.125***	0.00609		0.00953	0.151
	(0.048)	(0.047)		(0.048)	(0.12)
Height 2012			0.00631	0.00640	0.00778
			(0.0054)	(0.0055)	(0.0058)
Female		-0.129	-0.0782	-0.0780	-0.0749
		(0.085)	(0.089)	(0.090)	(0.090)
Age 2012		-0.108***	-0.108***	-0.109***	-0.118***
		(0.033)	(0.033)	(0.033)	(0.033)
Mother's education		0.0211	0.0202	0.0200	0.0172
		(0.014)	(0.014)	(0.014)	(0.014)
Father's education		0.00970	0.00832	0.00793	0.00210
		(0.013)	(0.013)	(0.013)	(0.013)
Assets 2nd grade		0.117**	0.116**	0.113**	0.0672
		(0.057)	(0.053)	(0.057)	(0.066)
School infrastructure 2nd grade		0.122***	0.123***	0.124***	0.133***
		(0.043)	(0.043)	(0.043)	(0.042)
Teacher's education		0.126***	0.127***	0.125***	0.101**
		(0.036)	(0.036)	(0.036)	(0.042)
Constant	0.292***	1.861**	0.852	0.862	1.007
	(0.045)	(0.80)	(1.15)	(1.15)	(1.14)
Observations	318	318	318	318	318
F	6.810	13.45	14.11	12.54	12.26
r2	0.0233	0.207	0.210	0.210	0.187
widstat					60.36

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school. Household asset index and school infrastructure index are constructed using factor analysis. Heteroscedasticity-robust standard errors in paranthesis. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table A-8: Impact of early life French score on adult French score

(a) Senegal

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	IV(1)
French 2nd grade	0.255***	0.216***		0.214***	0.0551
	(0.044)	(0.045)		(0.045)	(0.089)
Height 2012			0.00501	0.00286	0.00445
			(0.0059)	(0.0057)	(0.0058)
Age 2012		-0.0691***	-0.0665***	-0.0695***	-0.0673***
		(0.020)	(0.021)	(0.021)	(0.020)
Female		-0.0933	-0.0451	-0.0664	-0.0506
		(0.083)	(0.11)	(0.10)	(0.10)
Mother's education (Dummy)		0.0234	0.0262	0.0115	0.0224
		(0.14)	(0.16)	(0.15)	(0.15)
Father's education (Dummy)		0.0273	0.0313	0.0236	0.0293
		(0.11)	(0.12)	(0.11)	(0.12)
Assets 2nd grade		0.170***	0.212***	0.168***	0.201***
		(0.048)	(0.049)	(0.048)	(0.050)
School infrastructure 2nd grade		0.0592	0.0582	0.0594	0.0585
		(0.051)	(0.054)	(0.051)	(0.052)
Teacher's Education		0.0156	0.0184	0.0167	0.0180
		(0.016)	(0.017)	(0.017)	(0.017)
Constant	0.490***	1.969***	0.964	1.462	1.093
	(0.040)	(0.53)	(1.15)	(1.12)	(1.13)
Observations	349	349	349	349	349
F	33.06	9.533	5.852	8.537	5.320
r2	0.0785	0.159	0.109	0.160	0.132
widstat					111.9

Table A-8: Impact of early life French score on adult French score (cont.)

(b) Madagascar

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV
French 2nd grade	0.213***	0.0291		0.0354	0.0910
	(0.049)	(0.044)		(0.045)	(0.12)
Height 2012			0.0123*	0.0126*	0.0132**
			(0.0064)	(0.0065)	(0.0065)
Female		0.0336	0.135	0.135	0.135
		(0.080)	(0.100)	(0.10)	(0.099)
Age 2012		-0.0847**	-0.0862**	-0.0883**	-0.0917***
		(0.035)	(0.034)	(0.034)	(0.034)
Mother's education		0.0276**	0.0258*	0.0251*	0.0240*
		(0.014)	(0.014)	(0.014)	(0.014)
Father's education		0.0530***	0.0513***	0.0498***	0.0474***
		(0.013)	(0.013)	(0.013)	(0.014)
Assets 2nd grade		0.103	0.106	0.0951	0.0774
		(0.070)	(0.067)	(0.070)	(0.075)
School infrastructure 2nd grade		0.159***	0.159***	0.161***	0.164***
		(0.042)	(0.041)	(0.041)	(0.041)
Teacher's education		0.179***	0.183***	0.177***	0.168***
		(0.034)	(0.035)	(0.035)	(0.038)
Constant	0.288***	0.684	-1.310	-1.273	-1.215
	(0.049)	(0.84)	(1.33)	(1.33)	(1.31)
Observations	312	312	312	312	312
F	18.96	30.57	32.18	28.67	28.37
r2	0.0591	0.357	0.364	0.365	0.362
widstat					59.22

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school. Household asset index and school infrastructure index are constructed using factor analysis. Heteroscedasticity-robust standard errors in paranthesis. Significance: *** p<0.01, ** p<0.05, * p<0.10.

B Item response theory

The test scores used in this paper are constructed using Item Response Theory (IRT). IRT is still an uncommon measure in the education economics literature, apart from a few exceptions (Singh 2017; Das and Zajonc 2010). It is however used in evaluating results from large-scale tests such as the PISA, TIMMS and GRE.

The main principle of IRT is to differentiate between the latent ability of any given student to answer a question correctly, and the actual response given. This is done by three different parameters for any given item: the difficulty, discrimination, and the pseudo-guessing parameters.

The item response function (IRF) links the latent ability to the probability of success in that item for any given respondent. As Singh (2017); Das and Zajonc (2010), we use the three-parameter (3PL) logistic model introduced by Birnbaum (1968). Given the probability of a correct response $X_{ig} = 1$ for a given item g, given ability level θ_i, gives the probability of successful response:

$$P_g(X_{ig} = 1|\theta_i) = c_g + \frac{1 - c_g}{1 + \exp[-a_g(\theta_i - b_g)]} \tag{B-1}$$

Where b_g is the difficulty parameter, a_g is the discrimination parameter and c_g is the pseudo-guessing parameter. The difficulty parameter measures the overall difficulty of the item, the discrimination parameter tells how well a given item can differentiate between different levels of ability. Finally, the pseudo guessing parameter tells how much a success in a given item is random, and thus unrelated to the respondent's ability. Setting the pseudo-guessing parameter to zero will yield a two-parameter model (2PL), that we have used in the cases where the maximum likelihood function of the 3PL-model was not converging. We argue this is not an issue, since for the test scores that we were able to estimate with the 3PL, the 2PL and 3PL models are very strongly correlated (close to 99%).

For comparing the levels of the test scores between the two countries (Section 5.1), we construct the IRT scores from the joint distribution of the scores of the two countries.

The advantage of doing this is that the parameters of IRT are estimated jointly for the common items, which renders the scores comparable. For all the regression analysis we employ IRT scores estimated separately for each country, as we estimate country-specific regression models.

C Summary statistics

Table C-1: Summary statistics

(a) Senegal

	Obs	Mean	Std. Dev.	Min	Max
Highest Grade in 2012	405	8.93	3.83	0.00	15.00
French 2nd grade (pre)	405	-0.09	0.84	-1.47	1.89
French 2nd grade (post)	405	-0.12	0.86	-2.14	2.19
Math 2nd grade (pre)	405	-0.09	0.92	-1.69	2.60
Math 2nd grade (post)	405	-0.08	0.93	-2.59	2.22
Math and French 2nd grade (post)	405	-0.11	0.88	-2.65	2.16
Math and French 2nd grade (pre)	405	-0.07	0.92	-2.02	2.52
2012 Math score	349	0.45	1.44	-3.24	2.90
2012 French score	349	0.46	0.79	-0.86	1.91
2012 Math-French score	349	0.23	0.83	-2.48	1.30
Height in 2012	405	171.91	8.76	149.00	195.00
Female	405	0.41	0.49	0.00	1.00
Age 2012	405	23.76	2.04	16.00	29.00
Mother Education (Dummy)	405	0.09	0.28	0.00	1.00
Father Education (Dummy)	405	0.18	0.38	0.00	1.00
Assets 2nd grade	405	0.02	0.94	-1.09	1.92
School Infrastructure 2nd grade	405	-0.22	0.72	-0.90	1.89
Teacher's education	405	12.90	2.44	10.00	18.00

Table C-1: Summary statistics (cont.)

(b) Madagascar

	Observations	Mean	Std. Dev.	Minimum	Maximum
Highest grade in 2012	333	10.04	3.22	1.00	15.00
French 2nd grade (pre)	333	0.10	1.00	-2.11	2.70
French 2nd grade (post)	333	-0.09	0.99	-2.36	2.51
Math 2nd grade (pre)	333	0.06	0.96	-2.79	1.80
Math 2nd grade (post)	333	0.01	0.89	-2.42	2.15
Math and French 2nd grade (post)	333	-0.04	0.94	-2.43	2.54
Math and French 2nd grade (pre)	333	0.07	1.03	-2.89	3.00
2012 Math score	318	0.28	0.81	-2.01	2.75
2012 French score	312	0.28	0.88	-1.76	2.13
2012 Math and French score	310	0.31	0.83	-2.37	3.03
Height in 2012	333	160.17	7.91	142.00	180.00
Female	333	0.54	0.50	0.00	1.00
Age 2012	333	21.85	1.39	19.00	26.00
Mother's education	333	5.62	3.65	0.00	17.00
Father's education	333	6.21	3.92	0.00	17.00
Assets 2nd grade	333	-0.08	0.79	-0.76	3.26
School infrastructure 2nd grade	333	0.10	0.91	-1.79	1.16
Teacher's education	333	5.18	1.25	4.00	8.00

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Household asset index and school infrastructure index are constructed using factor analysis. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school.

