Essays in Applied Microeconomics

Francesco Amodio

TESI DOCTORAL UPF / ANY 2015

DIRECTOR DE LA TESI
Albrecht Glitz i Massimo Motta
Departament d'Economia i Empresa

A Marianna

Acknowledgements

All achievements are nothing but the collection of the effort of many. Listing all the names of those who contributed somehow to this thesis is a prohibitive task. For this reason, and as paradoxical as it may seem, I will thank here all those to whom I owe a lot more than a simple acknowledgement note.

I am thankful to Albrecht Glitz for his guidance, encouragement and support. This thesis would have not been the same without his frankness and effort to push me to do my best and make the most out of my projects, even when these were not perfectly aligned with his own research interests. Perhaps more importantly, he taught me incredibly much while making me feel more of a colleague rather than a student. I also owe many thanks to Alessandro Tarozzi. His arrival at UPF has been decisive for my professional and personal growth. It is his genuine fault if this thesis and my research agenda and mindset have now a strong development tag. The same is true for Giacomo De Giorgi, who gave invaluable comments on my papers, and shaped my way of thinking about research. I would also like to thank Massimo Motta for his help and guidance, especially during the first part of my PhD. Our discussions over research and the profession helped me to navigate it safely until now.

I owe many thanks to the applied micro faculty at UPF and IPEG. I hope they will forgive me for not going through the list, but all of their names should be here with no exceptions. Beyond and above the many workshops and seminars where I received valuable comments, I had multiple meetings with each one of the professors in the group. In terms of collegial support from the faculty members in my field, I truly believe that my experience as PhD student couldn't have been better.

I would also like to thank Stephen Hansen, Hannes Mueller and Jonas Hjort. They have been equally helpful at different stages of my PhD. I draw a fair amount of inspiration from them in thinking about myself as a junior scholar. The same is true for Michele Di Maio, whose perspective on research is of great value for me.

I owe many thanks to Lucia Freira, Diego Casaravilla, Rafael Di Tella, Ernesto Schargrodsky, the Research Department at CAF Development Bank, and Ramiro Gálvez. One entire chapter of this thesis would have simply not been there without their help.

Many of my fellow PhD students at UPF became good friends. I would like to thank them all: Tanya, Vicky, Alain, Andrei, Mapis, Marc, Pau, Andrea, Jacopo, Jagdish, Ricardo, Maria, Cristina, Ana, Francisco, Tomas, Dijana, Chris, Federica, Liza, Fernando, Caterina, Emma, Helena, Marco, Niklas. I owe special gratitude to Kizkitza, Oriol and Miguelito, who are always there. I am especially thankful to Tom, Gene, Felipe and Jörg for sharing with me the job market experience, and to Miguelón, who allowed me to enter the fabulous world of egg production in rural Peru. His sincerity and solidarity are uncommon. I would also like to thank Bruno, true comrade, fellow fighter and brother.

I owe a lot to many other friends and colleagues who enriched my life over the years in which this thesis was written. They made me a much better person. I am especially grateful to the Lepant crowd and whoever gravitated around it: Marco, Francesco, Karina, the little Sofia, Carmen, Fredy, Alfonso, Inés, Annini. And to Giulia, who patiently coped with my inside oldness. I also thank Giorgio, who taught me much more than what he would think along many different dimensions.

A special thanks goes to Michael and Jaime. You guys didn't know each other, but I often think about you.

I am especially thankful to Giovanni, Angelo, Roberto and Rodrigo: we are all sides of the same coin. And to John, who taught me to question life at the right time. I wish we could spend more time together.

All achievements also come from far away. I would like to thank all my dearest friends from my hometown. We are growing apart but together. Wherever we are, we all work hard for something, making every single one of our stories extraordinary. For this I thank the warmth of the Scirocco wind, which blows through our land and our minds. It taught us all how not to faint in the hot struggle for a better life.

There are no words to express my greatest gratitude to my family. I am thankful to my sister, who is the strongest of all. To the tough tenderness and the hard work of my father. To the silent perseverance and kindness of my mother. All I am is still nothing compared to them.

Finally, I am immensely grateful to Marianna. I wish I could say that I have been for her even only one half of what she has been for me. There were moments in which sharing a life with me couldn't get any more difficult. No single line of this thesis could have been there without her unconditional support, patience and understanding. I am sure that her strength, perseverance and hard work will find their place in this world very soon. We will be strong. We will grow stronger.

Abstract

This thesis provides an empirical investigation of externalities and social interaction mechanisms in various settings. In the first chapter, I show how input heterogeneity triggers productivity spillovers at the workplace. I find that the exogenous assignment of inputs of heterogeneous quality allows workers to free ride on each other, yielding negative productivity spillovers. In the second chapter, I investigate the impact of violent conflict on firm behavior. I show how conflict-induced distortions in the accessibility of foreign markets force Palestinian firms to substitute imported materials with domestically produced materials, diminishing their output value. In the third chapter, I explore the relationship between ethnic diversity and conflict in contemporary South Africa. Results show that ethnic diversity within the black majority was highly correlated with conflict incidence during the democratic transition. In the fourth chapter, I study spillovers among potential victims from investment in crime protection technologies. I find that burglary protection investment of neighbors significantly increases the likelihood of a given household of investing in the same technology.

Resumen

Esta tesis es un estudio empírico de externalidades y mecanismos de interacción social en varios contextos. En el primer capítulo muestro como heterogeneidad en la calidad de los insumos genera efectos derrame en el puesto de trabajo. Encuentro que la asignación exógena de los insumos genera un problema de *free riding*, con efectos de derrames negativos sobre productividad. En el segundo capítulo, investigo el impacto de un conflicto violento sobre la actividad de las empresas. Los resultados muestran como el conflicto genera distorsiones en el acceso a los mercados extranjeros, forzando las empresas palestinas a substituir materiales importados con materiales locales, con una consecuente disminución del valor de su producción. En el tercer capítulo, exploro la relación entre diversidad étnica y conflicto en el el Sudáfrica contemporáneo. Los resultados muestran como, durante del proceso de democratización, la diversidad étnica entre la mayoría negra estaba fuertemente correlacionada con la incidencia de conflicto a nivel local. En el cuarto capítulo, estudio efectos derrame de las inversiones en tecnologías de protección ante el crimen sobre las víctimas potenciales. Los resultados muestran que las inversiones en tecnologías de protección contra el robo en vivienda por parte de los vecinos aumentan de manera significativa la propensión a invertir en la misma tecnología.

Preface

This doctoral thesis brings together the results from four independent research projects at the intersection between labor economics, development economics and political economy. The four essays are tied together by the focus on the empirical analysis of externalities and social interaction mechanisms among economic agents, with theory-based applications to personnel economics and the economics of conflict and crime.

In the first chapter, co-authored with Miguel A. Martinez-Carrasco, I show how input heterogeneity triggers productivity spillovers at the workplace. We focus on the context of an egg production plant in rural Peru. Workers produce output combining effort with inputs of heterogeneous quality. Exploiting quasi-random variation in the productivity of inputs assigned to workers, we find evidence of a negative causal effect of an increase in coworkers' daily output on own output and its quality. We show both theoretically and empirically that the effect captures free riding among workers, which originates from the way the management informs its decisions on whether and who to dismiss. Evidence also suggests that the provision of monetary and social incentives can offset negative productivity spillovers. Our study and results show that production and human resource management practices interact in the generation of externalities at the workplace. Indeed, counterfactual analyses suggest productivity gains from the implementation of alternative input assignment schedules and dismissal policies to be up to 20%.

In the second chapter of my thesis, co-authored with Michele Di Maio, we investigate the effect of conflict on firms' output value and input misallocation in the context of Palestine during the Second Intifada. Using a unique establishment-level dataset, we compare firms' outcomes and input usage over time across districts experiencing differential changes in conflict intensity. We show how conflict diminishes the total and per-worker value of firms' output through the distortions it generates in firms' access to input markets. In particular, lack of access to the market for imported material inputs leads firms to adjust input usage accordingly, substituting domestically produced materials for imported ones. We also empirically identify the relative amount of conflict-induced input distortions. Furthermore, we find that conflict affects disproportionally more those sectors which were more intensive in imported materials and had higher average output value in pre-conflict years. Results thus show that conflict is particularly harmful for the most productive sectors of the economy.

In the third chapter, co-authored with Giorgio Chiovelli, we explore the extent to which changes over time in ethnic distribution correlate with contemporaneous changes in conflict incidence. We focus on the history of contemporary South Africa during democratization. Migration flows following the implementation and repeal of apartheid segregation laws induced cross-sectional and time variation in districts' ethnic composition. Ethnolinguistic diversity within the black majority is shown to be strongly informative of the incidence of armed confrontations between black-dominated organized groups through the democratic transition. In order to achieve identification, we compare the evolution of conflict across districts experiencing differential changes in ethnic composition. Results are robust when comparing neighboring localities, and to the implementation of an instrumental variable strategy where pairwise distance between districts is used to predict the location decision of internal migrants.

Finally, in the fourth chapter of my thesis, I study spillover effects among potential crime victims from investment in observable protection technologies. I first propose an original theoretical framework, where criminals and potential victims interact in a frictional market for offenses. Externalities within the two market sides arise as trading externalities, and their sign and size depend on the equilibrium changes in victimization probabilities. I then move to explore the issue empirically using household-level geo-referenced data from the City of Buenos Aires. The City is shown to exhibit a significant level of spatial clustering of burglary protection investment. More importantly, investment by neighbors is shown to significantly affect individual households' investment decisions. In order to achieve identification, I exploit variation in close neighbors' protection investment status as induced by their knowledge of crimes suffered by friends, relatives, acquaintances or others, occurred sufficiently far away. Evidence shows how neighbors' investment in CCTV cameras and alarms significantly increases a given household's propensity to invest in the same technology. No effect is found instead for special door locks, bars or outdoor lighting. Taken all together, results implicitly suggest the supply of criminals in the city to be relatively inelastic to the intensity of private protection in the average location, or perceived to be so by potential victims.

Contents

List of Figures

List of Tables

Chapter 1

INPUT ALLOCATION, WORKFORCE MANAGEMENT AND PRODUCTIVITY SPILLOVERS: EVIDENCE FROM PERSONNEL DATA

Joint with Miguel A. Martinez-Carrasco, UPF

1.1 Introduction

Differences in management practices explain a considerable amount of variation in firms' productivity and performance. Given the same inputs, better managed firms achieve higher sales value and growth, capital returns and survival probabilities compared to less well-managed ones, both within and across sectors and countries (Bloom and Van Reenen 2007, 2010; Bloom et al. 2010, 2013).

In particular, a number of studies show how human resource management practices may affect productivity through the externalities they generate among coworkers in their choice of effort. In their pioneering work, Bandiera et al. (2005) use personnel data from a leading fruit producer in the UK to show how fruit picking workers internalize the negative externalities generated by a relative performance evaluation pay scheme. As a result, average productivity increases by at least 50% when piece rate pay is introduced. More recently, Mas and Moretti (2009) investigate productivity spillovers among cashiers in a large US supermarket chain. Social pressure from working peers is there shown to be strong enough to offset the negative externalities that the worker evaluation and firing policy is assumed to generate. These studies show how, even in the absence of technological sources of externalities, personnel policies can make coworkers' choices of effort interdependent and generate productivity spillovers.

However, much less is known about how these arguments generalize and apply to more complex production environments. Workers often produce output by combining their effort with inputs of heterogeneous quality. Inputs of higher quality increase the marginal product of effort. For instance, in Bangladeshi garment factories, the quality of raw textiles affects the productivity of workers as measured by the number of items processed per unit of time. Likewise, the speed at which warehouse workers fill trucks is affected by the shape and weight of the parcels they handle. Similarly, the amount of time it takes for a judge to close a case depends on her own effort as well as on both observable and unobservable characteristics or complexity of the case itself (Coviello et al. 2014).

This chapter investigates whether and how the productivity of workers is affected by peers' productivity in those contexts where workers handle inputs of heterogeneous quality. The characteristics of inputs individually assigned to workers directly affect their productivity, and, in the presence of any source of externalities, it also triggers productivity spillovers among them. Is there any evidence of productivity spillovers of this origin? Do human resource management practices shape the size and sign of these spillovers?

Answering these questions is challenging for three main reasons. First, firms often do not maintain records on the productivity of individual workers. Second, even when such data exist, input quality is often unobservable or hard to measure. Finally, in order to credibly identify productivity spillovers from heterogeneous inputs, these inputs and their quality need to be as good as randomly assigned to workers.

We overcome these issues altogether by studying the case of a leading egg producing company in Peru. The production technology and arrangements at its plant are particularly suitable for our analysis. Workers are grouped in several sheds. Each worker is assigned a given batch of laying hens. Hens' characteristics and worker's effort jointly determine individual productivity as measured by the daily number of collected eggs. In particular, variation in the age of hens assigned to the worker induces variation in his productivity. Using daily personnel data, we exploit quasi-random variation in the age of hens assigned to coworkers in order to identify the causal effect of an increase in coworkers' productivity on the productivity of a given worker, conditional on his own hens' age.

We find evidence of negative productivity spillovers. Conditionally on own input quality, workers' productivity is systematically lower when the productivity of neighboring coworkers is exogenously raised by the assignment of higher quality inputs. A positive shift in average coworkers' inputs quality inducing a one standard deviation increase in their daily output causes a given worker's output to drop by almost a third of a standard deviation. In other words, if all workers are assigned the same number of hens, an increase in average coworkers' daily output of 500 eggs is associated with a decrease of own output of 150 eggs in the same day. We also find output quality to decrease significantly, with the effect in standard deviation units being similar in magnitude to the effect on quantity. We attribute these effects to a change in the level of effort exerted by the worker, which varies systematically with coworkers' productivity.

Along with the identification of productivity spillovers from heterogeneous inputs, we use both theory and empirics to identify the specific source of externalities in this setting. We focus on the role of human resource management practices, and, in particular, the worker evaluation and dismissal policies implemented by the firm. We build upon Mas and Moretti (2009), and provide a simple conceptual framework to characterize the worker's optimal effort choice. Daily productivity is a signal of the level of effort exerted by the worker, which is unobservable to the management. The latter combines information on individual and coworkers' productivity in evaluating employees and making dismissal decisions. If overall or average productivity positively affect to some extent worker evaluation, an increase in the productivity of coworkers increases a given worker's probability of keeping the job. As a result, workers free ride on each other: when coworkers' productivity increases, individual marginal returns from effort in terms of increased probability of keeping the job decrease for a given worker, and her optimal effort supply falls accordingly.[1]

[1]The opposite holds if the management attaches a negative weight to overall or average productivity

Workforce turnover information in the data allows us to see how employment termination probabilities correlate with individual and coworkers' productivity, validating the specific mechanism identified by theory. The probability for a given worker to keep the job is positively and significantly correlated with own productivity measures. Furthermore, conditionally on the latter, the same probability is positively and significantly correlated with coworkers' productivity as well. In line with the previous results, we find that returns from own productivity in terms of increased probability of keeping the job are systematically lower when coworkers' productivity is higher. Coworkers' productivity thus decreases the optimal amount of effort exerted by the worker, yielding negative production externalities.

In the second part of the chapter, we study whether and how the provision of incentives can counteract the workers' tendency to free ride and thus offset negative spillovers at the workplace. Rather than asking whether incentives increase workers' productivity, we investigate their effect on the size and sign of productivity spillovers. In our conceptual framework, monetary incentives provide extra marginal benefits from own effort, leveraged by the probability of keeping the job and earn the corresponding salary. By the same token, working along friends is more likely to induce peer pressure in the form of diminished marginal cost of effort (Kandel and Lazear 1992; Falk and Ichino 2006; Mas and Moretti 2009). As a result, both types of incentives bring about positive externalities among coworkers' in their optimal choice of productive effort, mitigating the previously identified negative effect of coworkers' productivity.

We exploit the specific features of the pay incentive regime in order to evaluate effect heterogeneity according to piece rate incentive exposure. Workers receive extra pay for every egg box they produce above a given threshold. Hens' age affects productivity, so that the probability of reaching the threshold and being exposed to piece rate pay changes for a given worker depending on the age of own assigned hens. Consistently with the above reasoning, we find no effect of coworkers' productivity when the worker is assigned highly productive hens, meaning he is more likely to reach the piece rate threshold and to be exposed to piece rate pay. On the contrary, the effect of coworkers' productivity is negative and significant when the same worker is assigned either

in evaluating a single worker, as in relative performance evaluation schemes. We allow our conceptual framework in Section 1.5.1 to be general enough to cover all these cases. We discuss the rationale for the implementation of the termination policy we observe at the firm in Section 1.5.2 and Appendix B.

young or old hens, meaning he is less likely to reach the piece rate threshold. Evidence thus suggests that monetary incentives push the sign of productivity spillovers towards positive values.

We also use elicited information on the friendship network among workers to test whether the average effect of coworkers' productivity is heterogeneous according to the workers' friendship status. Consistently with the previously outlined peer pressure argument, we do not find any significant effect of average coworkers' daily output when the given worker identifies any of his neighboring coworkers as friends. This finding also allows us to rule out the possibility that the observed average negative effect of coworkers' productivity on own productivity captures cooperative behavior among coworkers. Indeed, workers who are assigned highly productive inputs may benefit from the help of neighboring coworkers, with negative productivity spillovers on the latter. We would expect such cooperative strategy to be more sustainable among friends. The absence of any significant effect in this case speaks against this hypothesis. Moreover, this same result also allows us to rule out that negative spillovers are built in the production function, with their origin being technological in nature. Indeed, if this was the case, there would be no reason to expect the effect to be heterogeneous depending on the status of social relationships among workers.

Causal estimates of productivity spillovers are further validated by several robustness checks. First, we investigate whether variation in the average input quality of workers in non-neighboring production units or different sheds relates systematically to individual productivity. The structure of the production plant is such that workers not located one next to the other cannot observe each other. Therefore, we do not expect to find any significant relationship between the two. We thus frame this empirical exercise as a *placebo test*, which indeed provides non-significant results and estimates close to zero. Second, we replicate our main analysis employing an alternative measure of exogenous input quality, that is, the expected productivity of hens as reported by an independent bird supplier company. The estimates based on this alternative measure match closely the previous ones.