D Balance tests for attrition

Table D-1: Mean Comparison across panel and full sample of students at baseline

(a) Senegal: 1995-96

	Not in panel	Panel	Difference
French 2nd grade (pre)	-0.10	-0.09	-0.01
French 2nd grade (post)	-0.18	-0.12	-0.06
Math 2nd grade (pre)	-0.14	-0.09	-0.05
Math 2nd grade (post)	-0.17	-0.08	-0.09
Math and French 2nd grade (post)	-0.21	-0.11	-0.10
Math and French 2nd grade (pre)	-0.19	-0.07	-0.12*
Assets 2nd grade	-0.05	0.02	-0.07
School Infrastructure 2nd grade	-0.24	-0.22	-0.02
Teacher's education	13.17	12.90	0.26
Female 1995-96	0.36	0.40	-0.04
Age 2nd grade	8.19	8.31	-0.12*

(b) Madagascar: 1997-98

	Not in panel	Panel	Difference
French 2nd grade (pre)	-0.01	0.10	-0.11*
French 2nd grade (post)	0.02	-0.09	0.11*
Math 2nd grade (pre)	-0.01	0.06	-0.06
Math 2nd grade (post)	0.01	0.01	-0.00
Math and French 2nd grade (pre)	-0.01	0.07	-0.08
Math and French 2nd grade (post)	0.01	-0.04	0.06
Assets 2nd grade	0.02	-0.08	0.10**
School infrastructure 2nd grade	0.02	0.10	-0.08
Teacher's education	5.36	5.18	0.18**
Female	0.51	0.53	-0.03
Age 2nd grade	8.74	8.21	0.53***

Notes: Second grade denotes 1995-96 in the case of Senegal and 1997-98 in Madagascar. All test scores are constructed using country specific IRT. Height is reported in cm's. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Household asset index and school infrastructure index are constructed using factor analysis. Teacher education is in years in Senegal. In Madagascar it is the number of grades completed after primary school.

Chapter 5

Do Fences Make Good Neighbors? Evidence from an Insurgency in India

Do Fences Make Good Neighbors? Evidence from an Insurgency in India*

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Abstract

India has employed a variety of military, political and economic measures to combat the long running insurgency in Kashmir with little evidence on what contributes to stability in the region. This paper uses a variety of tests to detect structural breaks in the time series for violence over the period 1998-2014. We identify a transition from a high violence regime to a low violence regime that coincides with (i) the fencing of the border with Pakistan (ii) the implementation of a large-scale development program, and (iii) the phasing in of the Indian National Rural Employment Guarantee Scheme (NREGS). Our results highlight the complementary roles of development programs and security in reducing violence.

JEL Classification: C22, D74, F51
Keywords: Conflict, Multiple Structural Breaks, Nonlinear Time Series Models, Jammu and Kashmir, India

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1 Introduction

While the number of inter-state and civil wars have declined over time, close to 1.5 billion people remain affected by fragility, conflict and violence (World Bank, 2011). Undoubtedly, poverty and conflict go hand-in-hand and policymakers in developing countries continue to grapple with policies that could end the recurrent cycles of poverty and violence. In particular, researchers and policymakers have been demonstrating an increasing interest in examining the utility of development programs in the context of conflict reduction and the conditions necessary for their success. However, isolating the effect of such policies is complex, given that multiple policies maybe simultaneously implemented. In this paper, we utilize a variety of time series techniques to assess several policies implemented in the context of the ongoing insurgency in the Indian state of Jammu and Kashmir.

Beset with numerous insurgencies within its borders since independence, India has employed a combination of military, political and economic measures to combat them, yet there is little evidence on what factors may have contributed to stability. One such case is that of the ongoing conflict in the Indian state of Jammu and Kashmir. Both India and Pakistan claim territorial control over Kashmir with each currently controlling two-thirds and one-third of the area, respectively. The current insurgency started in 1989 with separatists, backed by Pakistan, contesting control of the Indian government (Chadha, 2005; Habibullah, 2008). A key security policy implemented to counter the insurgency was fencing of the Line of Control (LoC), the de facto border between Indian and Pakistan controlled parts of Kashmir, by the end of 2004. This was followed by the introduction of two large-scale development programs - the Indian National Rural Employment Guarantee Scheme (NREGS) and the Prime Minister's Reconstruction Plan for J&K (PMRP) in the state.

While understanding the linkages between conflict and socio-economic outcomes has long been considered important, there has been a recent shift in focus towards the effects of counterinsurgency policies in the last decade primarily due to the wars in Iraq and Afghanistan (Berman and Matanock, 2015). Although government forces are typically better equipped than insurgents, civilian support often plays a large part in successful operations. Cognizant of this, the “hearts and minds” approach aims to win over the population by providing them public services, with the expectation that once their grievances are addressed, the attitude of the population towards the government will improve. The civilians are then less likely to help or join the insurgents and more likely to share information with the counterinsurgents. Berman et al. (2011b) find that improved service provision through the Commanders Emergency Reconstruction Program (CERP) in Iraq reduced violence, especially in the case of small-scale projects implemented in consultation with local leaders.

A second related counterinsurgency mechanism banks on the opportunity-cost mechanism approach, which posits that an improved economic environment, access to the market, labor market conditions, etc. increases the costs of participating in the insurgency and reduces the supply of insurgents. Miaari et al. (2014) examine how restrictions on the employment of Palestinians in Israel following the outbreak of the Second Intifada affected the involvement of Palestinians in the conflict. Exploiting spatial differences in the decline of employment opportunities for Palestinians, they find a 1% point decline in the employment rate to be associated with an increase of 0.11 Palestinian fatalities. Similarly, Iyengar et al. (2011) find that labor-intensive projects under the CERP reduced violence levels in Iraq.[1]

On the other hand, it is also possible that such development programs could attract more violence though rent seeking or predatory behavior on the part of the insurgents. Insurgents may also try to sabotage developmental activities in an effort to undermine the government. For example, Crost et al. (2014) find that districts eligible for the KALAHI-CIDSS development assistance program in the Philippines witnessed an increase in violence. The authors’ hypothesis is that this is due to insurgents strategically trying to sabotage projects. Similarly, Beath et al. (2013) find that even though the National Solidarity Program (NSP) in Afghanistan improved villagers’ perception of the government, its effect on security was temporary and dissipated over time.

Thus, a crucial determinant for the success of development programs in reducing

[1] However, Berman et al.(2011a) find evidence against this mechanism.

violence may be a sufficiently low initial level of violence. This implies that security and development programs may complement each other, such that security policy must be effective first if initial violence levels are high. Indeed, Berman et al. (2013) argue that troop deployments and the resulting improvements in security played a crucial role in the success of the CERP program in Iraq. Emerging evidence from Afghanistan points to a similar relationship. Using geo-coded data, Sexton (2016) finds counter-insurgency aid reduced violence in areas that were already under the control of pro-government forces and Beath et al. (2013) find that the NSP program only had a positive effect on security in villages that had low initial levels of violence. This paper further highlights the role played by improved security in the effectiveness of development programs in reducing violence. Using a variety of time series techniques, we find that fencing of the border between India and Pakistan reduced the level of violence in the Indian state of Jammu and Kashmir by restricting the supply of insurgents. Development programs implemented subsequently in the improved security environment further reduced violence, particularly in the form of civilian casualties.

In this paper, we use various endogenous structural break models to test if the fencing of the LoC and the implementation of the PMRP and NREGS lead to structural changes in the insurgency in Jammu and Kashmir. Even when the start date is known, policy interventions may affect outcomes gradually over time making it difficult to precisely *ex-ante* identify a break date in the outcome variable. We explore a smooth break in the time series by employing Logistic Smooth Transition Regression (LSTR) with time as the threshold variable, and find that the level of violence depicts a nonlinear break centered around the beginning of 2005, corresponding to the fencing of the LoC. Estimates from the Bai and Perron (1998, 2003) methodology to detect multiple unknown structural breaks further underscore this result. Our results are robust to different model specifications and transformations of the data. We find a significant structural change marked by a decline in the insurgency (particularly the number of terrorists killed) in 2005. This is followed by a decline in the number of civilian and security forces casualties in 2006-07, indicating that the improved security coupled with the introduction of two large-scale development programs, the PMRP and NREGS, further helped reduce violence in the state. This pattern in the timing of breaks is indicative of the causal factors that may have been at play during the period of declining violence in the state.

This paper contributes to the literature examining conflict in India. In the Indian context, the evidence on the effect of NREGS on the long-running Maoist violence in central and eastern India is mixed. While Khanna and Zimmermann (2017) find that it increased violence in the short-run, Dasgupta et al. (2016) and Fetzer (2014) find that it reduced violence levels most likely due to the significant rural poverty reductions associated with the program.[2] Our results indicate that development programs are related to reduction in violence, albeit in the presence of improved security.

Finally, this paper also contributes to the use of nonlinear time series methods in the study of conflict. To our knowledge, the existing studies on conflict which are based on time series analysis only employ methods that detect sharp breaks, mainly using the Bai and Perron procedure (Bai and Perron, 1998; 2003).[3] For example, Amara (2012) utilizes a combination of endogenous sharp break models along with exogenous structural break tests of Chow (1960) and Quandt-Andrews (Andrews, 1993) to study the relationship between the U.S. military 'surge' and economic and security stability in Iraq. Similarly, using endogenous (but sharp) structural breaks, Enders and Sandler (2005) study incidents of transnational terrorism with a focus on the changes that may have been triggered by 9/11.[4] We focus, instead, on endogenous smooth breaks inferred using the LSTR framework in addition to sharp breaks given by the Bai and Perron procedure. This is because ongoing conflicts are more likely to adjust gradually to long run equilibriums than exhibit sharp movements. The presence of nonlinearities in our data allows us to gain a deeper understanding of the evolution of smooth breaks and violence in the state. It is noteworthy that both the smooth and sharp breaks are detected without *a*

[2] In related work, Singhal and Nilakantan (2016) assess the effectiveness of a security policy implemented to combat the Maoist insurgency.

[3] An exception is Enders et al. (2014) that finds a nonlinear relationship between income level and terrorism.

[4] Other papers which have employed sharp breaks in the context of conflict studies include Oosterlinck (2003), Waldenström and Frey (2008) and Chaney (2008).

priori assuming the dates when they take place. Our methodology, hence, lets "the data speak for itself".

The rest of the paper is organized as follows. In Section 2 we provide an overview of the ongoing conflict in the Indian state of Jammu and Kashmir. Section 3 outlines the empirical strategy and the data used in the study. The results are presented in Section 4 and Section 5 concludes.

2 The Context: Insurgency in Jammu and Kashmir

The low intensity conflict that started in 1989 is rooted in the dispute between India and Pakistan over the territory of Kashmir, ongoing since the partition of the Indian subcontinent in 1947. Currently, India and Pakistan control two-thirds and one-third of the original state of Jammu and Kashmir, respectively. The dispute has led to two open wars, in 1947 and 1965, and brought the two countries close to war on a number of other occasions. A map of the region is provided in Figure 1.

The current armed insurgency started in 1989 in the Kashmir Valley, spreading over time to other parts of the state. A variety of factors contributed to the rise and spread of the violent insurgency, including widespread discontent with elections in the state and active support from Pakistan in the form of arms and training (Business Standard, 2015).[5] The Indian army was summoned to quell the insurgency and it continues to run the counter-insurgency operations in the state in conjunction with central and state police forces. During the period from 1998 to 2014, the insurgency resulted in over 25,000 deaths (Source: SATP). However, the number of casualties has reduced drastically since 2005. The average number of total people killed during the periods 1991-1995, 1996-2000, 2001-2005, 2006-2010 and 2011-2015 were 2313, 2672, 2724, 637 and 170 respectively (Source: SATP). In addition to the considerable loss of life, recent research also finds that children born during the conflict are smaller and complete lesser years of schooling (Parlow, 2011

[5] The end of the Soviet occupation in neighboring Afghanistan in 1989 also resulted in the availability of excess arms and experienced fighters. For a more detailed discussion of the conflict in Jammu and Kashmir, see Chadha (2005).

Figure 1: Map of Kashmir & Jammu

and 2012).

Table 1 lists the important incidents related to the insurgency in Jammu and Kashmir. Figure 2 displays the timeline of the events along with the total monthly casualties during the insurgency. One of the important incidents involved the Kargil war and its aftermath. In early spring of 1999, armed intruders were discovered to have taken over strategic positions on the Indian side of the LoC. The Indian army was mobilized and moved to the border areas to repel the intruders. The war ended shortly in July when the Indian army successfully repulsed the intruders and chose not to widen to conflict with Pakistan. The quick movement of the army to the border regions disrupted their regular counterinsurgency operations in the interior regions. As a result, the interior areas vacated by the army were occupied by insurgents. Following the end of the Kargil war, the army had to (re)contest for control of the interior regions leading to an increase in violence that only came down by 2003, when India and Pakistan restored diplomatic ties and agreed to a cease-fire along the LoC (BBC News, 2003).

The Indian government has used a blend of military, political and economic policies to combat the insurgency. On the political front, the government has engaged with Pakistan at various points of time without any apparent success (except for the 2003 cease-fire agreement that has held despite a few violations). For example, a ceasefire negotiated with the primary militant groups from November 2000 to May 2001 collapsed without making much headway. The most significant political change in the 2000s has been the successful implementation of state elections. The state was under the President's Rule (i.e., the central government) for most of the 1990s and the dominant regional political party Jammu Kashmir National Conference (JKNC) was viewed as corrupt. The 2002 elections were a watershed in the electoral history of the state, allowing the popular Jammu Kashmir Peoples Democratic Party (PDP) to take charge (in coalition with the Indian National Congress, INC).

One of the key security measures undertaken by the government has been fencing the border with Pakistan. In terms of economic interventions, the notable intervention in the state during this time period was the introduction of the Prime Minister's Reconstruction

Table 1: List of Events

Date	Event
May-July 1999	Kargil War
Dec 2000- May 2001	Ramadan Cease fire
1st Oct 2001	Suicide attack by the JaisheMohammed (JeM) on the State Legislative Assembly complex in Srinagar
13th Dec 2001	Indian National Parliament attacked by Militants
Sept-Oct 2002	State elections, Jammu Kashmir Peoples Democratic Party (PDP) comes to power
25^{th} Nov 2003	India and Pakistan agree to a cease-fire along the LoC
Sept 2004	LoC fencing completed
Nov 2004	PM's Reconstruction Plan (PMRP) announced.
April 2005	PMRP starts
Feb 2006	Phase 1 of NREGS
April 2007	Phase 2 of NREGS
April 2008	Phase 3 of NREGS

Plan for J&K (PMRP) in 2005. Following this, the Indian National Rural Employment Guarantee Scheme (NREGS) was rolled out in the state over the period 2006-08. These policies are discussed in greater detail below.

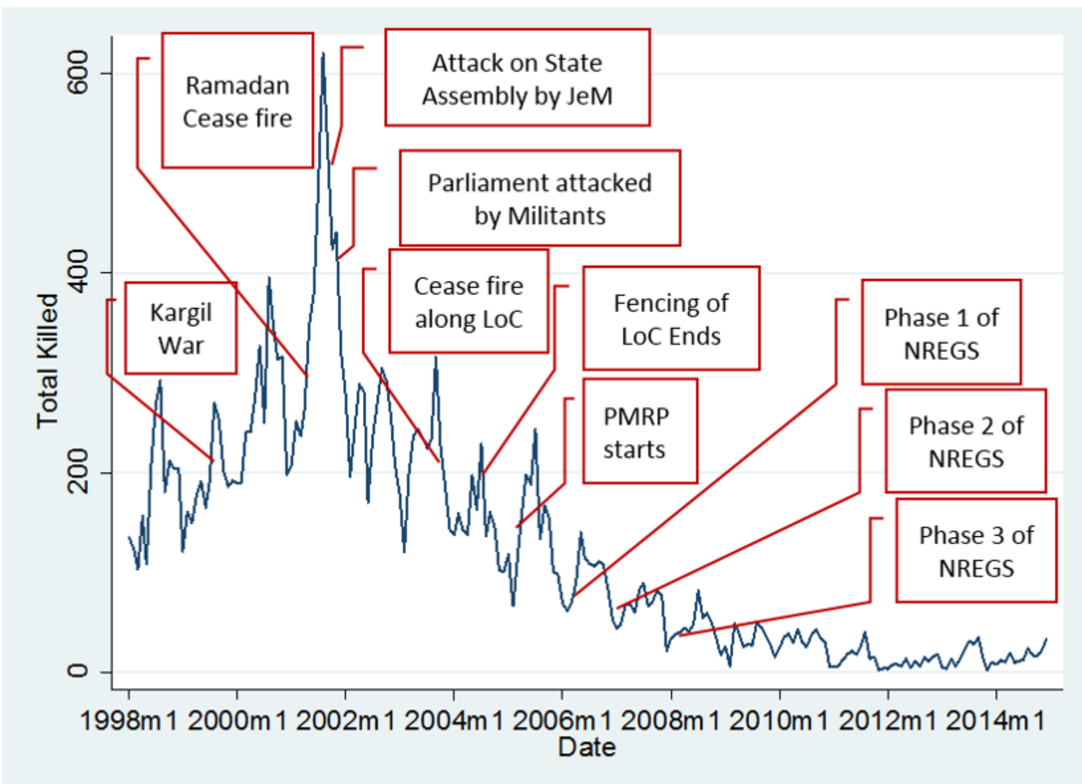
Fencing of the Line of Control

The erstwhile princely state of Jammu and Kashmir is delineated into the Indian and Pakistan controlled parts by the "Line of Control (LoC)".[6,7] India has fenced its border with Pakistan, both international and the LoC (Waldman, 2004). Fencing of the LoC, around 550 kilometers of the 740 kilometers allowing for breaks in the terrain, was completed by September 2004 and Indian security forces estimate that it has been particularly successful in reducing the infiltration of militants from Pakistan (Times of India, 2004; The Indian Express, 2014). Figure A4 in the Appendix 4 displays a photograph of the fence.

[6]This was originally called the Cease-fire line following the first war in 1947-48. It was re-designated as the "Line of Control" after the Shimla Agreement in 1972. While the Line of Control is not internationally recognized, it is considered the de-facto border between India and Pakistan.

[7]A small section of the border between Indian and Pakistan controlled parts is part of the internationally recognized border.

Figure 2: Timeline of Events



Prime Minister's Reconstruction Plan for J&K (PMRP)

The PMRP was announced by Prime Minister Dr. Manmohan Singh in November 2004. The objective of the plan was the long-term development of the state through the creation of infrastructure, provision of basic services, and creation of jobs. The infrastructure projects included within the ambit of the plan are expansion of the road network, power generation projects, rural electrification, construction of health centers and Anganwadis, and the construction of colleges.[8,9] Support was provided for the tourism industry through modernization of airports, conservation programs for various lakes, construction of tourist villages and training support for those in the tourism and hospitality industry. Income and employment generation in the agricultural sector was supported through various programs in the horticultural industry and construction of food storage units.[10]

As of August 2015, 36 out of 67 sanctioned projects had been completed. While the central government had allocated approximately 240 billion Rupees (or 4 billion USD at the exchange rate of 1 USD = 60 Rupees) for the initial four-year period (2005-08), as of March 2014, over 780 billion Rupees (13 billion USD) have been disbursed under the scheme. The yearly expenditures of the reconstruction plan are displayed in Figure 3.

Indian National Rural Employment Guarantee Scheme (NREGS)

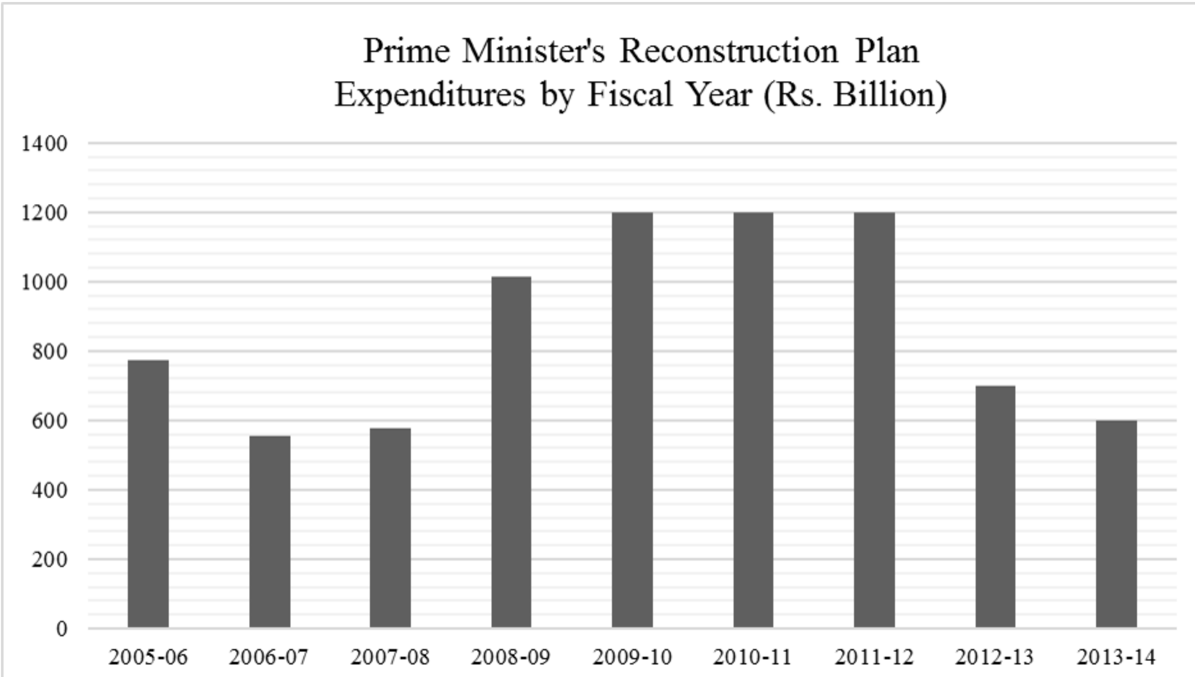
The NREGS guarantees 100 days of manual work at the minimum wage to all rural households. The objective is to protect the livelihood of rural households in times of dire need and is considered to be one of the largest safety net programs in the world. The National Rural Employment Guarantee Act (NREGA) was passed into law in August 2005 and the NREGS was phased in, in a non-random manner, between 2006 and 2008. More specifically, the NREGS was rolled out in three phases in India: in Phase 1, 200

[8] Anganwadis are government funded child-care centers in India.