Our case study provides empirical evidence of free riding among coworkers, imputable to the teamwork-type externalities generated by the firm's worker evaluation and termination policy. In this respect, our results add to the literature which investigates the externalities generated by human resource management practices. Bandiera et al.

(2005) explicitly explore the role played by social ties among coworkers in the internalization of negative externalities under relative performance evaluation, and their impact on productivity under individual performance pay (Bandiera et al. 2010). Bandiera et al. (2007, 2008, 2009) provide the first comprehensive analysis of managerial incentives, investigating their impact on productivity through endogenous team formation, and the consequences for lower-tier workers who are socially connected to managers. More recently, Bandiera et al. (2013) provide a theoretical and empirical investigation of team-based incentives and their relationship with social connections. Using daily personnel data from a flower processing plant in Kenya, Hjort (2014) shows how the ethnic composition of working teams affects productivity at the workplace, with the negative effect of ethnic diversity being larger when political conflict between ethnic blocs intensifies. He also shows how this effect is mitigated by the introduction of team-based pay.

The conceptual framework in our study builds upon Mas and Moretti (2009). They study peer effects and productivity among cashiers in a large US supermarket chain, exploiting variation in team composition across ten-minutes time intervals. This allows them to show how the productivity of a given worker changes with coworkers' permanent productivity, with variation in the latter being due to the entry and exit of peers into shifts. The empirical results of the study show that social pressure from observing high-ability peers is the central mechanism generating positive productivity spillovers, and speak against other potential explanation such as prosocial preferences or knowledge spillovers.

To the best of our knowledge, ours represent the first attempt to study the role of heterogeneous inputs and their allocation to working peers in triggering productivity spillovers at the workplace. Our study is thus relevant in that it has implications for several different aspects of both *production* and *human resource management*, ranging from input assignment to worker evaluation, dismissal and incentive regime policies. Indeed, we show how all these elements interact in determining the total amount of externalities in the system and thus overall productivity. In order to shed further light on these issues, we perform a structural estimation exercise based on our conceptual framework. Estimating the unobserved exogenous parameters of the model, we are able to conduct counterfactual policy analyses. Holding everything else constant, we estimate the implementation of alternative input assignment schedules to bring about up to 20% productivity gains. By the same token, the implementation of alternative termination policies is estimated to yield productivity gains still around 20%. Related to this, notice that the firm under investigation employs a relatively more labor intensive technology compared to firms in the same sector, but operating in developed countries. Our analysis and results are thus relevant in the microfoundation of productivity-enhancing management practices in developing countries. In this respect, our study is close to Hjort (2014) in that it highlights the efficiency cost of input misallocation among workers, and explores how properly designed incentives may partially eliminate these costs.

A number of other studies investigate the issue of productivity spillovers in a variety of settings. Gould and Winter (2009) focus on production externalities which are built in the technology of baseball teams. They show the sign of effort externalities among players in substitute or complement roles to be consistent with theoretical expectations. Arcidiacono et al. (2013) estimate spillovers in basketball teams, highlighting the role of heterogeneity in the positive spillovers generated by individual players, and discussing its implications for worker evaluation and team performance. Brown (2011) exploits instead variation in the presence of superstars in professional golf tournaments to identify competition externalities. She finds the presence of superstars to negatively affect the effort exerted by contestants. However, Guryan et al. (2009) previously found no average effect of other players' ability on own effort among professional golf players, attributable to the incentives determined by the steep prize structure. Cornelissen et al. (2013) use German social security data and exploit variation in one's working peers throughout her working life in order to identify productivity spillovers. They find only small peer effects on wages.

More generally, and in light of the identification challenges we face, our study contributes to the literature on empirical analysis of peer effects. After the seminal work of Manski (1993), a number of studies have delved into the empirics of social interactions mechanisms.[2] For example, Ichino and Maggi (2000) show evidence of peer effects in absenteeism and shirking behavior in a large Italian firm through exploiting variation in peer group composition induced by workers moving across firm branches. Sacerdote (2001) uses instead random assignment of peer college students to dorms and shows evidence of peer effects in academic achievement. An alternative identification approach based on variance decomposition is developed and adopted by Graham (2008) in pro-

[2]For a recent survey of the empirics of social interactions, see Ioannides and Topa (2010) and Blume et al. (2011).

viding evidence of peer effects among students involved in the Project STAR. More recently, a growing number of contributions exploit the variation induced by overlapping peer groups and identify peer effects adopting network-based strategies (Lee 2007; Bramoullé et al. 2009; De Giorgi et al. 2010; Blume et al. 2013).

While our empirical analysis is carried out using the tools which are peculiar of the peer effects literature, our study nonetheless focuses on productivity spillovers of different nature. In our context, these are triggered by the heterogeneity in inputs assigned to workers. We thus regard our analysis and results as complementary to the peer effects literature, possibly opening the way to a joint exploration of productivity spillovers of mixed nature.

The rest of the chapter is organized as follows. Section 1.2 provides the details of the setting. The data and the relevant baseline statistics are presented in Section 1.3. Section 1.4 shows the results from the empirical analysis, together with robustness checks and estimates of effect heterogeneity. The relevant mechanism and conceptual framework are presented in Section 1.5, together with the corresponding empirical analysis. The impact of monetary and social incentives is discussed in Section 1.6, while Section 1.7 presents the counterfactual analyses of alternative input assignment schedules and dismissal policies. Section 1.8 concludes.

1.2 The Context

Our aim is to investigate whether individual effort changes with coworkers' productivity in those contexts where workers handle inputs of heterogeneous quality. We take this question to the data by focusing on an egg production plant in Peru. The establishment belongs to a leading poultry firm having egg production as its core business. In the plant under investigation, production takes place in several *sectors*. An aerial photograph of a given production sector is shown in Figure 1.1. Each sector is divided into several different long-shaped *sheds*, as pictured in Figures 1.1 and 1.2. Each shed hosts one to four *production units* which constitute the ultimate unit of operations in the plant. A given shed hosting four production units is pictured in Figure 1.3.

Each production unit is defined by one worker and a given batch of laying hens assigned to him. Hens within a given batch are very homogeneous in their characteristics. In particular, they are all of the same age. This is because birds in the same batch are bought altogether when still eggs from an independent bird supplier company. After birth, they are raised in a dedicated sector. The entire batch is then moved to production when hens are around 20 weeks old, and discarded altogether when reaching around 80 weeks of age. The productive life of laying hens is thus approximately 60 weeks long. During that time, the batch is always assigned to the same production unit. The position of the worker is fixed over time as well. Worker's main tasks are: (i) to collect and store the eggs, (ii) to feed the hens and (iii) to maintain and clean the facilities.[3] Egg production establishments in developed countries are typically endowed with automatic feeders and automated gathering belts for egg handling and collection.[4] The production technology in the plant under investigation is thus more labor intensive relative to the frontier.

In this context, output is collected eggs. These are classified into good, dirty, broken and porous, so that measures of output quality can be derived accordingly. The batch of laying hens as a whole is instead the main production input. High quality hens increase the marginal product of effort for the worker. As we show later, hens' productivity varies with age, which generates both cross-sectional and time variation in input quality across workers.

Production units are independent from each other and no complementarities nor substitutabilities arise among them. Indeed, each worker independently produces eggs as output combining effort and the hens assigned as input to him. Egg storage and manipulation (selection, cleaning, etc.) is also independent across production units. As shown in Figure 1.3, each production unit is endowed with an independent warehouse for egg and food storage. Nonetheless, workers in neighboring production units in the same shed are likely to interact and observe each other. In particular, the productivity of working peers can be easily monitored as they take boxes of collected eggs to the warehouse located in front of each production unit. On the contrary, workers located in different sheds can hardly interact or see each other.

Workers in the firm are paid a fixed wage every two weeks. On top of this, a bonus

[3]The worker's typical daily schedule is reported in Table 1.A.1 in the Appendix A. Figure 1.A.1 in the same Appendix shows the distribution of the estimated worker fixed effects as derived as described at the end of Section 1.4. The variance of the distribution is indicative that, conditional on input quality, workers can have a substantial impact on productivity.

[4]American Egg Board, *Factors that Influence Egg Production*, `http://www.aeb.org`, accessed on December 27, 2013.

is awarded to the worker when his productivity on a randomly chosen day within the same two weeks exceeds a given threshold. In this case, a piece rate pay for each egg box exceeding the threshold is awarded. For simplicity, the piece rate component of pay will be ignored in the first part of the analysis. In the second part, the impact of both incentive pay and social incentives on productivity and externalities will be explored and tested.

1.3 Data and Descriptives

The basis for our empirical analysis is daily production data from one sector of the plant from March 11 to December 17 of 2012. The data are collected by the veterinary unit at the firm with the purpose of monitoring hens' health and productivity. Our unit of observation is one production unit as observed on each day during the sampling period. We observe a total number of 99 production units, grouped into 41 different sheds. The majority of sheds (21) is indeed composed of 2 production units. A total of 100 workers are at work in the sector for at least one day, while we can identify 171 different hen batches in production throughout the period. It follows that each production unit hosted an average of 1.73 batches and 1.01 workers over the sampling period. Batch replacement and hens' age represent the main sources of variation for identification of productivity spillovers.

For each production unit on each day, we can identify the assigned worker and the hen batch in production on that day. For each hen batch, we have information on the total number of living hens and their age in weeks on each day, together with a number of additional baseline batch quality measures as derived before the same was moved to production, such as mortality and weight distribution moments. Furthermore, we also have data on the weekly number of eggs that each hen in a given batch is expected to lay in each week of age. This information is provided by the independent bird supplier company from which laying hens were bought in the first place. Notice that such expected productivity measure is predetermined and thus exogenous to anything specific to the egg production phase, including workers' characteristics and their effort choice. In terms of output, we have precise information on the total number of collected eggs. We can thus derive a measure of worker's daily productivity as the average number of eggs per living hen collected by the worker in each production unit on each day. In this way, we can control for the variation in the number of living hens, which may by itself affect productivity.[5] The number of good, dirty, broken and porous eggs is reported as well, together with the daily number of hens dying on each day. Finally, the data also provide information on the daily amount of food handled and distributed among the hens by the worker as measured by the number of 50kg sacks of food employed.

Summary statistics for the variables of interest are shown in Table 4.1. Given the focus on productivity spillovers, observations belonging to sheds hosting a single production unit are excluded from the study sample, leading to a final sample size of 20,915 observations, one per production unit and day. As previously mentioned, the chosen productivity measure is the daily number of eggs per living hen. Its average across the whole sample is equal to 0.78. Consistently with the setting description above, hens' age varies between 19 and 86 weeks, while the average batch counts around 10,000 laying hens. There is substantial heterogeneity in the number of living hens in each production unit on each day, ranging from a minimum of 44 to a maximum of over 17,000. There are two main sources for this variation. First, hen batches are heterogeneous to begin with and already on the day they are moved to production. Second, within a given batch, a number of hens die as time goes by. Importantly, these are never replaced by new hens: only the entire hen batch is replaced as a whole when (remaining) hens are old enough. This is the reason why, at every point in time, all hens within a given batch have always the same age. Workers distribute an average daily amount of 112g of food per hen. This quantity is computed by dividing the number of 50kg sacks of food opened by the worker by the number of living hens on each day. Once the sack is opened, the food it contains does not need to be all distributed among the hens. This results in measurement error, and can explain why the maximum quantity of food per chicken in the data is almost 6kg. Derived output quality measures include the fraction of good, broken and dirty eggs over the total. On average, 86% of eggs produced by a production unit in a day are labeled as good, and are thus ready to go through packaging. 6% of eggs on average are instead labeled as dirty. Workers can turn a dirty egg into a good egg by cleaning it. Finally, an average fraction of 0.1% of hens in a batch die on a

[5]The number of living hens on a given day may be by itself endogenous to worker's effort. We discuss this possibility in greater details in Section 1.4. In particular, results from Table 1.5 show that the fraction of hens dying on each day does not change systematically with coworkers' productivity. We thus conclude that our estimates of productivity spillovers are not sensitive to the adjustment by the number of living hens.

daily basis.

We also collected information on the spatial arrangement of production units within the sector, and their grouping into sheds. For each production unit, we can thus combine this information with the above data to derive productivity and input quality measures for neighboring production units in the same shed. This allows us to compute a measure of coworkers' average daily output and the average age of hens assigned to coworkers. Not surprisingly, coworkers' average variables share the same support of individual measures, but standard deviations are lower.

Production data are complemented with those belonging to an original survey we administered in March 2013 to all workers employed at the time in the sector under investigation. The purpose of the questionnaire was to elicit demographic and personal information about the workers, and the friendship and social relationship among them.[6] For this purpose, we asked the workers to list those among their coworkers who they identify as friends, who they would talk about personal issues or go to lunch with. We will say that worker i recognizes worker j as a friend if the latter appears in any of worker i's above lists. 63 of the interviewed workers were already employed in the period for which production data are available, so that relevant worker information can be merged accordingly. The corresponding figures will be investigated when addressing the role of monetary and social incentives in Section 1.6.

1.4 Empirical Analysis of Productivity Spillovers

1.4.1 Preliminary Evidence and Identification Strategy

The batch of laying hens as a whole is the main production input in this context. The worker is assigned the same batch of equally aged hens from the moment they are moved to production until they are discarded. Crucially, hens' productivity varies with age. The more productive hens are the higher is the marginal product of effort. We thus regard input quality and effort as complements in production.[7] Figure 1.4 plots the chosen productivity measure - average daily number of eggs per hen - against hens' age in

[6]The questionnaire is available from the authors upon request.

[7]In order to understand this, let effort be measured as the amount of time devoted to a given task. A marginal increase in the time devoted to egg collection is more productive in terms of number of collected eggs the more productive hens are.

weeks. The figure plots the smoothed average together with a one standard deviation interval around it. Furthermore, for all given week of age, each bin in the scatterplot shows productivity values as averaged across all observations belonging to production units hosting hens of that given age.

Figure 1.4 shows how productivity is typically low when hens are young and have been recently moved to production, but starts to increase thereafter. It reaches its peak when hens are around 40 weeks old. From that age onwards, productivity starts to decrease first slowly and then more rapidly once hens are over 70 weeks old. Hens' age thus induces meaningful variation in productivity. This is especially the case through the beginning and the end of the hens' life cycle, meaning from week 16 to week 32 and from week 75 to 86. These time intervals together account for around 40% of the overall productive life span.[8]

Hens' age exogenously shifts input quality and thus productivity as measured by daily output y_i. This source of variation can be exploited in order to identify productivity spillovers. Specifically, we start by considering the following regression specification

$$y_{igt} = \varphi + \gamma \, \bar{y}_{-igt} + \alpha \; age_{igt} + \beta \; age^2_{igt} + \sum_{s=t-3}^{t-1} \lambda_s \mathit{food}_{igs} + \varepsilon_{igt} \tag{1.1}$$

where y_{igt} is the daily number of eggs per hen collected by worker i in shed g on day t. $\bar{y}_{-igt}$ captures the corresponding average value for coworkers in neighboring production units on the same day. The variable age_{igt} is the age in weeks of hens assigned to worker i. Its square is included as well in order to capture the inverted U shape relationship between hens' age and productivity previously shown in Figure 1.4.[9] We also include three lags of total amount of food distributed food_{igs} as controls. This is because we want to explore the relationship between the variables of interest at time t and conditional on one relevant dimension of effort exerted by the worker on previous days.[10] Finally, ε_{igt}

[8]As shown in Table 4.1, around 48% of the observations in the overall sample correspond to workers whose assigned hens are in the first or the fourth age distribution quartile.

[9]In Section 1.4.2, we also use week-of-age dummies in order to better fit the productivity-age profile shown in Figure 1.4. Parameter estimates are highly comparable across specifications. In our baseline specification, we prefer to adopt a quadratic functional form in oder to avoid the *many weak instruments* problems that would arise by using the full set of week-of-age dummies as instruments for coworkers' productivity.

[10]Results are qualitatively the same if we use lags of food per hen distributed by the worker.

captures idiosyncratic residual determinants of worker's productivity. Notice that, by conditioning on both own hens' age and food distributed on previous days, we aim to disclose the presence of any systematic relationship between coworkers' productivity and individual unobserved effort e_i on day t as captured by γ.

Our goal is to identify the causal effect of peers' productivity on own output, conditional on own input quality. OLS estimates of the parameter of interest γ in the above equation are likely to be biased. The proposed specification defines productivity simultaneously for all workers, leading to the so-called reflection problem first identified by Manski (1993).[11] Furthermore, sorting of hens or workers with the same unobserved characteristics into sheds or the presence of idiosyncratic shed-level shocks may push in the same direction the productivity of peers on the same day, generating a spurious correlation between coworkers' outcomes (Manski 1993; Blume et al. 2011). Nonetheless, hens' age represents a powerful source of variation. Changes in the age of hens assigned to working peers induces exogenous variation in their productivity, so that any systematic relationship between the former and own outcomes can be interpreted as evidence of productivity spillovers.

Notice that, by using hens' age as a source of variation for coworkers' productivity, we do not need to rely on the assumption that the initial assignment of batches to workers is as good as random. Indeed, we cannot rule out that batches which are expected to be of a given quality are assigned to specific workers. Our identification strategy exploits instead variation in hens' age over time within a given batch, and its realized match with a given worker. Still, in order to identify a causal effect, the age of coworkers' hens needs to be as good as randomly assigned and have no effect on own outcomes other than through changes in coworkers' productivity.