[9] Some of the rural electrification objectives are included under the Rajiv Gandhi Grameen Vidyutikaran Yojana (RGGVY), a large India-wide program launched in 2005 with the objective of providing electricity access to hitherto un-electrified villages.

[10] The plan also provided funds for the rehabilitation of families affected by militancy in the state. Further details are available at `<http://pib.nic.in/newsite/erelcontent.aspx?relid=4947>` (accessed Jan 18, 2016).

Figure 3: Expenditures of the Prime Minister's Reconstruction Plan



Source: Authors' calculations based on information received from the Ministry of Home Affairs, Government of India. All figures are in nominal terms.

districts received the scheme beginning February 2006; in Phase 2, an additional 130 districts were added to the program starting April 2007; and finally, in Phase 3 all the remaining districts were covered in April 2008. In Jammu and Kashmir, 3 districts were covered under Phase 1 namely Doda, Kupwara and Poonch. In Phase 2, Anantnag and Jammu were added to the scheme and, finally, the scheme was operational in all districts of the state by the start of Phase 3.[11]

3 Empirical Methodology and Data

This section deals with the empirical methodology and data utilized in the study. First, motivated by the nonlinear nature of our data, we use the logistic smooth transition re-

[11] NREGA was later renamed Mahatma Gandhi National Rural Employment Guarantee Act. Further details regarding the policy are available at `<www.nrega.nic.in/>` (accessed Jan 18, 2016).

gression (LSTR) methods to discern a nonlinear structural change in the data. Thereafter, we use Bai and Perron (1998, 2003) technique to detect multiple sharp structural breaks in keeping with the existing literature utilizing time-series methods to identify structural breaks in conflicts (Enders and Sandler 2005; Amara 2012).

3.1 Logistic Smooth Transition Regression (LSTR)

Economic variables are likely to depict a structural change with gradual shift over time. One of the possible reasons for such a behavior could be a slow reaction of the economic agents to policy measures. Therefore, in our analysis, we focus on the existence of smooth breaks in the data. In order to incorporate nonlinear breaks, we consider a logistic smooth transition regression model (LSTR) with time as the threshold variable (Teräsvirta, 1994; 1998; Lin and Teräsvirta, 1994; Enders, 2015).[12]

We now introduce the nonlinear framework for time series analysis, specifically the LSTR model. A nonlinear autoregressive model is a generalization of the standard time series model with autoregressive coefficients and can be depicted as follows:

$$y_t = \eta' z_t + \theta' z_t H(\gamma, c, t) + u_t; \quad t = 1, \ldots, T \tag{1}$$

where $z_t = (y_{t-1}, \ldots, y_{t-p})$ is the vector of past realizations of the dependent variable y_t (and could also include exogenous regressors); $\eta = (\eta_0, \eta_1, \ldots, \eta_m)'$ and $\theta = (\theta_0, \theta_1, \ldots, \theta_m)'$ denote the parameter vectors and u_t is the error term. The smooth, bounded and continuous transition function is given by $H(\gamma, c, t)$ with transition variable time, i.e. t. The smoothness parameter is denoted by γ is and c is the centrality parameter. In this model, the AR decay is dependent on the value of time t as time is the threshold variable. As a result, the intercept and AR coefficients smoothly vary across

[12] If the series display a smooth structural break which leads to a gradual movement across the regimes, we need a nonlinear framework, such as a smooth transition regression, in order to capture the smoothed break in such phenomenon. One of the plausible assumptions that we could impose to gauge such a nonlinear break in the series is to consider a logistic break with time as the threshold variable within in the STR framework. To choose the appropriate model for capturing the behavior of our data, first we run nonlinearity tests to see whether a model in the STR family would be appropriate. After that, we study whether an LSTR model is appropriate by running an auxiliary regression. The detailed results of model selection are presented in section 4.

the regimes.

Further, the LSTR model assumes that the transition function governing the movement across the states is a logistic function, therefore, the above model takes the following form:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + \theta\left[\lambda_0 + \lambda_1 y_{t-1} + \cdots + \lambda_p y_{t-p}\right] + u_t \tag{2}$$

with $\theta = \left[1 + \exp\left(-\gamma\left(t - c\right)\right)\ \right]^{-1}$ with intercepts α_0 and λ_0, AR coefficients $\alpha_1, \ldots, \alpha_p$ and $\lambda_1, \ldots, \lambda_p$ and with optimal lag length p.
Finally,

$$y_t = \begin{cases} \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + u_t,\ if\ t < c \\ \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + \theta\left[\lambda_0 + \lambda_1 y_{t-1} + \cdots + \lambda_p y_{t-p}\right] + u_t,\quad if\ t \geq c \end{cases} \tag{3}$$

since $H_{-\infty} = 0$ as $t \to -\infty$, $\theta = 0$ and $H_{\infty} = 1$ as $t \to \infty$, $\theta = 1$.

Over time, the value of θ goes from 0 to 1 and the AR coefficients gradually shift from the first state to the second state.

In the present study, we specify a LSTR model such that the constant varies across the states and the model simplifies to:[13]

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + \lambda_0 [1 + \exp\left(-\gamma\left(t - c\right)\right)\ ]^{-1} + u_t \tag{4}$$

However, we need to test for the existence of nonlinear breaks or the appropriateness of the LSTR model with time as the threshold variable using an auxiliary regression assuming $\theta = \left[1 + \exp\left(-\gamma\left(t - c\right)\right)\ \right]^{-1}$. Lin and Teräsvirta (1994) suggest adoption of a Taylor series expansion of θ and so we estimate the following auxiliary regression equation (Enders, 2015):

$$y_t = a_0 + a_1 t + a_2 t^2 + a_3 t^3 + \sum_{i=1}^{p} b_i y_{t-i} + \varepsilon_t \tag{5}$$

[13] The constant and trend specifications were also attempted but the trend variable was insignificant.

where, in order to test for the existence of a LSTR break, we test the null hypothesis that $a_1 = a_2 = a_3 = 0$.

3.2 Bai and Perron (BP) Methodology

The detection of structural breaks using the dummy variable approach, which has been standard in the literature, is essentially based on the assumption that the breaks are sharp and the impact on the variable of interest at a break date is observed immediately at that point of time.[14]

The general formulation of the model with m breaks and $m+1$ regimes is:

$$y_t = x_t'\beta + z_t'\delta_j + u_t, \quad t = T_{j-1} + 1, \ldots, T_j \tag{6}$$

for $j = 1, \ldots, m+1$. In the model y_t is the observed dependent variable at time t; x_t $(r \times 1)$ and z_t $(q \times 1)$ are vectors of covariates and β and δ_t denote the vectors of coefficients and u_t is the error term. The indices of the break points $T_1, \ldots, T_m$ are treated as unknown. This is called a general partial structural change model, since β is not subject to shifts and is estimated using the full sample. A pure structural break model occurs thus when $r = 0$.

Various test statistics can be employed to determine the number of breaks given a maximum number of breaks m.[15] The $F\,(l+1|\,l)$ test statistic tests the hypothesis of $l+1$ against l structural breaks and the $supF(k;q)$ test statistic tests the hypothesis of zero breaks against k breaks with q break parameters (i.e., endogenous regressors). The UDmax statistic tests the null hypothesis of no structural break against an unknown number of breaks.

To determine the exact number of breaks one can use several information criteria: BIC (Bayesian Information Criterion), LWZ (Modified Schwarz Criterion) or a sequential procedure based on the $(l+1|\,l)$ test statistic. Bai and Perron (2003) point out that

[14] However, this seems to be a strong assumption in the case of economic time series and can be replaced by the more plausible assumption of smooth breaks instead.

[15] Bai and Perron (2003) provide examples with $m = 5$.

when breaks are present, BIC performs well, while LWZ performs better under the null, and might underestimate the number of breaks when the null is rejected. A drawback of the sequential procedure, according to Enders (2015), is that it may perform poorly if the series is highly persistent. Since our data display high persistence and the UD max and $supF(k;q)$ statistic firmly reject the null, we use the BIC procedure to determine the number of breaks.

Our main results are obtained by estimating a model where the vector z_t' includes a constant and a trend, and $p = 0$, so we do not have exogenous regressors.

$$y_t = \delta_{1j} + \delta_{2j}t + u_t, \quad t = T_{j-1} + 1, \ \ldots, \ T_j \tag{7}$$

As a robustness check, we also show results with AR-terms as exogenous regressors.[16] The model then becomes:

$$y_t = \delta_{1j} + \delta_{2j}t + \beta_i \sum_{i=1}^{p} y_{t-i} + u_t, \quad t = T_{j-1} + 1, \ \ldots, \ T_j \tag{8}$$

where p is the number of lags.

3.3 Data

We use two indicators of violence – the number of casualties and the number of incidents involving the use of explosives (landmines, grenades, IEDs, etc.). Both are available at the monthly level and are collected from the website of the South Asian Terrorism Portal (SATP), which bases these estimates on newspaper reports on terrorism related incidents in Jammu and Kashmir.[17] While the data on the number of incidents involving explosives are available from January 2001 to December 2014, the data on the number of casualties are available for the period January 1998 to December 2014. We are able to disaggregate the data on casualties further into the number of civilians, security personnel, and terrorists killed, which allows us to examine if the results are driven by violence against

[16]The selection of the number of lags k is presented alongside the results.

[17]See `<http://www.satp.org/>` for details.

Table 2: Descriptive Statistics

	y_{TOT}	y_{CIV}	y_{TER}	y_{SP}	y_{EXP}
Mean	123.6225	34.5049	70.2598	18.85784	10.5298
Std. Dev	116.1502	34.3978	71.1165	18.2096	11.6906
Skewness	1.1881	0.7268	1.8292	1.2211	1.5694
Kurtosis	4.5189	2.5820	7.6228	3.8229	5.9879
Maximum	621	150	432	81	64
Minimum	2	0	0	0	0
Observations	204	204	204	204	168

Note: y_{TOT} denotes the total killed, y_{CIV} denotes the civilians killed, y_{TER} denotes the terrorist killed, y_{SP} denotes the security personnel killed and y_{EXP} denotes the incidents involving explosives.

a particular group. Additionally, we also use data from the J&K police records of foreign terrorists killed during the period 2003-2010 for robustness check.[18] The descriptive statistics for the series are given in Table 2 and the time series are plotted in Figure 4 (Panels 4a to 4e).

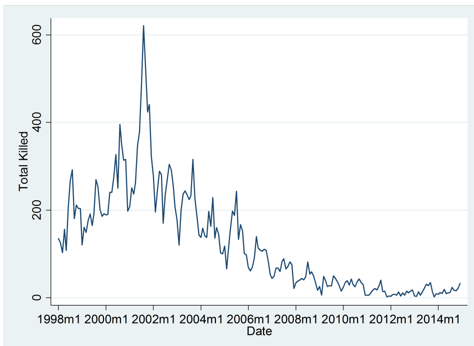
Before proceeding to the time series analysis, we check for the presence of unit roots in all the series in the following way. First, we select the optimal lag length for the unit root tests. In order to do that, we utilize the conventional lag length criterion viz. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn (HQ) and F-statistic along with the lag exclusion tests to choose the appropriate lag length for each of the series.[19] Thereafter, we test for the existence of a unit root in the time series. In view of suspected structural breaks in our data, we conduct the Lee and Strazicich test for the presence of a unit root with structural breaks and the results are given in Table 3.[20] The null hypothesis of a unit root process in the presence of structural breaks in rejected at 1% level of significance in all the cases. We, therefore, conclude that the series are stationary in levels and employ these for the analysis of structural breaks.

[18]The data and analysis of foreign terrorists killed are presented in Appendix A

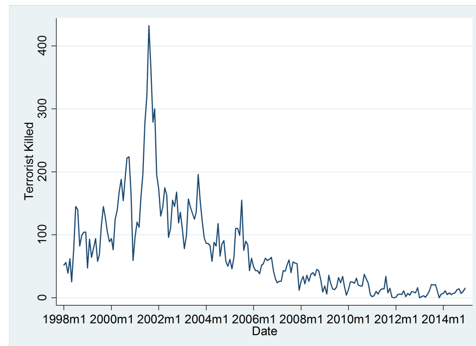
[19]Detailed results of the lag selection and lag exclusion tests are available with the authors on request.

[20]Lee and Strazicich (2003) propose a two-break minimum LM unit root test with breaks in the level and trend under the null hypothesis which they argue, conclusively implies trend stationarity under the alternative hypothesis.

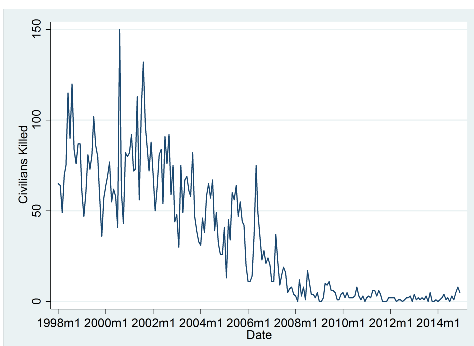
Figure 4: Time Series for Killings in Jammu and Kashmir



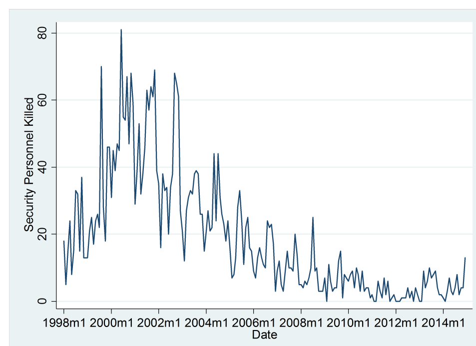
(a) Total Killed



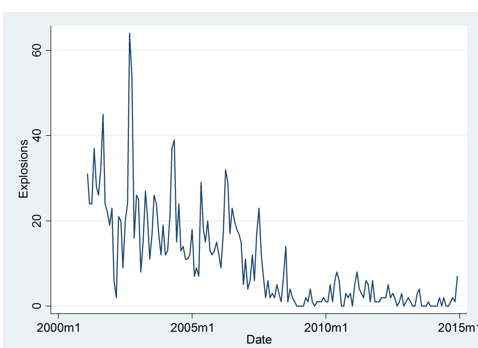
(b) Terrorists Killed



(c) Civilians Killed



(d) Security Personnel Killed



(e) Number of Incidents Involving Explosives

Table 3: Lee-Strazicich Test for a Unit Root with Structural Breaks

Variable	Trend Break Model	Inference
$\boldsymbol{y_{TOT}}$	-59.355	I(0)
$\boldsymbol{y_{CIV}}$	-64.992	I(0)
$\boldsymbol{y_{TER}}$	-75.268	I(0)
$\boldsymbol{y_{SP}}$	-57.886	I(0)
$\boldsymbol{y_{EXP}}$	-6.069	I(0)

Critical Values

Trend Break Model		λ_2	
λ_1	0.4	0.6	0.8
0.2	-6.16, -5.59, -5.27	-6.41, -5.74, -5.32	-6.33, -5.71, -5.33
0.4	-	-6.45, -5.67, -5.31	-6.42, -5.65, -5.32
0.6	-	-	-6.32, -5.73, -5.32

Note: y_{TOT} denotes the total killed, y_{CIV} denotes the civilians killed, y_{TER} denotes the terrorist killed, y_{SP} denotes the security personnel killed and y_{EXP} denotes the incidents involving explosives. Critical values are at the 1%, 5% and 10% levels, respectively. λ_j denotes the location of breaks.

4 Results

This section presents results of the time series analysis of the casualties and incidents involving explosives during the insurgency in Jammu and Kashmir. To begin with, we investigate the existence of nonlinear smooth breaks and sharp breaks to understand the evolution of the conflict. This is followed by a brief discussion on the robustness checks.

4.1 Nonlinear Breaks

As discussed in Section 3.1, most economic time series depict a smoothed break, which takes place over a period of time instead of a sudden change. This is the case for instance, when economic variables respond slowly to a change in economic policy. In such scenarios, a smooth transition model can be applied which captures transitions from one economic regime to another that is typical of nonlinear time series data. In order to capture smooth breaks, we resort to smooth transition regression models with time as the threshold variable.

First, we test if the violence series are indeed nonlinear using the tests proposed by

Tsay (1986) and Luukkonen et al. (1988). The null hypothesis of both the tests is linearity. The alternative hypothesis of Tsay's test is nonlinearity and that of Luukkonen et al. (1988)'s test is a smooth transition autoregressive (STAR) model. From Table 4, we observe that both tests indicate that the series are nonlinear. In particular, results of the Luukkonen et al. (1988) test suggest that a STAR model may be appropriate. Next, we need to select the optimal lag for the nonlinear models. In this regard, following Franses and van Djik (2000), we choose optimal lag lengths based on the information criterion (AIC, BIC and HQ) and then estimate the corresponding nonlinear models using the suggested lag lengths. We estimate the LSTR model with the optimal lag lengths and pare down lags in the model by dropping variables which are insignificant. We finally select one lag for the civilians killed, terrorist killed and total killed, two lags for security personnel killed, and one lag for incidents involving explosives.

Table 4: Tests for Nonlinearity

Variable	**Tsay (1986) Test Statistic**	**Luukkonen et al. (1988) Test Statistic**
y_{TOT}	5.59***	3.42***
y_{TER}	4.55***	4.26***
y_{CIV}	8.19***	5.43***
y_{SP}	6.10***	3.95***
y_{EXP}	4.33***	2.96***

Note: y_{TOT} denotes the total killed, y_{CIV} denotes the civilians killed, y_{TER} denotes the terrorist killed, y_{SP} denotes the security personnel killed and y_{EXP} denotes the incidents involving explosives. *, **, *** denote significance at 10%, 5% and 1% respectively.

The estimates of the LSTR models for the series are given in Table 5. Table 5a presents the results for the auxiliary regression given in equation 5. The F-statistic corresponds to the null hypothesis of no smooth transition in the threshold variable, time. The null hypothesis is rejected in all the five cases at 1% level of significance, confirming the existence of a smooth transition regression process with time as the transition variable.

In Table 5b, we present the main results of the nonlinear model given in equation4 which estimates the LSTR model with time as the threshold variable.[21] It is notable that

[21]We also estimate the LSTR models with two smoothed breaks for all the series. The modified AIC

λ_0 is negative in all the cases which signifies that the mean of the process is decreasing as $\theta \to 1$. There seems to exist two states in the all the time series on casualties: a high casualties state until 2003 and a low casualties state from 2007 onwards, and the period in between, from 2003 to 2006, is the transition period from the high to the low violence regime that indicates presence of a smooth break. The transition functions for the series depicting the number of casualties have been plotted in Figure 5. The Ljung-box statistics for the residuals of the series show that there is no remaining serial correlation at 1% level of significance and the model specification is appropriate.

Recall that the series for incidents involving explosives is truncated as data is only available from 2001 onwards. Nonetheless, results from the nonlinear model are similar: the high violence regime with incidents involving explosives stretches until mid-2003 and the series transitions up to early 2009 to the low violence state. Detailed graphs for all the five series are given in Figure 6 (Figures 6a to 6e).