Given the assigned batches, coworkers' and own hens' age in weeks are both a function of time. We thus explore the correlation between the two variables conditional on the full set of day fixed effects. Even conditionally on the latter, own hens' age in weeks is found to be positively correlated with the corresponding average value for coworkers in neighboring production units on the same day, as reported in the first column in the top panel of Table 4.5. The corresponding correlation coefficient is equal

[11] The suggested specification differs from the basic treatment in Manski (1993) in that it adopts a leave-out mean formulation, as the average productivity regressor is computed excluding worker i. Nonetheless, the simultaneous nature of the equation makes the reflection problem still relevant (Bramoullé et al. 2009; Blume et al. 2011; Angrist 2014).

to 0.896, significantly different from zero. This is because the management allocates batches to production units in a way to replace those in the same shed approximately at the same time. It follows that hen batches in neighboring production units have approximately the same age. However, there is still residual variation to exploit. The second column in the top panel of Table 4.5 shows how the same correlation between coworkers' and own hens' age falls to zero when computed conditional on the full set of shed-week fixed effects.[12] The *p-value* from the test of the null hypothesis of zero correlation between the two variables is equal to 0.53. In other words, daily deviations in the age of hens in each production unit from the corresponding shed-week and day averages are orthogonal to each other. This same hypothesis can be tested by means of the regression specification proposed by Guryan et al. (2009), which in our case becomes

$$age_{igwt} = \pi_1 \, \overline{age}_{-igwt} + \pi_2 \, \overline{age}_{-igw} + \psi_{gw} + \delta_t + u_{igwt}$$

where age_{igwt} is the age in weeks of hens assigned to worker i in shed g in week w on day t. $\overline{age}_{-igwt}$ is the corresponding average value for coworkers in neighboring production units on the same day, while $\overline{age}_{-igw}$ is the average value for peers in the same shed in all days of the week. The hypothesis of daily random assignment of age of coworkers' hens within each shed-week group is equivalent to the null $H_0 : \pi_1 = 0$. Regression results are shown in the bottom panel of Table 4.5. Standard errors are clustered along the two dimensions of shed and day. According to our results, the H_0 cannot be rejected.

Evidence shows that, conditioning on the whole set of day δ_t and shed-week fixed effects ψ_{gw}, the age of hens assigned to coworkers is as good as randomly assigned to a given worker and his own hens' age. It follows that the age of coworkers' hens can be used as a source of exogenous variation in order to identify the causal effect of an increase in coworkers' productivity on own productivity.[13] Nonetheless, before

[12]Since every hen batch in the sample is neighbor of some other batch, within-group correlation estimates using the whole sample suffer from mechanical downward bias, a problem already noted by Bayer et al. (2008) and discussed extensively in Guryan et al. (2009) and Caeyers (2014). The bias in this case is of the same nature as the so-called Nickell-Hurwicz bias arising in fixed effects panel estimations with short time series (Nickell 1981). In order to overcome this problem, when estimating conditional correlations we follow Bayer et al. (2008) and randomly select one production unit per group as defined by the shed-week interaction (g, w). Estimates are computed using the same resulting subsample.

[13]Several contributions in the literature exploit within-group random variation in peer characteristics in order to identify peer effects (see for instance Sacerdote 2001; Ammermueller and Pischke 2009;

showing the results, it is important to understand whether the variation we exploit for identification is meaningful. Conditional on day fixed effects, within-shed-week variation accounts for 5.4% of the total variation in the age of coworkers' hens in the sample, measured in weeks. The same fraction goes up to 35% for observations belonging to those weeks in which any batch replacement took place in the shed.[14]

1.4.2 Baseline Results

The first set of regression results is reported in Table 1.3. In the first column, the daily average number of eggs per hen collected by the worker is regressed over the age of hens in weeks and its square. The full set of day fixed effects are included as well. The proposed specification yields a quadratic fit of the dependent variable as a function of hens' age which is consistent with the evidence in Figure 1.4.[15] Coefficient estimates are significant at the 1% level and confirm the existence of a concave relationship between hens' age and productivity. Standard errors are clustered along the two dimensions of shed and day in all specifications. Idiosyncratic residual determinants of productivity are thus allowed to be correlated both in time and space, specifically among all observations belonging to the same working day and all observations belonging to the same shed. In its quadratic specification, together with day fixed effects, hens' age explains 0.41 of the variability in the dependent variable. The same number rises to 0.43 when lags of the amount of food distributed are included in Column 2. The full set of shed-week dummies is included in Column 3. Notice that, despite its measurement in weeks, the age variable still induces meaningful variation in productivity as measured by the average number of eggs per hen collected: coefficients are almost unchanged with respect with those estimated in Column 2. The fraction of total variability explained is now up to 0.86.

The average age of hens assigned to coworkers in neighboring production units is

Guryan et al. 2009). They aim to find evidence of a systematic relationship between own outcomes and peer predetermined characteristics, leaving aside the issue of differentiating between *endogenous* and *exogenous* peer effects (Manski 1993). In this context, the parameter γ can be correctly identified under the additional assumption of no effect of the age of coworkers' hens on own productivity other than through changes in coworkers' productivity, as discussed in the next section.

[14]We estimated separately the effect of interest for observations belonging to weeks with and without any batch replacement, finding similar results. Results are shown in Table 1.A.3 of Appendix A.

[15]As previously mentioned, in Section 1.4.2 we also use hens' week-of-age dummies in order to better fit the productivity-age profile.

included in Column 4 of Table 1.3, together with its square.[16] Consistently with the conditional correlation result in Table 4.5, the coefficients of the own hen's age variables experience almost no change in magnitude, confirming the absence of any systematic relationship between own and coworkers' hens' age within each shed-week group.[17] Any systematic relationship between the average age of coworkers' hens and own productivity can thus be interpreted as reduced-form evidence of productivity spillovers. The corresponding coefficients are highly significant and opposite in sign with respect to the ones of own hens' age.[18] This result is confirmed in Column 5 of Table 1.3, which also includes worker fixed effects. The latter allow to detect systematic differences in the outcome of the same worker according to differences in the average age of coworkers' hens. The corresponding R^2 is now equal to 0.88. Consistently with regression results, Figure 1.5 shows how, once own hens' age, day and shed-week fixed effects are controlled for, the relationship between residual productivity and the age of coworkers' hens is u-shaped: the opposite with respect to the one between productivity and own hens' age. Therefore, conditional on own hens' age, workers' productivity is systematically higher when coworkers' assigned hens are on average either young or old, and thus of low productivity. The opposite holds when the age of coworkers' assigned hens is close to the productivity peak. In other words, conditional on own input quality, workers' productivity is systematically lower (higher) when coworkers are assigned inputs of higher (lower) quality. We interpret this result as reduced-form evidence of negative productivity spillovers.

Hens' age induces meaningful variation in workers' productivity. Quasi-random variation in the average age of coworkers' hens can thus be exploited in order to identify the parameter γ from the main specification above. However, in order to do so, the age of coworkers' hens needs to have no direct effect on own outcomes. If the exclusion restriction is met, the effect of coworkers' productivity can be correctly identified by means of a 2SLS estimator.[19] In this respect, the specific features of the production

[16] Caeyers (2014) shows that no mechanical downward bias arises in the estimation of the parameters of interest in this reduced form specification.

[17] The coefficients of the own hen's age variables do not change even adding coworkers' hens' age and its square separately as controls one by one, as shown in Table 1.A.2 in the Appendix A.

[18] Notice that residual correlation between coworkers' and own hens' age would let the coefficient of the corresponding variables be of the same sign.

[19] Again, Caeyers (2014) shows that no mechanical downward bias arises in the estimation of the parameters of interest in the specification of interest using 2SLS.

environment under investigation suggest the absence of any effect of the characteristics of coworkers' hens on own productivity. In particular, the production technology is independent among production units. One possible concern is that hens may be more prone to experience transmittable diseases as they get old, and the disease may spread to neighboring production units. However, notice that coworkers' productivity would be positively correlated in this case, while results from Table 1.3 already suggest the effect of interest to be negative. The true value of the parameter of interest would be even more negative than its estimate in this case.

As a further attempt to explore the relationship between the productivity of neighboring coworkers, Figure 1.6 plots the distribution of own productivity separately for those workers whose coworkers' average productivity is above or below the median in the same day. Productivity is still measured by the daily average number of eggs per hen collected by the worker. The left figure shows the resulting distributions for unconditional productivity. The distribution for workers whose coworkers are highly productive is found to be on the right of that for workers whose coworkers are of low productivity. This is consistent with the unconditional positive correlation result on own and coworkers' hens age as reported in Table 4.5. Nonetheless, once shed-week averages are netted out, the picture reverses. The distribution of residual productivity for workers whose coworkers have residual average productivity above the median is now on the left of that for workers in the other group, consistently with the negative correlation results in Table 1.3.

The first column in Table 1.4 reports OLS estimates of the parameters from the main regression specification. As mentioned before, the parameter estimate $\hat{\gamma}_{OLS}$ is likely to be biased in this case. Column 2 provides 2SLS estimates of the parameter of interest. Using both the average age of hens assigned to coworkers and its squared as instruments for coworkers' productivity, the value of the *F-statistic* of a joint test of significance of the instruments in the first stage regression is equal to 43.68. The two instruments together are thus relevant in inducing variation in the regressor of interest.[20] More importantly, the 2SLS estimate $\hat{\gamma}_{2SLS}$ is negative and significant at the 1% level. OLS and 2SLS estimates are of very similar magnitude. One possible explanation for this

[20]The *p-value* from the Sargan-Hansen test of overidentifying restrictions is higher than 0.10. We thus cannot reject the null hypothesis that both instruments being exogenous once one is assumed to be exogenous. However, the variables we use as instruments are both functions of the same hens' age variable, so that the rationale for this test can be questioned.

result is that the different sources of bias of OLS estimate in this case work both in the positive (sorting, correlated effects) and negative direction (reflection, mechanical bias from the inclusion of group fixed effects as discussed in Guryan et al. 2009 and Caeyers 2014), and they may cancel each other out. One other possibility is that the inclusion of a full set of day, shed-week and worker fixed effects already solves for the bias due to unobserved common shocks and sorting to a large extent, while the relatively high large number of observations per shed-week group makes the reflection and mechanical bias problems less salient. Estimates imply that a one standard deviation increase of average coworkers' daily output is associated with a decrease in own daily output of almost a third of its standard deviation. If all workers are assigned the same number of hens, an increase of average coworkers' daily output of 500 eggs causes the number of own collected eggs to fall by 150.

The use of hens' age and its square as predictors of daily output imposes a precise functional form to the relationship between the two variables. The parameter of interest can be identified more precisely using the full set of own and coworkers' hens week-of-age dummies respectively as regressors and instruments. Column 3 shows the 2SLS parameter estimates from this alternative regression specification, which do not change with respect to the previous ones. The *F-statistic* of a joint test of significance of all the instrument dummies in the first stage is equal to 27.19, and the R^2 turns out to be equal to 0.92. Finally, in the last column, the full set of hen batch fixed effects is included. This allows to exploit variation in hens' age over time within each assigned batch, netting out time-invariant batch characteristics which can be correlated with productivity. The first-stage *F-statistic* is now equal to 251.29, and the 2SLS estimate of the effect of interest remains unchanged and significant at the 1% level. Overall, the evidence supports the hypothesis of negative productivity spillovers among coworkers in neighboring production units.

In order to correctly interpret the above results, it is important to understand whether the effect we find is plausible, meaning whether the variation in the productivity of coworkers induced by changes in their hens' age is actually detectable by a given worker. The average difference between own and coworkers' hens' age is 3.22 weeks, corresponding to an average productivity difference of 0.06 daily eggs per hen. Figure 1.4 suggests that the same 3-weeks difference in age can amount to large or small productivity differences, depending on the hens' stage of life. For example, the average daily number of eggs per hen is 0.06 when hens are 19 weeks old, but is more than 8 times larger at age 22, being equal to 0.50: a 0.44 productivity difference, equal to 4,400 eggs more for a batch of 10,000 hens. A similar but opposite pattern holds when productivity starts to decrease in the last stages of a hen's life. This means that even a small variation in hen's age can have a sizable and observable impact on daily output, at least when hens are far from their productivity peak age.

The previous results show how, conditional on own input quality, workers' productivity is systematically lower (higher) when the productivity of neighboring coworkers exogenously increases (decreases). We claim that such negative spillover effect is due to changes in the level of effort exerted by the worker. In this respect, hens' feeding represents one observable dimension of effort which is worth investigating. For this purpose, the average amount of food per hen distributed by the worker can be replaced as outcome in the main specification. 2SLS estimates of the coefficient of average coworkers' productivity are shown in the first column of Table 1.5. The coefficient of interest is estimated as negative, consistently with the interpretation of previous results. However, the estimated parameter is not significantly different from zero. We thus claim the effect of coworkers' productivity to work through changes in the unobservable dimensions of effort.

Going beyond the negative effect on own output, the structure of the data allows to derive a wide range of output quality measures. The effect of average coworkers' productivity on own output quality can be investigated accordingly. 2SLS estimates are shown in Column 2 to 5 of Table 1.5, where again the full set of own and coworkers' hens week-of-age dummies are included as regressors and instruments respectively. The *F-statistic* of a joint test of significance of all the instrument dummies in the first stage is sufficiently high in all specifications. An increase in coworkers' average output is associated with a systematic decrease in the own fraction of good eggs over the total. The coefficient of interest is equal to -0.15 significant at the 1% level. A one standard deviation increase in coworkers' productivity causes a 2.85 percentage points decrease in the own fraction of good eggs over the total. The estimated coefficient of interest is instead positive when the own fraction of broken eggs over the total is investigated as outcome in Column 3, even if not statistically significant. An increase in average coworkers' productivity is instead found to significantly increase the own fraction of dirty eggs over the total.[21] Indeed, the estimated coefficient in Column 4 is significant at the 5% level and equal to 0.06: a one standard deviation increase in average coworkers' output is associated with a 1.24 percentage point increase in the own fraction of dirty eggs over the total. Finally, the fraction of hens dying in the day is considered as outcome in Column 5. The estimated coefficient of interest is negative, but not statistically different from zero. Overall, results from Table 1.5 suggest coworkers' productivity to negatively affect not only own output but its quality as well.

1.4.3 Robustness Checks and Effect Heterogeneity

Workers in non-neighboring production units can hardly interact or observe each other. This specific feature of the production environment can be exploited to further validate previous results by means of a *placebo test*. First, the average number of eggs per hen collected by workers in the adjacent shed can be replaced as regressor in the main specification, and age of their hens can be again used as a source of exogenous variation for their productivity. Column 1 of Table 1.6 reports the 2SLS estimate of the corresponding coefficient using as instrument the full set of coworkers' hens week-of-age dummies. In this case, coworkers' variables are the same for all workers in a shed, so no daily within-shed variation is exploited. Therefore, the strength of the first stage relationship is lower than in the main specification, but the corresponding *F-statistic* of a joint test of significance of the instruments is still high and equal to 21.65. As expected, the resulting 2SLS point estimate is negligible in magnitude and not significantly different from zero. The same holds when restricting the sample to workers located in sheds with more than two production units, and considering as main regressor the average number of eggs per hen collected by workers in non-neighboring production units in the same shed. Results are reported in Column 2. Taken together, we interpret these findings as evidence that observability between workers plays a crucial role for the effect we find.[22]

Furthermore, the natural logarithm of the daily average number of eggs per hen collected can be replaced as outcome in the main specification.[23] Adopting the same

[21] Recall that workers can turn a dirty egg into a good egg by cleaning it.

[22] We find the same results when using the age of own and coworkers' hens and their square as controls and instruments respectively as in the first proposed specification.

[23] Such transformation is needed in order to match the conceptual framework proposed in Section 1.5.

identification strategy, as shown in Column 3 of Table 1.6, the coefficient of coworkers' productivity is found to still be significant at the 1% level and equal to -1.48. In other words, an increase in coworkers' average output of one standard deviation is associated with a 29% decrease in own output. Finally, in Column 4 of Table 1.6, we implement an alternative identification strategy where the expected hens' productivity is used as instrument for coworkers' average result. Such expected productivity measure is elaborated by an independent bird supplier company, which sells the animals to the firm under analysis. The variable is thus exogenous to anything peculiar of the firm and its production process. The measure gives the average number of eggs per week each hen is expected to produced at every week of its age. We divided it by 7 in order to derive the expected daily productivity. In the causal framework under investigation, expected productivity can be readily interpreted as the *assignment-to-treatment* variable, with the *treatment* being actual coworkers' productivity. The first-stage *F-statistic* turns out to be equal to 29.61. The estimated parameter of interest is highly significant and remarkably similar to the ones derived before.[24]

The average result of negative productivity spillovers can be further explored along one specific dimension of heterogeneity: workers' ability. Similarly to Bandiera et al. (2005) and Mas and Moretti (2009), we estimate the full set of worker fixed effects in a regression specification where hens' week-of-age dummies, batch and day fixed effects are also included as regressors.[25] We then split the workers into *high* and *low* ability according to their position relative to the median in the estimated fixed effects distribution, and assign observations belonging to the worker's assigned production unit to two corresponding subsamples. The parameter of interest is estimated separately and results reported in Columns 5 and 6 of Table 1.6. Estimated coefficients are negative and highly significant in both cases. Low and high ability workers seem thus to be equally

Indeed, if effort e_i and input quality s_i are complements and $y_i = e_i s_i$, then $\ln y_i = \ln e_i + \ln s_i$. Variable values are augmented by 0.01 before taking the log. Implementing a log-log specification we can estimate the elasticity of own productivity with respect to coworkers' productivity, equal to 0.35, with the estimate being significant at the 1% level.

[24]We also perform two additional robustness checks. First, we address the identification concerns in Angrist (2014) by explicitly separating the subjects who are object of the study from their peers. Specifically, we randomly select one production unit per each shed-week and run the main identifying regression over the restricted sample only. Second, we drop out all observations belonging to those days in which the worker assigned to a given production unit was listed as absent. Results are in line with previous estimates in both cases, as shown in Table 1.A.3 in the Appendix A.

[25]The distribution of workers' ability is shown in Figure 1.A.1 in the Appendix A.

responsive to changes in coworkers' productivity.

1.5 The Mechanism

Results from the previous section provide evidence of negative productivity spillovers. The productivity of coworkers in neighboring production units is found to negatively affect individual daily output and its quality. Our claim is that, while triggered by input heterogeneity, the source of externalities in this context lies in human resource management. A close inspection to the data reveals that turnover is exceptionally high at the firm under investigation. Indeed, throughout the 9 months of observations in our sample, we observe 26 terminations of employment relationship over a workforce of around 100 workers. The firm we are studying is close to have monopsony power in the local labor market. Indeed, it is located in rural Peru, it pays over the sampling period an average wage which is more than 50% higher than the legally established minimum wage in the country, and close to the nationwide average wage in the period.[26] The firm is the biggest employer in the three closest small towns. Although the data we have do not allow us to distinguish between dismissals and voluntary quits, evidence is in favor of an efficiency wage argument, where the firm strategically combines high wages with high dismissal rates as disciplinary devices (Shapiro and Stiglitz 1984).

Figure 1.7 plots the survival probability in the firm for the average worker over time, computed separately according to his initial productivity. The latter is measured as the daily number of eggs per hen collected by the worker on the first day on the job. Even eight months after the start, workers who are initially more productive than average are more likely to still be at work compared to those whose initial productivity is below the average. On top of this, our claim is that externalities exist among workers in their probability of keeping the job. Figure 1.8 provides preliminary evidence on this point. The figures show how the survival probabilities of a given worker relate with the initial productivity of coworkers in neighboring production units. The left and right figures are derived separately for workers whose initial productivity is respectively below and above the average. Conditionally on own productivity, the more productive coworkers initially are the higher is the probability for a given worker to keep his job. Furthermore,

[26] See Section 1.6.2 and Table 1.8 for more detailed information on the wage schedule of workers at the firm. Average and minimum wage data are from the World Bank.

returns from being next to highly productive coworkers in terms of probability of keeping the job seem to be higher for those workers who are initially less productive. All this is true even five months after the start, and suggests that productivity at the shed level matters for worker evaluation and dismissal. We develop these arguments theoretically and validate them empirically in the remainder of this section.

1.5.1 Conceptual Framework

The main features of the production environment can be formalized by means of a simple analytical framework. N workers independently produce output $y_i \geq 0$ combining effort $e_i \geq 0$ with a given input of quality $s_i \geq 0$, with $i \in \{1, 2, ., N\}$. Effort cost is positive and convex, so that $C(e_i) = ce_i^2/2$ with $c > 0$. Output at a moment in time is given by

$$y_i = f(e_i, s_i) \tag{1.2}$$

Effort and input quality are complement in production. In particular, let $f(e_i, s_i) = e_i s_i$. Input quality s_i can be thought of as a function of both observable and unobservable input characteristics. Effort is unobservable to the management, so that y_i is a signal of worker's exerted effort.[27]

As for now, let each worker earn a fixed salary ω from which she derives utility $U(\omega)$. Similarly to Mas and Moretti (2009), with probability Q_i the worker keeps her job and earns the corresponding fixed salary. In case the employment relationship terminates, the worker does not earn any salary and derives zero utility. The threat of dismissal works as an incentive device aimed to solve for the moral hazard problem. Indeed, Q_i is set by the management as a function of both individual and coworkers' average output, meaning $Q_i = q(y_i, \bar{y}_{-i})$. The shape of the $q(\cdot)$ function captures the features of the implemented termination policy, together with the externalities it generates among coworkers. Unlike Mas and Moretti (2009), we do not rely on any specific functional form, and only assume $q_1(\cdot) > 0$ and continuously differentiable, $q_{11}(\cdot) \leq 0$ and that $q_{12}(\cdot)$ exists. As shown later, this allows to take into consideration several alternative termination policies.

[27] One specific example is given in Appendix B, where we also consider the possibility for the principal to net out observable input characteristics in deriving a signal of worker's exerted effort.

Each worker chooses the effort level $e_i \geq 0$ which maximizes her expected utility

$$\max_{e_i} U(\omega)\ q(y_i, \bar{y}_{-i}) - c\frac{e_i^2}{2} \tag{1.3}$$

Taking the corresponding first order condition yields

$$U(\omega)\ q_1(y_i, \bar{y}_{-i})\ s_i = ce_i \tag{1.4}$$

With q_1 continuously differentiable, the implicit function theorem can be applied to the above equation in order to derive how the worker's optimal effort level changes with coworkers' average output, meaning

$$\frac{\partial e_i^*}{\partial \bar{y}_{-i}} = \frac{U(\omega)\ q_{12}(y_i, \bar{y}_{-i})\ s_i}{c - U(\omega)\ q_{11}(y_i, \bar{y}_{-i})\ s_i^2} \tag{1.5}$$

Notice that the denominator is always positive, and the sign of the above derivative is uniquely determined by the sign of $q_{12}(\cdot)$. The cross derivative of the $q(\cdot)$ function captures how marginal returns from own output in terms of increased probability of keeping the job change with coworkers' average output. Such relationship is built into the termination policy specified by the management.

For instance, forced-ranking procedures or relative performance evaluation schemes in general may let an increase in coworkers' average output affect marginal returns from own output positively. Still under the assumptions of $q_1(\cdot) > 0$ and $q_{11} \leq 0$, this is the case if, for example, $Q_i = q\left(\alpha y_i - \beta \bar{y}_{-i}\right)$ with $0 < \beta < \alpha$, which implies $q_{12}(\cdot) > 0$. In this case, the worker's optimal level of effort will increase with an increase in coworkers' average output. On the contrary, if total output positively matters to some extent for worker evaluation, teamwork-type externalities will arise. An increase in coworkers' average output decreases marginal returns from own output in this case. At the extreme, one can think at Q_i as being a function of total output only and thus equal for all i, meaning $Q_i = q\left(y_i + (N-1)\bar{y}_{-i}\right)$. This implies $q_{12}(\cdot) < 0$. The worker's optimal effort level will thus fall with an increase in coworkers' average output. In other words, workers free ride on each other.

In this framework, the termination policy implemented by the management generates externalities among coworkers in their optimal choice of effort. Workers best-respond to each other in equilibrium.[28] It is worth highlighting that the proposed conceptual background departs from the one in Mas and Moretti (2009) along two relevant dimensions. First, we explicitly model the role of production inputs other than effort. Heterogeneity in their productivity induces variation in both own and coworkers' productivity. Second, we leave the probability of keeping the job function $q(\cdot)$ unspecified along the relevant margin of its cross derivative. We thus consider *a priori* a large family of implementable policies linking own and coworkers' results to termination probabilities.

1.5.2 Termination Policy: Empirics

Within the above conceptual framework, the evidence of negative productivity spillovers we previously found is consistent with the hypothesis that a positive shift in coworkers' productivity decreases the marginal benefits from own effort in terms of increased probability of keeping the job.[29] We already showed in Figure 1.8 how survival probability in the firm for a given worker is higher when coworkers' productivity is higher, consistent with the hypothesis that the management attaches to the latter a positive weight in the evaluation of individual workers.

We investigate these issues further through implementing a logistic hazard model and study the relative odds of the probability $1 - q(\cdot)$ of losing the job in period t as defined by

$$\frac{1 - q(t)}{q(t)} = \frac{h(t)}{1 - h(t)} = \exp\{\ \gamma_t + \alpha\, y_{it} + \beta\, \bar{y}_{-it} + \kappa\, y_{it} \times \bar{y}_{-it}\ \} \tag{1.6}$$

where, y_{it} is daily average number of eggs per hen collected by worker i at time t or, alternatively, its *moving average* in period $[t - \tau, t]$, while $\bar{y}_{-it}$ is average output of coworkers in neighboring production units in the same period. γ_t captures the baseline hazard function. The interaction term aims to disclose any systematic relationship between changes in coworkers' productivity and marginal returns from own effort. In

[28]Notice that utility functions are quasi-concave with respect to e_i, the strategy space of workers is convex and the continuous differentiability of $q_1(\cdot) > 0$ ensures best-reply function to exist and be continuous. Hence, the Kakutani fixed-point theorem applies and equilibrium exists.

[29]Notice that, in our conceptual framework, an increase in input quality s_i increases productivity y_i if and only if the elasticity of effort with respect to input quality is sufficiently low in absolute value, meaning $\eta_{es} = \frac{\partial e_i}{\partial s_i}\frac{s_i}{e_i} > -1$.

particular, the latter would decrease with coworkers' daily output if $\alpha < 0$ and $\kappa > 0$.

Maximum likelihood estimated coefficients are reported in Table 1.7. Two alternative definitions of baseline hazard are specified across columns. Daily productivity measures are considered as regressors in Columns 1 to 3, while 7-days moving averages are used in Columns 4 to 6.[30] Furthermore, in Columns 3 and 6 we again rely on the age of coworkers' hens as an exogenous source of variation for their productivity. Given the non-linear nature of the second stage, we follow Terza et al. (2008) and adopt a two-stage residual inclusion (2SRI) approach. As before, we use the age of coworkers' hens $\overline{age}_{-it}$ and its square as instruments for coworkers' productivity $\bar{y}_{-it}$, and their interaction with own productivity as instruments for $y_{it} \times \bar{y}_{-it}$. Identification of the effect of coworkers' productivity on termination probabilities is here achieved through exploiting the variability induced by the age of coworkers' hens, consistent with the previous analysis.

Table 1.7 shows that an increase in own productivity is significantly associated with a decrease in the odds of the probability of employment termination. Conditionally on own productivity, an increase in coworkers' productivity is also significantly associated with the a decrease in the odds of termination, with the point estimate being lower in magnitude with respect to the former. Shed-level output thus seems to matter to some extent for individual termination probabilities. More importantly, the coefficient of the interaction term is positive and highly significant across specifications. Returns from own productivity in terms of the probability of keeping the job are thus lower at the margin when coworkers' productivity increase, consistent with the proposed conceptual framework and evidence of negative productivity spillovers.

The adoption of such a policy on behalf of the management can be explained by the impossibility for the latter to completely net out inputs' contribution to output and perfectly infer worker's effort. In this case, coworkers' productivity conveys relevant

[30]We also estimated the same specification using different time windows τ for computing the productivity moving averages, keeping the function γ_t the same. Coefficient signs are found to be stable across specification. In order to evaluate the goodness-of-fit across specifications with different choice of τ, we calculated a modified *pseudo* R^2, equal to $1 - \frac{\ln L_{UR}}{\ln L_R}$, where L_{UR} is the likelihood of the estimated logistic model with all regressors, while L_R is the likelihood of the model where only γ_t is included as explanatory variable. The proposed measure of goodness-of-fit is found to decrease monotonically with τ. Furthermore, we estimated the same specification after collapsing data by pay period. Results are qualitatively similar to previous ones. The same holds if we estimate a linear probability model. Additional results are available upon request.

information about the workers' effort distribution. We provide a specific example of this kind in Appendix B, where we present a modified version of the conceptual framework in Mas and Moretti (2009). We describe the learning process of the principal, who computes the expected workers' effort choice on the basis of available information on both output levels and observable input characteristics. This leads her to attach a positive weight to the average of productivity signals. The same holds when all information about individual productivity and input quality is sufficiently costly to process.[31] Limited managerial attention can then lead managers to process and rely positively on information about shed-level productivity in the evaluation of workers' performance (Kahneman 1973; Gifford 1998; Hirshleifer and Teoh 2003). As a result, the more productive coworkers are, the less likely is the shed to be targeted by the management for termination measures. In both cases, positive teamwork-type externalities arise in the probability of keeping the job, leading to free riding among workers.

Finally, notice that some of the results from Section 1.4 allow us to rule out alternative explanations for the effect we find. Suppose that workers were to be monitored on the job by the management, that such monitoring efforts were limited, and targeted disproportionally more towards workers whose hens are highly productive. The negative causal effect of an increase in coworkers' productivity on own productivity could then be attributed to higher shirking which follows to a reallocation of monitoring efforts on behalf of the management. However, if this was the case, a negative effect would also have been found when using as explanatory variable the average productivity of coworkers in non-neighboring production units in the same shed. Results from the placebo exercise in Column 2 of Table 1.6 show that this is not the case. Even in absence of monitoring, one could imagine that workers can steal eggs from each other. If this was the case, though, we should expect an increase in coworkers' input quality to increase own productivity, as stealing opportunities would increase with coworkers' productivity. The effect we find goes instead in the opposite direction.

[31] Notice that the data we use in our analysis of productivity spillovers are collected by the veterinary unit and they are not processed by the human resource management department.

1.6 Monetary and Social Incentives

1.6.1 Extended Conceptual Framework

Does incentive provision shape externalities in this context? Can sufficiently strong incentives offset the workers' tendency to free ride on each other and solve for the negative productivity spillovers as previously identified? Peer pressure mechanisms decrease the marginal cost of own effort, while monetary incentives increase its marginal returns. How does this affect how individual effort responds to changes in coworkers' productivity?

We first investigate these arguments in light of the suggested conceptual framework. Social incentives can be framed as *peer pressure*. In its original formulation by Kandel and Lazear (1992), peer pressure operates through the effort cost function: coworkers' effort diminishes the marginal cost of effort for the worker. The theoretical approach in Falk and Ichino (2006) and Mas and Moretti (2009) is built around the same argument. In the context of this chapter, output is not only a function of worker's effort, but also of the quality of the assigned input. We thus adopt a slightly modified approach and model peer pressure as operating through a decrease in the cost of effort following an increase in coworkers' productivity $\bar{y}_{-i}$. Starting from the same framework presented above, the worker's problem becomes the one of choosing effort level $e_i \geq 0$ which maximizes the expected utility

$$\max_{e_i} U(\omega)\; q(y_i, \bar{y}_{-i}) - c\frac{e_i}{2}\,(e_i - \lambda\, \bar{y}_{-i}) \tag{1.7}$$

where $\lambda > 0$ is a generic parameter capturing the intensity of peer pressure mechanisms. Deriving the corresponding first order condition and applying the implicit function theorem yields

$$\frac{\partial e_i^*}{\partial \bar{y}_{-i}} = \frac{U(\omega)q_{12}(\cdot)s_i + \lambda\frac{c}{2}}{c - U(\omega)q_{11}(\cdot)s_i^2} \tag{1.8}$$

While the denominator of the above remains unchanged with respect to the corresponding result in the original formulation, the numerator is now ambiguous when $q_{12} < 0$. While the firm's implemented termination policy still generates positive teamwork-type externalities, peer pressure pushes the same in the opposite direction, possibly changing the sign of productivity spillovers.

As for monetary incentives, their impact can also be incorporated in the original framework. For simplicity, let utility $U(\cdot)$ be linear in its argument. We depart from the previous formulation in that the wage now incorporates a piece rate component related to own daily output, meaning $\omega = F + \kappa y_i$. As before, the worker chooses the effort level $e_i \geq 0$ which maximizes her expected utility

$$\max_{e_i} \, (F + \kappa y_i) q(y_i, \bar{y}_{-i}) - c\frac{e_i^2}{2} \tag{1.9}$$

The corresponding first order condition is now

$$(F + \kappa y_i) q_1(\cdot) s_i + \kappa q(\cdot) s_i = c e_i \tag{1.10}$$

Compared to the fixed-wage case, piece rate incentives provide extra motivation for effort, as captured by the second term on the left-hand side. In particular, notice that monetary incentives are leveraged by the probability $q(\cdot)$ of keeping the job. Applying the implicit function theorem we can see how optimal effort responds to coworkers' productivity in this case

$$\frac{\partial e_i^*}{\partial \bar{y}_{-i}} = \frac{(F + \kappa y_i) q_{12}(\cdot) s_i + \kappa q_2(\cdot) s_i}{c - (F + \kappa y_i) q_{11}(\cdot) s_i^2 - 2\kappa q_1(\cdot) s_i^2} \tag{1.11}$$

Provided that c is high enough, the denominator of the above expression is positive.[32] More importantly, the sign of the numerator is no longer uniquely determined by the sign of the cross derivative $q_{12}(\cdot)$. If the firm's implemented termination policy is such that the latter is negative, own optimal effort may still increase with coworkers' productivity if the second term in the numerator is high enough. In other words, if total output matters to some extent, coworkers' productivity increases the probability of keeping the job. Even if this lowers the marginal impact of own productivity on the probability of keeping the job, it leverages the power of monetary incentives, as these are earned only if the job is kept. The latter effect may dominate the former, yielding positive productivity spillovers.

[32]In particular, a sufficient condition for this to happen is $c > 2\kappa q_1(y_i, \bar{y}_{-i}) s_i^2$ for all $s_i, y_i, \bar{y}_{-i}$.

1.6.2 Empirics

The setting under investigation carries with it sufficient variation in both the payment schedule and the social relationships among coworkers. Such variation can be exploited in order to formally test for the impact of both monetary and social incentives as derived above.

We start by providing additional information about the workers' pay schedule. In the period under consideration, workers are paid every two weeks. Their wage corresponds to the sum of a base salary plus a variable amount. The latter is conditional on and linear in the number of boxes of eggs collected by the worker in a randomly chosen day within the two weeks. Specifically, wage is calculated according to the following formula

$$w_i = \omega \ + \ \delta \ + \ \max\{\,0\,,\ \gamma \times [\,2Y_i - r\,]\,\} \tag{1.12}$$

where ω is the base pay and Y_i is the amount of boxes of eggs collected by the worker in the randomly chosen day. This quantity is multiplied by 2 and, if the resulting quantity exceeds a given threshold r, a piece rate pay γ is awarded for each unit above the threshold. On top of base pay, almost all workers are awarded an extra amount δ. Table 1.8 shows the corresponding summary statistics for the base pay, the bonus component and total pay. Average base pay (ω) is equal to 505 PEN (Peruvian Nuevo Sol), equal to around 190 USD. The average of the bonus component of pay ($\delta + \max\{0, \gamma \times [\,2Y_i - r\,]\}$) is instead equal to 82 PEN, around 30 USD (δ=40 PEN). The bonus component is thus on average equal to 15% of the base pay. As a result, average total pay in the two-weeks period is equal to the equivalent of 220 USD.