Table 5c provides the break dates for the time series for casualties as well as explosion incidents. The dates for all the four series on casualties are clustered in 2005 from January to April, while the break date for the incidents involving explosives is June 2006.[22]

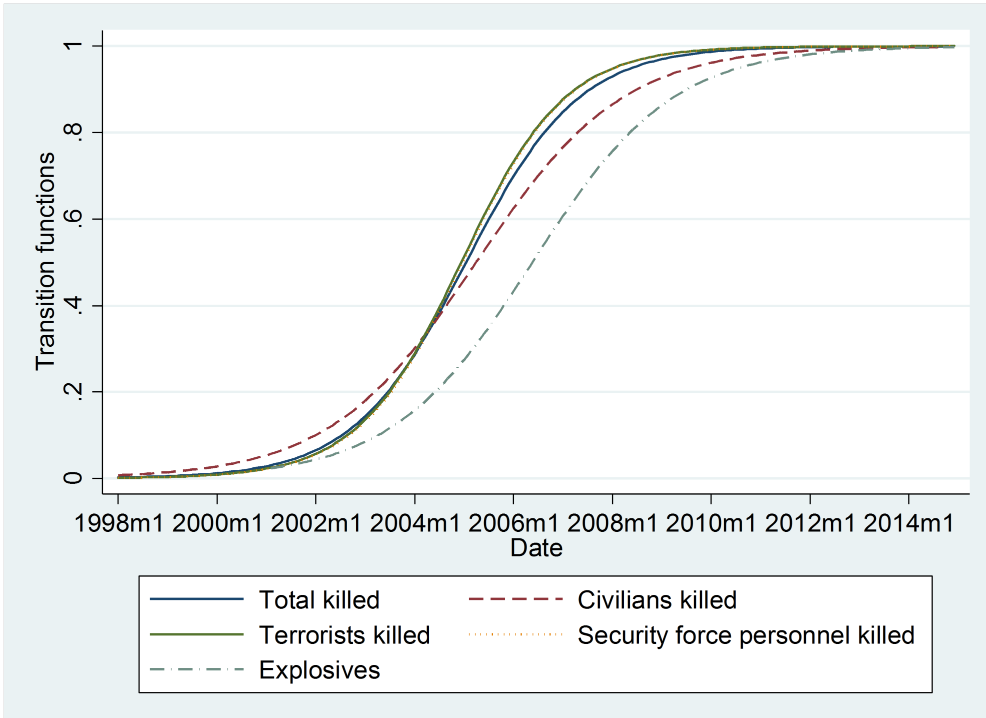
Table 5d provides the descriptive statistics of the violence series across the high, transition and low violence regimes. We observe that there has been a secular decline in violence in the state of Jammu and Kashmir over the period of study. This is depicted by the decline in the maximum, minimum and average levels of violence as we transit across the regimes.

So far in the analysis, we have utilized the violence count data but have not imposed a Poisson process on the time series models. An alternative approach could be to consider a linear mapping of the count data which maintains the order of the realizations in the original time series sequence. The transformed data constructed in such a way would

statistic (Enders and Holt, 2012) is utilized to select the final model, $AIC = T\log\left(\sum_{t=1}^{T}\hat{u}_t^2\right) + 2r$, where T is the number of time periods, r is the number of parameters estimated in the respective models and i $\hat{u}_t$ are the residuals of the model. The best model in all the cases is the LSTR model with a single smooth break.

[22] Our results for nonlinear break dates were robust across grid search procedures and different starting values.

Figure 5: Transition Functions Estimated from the LSTR Model



no longer have counts. As a robustness check, we implement the LSTR model on such transformed data, which we calculate by standardization of the data for violence in the state. The results of the LSTR models for the standardized series are given in Appendix 2 and indicate that the break dates are the same as those from the LSTR models for the non-standardized count data discussed above.[23]

[23]The LSTR results were also implemented with seasonality adjusted series using the X-12-ARIMA adjustment. The results remain similar to the ones presented in the paper and are available from the authors on request.

Table 5: Estimates of Smooth Transition Regressions

(a) Auxiliary Regressions to Test for Time as the Threshold Variable

Variable		**F-statistic**	**p-value**
$\boldsymbol{y_{TOT}}$		6,92	0
	$\boldsymbol{y_{TER}}$	5,08	0,002
	$\boldsymbol{y_{CIV}}$	29,32	0
	$\boldsymbol{y_{SP}}$	10,05	0
$\boldsymbol{y_{EXP}}$		7,95	0

(b) Estimates of LSTR model with time as the threshold variable

Variable	α_0	α_1	α_2	λ_0	$\boldsymbol{c}$	γ	**LB stat**
$\boldsymbol{y_{TOT}}$	58.044***	0.780***	-	-53.366***	85.477***	0.073*	4.212 (0.5193)
$\boldsymbol{y_{TER}}$	28.127***	0.810***	-	-25.279***	84.320***	0.079	2.029 (0.8451)
$\boldsymbol{y_{CIV}}$	58.220***	0.263***	-	-57.500***	87.940***	0.056***	2.236 (0.8156)
$\boldsymbol{y_{SP}}$	15.921***	0.456***	0.141**	-13.972***	84.71***	0.079*	6.189 (0.2882)
$\boldsymbol{y_{EXP}}$	14.310***	0.415***	-	-13.632***	65.609***	0.058**	10.368 (0.0655)

Table 5: Estimates of Smooth Transition Regressions (cont.)

(c) Estimated Break Dates

Variable		c	**Break Date**
y_{TOT}		85.48***	February, 2005
	y_{TER}	84.32***	January, 2005
	y_{CIV}	87.94***	April, 2005
	y_{SP}	84.71***	January, 2005
y_{EXP}		65.61***	June, 2006

(d) Descriptive Statistics across Regimes

		High-Killing Regime			Transition Phase			Low-Killing Regime		
Variables		Mean	Max	Min	Mean	Max	Min	Mean	Max	Min
y_{TOT}		253.5	621	103	148.6	316	44	25.2	82	2
	y_{TER}	77.3	150	36	39.4	92	0	2.8	11	0
	y_{CIV}	140.5	432	25	84.6	196	24	18.0	60	0
	y_{SP}	37.3	81	5	22.1	65	3	5.3	25	0
y_{EXP}		25.5	64	2	12.0	39	0	2.1	8	0

Note: y_{TOT} denotes the total killed, y_{CIV} denotes the civilians killed, y_{TER} denotes the terrorist killed, y_{SP} denotes the security personnel killed and y_{EXP} denotes the incidents involving explosives. The optimal number of lags included in the model are one for civilians killed, terrorist killed and total killed, two for security personnel killed and one for incidents involving explosives. *, **, *** denote significance at 10%, 5% and 1% respectively. Column LB stat in (b) denotes the Ljung-Box test statistic for autocorrelation in the residuals.

4.2 Bai and Perron (BP) Breaks

Enders (2015) suggests that the Bai and Perron (1998, 2003) procedure precludes the possibility of a nonlinear break in the series. We nevertheless use the procedure in the same manner as Enders and Sandler (2005) and Amara (2012) to detect breakpoints as structural breaks in the evolution of a conflict.

In this section, we first discuss the exact break dates found by BP procedure and the events that coincide with these breaks. Thereafter, we relate these breaks to the smooth breaks that we detected and discuss the overall evidence.

Table 6 displays results of the BP procedure, i.e. results from estimating equation 6, where the number of breaks (m) is selected by using BIC. Table 6 reports the point estimate for each break date, the 95 percent confidence intervals around the break dates (the columns Lower and Upper), as well as the estimated intercept and trend in the $(m+1)$ regimes. Hence, on the row for each series, the last two columns report the mean and trend *prior* to the break date for the series.

We find four break dates in total killed and terrorists killed, three for civilians and incidents involving explosions, and two for security force personnel killed. The series total killed is a sum of terrorists, civilians and security force personnel killed and, thus, reflects the overall situation. As the numbers in the terrorist series are by far the highest, the break dates we observe in the series for total killed are similar to those in the terrorist killed series.

The first breakpoints in the series in 2001 identified in all the killings series, mark the peak in the trend of casualties. The events explaining this breakpoint are related to, on one hand, diminished support to militant groups from Pakistan in the face of international scrutiny post 9/11 and, on the other hand, Indian security forces regaining control of urban areas lost due to troop movements during the Kargil war. A breakpoint in 1999 in the civilians killed series is also a possible result of the turbulence during that time-period.

In the aggregate casualties' series, we find the key break date to be March 2005. This comes shortly after the completion of the fencing of the LoC, indicating that the fence had a significant effect on the level of violence in the state. The break date also happens to be in the same month when the reconstruction plan was implemented although it was announced much earlier. The terrorists killed and the incidents involving explosions series also capture the exactly same breakpoint, as does the series on the foreign terrorists killed (presented in Appendix 1).

The breakpoints for the civilian and security force personnel casualty series lag behind the break date for the terrorist casualties (2006 November for security force personnel and August 2007 for civilians, respectively). This indicates that the improved security environment provided by the fencing of the LoC, allowed for effective implementation of the large PMRP and the NREGS, which in turn led to a decline in the number of terrorist

Table 6: Estimates of Bai and Perron Multiple Structural Breaks

Series		Breakdate	Lower	Upper	Intercept	Trend
$\boldsymbol{y_{TOT}}$		2001:06	2000:12	2001:07	143	3.99
		2003:02	2003:01	2005:06	1213	-17.6
		2005:03	2004:11	2005:08	629	-6.15
		2006:11	2006:10	2007:07	620	-5.13
					114	-0.55
	$\boldsymbol{y_{TER}}$	2001:05	2000:10	2001:06	58	2.65
		2003:03	2003:02	2004:08	819	-12.22
		2005:03	2005:01	2005:07	440	-4.57
		2007:03	2007:02	2008:03	411	-3.53
					81	-0.4
	$\boldsymbol{y_{CIV}}$	1999:09	1999:07	2000:01	75	0.38
		2001:09	2001:08	2001:11	6	2.15
		2007:08	2007:07	2007:11	113	-0.83
					11	-0.05
	$\boldsymbol{y_{SP}}$	2001:11	2001:10	2002:01	13	1.08
		2006:11	2006:10	2008:01	59	-0.44
					15	-0.06
$\boldsymbol{y_{EXP}}$		2002:08	2002:05	2003:01	35	-1.17
		2005:04	2004:12	2008:01	45	-0.70
		2007:08	2007:07	2008:04	34	-0.27
					6	-0.03

Note: y_{TOT} denotes the total killed, y_{CIV} denotes the civilians killed, y_{TER} denotes the terrorist killed, y_{SP} denotes the security personnel killed and y_{EXP} denotes incidents involving explosives. Shifting regressors are constant and a trend. The lower and upper columns denote 95% confidence intervals. The intercept and trend are the coefficient estimated for the regime prior that break. Number of breaks is determined by BIC with the maximum number of breaks set to 5 and the minimum length of the regime set to 20.

killed initially and then the civilians and security forces killed. It subsequently paved way for the success of the economic development programs and, hence, a further decline in violence across the board as suggested by the opportunity cost mechanism.

These breakpoints are succeeded by breakpoints in November 2006 for the total series and security force personnel and March 2007 for the terrorists killed and August 2007 for the civilians killed and incidents involving explosions. These breakpoints are succeeded by a period of lower violence, declining at a slower pace, especially in the incidents involving explosions series.

Moreover, we observe a breakpoint in early 2003 for the terrorist and total killed. This breakpoint is characterized by decrease in violence, and it coincides with the year when India and Pakistan restored their diplomatic ties. This is also the year when the smooth transition of the LSTR model into the low-violence regime starts for all of the series.

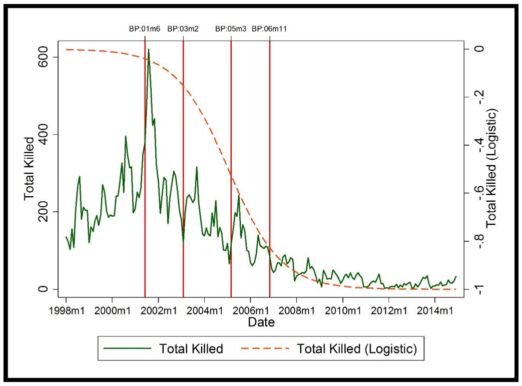
Figures 6a to 6e depict the break points obtained from BP and LSTR models. It is interesting to note that the killings begin declining from 2003 and transit to the low killings regime by the beginning of 2007 in all the cases. This is the time-period where the sharp BP and smooth breaks are also clustered. Hence, we have evidence that events taking place between 2003—2006 must have contributed to the reduction in the violence level.

This period marks a change with the Indian troops recapturing interior areas post Kargil and the diplomatic dialogue between India and Pakistan resuming in 2003, fencing of the J&K border with Pakistan being completed in 2004, the PMRP coming into force in 2005 and, finally, NREGS being rolled out in 2006. Similarly, the BP and LSTR break dates for the incidents involving explosions are found from late 2002 until 2008. It seems that the nonlinear methodology captures the transition periods in the series while the BP technique re-emphasizes similar results by highlighting some of the key turning points in the series.

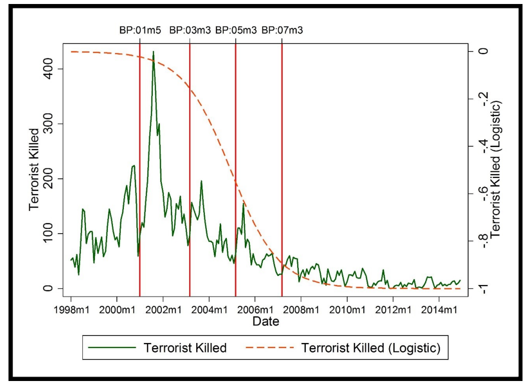
4.3 Robustness checks

As a robustness check we estimate equation 8, which extends equation 7 by adding AR terms as exogenous regressors (Enders and Sandler, 2005). The results are presented in Table 7 and in a number of cases are similar to those reported in Table 6. The major differences are that we find a few more break dates (four for civilians and three for security force personnel) and more importantly, the confidence intervals around the break dates are now narrower, hence, providing even more firm evidence in favor of the break dates presented in Table 6. For instance, the confidence intervals of the 2005 breakpoints are just four months for the total killed and three for the terrorists killed series. We also find a break point in April 2005 for the civilian casualties series, confirming our previous

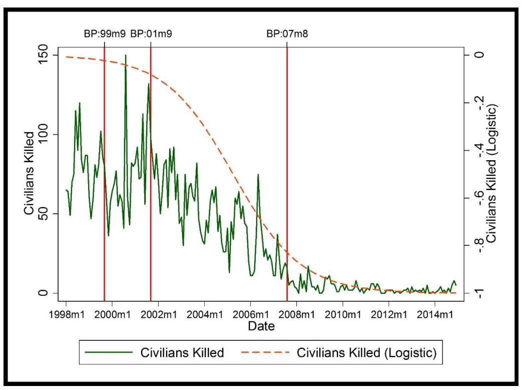
Figure 6: Structural Breaks



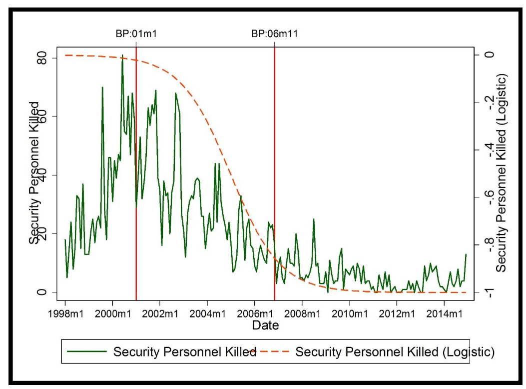
(a) Total Killed



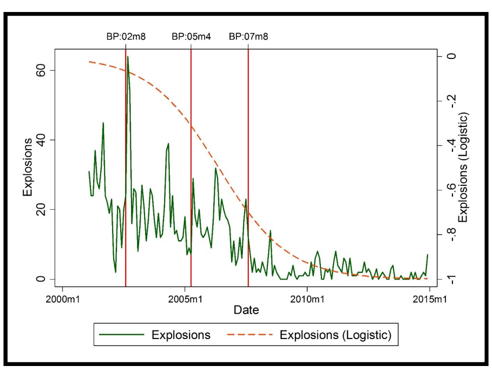
(b) Terrorists Killed



(c) Civilians Killed



(d) Security Personnel Killed



(e) Number of Incidents Involving Explosives findings. Finally, the new breakpoint for security force personnel killed, namely that at 2013, marks the time when the series converges to nearly zero.

Furthermore, since the data contains zeros and low values especially in the low violence regimes, we do a robustness check with quarterly sums of the monthly series both with and without the exogenous AR-terms. The results are qualitatively similar to those of Tables 6 and 7. These results are reported in Appendix 3.

We also conduct Chow's (1960) test for the joint significance of the break dates detected using the Bai and Perron procedure and reject the null of no breaks at the 1% significance level in all the four series.[24]

Finally, Appendix 1 presents the Bai and Perron results for foreign terrorists killed using data gathered from J&K police records, which find a breakpoint in March 2005, which coincides exactly with the breakpoints in both terrorists and total killed. Further, we can see from Figure A1 that even though the number of foreign terrorists killed did decrease significantly after the completion of the fence it has stayed constantly above zero. Hence, while the fence has decreased infiltration, crossing the border is still possible.

5 Conclusion

Over two and a half decades since the beginning of the conflict, the Indian government continues to search for policies to address the ongoing insurgency in Jammu and Kashmir. In this paper, we used a variety of time series techniques to assess the role played by several military, political and economic measures in reducing conflict in the state. The effect of policy interventions on conflict may gradually manifest over time, making it difficult to ex-ante pinpoint break dates in the time series data on violence. In this study, we go beyond the standard tests for sharp structural breaks used in the literature (Bai and Perron, 1998 and 2003; Chow, 1960; Andrews, 1993) by using endogenous nonlinear smooth break tests based on the LSTR model (Teräsvirta, 1994; 1998; Lin and Teräsvirta, 1994) to examine insurgency in the Indian state of Jammu and Kashmir over the period 1998-2014.

[24] We test for a break in both in the constant and trend of the series. The results are available from the authors on request.

Table 7: Estimates of Bai and Perron Multiple Structural Breaks (with exogenous AR terms)

Series		Breakdate	Lower	Upper	Intercept	Trend
$\boldsymbol{y_{TOT}}$		2001:06	2001:05	2001:07	150	5.89
		2003:02	2003:01	2003:05	1227	-16.12
		2005:03	2005:02	2005:05	751	-6.96
		2007:11	2007:10	2007:12	563	-4.18
					128	-0.6
	$\boldsymbol{y_{TER}}$	2001:05	2001:04	2001:06	46	3.38
		2003:03	2003:02	2003:06	680	-9.2
		2005:02	2005:01	2005:03	446	-4.47
		2006:10	2006:09	2006:11	332	-2.66
					90	-0.44
	$\boldsymbol{y_{CIV}}$	2001:04	2001:02	2001:05	98	0.14
		2003:02	2003:01	2003:12	265	-3.05
		2005:04	2004:11	2005:06	183	-1.54
		2007:04	2007:03	2007:06	213	-1.65
					20	-0.1
	$\boldsymbol{y_{SP}}$	2001:11	2001:10	2000:12	-14	3.6
		2006:07	2006:06	2006:09	137	-1.12
		2013:02	2013:01	2014:02	57	-0.31
					23	-0.07
$\boldsymbol{y_{EXP}}$		2003:08	2003:07	2003:10	37	0.52
		2006:02	2006:01	2006:04	55	-0.45
		2008:07	2008:06	2008:08	116	-1.18
					10	-0.04

Note: y_{TOT} denotes the total killed, y_{CIV} denotes the civilians killed, y_{TER} *d*enotes the terrorist killed, y_{SP} denotes the security personnel killed and y_{EXP} denotes incidents involving explosives. Shifting regressors are constant and a trend. The lower and upper columns denote 95% confidence intervals. The intercept and trend are the coefficient estimated for the regime prior that break. Number of breaks is determined by BIC with the maximum number of breaks set to 5 and the minimum length of the regime set to 20. The AR structure is chosen by using AIC, BIC and HQ criteria. The number of exogenous AR-terms chosen are 8, 9, 12, 12 and 12 for the series Total killed, Terrorists, Civilians, Security Force Personnel, and Explosions, respectively.

The nonlinear LSTR models indicate transition from a high violence state to a low violence state around 2005 corresponding to the fencing of the border between India and Pakistan. Subsequent large scale employment generation and infrastructure development programs implemented in the improved security environment coincide with a further reduced violence particularly that directed against civilians. The results from the Bai and Perron test procedure further validate this finding, and our results are robust to different model specifications and transformations of the data. This pattern in the timing of breaks is indicative of the causal factors that may have been at play during the period of declining violence in the state. In particular, the results provide suggestive evidence on the complementary relationship between security and development programs, which is supported by recent literature.

As further data becomes available, future research could extend the analysis to a more micro level. As discussed earlier, Berman et al. (2011b) find that small-scale projects implemented with local collaboration were successful in reducing violence in Iraq. While most the development projects in India are rather large scale, spatial and temporal variation in their effect on violence and their interaction with security policies could provide a fruitful avenue to gain a deeper understanding of the effect of development programs on conflict.

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Appendix

A Foreign terrorists killed

We can differentiate foreign terrorists killed from the aggregate number of terrorists killed by using police records of foreign terrorists killed for the period January 2003–December 2010.[25] The records are available for the period October 1998–April 2010. However, no foreign terrorist casualties are reported for the period April 2002 - June 2003. Given the number of casualties reported before and after this period, we regard this data as missing and only consider data from July 2003-December 2010 for our analysis. In line with the main analysis, we have aggregated the data to monthly level (to 82 observations). The summary statistics for both the full sample and the sample without gaps are presented in Table A-1a and the Lee and Strazicich unit root test result with the assumption of one break is reported in Table A-1b. Our results suggest no unit root under this assumption.