As shown before, a strong relationship exists between the age of hens assigned to a worker and his productivity. Notice that no component of worker's pay is adjusted by the age of hens the worker is assigned in the pay period. As a result, the probability for the worker of earning extra pay also depends on hens' age. Figure 1.9 plots the distribution of the average number of daily egg boxes collected by the worker within each pay period per quartiles of the hens' age distribution. For each quartile, the boundaries of each box indicate the 10th and 90th percentile of the egg boxes distribution, while the horizontal lines within each box correspond to the mean. The ends of the vertical lines indicate the 1st and 99th percentile. The straight horizontal line corresponds to the normalized bonus threshold $r/2$. First, notice that the inverted U shape relationship between hens' age and productivity can be still observed when considering egg boxes as a measure of productivity. Second, the probability of reaching the threshold and be exposed to incentive pay is higher for those workers whose hens are of high productivity, meaning they belong to the second and third quartiles of the hens' age distribution. On the contrary, the average worker whose hens belong to the first or fourth quartile of the hens' age distribution does not reach the bonus threshold.

Table 1.9 shows the average base pay, bonus pay and total pay for the average worker across the assigned hens' age distribution, confirming the existence of a strong relationship between hens' age and bonus pay. Notice that small variations in base pay are observed across productivity categories. Base pay can indeed still vary with workers' age, tenure and base contract. Nonetheless, most of the variation in total pay is due to variations in the bonus pay component. Finally, Figure 1.10 shows the distribution of bonus pay for workers in each quartile of the assigned hens' age distribution. Consistently with the previous description of the pay scheme, a more pronounced peak is observed around the value of δ in the distribution for workers whose assigned hens are either young or old, meaning that few of them make it to the threshold and gain the piece rate component of bonus pay.

In order to provide suggestive evidence on the role of monetary and social incentives, we explore effect heterogeneity through the following regression specification

$$\begin{aligned} y_{igwt} \;&=\; \varphi_{gw} + \textstyle\sum_d \psi_d \, D_{digwt} \\ &\quad + \textstyle\sum_d \left\{ \gamma_d \, \bar{y}_{-igwt} \;+\; \alpha_d \, age_{igwt} \;+\; \beta_d \, age^2_{igwt} \right\} \times \; D_{digwt} \qquad (1.13) \\ &\quad + \textstyle\sum_{s=t-3}^{t-1} \lambda_s \, food_{igsw} \;+\; \mu_{igwt} \end{aligned}$$

where φ_{gw} are the shed-week fixed effect and D_d are dummy variables which identify the heterogeneous categories of interest. The same dummy is interacted with both own hens' age variables and coworkers' productivity. With the additional inclusion of worker fixed effects, this specification allows to exploit within-worker variation and separately estimate the effect of coworkers' productivity for the same worker across heterogeneous categories. In order to solve for the endogeneity of the variable of interest, both $\overline{age}_{-i}$ and $\overline{age}^2_{-i}$ are multiplied by D_d, and the resulting variables are used as instruments for the endogenous interaction variables $\bar{y}_{-igwt} \times D_d$.[33]

We first focus on monetary incentives and define two categories according to the distribution of assigned hens' age. As previously shown, workers whose assigned hens are either young or old are less likely to make it to the productivity threshold and thus to be exposed to piece rate pay. We thus define a first *low productivity age* subsample of production units whose hens' age is in the first or the fourth age distribution quartile, and group the rest of observations in a second *high productivity age* subsample. As shown in Table 4.1, around 48% of the observations in the overall sample correspond to workers whose assigned hens are in the first or the fourth age distribution quartile. Column 1 of Table 1.10 provides the corresponding 2SLS estimates from the above specification, with D_d identifying the two resulting subsamples. The Table reports the *F-statistic* from the Angrist-Pischke multivariate F test of excluded instruments (Angrist and Pischke 2009), which confirms the first stage relationship to be strong enough. Consistently with the modified conceptual framework, no significant effect of coworkers' productivity on own productivity is found when the worker is assigned highly productive hens. The effect is instead negative and highly significant for the same worker when assigned hens are less productive and the piece rate threshold is less likely to be achieved. However, since most of the variation in productivity belongs to this region, the result can only be interpreted as suggestive evidence.

In order to explore the role of social incentives, we rely instead on the information about the friendship network among coworkers as elicited through the questionnaire we administered in March 2013. Linking the relevant information with productivity data, we identify those workers working along someone they recognize as a friend. We thus define two separate categories accordingly and let dummy variables D_d identify the corresponding subsamples. We then implement the above regression specification and get two separate estimates of the effect of coworkers' productivity, according to workers' friendship status. As reported in Table 4.1, 24% of the observations in the overall sample correspond to workers we interview in March 2013 who recognize at least one of

[33] We also estimate the main regression specification using 2SLS separately for each subsample as identified by the dummy D_d. Results are shown in Table 1.A.4 in the Appendix A. Even if still consistent with the extended model's prediction, they are somewhat weaker with respect to what we find by implementing the proposed specification with interaction variables. The difference can be explained by the fact that the latter constrains the fixed effects estimates and coefficients of food variables to be the same across categories.

their coworkers in neighboring production units as their personal friend. 2SLS estimates are reported in Column 2 of Table 1.10.[34] Productivity spillovers are estimated to be negative and significant only for those workers who do not work along friends. Consistently with the peer pressure argument outlined before, a positive point estimate is instead found for the coefficient of coworkers' productivity when the worker recognizes any of his coworkers as a friend, even if the 2SLS estimate is not statistically significant. Perhaps more importantly, this result allows to rule out the possibility that the negative effect we find is the result of some cooperative behavior workers are engaged in. For instance, workers whose hens are at their age productivity peak could benefit from the help of neighboring coworkers, with negative productivity spillovers on the latter. Such cooperative strategy would be sustainable in a repeated interaction framework. In particular, we expect such strategy to be even more sustainable among friends, due to the supposedly higher costs of deviation from the cooperation path. The absence of any significant effect in this case speaks against this hypothesis.[35]

Questionnaire data can further be explored to study effect heterogeneity according to workers' experience. We again implement the same specification as above, but define the two dummies D_d as capturing whether the worker's experience in the firm is above or below the median. 52% of observations in the overall sample to belong to workers with on-the-job experience above the median, as shown in Table 4.1. Estimation results are shown in Column 3 of Table 1.10. Negative highly significant estimates of the coefficient of coworkers' productivity are found for more experienced workers, while the same estimated parameter is positive but non-significant for less experienced workers. Results can be interpreted in light of the termination policy mechanism originating negative productivity spillovers. Indeed, it is reasonable to think of experienced workers as having learned over time and thus being more aware of management policies. It is thus not surprising to find that the effect arises in this category.[36]

[34]Notice that the number of observation is reduced. This is because we are forced to restrict the sample to only those observations which we can merge with workers' information elicited in March 2013.

[35]Notice that allowing the friendship relationship measure as elicited in March 2013 to be endogenous to the implementation of cooperative strategies makes this point even stronger. Indeed, we should find even more of a negative effect of coworkers' productivity in this case for those workers who are working along friends.

[36]Further exploring effect heterogeneity, we can estimate the parameters of this same regression specification separately for those observations belonging to workers working along more and less experienced coworkers respectively. The negative effect of coworkers' productivity is the biggest in magnitude for ex-

Finally, we investigate the effect heterogeneity according to the difference (in absolute value) between the age of own and coworkers' hens. In particular, we now define the two dummies D_d depending on whether such difference is higher or lower than the mean difference in the sample, equal to 3.22 weeks. We estimate the corresponding equation with 2SLS for the *low productivity age* and the *high productivity age* subsamples separately, where the latter are defined as in Column 1. If the free riding mechanism in the absence of piece rate incentives is responsible for the average effect we find, we should expect the negative effect of coworkers' productivity to be the highest in magnitude when the scope of free riding is the widest. This corresponds to the situation in which a given worker is assigned lowly productive hens while coworkers are assigned highly productive ones. The size of the effect should then be lower when both workers are assigned lowly productive hens. The same magnitude should be even lower when both workers are assigned highly productive hens, and the lowest when the worker is assigned highly productive hens and his coworkers are assigned lowly productive ones. Evidence from Column 5 and 6 is supportive of this hypothesis. The effect is only statistically significant when workers' hens are lowly productive (i.e., drawn from the first or fourth quartile of the hens' age distribution) and the absolute difference in age with coworkers' hens is high, meaning coworkers' hens are more likely to be in their high productivity age. Point estimates are ordered as suggested above, even if none of the three other 2SLS estimates is statistically significant.

1.7 Counterfactual Policy Analysis

1.7.1 Termination Policy

The evidence gathered so far suggests that the worker evaluation and termination policy implemented at the firm generates negative productivity spillovers among coworkers. In order to shed light on the salience of this issue and its consequences on aggregate productivity, we now aim to evaluate counterfactual productivity outcomes under alternative termination policies implementable by the management. In other words, our

perienced workers working along experienced coworkers. This allows to rule out the possibility that the result in Column 3 of Table 1.10 is driven by experienced workers helping less experienced neighboring coworkers. Additional results are available upon request.

objective is to estimate workers' average productivity under different specifications of the $q(\cdot)$ function. We start by recalling the first order condition of the worker's effort maximization problem

$$\frac{U(\omega)}{c} \; q_1(y_i, \bar{y}_{-i}) \; s_i = e_i \tag{1.14}$$

Multiplying both sides of the expression by the input productivity variable s_i and taking logarithms we get

$$\ln y_i = \ln \frac{U(\omega)}{c} s_i^2 + \ln q_1(y_i, \bar{y}_{-i}) \tag{1.15}$$

Assuming such relationship holds at equilibrium, our objective is to simulate daily productivity y_{it} for all workers under a new alternative policy $\tilde{q}(\cdot)$. In particular, we are interested in the productivity effect of shutting down the externalities among coworkers generated by and built in the current policy. It is thus reasonable to evaluate productivity counterfactuals under a policy of the formÊ

$$\tilde{q}(y_{it}) = \alpha_0 + \alpha_1 \; y_{it} + \alpha_2 \; y_{it}^2 \tag{1.16}$$

with $\tilde{q}_1(\cdot) > 0$ and $\tilde{q}_{11}(\cdot) \leq 0$. We can thus substitute the first derivative of the alternative policy function $\tilde{q}_1(\cdot)$ in the above equation and get

$$\ln y_{it} = \ln \frac{U(\omega)}{c} s_{it}^2 + \ln(\alpha_1 + 2\alpha_2 \; y_{it}) \tag{1.17}$$

where input quality s_{it} is now allowed to vary over time.

However, notice that the first term on the RHS of the above equation is not observable in the data, so that the policy counterfactual cannot be computed directly by solving the above for y_{it}. In order to overcome this issue, we start from estimating the actual termination policy function $q(\cdot)$ by regressing a dummy q_{it} equal to one when the worker is not dismissed (and thus observed to be at work the day after) over a third order polynomial time trend $t + t^2 + t^3$ and a third order polynomial of own and coworkers' productivity $(y_{it}, \bar{y}_{-it})$. We then use the corresponding parameter estimates and actual productivity values to compute the derivative of the function with respect to y_{it}. We obtain an estimate $\hat{q}_{1,it}$ of the marginal returns from own productivity in terms of probability of keeping the job, which can be replaced in the rearranged expression of worker's first order condition. Splitting further the first term of the RHS we get

$$\ln y_{it} = \ln U(\omega) + \ln s_{it}^2 + \ln \hat{q}_{1,it} - \ln c_i \tag{1.18}$$

where the effort cost parameter c_i is allowed to vary across workers. This equation can be estimated through the following regression specification

$$\ln y_{it} = \alpha + \psi_{wi} + \beta \ \ln \hat{q}_{1,it} + \theta_i + \varepsilon_{it} \tag{1.19}$$

where we use the full set of hens' week-of-age dummies ψ_{wi} as a proxy for the input quality term $\ln s_{it}^2$ and let worker fixed effects θ_i capture the variability in $\ln c_i$. It follows that

$$\widehat{\ln y_{it}} - \hat{\beta} \ \ln \hat{q}_{1,it} = \hat{\alpha} + \hat{\psi}_{wi} + \hat{\theta}_i = \hat{m}_{it} \tag{1.20}$$

where $m_{it} = \ln \frac{U(\omega)}{c_i} s_{it}^2$. Following (17), worker's productivity under the alternative policy $\tilde{q}(\cdot)$ can finally be estimated through solving the following equation for y_{it}

$$\ln y_{it} = \hat{m}_{it} + \ln(\alpha_1 + 2\alpha_2 \ y_{it}) \tag{1.21}$$

We provide numerical solutions to the above equation, thus estimating the daily number of eggs per hen collected by the worker over the period under $\tilde{q}(\cdot)$. Table 1.11 shows counterfactual productivity gains and losses as predicted under the alternative termination policy, following the procedure described above. For each parameter values, each entry shows the simulated percentage change in productivity as measured by average daily number of eggs per hen collected by the worker over the period. The table also reports 95% confidence intervals as computed by repeating the above estimation procedure 200 times using bootstrapped samples. As the the coefficient α_1 in the alternative termination policy function gets high enough, productivity gains are remarkably stable and as high as 20%. A visual representation of such gains can be find in Figure 1.11, which plots the smoothed average of daily productivity values over time in the sampling period. The continuous line reports the smoothed average of actual daily productivity, while the dashed line shows its value as predicted under $\alpha_1 = 5$ and $\alpha_2 = -1$.

1.7.2 Input Allocation

While the source of externalities lies in human resource management practices, evidence shows how these are triggered by the heterogeneity in inputs assigned to neighboring coworkers. Therefore, we expect the way inputs are allocated among workers to affect overall productivity. Notice that, in our basic regression specification, coworkers' productivity enters linearly in the equation defining worker's productivity. As a result, in this framework, the effect of input reallocation on overall productivity will only operate through pairwise exchanges between production units both within and across sheds of different size. In order to understand this, think about the extreme case of a given number of sheds each hosting two production units. In this specific case, input reallocation would not affect the total amount of externalities and aggregate productivity would not be affected. If instead some sheds host one or more than two production units, input reallocation within and between sheds will affect the total amount of externalities generated in the system. Aggregate productivity will respond accordingly.

The impact of input allocation in our setting can be evaluated by means of a counterfactual simulation exercise. We first implement a fully specified reduced-form regression model where the daily average number of eggs per hen y_{it} is regressed over the full sets of own and coworkers' hens' week-of-age dummies, together with shed-week fixed effects. Starting with the hen batches in production in the first week of the sample and keeping their allocation fixed, we then simulate their age profiles over the sampling period, assuming hens were replaced after the 86th week of life. Using parameter estimates from the previously specified regression specification, we then predict the daily productivity of workers in each production unit. The dash-dot red line in Figure 1.12 shows the smoothed average of daily productivity as predicted following the procedure described above. The continuous blue line is instead the smoothed average of actual daily productivity. The two curves match closely, except for some weeks in the second half of the sampling period, when, according to the management, some sheds were affected by bird disease.

The same parameter estimates used to predict daily productivity of workers under the actual input allocation can be used to predict productivity under alternative input allocations. For example, taking the batches in production in the first week of the sample, it is possible to reallocate them among production units following a *hierarchical clus-*

tering procedure which minimizes the variance of the age of hens within the same shed, which seems to be the goal the management tries to achieve. We simulate hens' age profiles over the period under the alternative allocation (assuming the same replacement policy as before), and predict worker's daily productivity using the same parameter estimates derived at the beginning. The smoothed average of estimated productivity is depicted by the dashed green line in Figure 1.12. Productivity gains are substantial, up to 20% in a given day, even though counterfactual productivity values are also more volatile than actual ones. When averaged throughout the period, the difference between the counterfactual and actual productivity is equal to 0.08, which corresponds to a 10% increase.

Counterfactual productivity can be also estimated under alternative scenarios. In particular, the same batches in production in the first week of the sample can be randomly allocated to production units. Simulated hens' age profiles and predicted worker's daily productivity can be derived accordingly with the same procedure described above. Figure 1.13 shows the distribution of the average productivity difference throughout the sample period between the actual productivity and the productivity estimated under 100 alternative scenarios of this kind, where hen batches are randomly allocated to production units. The difference is always positive, with the average being equal to 0.0136 and significantly different from zero. Results confirm that, helding everything else constant, lowering the variance of the age of hens within the same shed has a positive impact on average productivity. By comparing the actual allocation of batches to a random one, we can see how the firm has already gone a long way towards internalizing this.

1.8 Conclusion

Production and human resource management practices interact and generate externalities among coworkers in their choice of productive effort. When workers produce output using both effort and inputs of heterogeneous quality, and workforce management brings about externalities among workers, input allocation determines the total amount of externalities in the system, and matters for aggregate productivity. In the specific case of worker evaluation and dismissal policies, if these generate teamwork-type externalities, input allocation triggers free riding and negative productivity spillovers among neighboring working peers.

Thanks to the peculiarities of the setting under consideration, we exploit quasi-random variation in the productivity of workers' assigned inputs in order to identify and measure the effect of an increase of coworkers' productivity on own output and its quality. We find evidence of negative productivity spillovers. A one standard deviation increase in coworkers' average daily output causes a given worker's output to drop by almost a third of a standard deviation. We also find negative and equally sizable effects on output quality. This evidence is contrasted with the results from the analysis of workforce turnover data, which validate the specific mechanism identified by theory. A given worker's probability of keeping the job is positively associated with both own and coworkers' productivity, with the latter diminishing marginal returns own productivity. Workers thus free ride on each other and lower their effort supply when coworkers' productivity increases. In the second part of the chapter, we also provide suggestive evidence that both monetary and social incentive provision can mitigate the workers' tendency to free ride on each other and offset negative productivity spillovers. Indeed, we find no effect of coworkers' productivity when workers are exposed to piece rate pay or work along friends. Finally, counterfactual policy analysis derived from structural estimations reveal the impact of both input allocation and dismissal policy to bring about up to 20% average productivity gains.

This chapter shows that the analysis of relatively more complex production environments may uncover additional aspects of human resource management practices in their interaction with production management. In this respect, our focus on production inputs and their allocation to working peers represents the main innovation with respect to the previous literature on the topic. What is also crucial for the external validity of our study is the absence of any technological externality among workers within the same organizational tier. This allows to isolate productivity spillovers of alternative origins. We here focus on the way the management informs its decisions on whether and who to dismiss as the mechanism behind the negative productivity spillovers we find, and how incentive provision can neutralize them. Nonetheless, the same logic can be applied in the empirical study of other types of spillovers. In a companion project still work in progress, we aim at investigating both theoretically and empirically how workers influence each other in their choice of inputs while updating information on the productivity of the latter from own and coworkers' experience.