Due to the lack of data from the beginning of our time period of interest, we do not perform the analysis using the LSTR model. In Table A-1c we present the Bai and Perron results corresponding to the specification in Table 6. We find one breakpoint in March 2005, which coincides exactly with the breakpoints in the time series for both terrorists and total killed.

Figure A-1 depicts the dataset in full, where the dashed line presents the period October 1998 - June 2003 not used in the analysis. We can see that the average levels of killings were much higher before the breakpoint in 2005. Further discussion about the interpretation of the results is presented alongside with the results in the main text.

[25] These data were obtained from the J&K police website (`<http://www.jkpolice.gov.in/index.htm>`) in 2014.

Figure A-1: Foreign terrorists killed

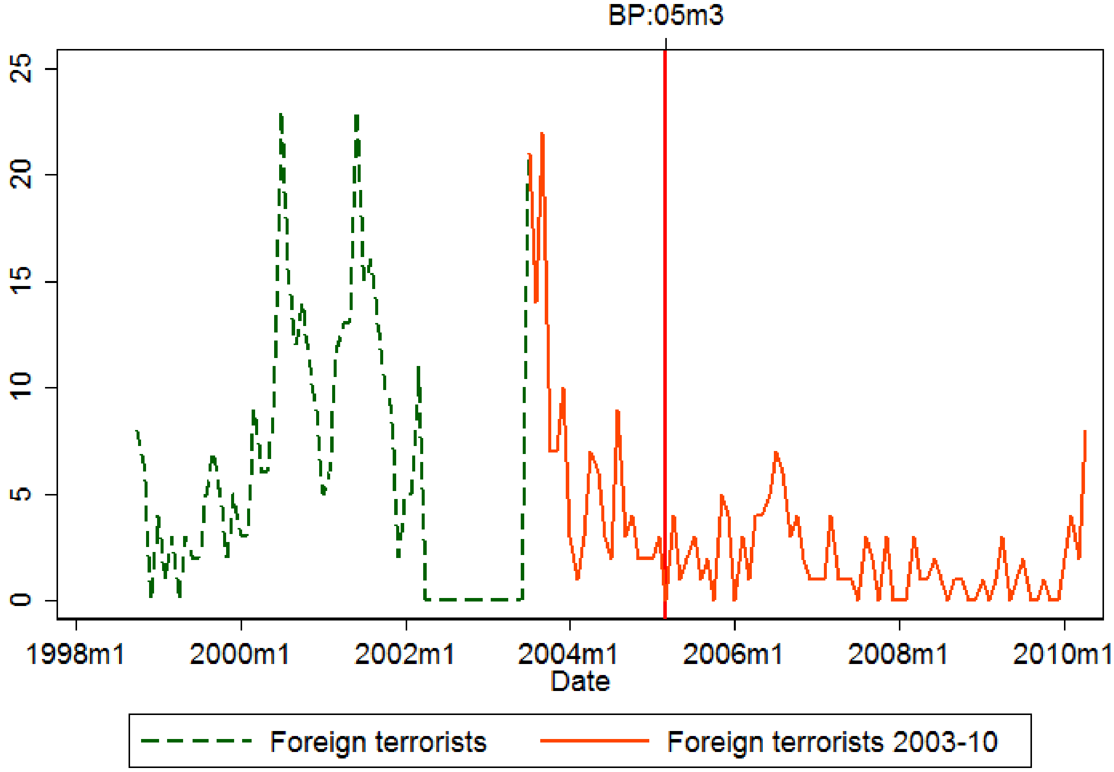

Table A-1: Foreign terrorists killed

(a) Descriptive statistics

Variable	y_{FT03}	y_{FT}
Mean	2.99	3.70
Std. Dev	3.94	4.93
Skewness	3.00	1.94
Kurtosis	11.17	3.92
Maximum	22	23
Minimum	0	0
Observations	82	156

(b) Unit root test (Lee-Strazicich, 2003)

Variable	**Trend Break Model**		**Inference**
$\boldsymbol{y_{FT03}}$	-4.5883		I(0)
	Critical Values		
Crash Model	1%	5%	10%
$\boldsymbol{LM_\tau}$	-4.545	-3.842	-3.504

(c) Estimates of Multiple Structural Break Dates

Variable	Breakdate	Lower	Upper	Intercept	Trend
y_{FT03}	2005:03	2005:02	2007:01	60	-0,71
				5	-0,03

Note: y_{FT03} denotes the foreign terrorists killed for the period 2003-2010 without the gap and y_{FT} denotes the full sample. Shifting regressors are constant and a trend. The lower and upper columns denote 95% confidence intervals. The intercept and trend are the coefficient estimated for the regime prior that break. Number of breaks is determined by BIC with the maximum number of breaks set to 3 and the minimum length of the regime set to 15.

B Nonlinear Breaks in Transformed Data

As a robustness check, we transform our data using a linear mapping which preserves the order of the values. This is achieved by standardization of the time series by deducting the mean and dividing by the sample standard deviation For a series x_t, then, the transformed series will be given by $x_{tT} = \frac{x_t - mean}{standard\ deviation}$. In order to confirm the break dates, we redo the nonlinear analysis on the transformed data and estimate the LSTR model to detect the smooth breaks. The results are given in Table B-1 below.

From Table B-1 we find that the results for the transformed data are identical to those stated before. The break dates are correspondingly the same as before. This suggests that the break dates are robust.

Table B-1: LSTR Model for the Transformed Data

(a) Estimates of LSTR model with time as the threshold variable

Variable		α_0	α_1	α_2	λ_0	c	γ
y_{TOTT}		0.266***	0.780***	-	-0.459***	85.478***	0.073*
	y_{TERT}	0.209***	0.811***	-	-0.356 ***	84.320***	0.079
	y_{CIVT}	0.953***	0.263***	-	-1.672***	87.940***	0.056***
	y_{SPT}	0.457***	0.456***	0.141**	-0.768***	84.717***	0.079*
y_{EXPT}		0.697***	0.415***	-	-1.166***	65.609***	0.058**

(b) Estimated Break Dates

Variable		c	Break Date
y_{TOTT}		85.48***	February, 2005
	y_{TERT}	84.32***	January, 2005
	y_{CIVT}	87.94***	April, 2005
	y_{SPT}	84.72***	January, 2005
y_{EXPT}		65.61***	June, 2006

Note: y_{TOTT} denotes the total killed, y_{CIVT} denotes the civilians killed, y_{TERT} denotes the terrorist killed, y_{SPT} denotes the security personnel killed and y_{EXPT} denotes the incidents involving explosives using the transformed data. The optimal number of lags included in the model are one for civilians killed, terrorist killed and total killed, two for security personnel killed and one for incidents involving explosives. *, **, *** denote significance at 10%, 5% and 1% respectively. Column LB stat in (b) denotes the Ljung-Box test statistic for autocorrelation in the residuals.

C Estimates of Bai and Perron Multiple Structural Breaks with Quaterly Data

Since our data contains some zeros and low values especially in the low violence regimes, we do a robustness check with quarterly sums of the monthly series. The results are reported in Table C-1. Table 6 is equivalent to Table 6 and Table C-1b is equivalent to Table 7 of the main paper.

Due to taking quarterly sums, we have just one fourth of the observations relative to the results in Tables 6 and 7. In all the killings series the number of observations is 68 and in the explosions series it is 56.

The results of both Table C-1a and C-1b are qualitatively similar to those of Tables 6 and 7. In Table C-1 the beginning and the end point of the smooth structural breaks are picked up by the procedure in the killings series, which is natural given that the intercept and the trend change the most at those points. The first break points are in 2001-2002 and the second ones in 2006-2007 in Table C-1a, and somewhat lagged in the specifications in Table C-1b where the AR terms are taken into account.

There are several reasons, why the differences between the results in Table C-1 and Tables 6 and 7 arise: The restriction of the minimum length of one regime determines that we cannot find breaks as close to each other than in the main specification. Also, due to the data being smoother, it is less informative of the monthly fluctuations and hence the procedure is less likely to find breaks in the series.

Table C-1: Estimates of Multiple Structural Breaks, Quarterly Data

(a) Multiple Structural Breaks without AR-terms, Quarterly Data

Series	Breakdate	Lower	Upper	Intercept	Trend
Total	2001:Q4	2001:Q3	2002:Q2	364	53.59
	2007:Q4	2007:Q3	2008:Q1	1198	-26.87
				264	-3.62
Terrorists	2001:Q4	2001:Q3	2002:Q2	103	42.32
	2006:Q4	2006:Q3	2007:Q2	713	-16.58
				230	-3.38
Civilians	2002:Q3	2002:Q2	2004:Q2	222	0.94
	2007:Q3	2007:Q2	2007:Q4	312	-6.76
				34	-0.46
Security Force Personnel	2001:Q4	2001:Q3	2002:Q1	45	9.09
	2006:Q4	2006:Q3	2007:Q2	179	-4.04
				48	-0.61
Explosions	2007:Q3	2007:Q2	2008:Q1	105	-1.87
				18	-0.22

(b) Estimates of Multiple Structural Breaks with Exogenous AR-terms, Quarterly Data

Series	Breakdate	Lower	Upper	Intercept	Trend
Total	2002:Q2	2002:Q1	2002:Q3	510	70.12
	2008:Q1	2007:Q4	2008:Q2	1872	-41.48
				452	-6.37
Terrorists	2003:Q4	2003:Q3	2004:Q1	300	29.73
	2008:Q3	2008:Q2	2008:Q4	1.171	-23.50
				452	-6.56
Civilians	2003:Q1	2002:Q4	2004:Q2	292	0.12
	2007:Q1	2006:Q4	2007:Q2	407	-8.11
				100	-1.54
Security Force Personnel	2003:Q4	2003:Q3	2005:Q3	109	-4.47
				21	-0.31
Explosions	2006:Q1	2005:Q4	2006:Q2	220	-4.11
	2009:Q1	2008:Q4	2009:Q2	453	-10.08
				35	-0.40

Notes: Shifting regressors are constant and a trend. The lower and upper columns denote 95% confidence intervals. The intercept and trend are the coefficient estimated for the regime prior that break. The number of observations is 68 in all the killings series and 56 in the Explosions series. Number of breaks is determined by BIC with the maximum number of breaks set to 3 and the minimum length of the regime set to 15 for all killings series, and 12 for explosions due to the smaller amount of data. In Panel A there are no exogenous AR-terms. In Panel B the AR structure is chosen by using AIC, BIC and HQ criteria. The number of exogenous AR-terms chosen are 3, 8, 6, 6 and 4 for the series Total, Terrorists, Civilians, Security Force Personnel and Explosions, respectively.

D The Fence

Figure D-1: The fence at the Line of Control (source: Rediff news)