Tables and Figures

TABLE 1.1: SUMMARY STATISTICS

Variable	Obs.	Mean	St. Dev.	Min	Max
Daily Eggs per Hen, y_i	20,915	0.784	0.2	0	1
Hens' Age (weeks)	20,915	45.274	16.944	19	86
No. of Hens	20,915	9,974.023	3,884.469	44	17,559
Food (50kg sacks)	20,915	22.416	8.967	0	40
Food per Chicken (g)	20,915	112.067	50.495	0	5,947.137
Good/Total	20,755	0.857	0.093	0	1
Broken/Total	20,755	0.024	0.037	0	0.357
Dirty/Total	20,755	0.059	0.049	0	1
Porous/Total	20,755	0.05	0.06	0	1
Deaths/No. of Hens	19,343	0.001	0.017	0	0.782
Daily Eggs per Hen Coworkers' Average, $\bar{y}_{-i}$	20,915	0.784	0.197	0	0.999
Hens' Age Coworkers' Average (weeks)	20,915	45.194	16.526	19	86
Dummies:					
Low Productivity Hens' Age	20,915	0.476	0.499	0	1
Working Along Friend	16,318	0.24	0.427	0	1
Experience Above Median	16,318	0.522	0.5	0	1

Notes. The table reports the summary statistics for all the variables used throughout the empirical analysis. The unit of observation is the production unit in the sector under investigation in each day from March 11 to December 17 of 2012. Sheds hosting only one production units are excluded from the sample.

TABLE 1.2: COWORKERS' AND OWN HEN'S AGE: CONDITIONAL CORRELATION

	Correlation Coefficients	
	(1)	(2)
Corr $(age_{igwt}, \overline{age}_{-igwt})$	0.8964	0.0067
p-value	(0.0000)	(0.5285)
Day FEs	Y	Y
Shed-Week FEs	N	Y
Observations	8745	8745

	Own Hens' Age, age_{igwt}
$\overline{age}_{-igwt}$	0.061
	(0.047)
$\overline{age}_{-igw}$	-0.397
	(0.399)
Day FEs	Y
Shed-Week FEs	Y
Observations	20907

Notes. The top panel reports estimates of the correlation between the age of hens assigned to workers age_{igwt} and the average of hens assigned to coworkers in neighboring production units in the same shed on the same day $\overline{age}_{-igwt}$. Age variable is in weeks. When estimating conditional correlations, in order to solve for the mechanical negative bias discussed in the chapter, one production unit per shed-week is randomly selected and included in the estimation sample (Bayer et al. 2008). Regression results in the bottom panel are based on Guryan et al. (2009) as discussed in the chapter. As before, $\overline{age}_{-igwt}$ is average age of hens assigned to coworkers in neighboring production units on the same day, while $\overline{age}_{-igw}$ is the average value for peers in the same shed in all days of the week. Two-way clustered standard errors are estimated, with residuals grouped along both shed and day. Sample is restricted to all production units in sheds with at least one other production unit.

TABLE 1.3: OWN AND COWORKERS' HENS' AGE AND PRODUCTIVITY

	Daily Number of Eggs per Hen, y_i				
	(1)	(2)	(3)	(4)	(5)
age_i	0.04076***	0.03903***	0.03859***	0.03803***	0.03249***
	(0.0024)	(0.0023)	(0.0059)	(0.0058)	(0.0058)
age_i^2	-0.00040***	-0.00038***	-0.00038***	-0.00038***	-0.00032***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
$\overline{age}_{-i}$				-0.00387***	-0.00646***
				(0.0013)	(0.0024)
$\overline{age}^2_{-i}$				0.00003**	0.00005*
				(0.0000)	(0.0000)
$food_{t-1}$		0.00184*	0.00139***	0.00143***	0.00460***
		(0.0009)	(0.0005)	(0.0004)	(0.0012)
$food_{t-2}$		0.00093*	0.00079**	0.00082***	0.00304***
		(0.0005)	(0.0003)	(0.0003)	(0.0011)
$food_{t-3}$		0.00074	-0.00000	-0.00002	0.00316**
		(0.0010)	(0.0004)	(0.0004)	(0.0012)
Day FEs	Y	Y	Y	Y	Y
Shed-Week FEs	N	N	Y	Y	Y
Worker FEs	N	N	N	N	Y
Observations	20915	20915	20907	20907	20907
R^2	0.411	0.434	0.857	0.858	0.885

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) Ordinary Least Square estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the average number of eggs per hen collected by the worker. age_i is own hens' age in weeks, while $\overline{age}_{-i}$ is average age of coworkers' hens in neighboring production units. $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE 1.4: COWORKERS' AND OWN PRODUCTIVITY

	Daily Number of Eggs per Hen, y_i			
	(1)	(2)	(3)	(4)
	OLS	2SLS	2SLS	2SLS
Coworkers'	-0.29539***	-0.30258***	-0.28877***	-0.29019***
Eggs per Hen, $\bar{y}_{-i}$	(0.0765)	(0.0689)	(0.0697)	(0.0984)
age_i	0.03067***	0.03059***		
	(0.0057)	(0.0060)		
age_i^2	-0.00030***	-0.00030***		
	(0.0001)	(0.0001)		
$food_{t-1}$	0.00431***	0.00431***	0.00404***	0.00408***
	(0.0012)	(0.0012)	(0.0011)	(0.0012)
$food_{t-2}$	0.00277***	0.00276***	0.00252***	0.00261***
	(0.0011)	(0.0011)	(0.0009)	(0.0010)
$food_{t-3}$	0.00268**	0.00268**	0.00214**	0.00217**
	(0.0011)	(0.0011)	(0.0010)	(0.0011)
1st Stage F-stat	n.a.	43.68	27.19	251.29
Shed-Week FEs	Y	Y	Y	Y
Age Dummies	N	N	Y	Y
Day FEs	Y	Y	Y	Y
Worker FEs	Y	Y	Y	Y
Batch FEs	N	N	N	Y
Observations	20907	20907	20907	20907
R^2	0.891	0.891	0.918	0.927

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) (1), OLS estimates; (2)-(4) 2SLS estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the average number of eggs per hen collected by the worker. Main variable of interest is average daily number of eggs per hen collected by coworkers in neighboring production units, $\bar{y}_{-i}$. age_i is own hens' age in weeks. In (2) average age of coworkers' hens and its square $(\overline{age}_{-i}, \overline{age}^2_{-i})$ are used as instruments in the first stage. The full set of coworkers' hens' age dummies is used in the first stage in (3) and (4). $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE 1.5: FEEDING EFFORT AND OUTPUT QUALITY

	Food (gr)	Good/Total	Broken/Total	Dirty/Total	Deaths/Total
	(1)	(2)	(3)	(4)	(5)
Coworkers'	-40.79075	-0.15111***	0.01154	0.06285**	-0.01586
Eggs per Hen, $\bar{y}_{-i}$	(61.9546)	(0.0415)	(0.0131)	(0.0318)	(0.0169)
$food_{t-1}$	0.39094	0.00173***	-0.00030***	-0.00095***	0.00003
	(0.6379)	(0.0005)	(0.0001)	(0.0003)	(0.0001)
$food_{t-2}$	1.12516**	0.00107**	-0.00012	-0.00069**	-0.00020**
	(0.5456)	(0.0005)	(0.0001)	(0.0003)	(0.0001)
$food_{t-3}$	0.33582	0.00003	-0.00005	-0.00018	-0.00003
	(0.2791)	(0.0005)	(0.0001)	(0.0003)	(0.0001)
1st Stage F-stat	251.29	42.48	42.48	42.48	116.79
Shed-Week FEs	Y	Y	Y	Y	Y
Age Dummies	Y	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y	Y
Worker FEs	Y	Y	Y	Y	Y
Batch FEs	Y	Y	Y	Y	Y
Outcome Mean	22.416	0.875	0.024	0.059	0.001
Observations	20907	20746	20746	20746	19398
R^2	0.238	0.845	0.909	0.714	0.269

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) 2SLS estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable are: average daily amount of food in grams distributed (1), fraction of good eggs over the total (2), fraction of broken eggs over the total (3), fraction of dirty eggs over the total (4), fraction of hens dying in the day (5). Main variable of interest is average daily number of eggs per hen collected by coworkers in neighboring production units, $\bar{y}_{-i}$. The full set of own hens' age dummies are included as controls, while the full set of coworkers' hens' age dummies is used in the first stage in all specifications. $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE 1.6: ROBUSTNESS CHECKS AND EFFECT HETEROGENEITY

	Daily Number of Eggs per Hen, y_i					
	(1)	(2)	(3) $\ln y_i$	(4)	(5) High Ability	(6) Low Ability
Other Shed Workers' Eggs per Hen, $\tilde{y}_{-i}$	0.01170					
	(0.0390)					
Non-neighboring Workers' Eggs per Hen, $\tilde{y}_{-i}$		-0.01822				
		(0.05726)				
Coworkers' Eggs per Hen, $\bar{y}_{-i}$			-1.48038***	-0.28735***	-0.47082***	-0.32137***
			(0.3688)	(0.0661)	(0.1671)	(0.0631)
$food_{t-1}$	0.00409***	0.00459***	0.01250***	0.00408***	0.00438***	0.00441***
	(0.0012)	(0.00123)	(0.0043)	(0.0012)	(0.0016)	(0.0012)
$food_{t-2}$	0.00274***	0.00300***	0.01131***	0.00261***	0.00153*	0.00394***
	(0.0010)	(0.00081)	(0.0038)	(0.0010)	(0.0008)	(0.0012)
$food_{t-3}$	0.00236**	0.00220***	0.00964**	0.00217**	0.00061	0.00444***
	(0.0011)	(0.00081)	(0.0040)	(0.0011)	(0.0009)	(0.0011)
1st Stage F-stat	21.65	85.03	251.29	29.61	31.60	193.21
Shed-Week FEs	Y	Y	Y	Y	Y	Y
Age Dummies	Y	Y	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y	Y	Y
Worker FEs	Y	Y	Y	Y	Y	Y
Batch FEs	Y	Y	Y	Y	Y	Y
Observations	19936	8294	20907	20907	10917	9980
R^2	0.925	0.888	0.899	0.927	0.9164	0.948

Notes. (* p-value$<$0.1; ** p-value$<$0.05; *** p-value$<$0.01) 2SLS estimates. Sample is restricted to all production units in sheds with at least one other production unit. Subsamples in (5) and (6) are derived as discussed in Section 1.4.3. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is average number of eggs per hen collected by the worker in all columns but (3), where the log of its value augmented by 0.01 is considered. Main variable of interest in (1) is average daily number of eggs per hen collected by coworkers in adjacent shed; in (2) is average daily number of eggs per hen collected by coworkers in the same shed, but in non-neighboring production units; in (3) to (6) is average daily number of eggs per hen collected by coworkers in neighboring production units, $\bar{y}_{-i}$. The full set of own hens' age dummies are included as controls. The full set of coworkers' hens' age dummies is used in the first stage in all columns but (4), where expected hens' productivity per week of age as reported by bird producer is used as instrument. $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE 1.7: TERMINATION POLICY

	Logit of Termination Probability (Coefficients)					
	Values at time t			Moving Averages $[t-7, t]$		
	(1)	(2)	(3)	(4)	(5)	(6)
y_{it}	-6.598***	-8.287***	-13.322***	-8.489***	-11.505***	-15.983***
	(2.247)	(2.497)	(4.288)	(3.226)	(3.365)	(4.894)
$\bar{y}_{-it}$	-4.537***	-5.515***	-7.245***	-1.520	-2.574	-6.532***
	(1.615)	(1.736)	(1.785)	(1.498)	(1.583)	(2.371)
$y_{it} \times \bar{y}_{-it}$	8.277***	10.755***	14.126***	7.770**	11.449***	15.986***
	(2.597)	(2.736)	(4.932)	(3.501)	(3.533)	(5.500)
γ_t	$\ln t$	$t + t^2 + t^3$	$t + t^2 + t^3$	$\ln t$	$t + t^2 + t^3$	$t + t^2 + t^3$
Observations	17981	17981	17981	15939	15939	15939

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) Logit estimates. Sample is restricted to all production units in sheds with at least one other production unit. Dependent variable is dummy equal to 1 if employment relationship terminates on day t. $\bar{y}_{it}$ is own daily number of eggs per hen collected on day t or its 7-days moving average in (4) to (6), while $\bar{y}_{-it}$ is the corresponding value for coworkers in neighboring production units in the same shed. (3) and (6) are Two-stage residual inclusion estimates with bootstrapped standard errors from 100 repetitions (Terza et al. 2008).

TABLE 1.8: PAY: SUMMARY STATISTICS

Variable	N	Mean	St. Dev.	Min	Max
Base Pay (PEN)	1470	505.34	66.42	26	704
Bonus Pay (PEN)	1470	81.77	50.28	0	442
Total Pay (PEN)	1470	588.42	89.34	29	972

Notes. The Table reports summary statistics for the pay data. Workers are paid every two weeks. The wage formula is presented and discussed in Section 1.6 of the chapter. The bonus component is calculated using the number of eggs boxes produced in a randomly chosen day within the same two weeks. 1 PEN = 0.38 USD (June 30, 2012), with minimum wage in the period being 750 PEN (285 USD).

TABLE 1.9: HENS' AGE AND BONUS PAY

	Averages across Hens' Age Distribution			
	1st Quartile	*2nd Quartile*	*3rd Quartile*	*4th Quartile*
Base Pay (PEN)	509.43	519.84	522.09	515.20
Bonus Pay (PEN)	87.64	107.53	89.45	67.42
Total Pay (PEN)	598.77	625.61	612.93	583.72

Notes. Average bonus pay per quartiles of hens' age distribution. 1 PEN = 0.38 USD (June 30, 2012).

TABLE 1.10: INCENTIVE HETEROGENEITY

	Daily Number of Eggs per Hen, y_i				
	(1)	(2)	(3)	(4) High Prod. Age	(5) Low Prod. age
$\bar{y}_{-i}$ × High Productivity Age	-0.09785				
	(0.3148)				
$\bar{y}_{-i}$ × Low Productivity Age	-0.21834**				
	(0.1071)				
$\bar{y}_{-i}$ × Friend		0.22713			
		(0.1747)			
$\bar{y}_{-i}$ × No Friend		-0.43580**			
		(0.2104)			
$\bar{y}_{-i}$ × Experienced			-0.60567***		
			(0.1189)		
$\bar{y}_{-i}$ × Not Experienced			0.23650		
			(0.1587)		
$\bar{y}_{-i}$ × Low Age Difference				-0.13943	-0.38903
				(0.4793)	(0.3628)
$\bar{y}_{-i}$ × High Age Difference				-0.02430	-0.48440**
				(0.1338)	(0.2241)
$food_{t-1}$	0.00491***	0.00594***	0.00494**	0.00072***	0.00405***
	(0.0015)	(0.0019)	(0.0020)	(0.0003)	(0.0012)
$food_{t-2}$	0.00322**	0.00366**	0.00306**	-0.00010	0.00285***
	(0.0013)	(0.0016)	(0.0015)	(0.0001)	(0.0010)
$food_{t-3}$	0.00317**	0.00389**	0.00305**	-0.00027	0.00194*
	(0.0013)	(0.0016)	(0.0015)	(0.0002)	(0.0012)
1st Stage F-stat	17.16	32.39	21.36	5.45	4.90
	20.78	13.22	24.71	5.95	28.13
Shed-Week FEs	Y	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y	Y
Worker FEs	Y	Y	Y	Y	Y
Batch FEs	Y	Y	Y	Y	Y
Observations	20907	16313	16313	10950	9950
R^2	0.902	0.915	0.935	0.839	0.933

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) 2SLS estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the average number of eggs per hen collected by the worker. Main variable of interest is average daily number of eggs per hen collected by coworkers in neighboring production units $\bar{y}_{-i}$ and its interactions. In all specifications, the average age of coworkers' hens and its square $(\overline{age}_{-i}, \overline{age}^2_{-i})$ are interacted with dummy categories and used as instruments for the corresponding endogenous interaction regressor in the first stage. $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE 1.11: TERMINATION POLICY COUNTERFACTUAL: RESULTS

		α_2				
		-0.25	-0.5	-0.75	-1	-1.25
α_1	2	16.66	1.75	-15.91	-28.33	-37.52
		[13.62;18.11]	[-2.65;4.47]	[-19.10;-14.05]	[-30.72;-26.93]	[-39.38;-36.42]
	3	20.06	19.39	18.06	7.50	-6.28
		[19.17;20.86]	[18.45;20.30]	[15.72;19.26]	[3.92;9.60]	[-9.07;-4.63]
	4	21.45	21.11	20.69	20.18	19.04
		[20.67;22.19]	[20.32;21.86]	[19.89;21.45]	[19.27;20.96]	[17.10;20.08]
	5	22.40	22.15	21.88	21.58	21.20
		[21.74;23.15]	[21.48;22.89]	[21.18;22.62]	[20.86;22.32]	[20.47;21.92]
	6	23.20	22.96	22.73	22.50	22.25
		[22.48;23.96]	[22.28;23.72]	[22.08;23.47]	[21.88;23.23]	[21.62;22.97]

Notes. The Table shows productivity gains and losses from counterfactual termination policy as discussed and implemented in Section 1.7.2. 95% Confidence Intervals in square brackets, computed using bootstrapped samples from 200 repetitions. Productivity is measured as average daily number of eggs per hen over the period. Entries are percentage change with respect to actual data, with counterfactual productivity being derived using the corresponding parameter values.

FIGURE 1.1: ONE SECTOR

Notes. The picture shows a given production sector in the plant under investigation. Each one of the long-shaped building is a shed.

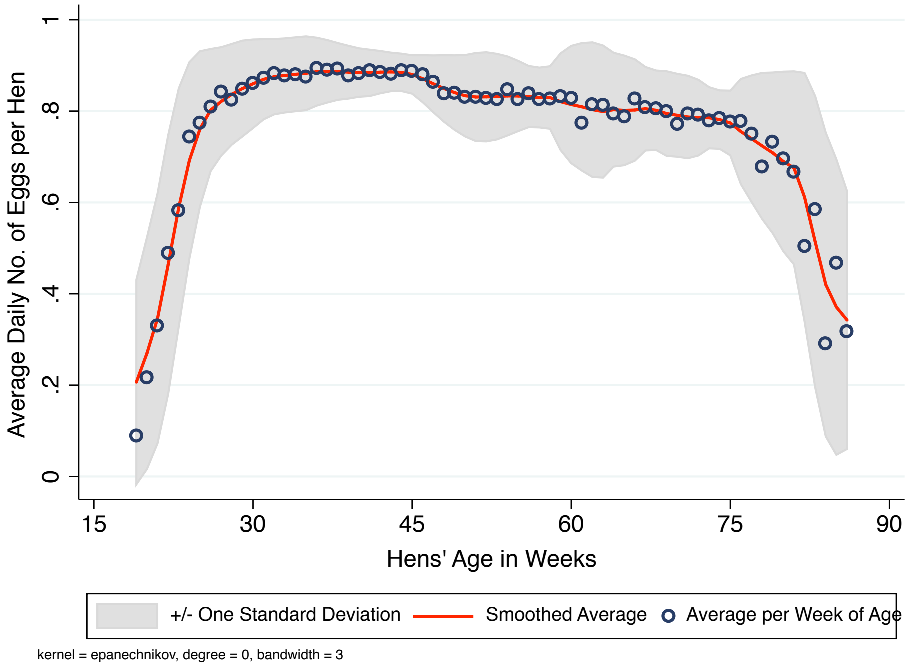
FIGURE 1.2: SHEDS

Notes. The picture of a shed in the plant under investigation.

FIGURE 1.3: PRODUCTION UNITS

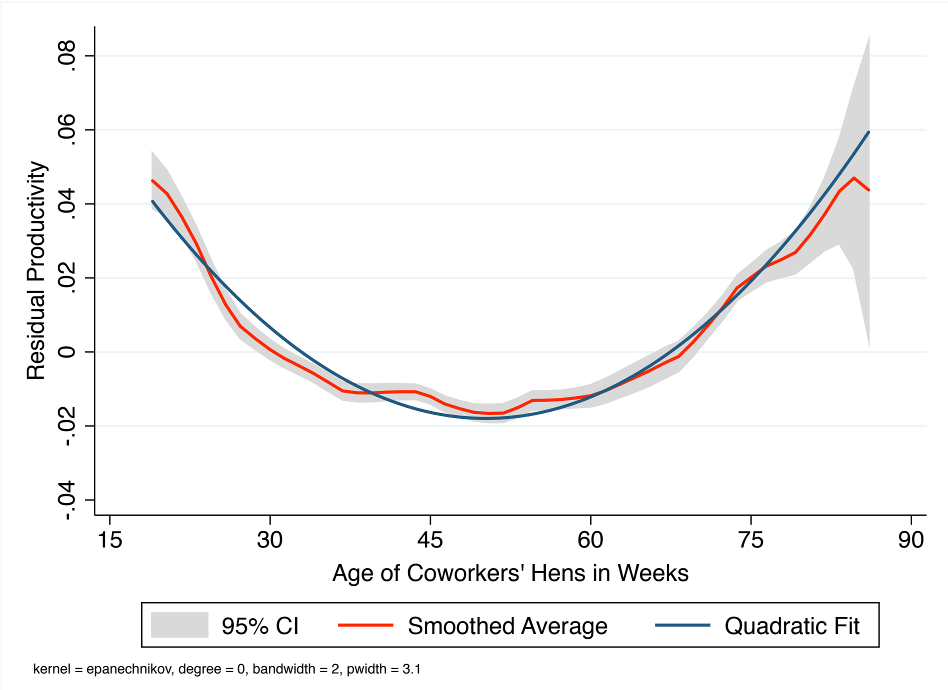
Notes. The picture of a particular shed hosting four production units. Each production unit is defined by one worker and the batch of laying hens assigned to him. We can distinguish in the picture the four production unit's warehouses located across the street from the shed.

FIGURE 1.4: HENS' AGE AND PRODUCTIVITY



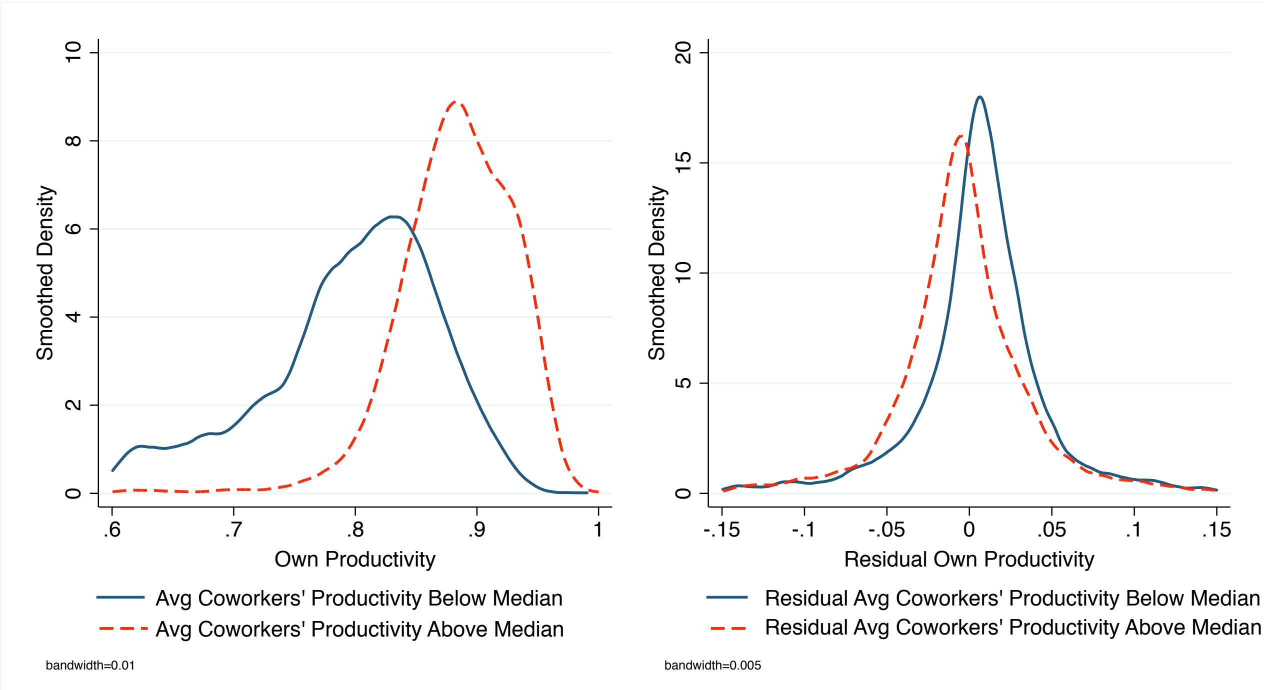
Notes. The average daily number of eggs per hen collected by the worker is plotted against the age of hens in weeks. Recall that hens in a given batch are all of the same age. The graph shows the smoothed average together with a one standard deviation interval around it. Epanechnikov kernel function is used for smoothing. Furthermore, for all given week of age, each bin in the scatterplot shows the average daily number of eggs per hen as averaged across all observations belonging to production units hosting hens of that given age. Productivity is typically low when hens are young, it reaches a peak when hens are around 40 weeks old, and then decreases thereafter until hens are old enough and the batch is discarded.

FIGURE 1.5: RESIDUAL PRODUCTIVITY AND AGE OF COWORKERS' HENS



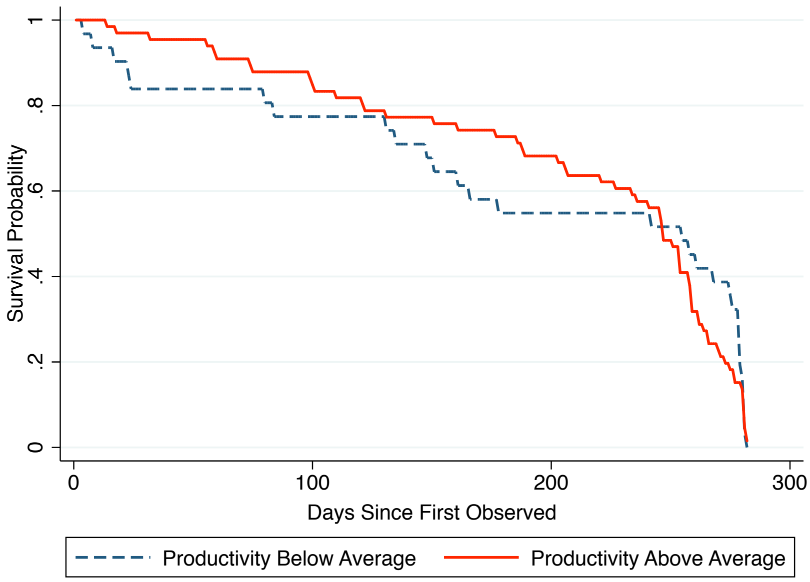
Notes. Once own hens' age, day and shed-week fixed effects are controlled for, residual productivity is plotted against the age of coworkers' hens in weeks. Productivity is measured as the average daily number of eggs per hen collected by the worker. Recall that hens in a given batch are all of the same age. The graph shows the smoothed average and its 95% confidence interval, together with the quadratic fit. Conditional on own hens' age, day and shed-week fixed, workers' residual productivity is higher (lower) when coworkers are assigned hens of low (high) productivity.

FIGURE 1.6: OWN AND COWORKERS' PRODUCTIVITY



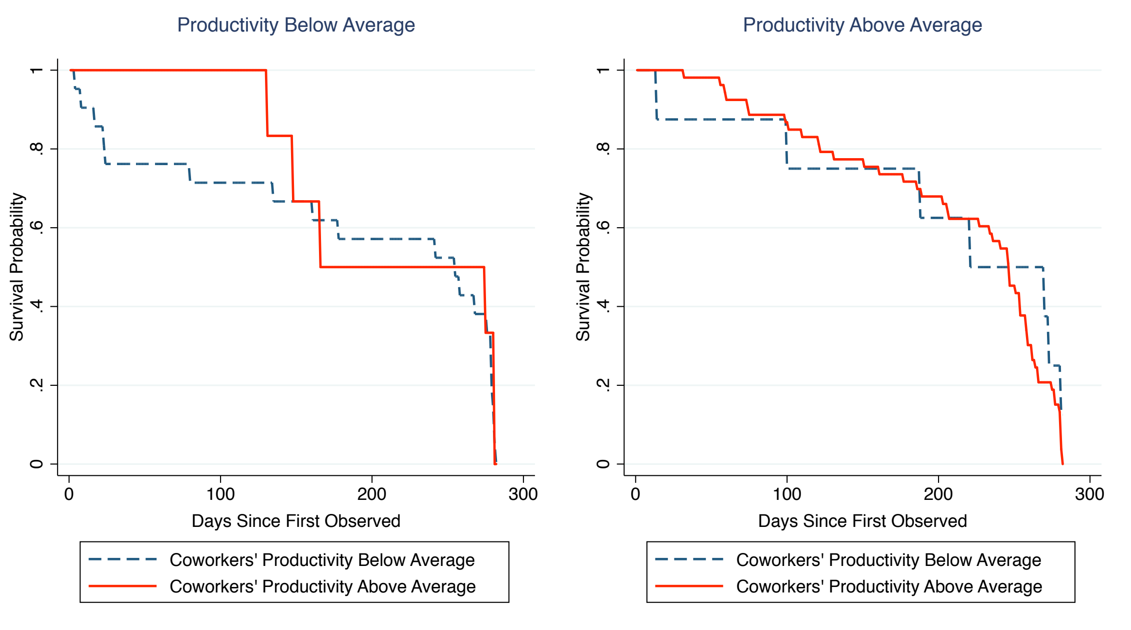
Notes. The figure plots the distribution of own productivity separately for those workers whose coworkers' average productivity is above and below the median. Productivity is measured as the average daily number of eggs per hen collected by the worker. The left figure refers to unconditional productivity. The right figure plots instead the distributions of residual productivity net of shed-week fixed effects. While own and coworkers' productivity appear to be positively correlated, conditioning on the full set of shed-week fixed effects yields the opposite result.

FIGURE 1.7: SURVIVAL PROBABILITY AND PRODUCTIVITY



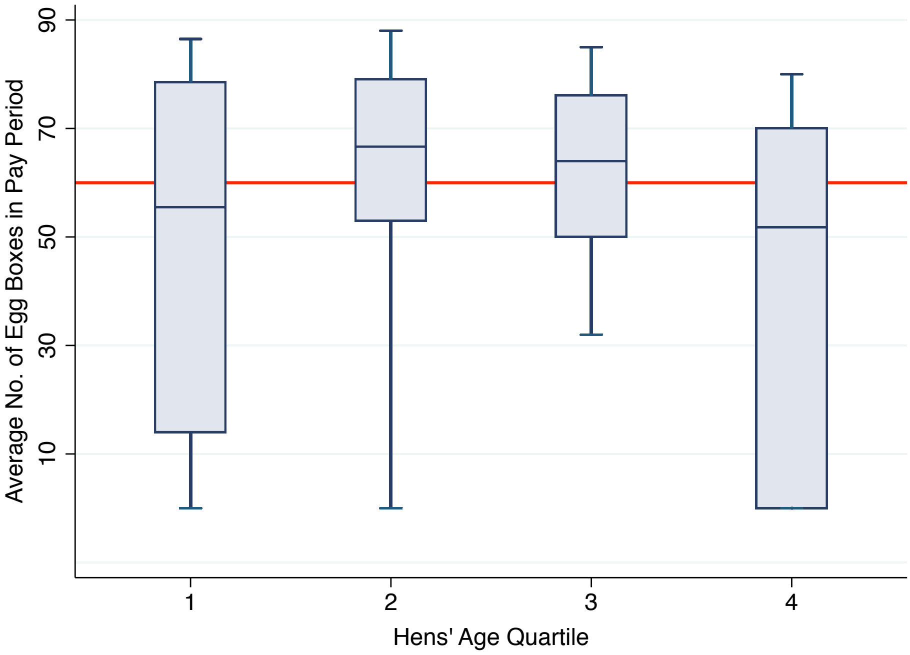
Notes. The figure plots the survival probability in the firm for the average worker over time throughout the sample period. The survival probability is computed separately for workers whose initial productivity (measured as daily average number of eggs per hen) is above and below the average productivity in the sample. Workers with higher initial productivity have higher survival probabilities.

FIGURE 1.8: SURVIVAL PROBABILITY AND COWORKERS' PRODUCTIVITY



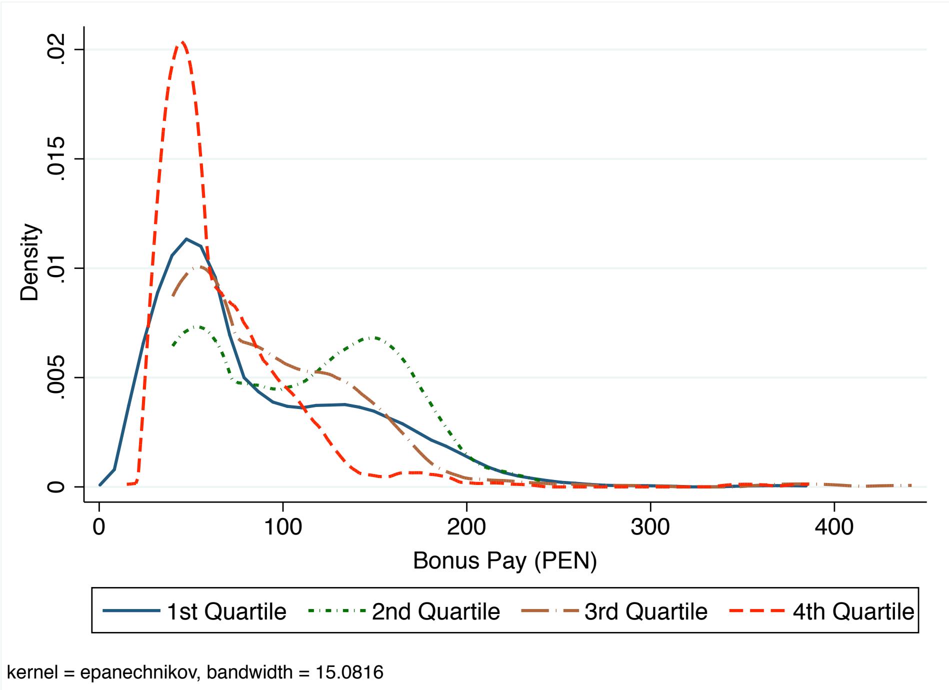
Notes. The figures plot the survival probability in the firm for the average worker over time throughout the sample period. In the left figure the sample is restricted to workers whose initial productivity (measured as daily average number of eggs per hen) is below the average productivity in the sample. The survival probability is shown separately for workers whose neighboring coworkers have productivity above and below the average. The probability of survival is higher when coworkers' productivity is higher over most of the support. The right figure shows instead the corresponding figures for workers whose initial productivity is above the average. Again, their probability of survival is higher when coworkers' productivity is higher.

FIGURE 1.9: HENS' AGE AND NUMBER OF EGG BOXES



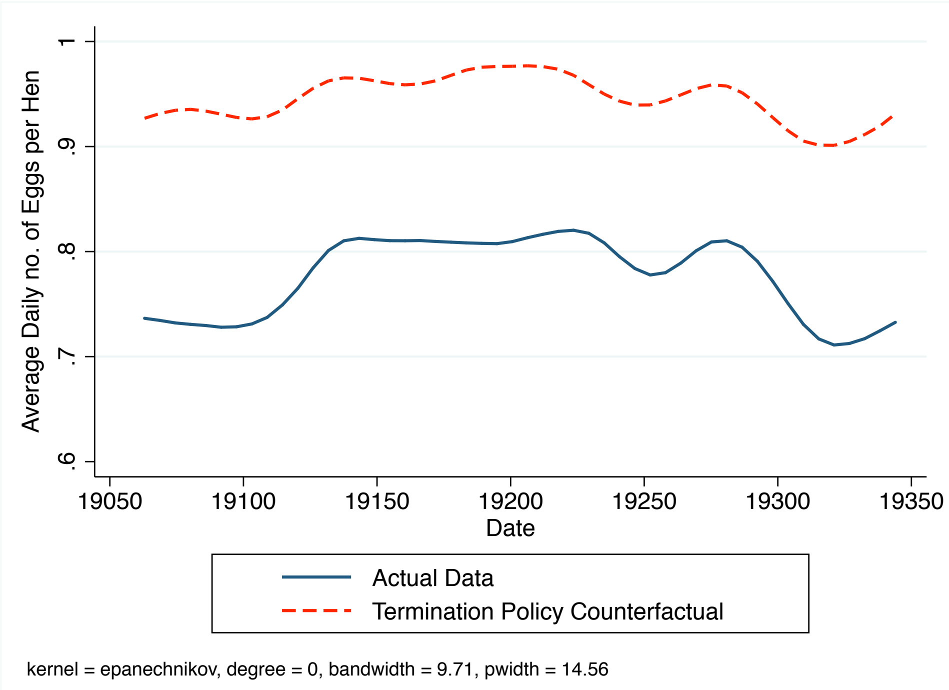
Notes. The figure plots the distribution of the average number of boxes collected by the worker in each two-weeks pay period. Within each age quartile, the bottom and top of the box correspond to the 10th and 90th percentile respectively, while the horizontal line corresponds to the mean. The ends of the vertical lines indicate the 1st and 99th percentile. The probability of reaching the bonus threshold is higher for workers whose assigned hens belong to the 2nd or 4th quartile of the age distribution, meaning of high productivity.

FIGURE 1.10: PRODUCTIVITY AND BONUS PAY



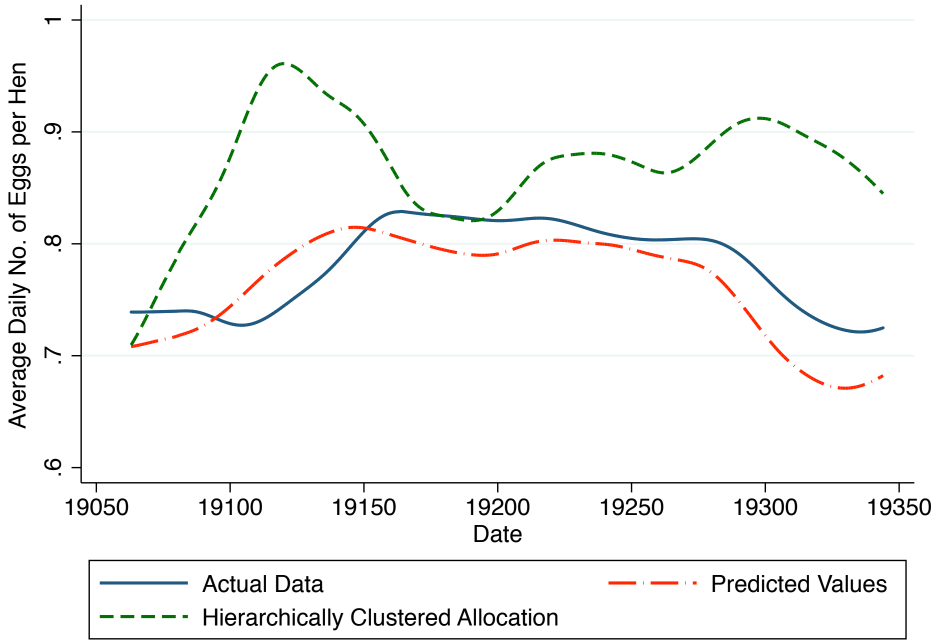
Notes. The figure plots the distribution of bonus pay for workers in different quartiles of the hens' age distribution. A more pronounced peak can be observed in the distribution of workers whose assigned hens are either young or old, and hence less productive. The first peak corresponds to the value of the fixed component δ of bonus pay. Density at this value is higher for workers whose assigned hens are in the 1st or 4th quartile of the hens' age distribution, meaning of low productivity. 1 PEN = 0.38 USD (June 30, 2012).

FIGURE 1.11: TERMINATION POLICY COUNTERFACTUAL



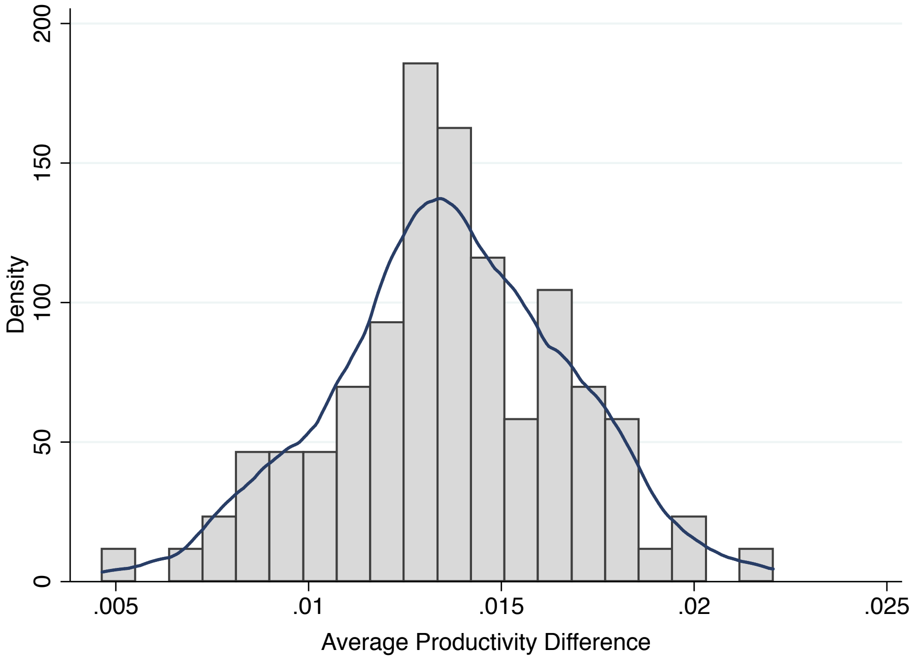
Notes. The figure plots the true and counterfactual average worker's productivity over time in the period under investigation. Counterfactual productivity estimates are derived under an alternative termination policy which does not carry externalities among coworkers, as explained in full details in Section 1.7.2 (parameter values $\alpha_1 = 5$ and $\alpha_2 = -1$). Average counterfactual productivity is always higher than the actual one.

FIGURE 1.12: INPUT ALLOCATION AND PRODUCTIVITY



Notes. The figure plots the true, predicted and counterfactual average worker's productivity over time in the period under investigation. Predictions are derived starting with the batches in production in the first week of the sample, and simulating their age profiles over the period, assuming that hens were replaced after the 86th week of life. Reduced-form estimates from a fully specified model where the full sets of own and coworkers' hen's week-of-age dummies and shed-week fixed effects are included are then used to predict average daily productivity. Counterfactual productivity is derived using the same estimates, but reallocating hen batches in production in the first week of the sample among production units following a *hierarchical clustering* procedure which minimizes the variance of the age of hens within sheds. Average counterfactual productivity is higher than the actual one, and up to 20% higher than the predicted one.

FIGURE 1.13: RANDOM INPUT ALLOCATION AND PRODUCTIVITY



Notes. The figure plots the distribution of the difference between the average productivity of workers throughout the sample period and the counterfactual average productivity obtained under 100 alternative scenarios where hen batches in production in the first week of the sample are randomly assigned to production units. Their age profiles are then simulated over the period assuming that hens were replaced after the 86th week of life. The difference is always positive, with a mean of 0.0136 and a standard deviation of 0.003. The average difference is thus significantly different from zero at the 5% level.

1.9 Appendix A

TABLE 1.A.1: WORKER'S TYPICAL WORKING DAY

6.20am	Breakfast at the cafeteria, a truck takes them to the assigned production unit
7.00am	Hens' feeding, food distribution and even up
9.00am	Egg collection
11.30am	Egg classification (good, dirty, porous and broken) and cleaning
12.30am	Truck arrives to collect egg baskets
1.00pm	Lunch at the cafeteria
1.30pm	Eggs moved to boxes
2.30pm	Truck takes them back to production unit
3.00pm	Cleaning of cages and facilities
3.30pm	Hens' feeding, food distribution and even up
5.00pm	End of working day

TABLE 1.A.2: OWN AND COWORKERS' HENS' AGE AND PRODUCTIVITY: ADDITIONAL RESULTS

	Daily Number of Eggs per Hen, y_i			
	(1)	(2)	(3)	(4)
age_i	0.03859***	0.03870***	0.03899***	0.03803***
	(0.0059)	(0.0058)	(0.0058)	(0.0058)
age_i^2	-0.00038***	-0.00038***	-0.00039***	-0.00038***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\overline{age}_{-i}$		-0.00136***		-0.00387***
		(0.0005)		(0.0013)
$\overline{age}^2_{-i}$			-0.00001**	0.00003**
			(0.0000)	(0.0000)
$food_{t-1}$	0.00139***	0.00141***	0.00140***	0.00143***
	(0.0005)	(0.0005)	(0.0005)	(0.0004)
$food_{t-2}$	0.00079**	0.00082***	0.00082***	0.00082***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$food_{t-3}$	-0.00000	-0.00002	-0.00002	-0.00002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Day FEs	Y	Y	Y	Y
Shed-Week FEs	Y	Y	Y	Y
Worker FEs	N	N	N	N
Observations	20907	20907	20907	20907
R^2	0.857	0.858	0.858	0.858

Notes. (* p-value$<$0.1; ** p-value$<$0.05; *** p-value$<$0.01) Ordinary Least Square estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the average number of eggs per hen collected by the worker. age_i is own hens' age in weeks, while $\overline{age}_{-i}$ is average age of coworkers' hens in neighboring production units. $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE 1.A.3: BATCH REPLACEMENT AND FURTHER ROBUSTNESS CHECKS

	Daily Number of Eggs per Hen, y_i			
	(1) Non-replacement Weeks	(2) Replacement Weeks	(3)	(4)
Coworkers'	-0.31800***	-0.32766**	-0.18025*	-0.28353***
Eggs per Hen, $\bar{y}_{-i}$	(0.0737)	(0.1665)	(0.0968)	(0.0972)
age_i	0.02927***	-0.00683		
	(0.0070)	(0.1332)		
age_i^2	-0.00029***	-0.00027		
	(0.0001)	(0.0013)		
$food_{t-1}$	0.00440***	0.00037	0.00534***	0.00412***
	(0.0012)	(0.0017)	(0.0013)	(0.0012)
$food_{t-2}$	0.00260**	-0.00036	0.00415***	0.00249**
	(0.0011)	(0.0163)	(0.0016)	(0.0010)
$food_{t-3}$	0.00256**	0.02167	0.00391**	0.00219**
	(0.0011)	(0.0235)	(0.0012)	(0.0011)
1st Stage F-stat	16.43	30.81	119.72	76.13
Shed-Week FEs	Y	Y	Y	Y
Age Dummies	N	N	Y	Y
Day FEs	Y	Y	Y	Y
Worker FEs	Y	Y	Y	Y
Batch FEs	Y	Y	Y	Y
Observations	20773	134	8726	20594
R^2	0.893	0.978	0.967	0.926

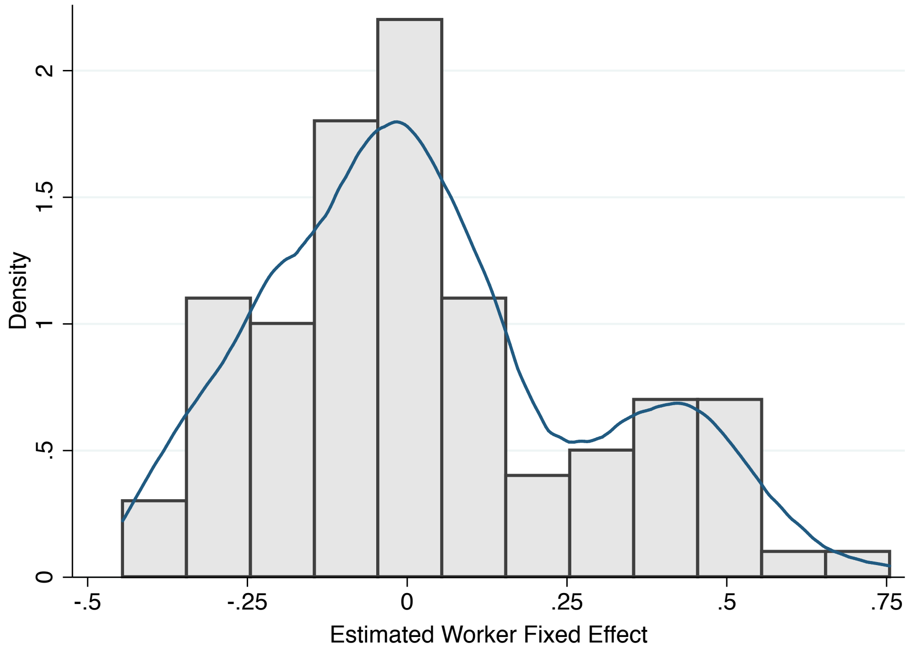
Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) 2SLS estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Subsample in (1) contains observations belonging to weeks with no replacement in the correspondent shed. Subsample in (2) contains observations belonging to weeks with any replacement in the correspondent shed. A random sample of production units per shed-week is considered in column (3). Subsample excluding observations belonging to days where worker was listed as absent is considered in column (4). Dependent variable is the average number of eggs per hen collected by the worker. Main variable of interest is average daily number of eggs per hen collected by coworkers in neighboring production units, $\bar{y}_{-i}$. age_i is own hens' age in weeks. In (1) and (2) average age of coworkers' hens and its square ($\overline{age}_{-i}, \overline{age}^2_{-i}$) are used as instruments in the first stage. The full set of coworkers' hens' age dummies is used in the first stage in (3) and (4). $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE 1.A.4: INCENTIVES HETEROGENEITY: ESTIMATION ACROSS SUBSAMPLES

	Daily Number of Eggs per Hen, y_i					
	(1) Low Prod. Age	(2) High Prod. Age	(3) Coworker is Friend	(4) Coworker is Not Friend	(5) Experience > Median	(6) Experience < Median
Coworkers'	-0.26615***	-0.12017	-0.19371**	-0.30046***	-0.47681***	-0.33110***
Eggs per Hen, $\bar{y}_{-i}$	(0.0639)	(0.1043)	(0.0892)	(0.0956)	(0.0717)	(0.1034)
$food_{t-1}$	0.00388***	0.00063**	0.00253**	0.00592***	0.00315**	0.00484***
	(0.0011)	(0.0003)	(0.0012)	(0.0017)	(0.0014)	(0.0018)
$food_{t-2}$	0.00268***	-0.00011	0.00197**	0.00312**	0.00088	0.00333***
	(0.0009)	(0.0001)	(0.0008)	(0.0013)	(0.0009)	(0.0008)
$food_{t-3}$	0.00170*	-0.00026	0.00169*	0.00307**	0.00170*	0.00144
	(0.0009)	(0.0002)	(0.0009)	(0.0013)	(0.0009)	(0.0009)
1st Stage F-stat	139.87	24.04	135.53	248.03	238.44	33.82
Shed-Week FEs	Y	Y	Y	Y	Y	Y
Age Dummies	Y	Y	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y	Y	Y
Worker FEs	Y	Y	Y	Y	Y	Y
Batch FEs	Y	Y	Y	Y	Y	Y
Observations	9950	10950	3913	12399	8519	7790
R^2	0.949	0.851	0.969	0.937	0.949	0.969

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) 2SLS estimates. Sample is restricted to all production units in sheds with at least one other production unit. Subsamples for each column are derived as discussed in Section 1.5. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is average number of eggs per hen collected by the worker. Main variable of interest is average daily number of eggs per hen collected by coworkers in neighboring production units, $\bar{y}_{-i}$. The full set of own hens' age dummies are included as controls. The full set of coworkers' hens' age dummies is used in the first stage in all columns. $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

FIGURE 1.A.1: DISTRIBUTION OF ESTIMATED WORKER FIXED EFFECTS



Notes. The figure plots the distribution of worker fixed effects as estimated from a regression specification where hens' week-of-age dummies, batch and day fixed effects are also included as regressors. Conditional on input quality, workers have a substantial impact on productivity.

1.10 Appendix B

1.B.1 Termination Policy and Observable Input Quality

In this section, we further extend the conceptual framework in Mas and Moretti (2009) in order to incorporate additional features of the production environment under investigation. We describe the learning process of the principal, who computes the expected workers' effort choice on the basis of available information on both output levels and observable input characteristics.

Let input quality s_i be a function of both observable and unobservable input characteristics. In particular, let

$$s_i = g(a_i)^{\eta_i} \tag{1.1}$$

where $g(a_i)$ is a deterministic function of hens' age whose domain is in the $(0, 1)$ interval, while η_i is an idiosyncratic random shock. The latter is independent across workers and identically distributed on the $[0, 1]$ interval according to a uniform distribution. It follows that output in a moment in time is equal to

$$y_i = g(a_i)^{\eta_i} e_i \tag{1.2}$$

The principal computes the expected value of individual workers' effort choices conditionally on the observed productivity y_i and the age of hens a_i assigned to the worker. The principal knows the shape of the $g(\cdot)$ function, and can thus partially net out the observable component of input contribution to output by calculating

$$\mathbb{E}\left\{g(a_i)^{\eta_i}|a_i\right\} = \int_0^1 g(a_i)^{\eta_i} d\eta_i = \frac{g(a_i) - 1}{\ln g(a_i)} > 0 \tag{1.3}$$

It follows that the principal divides productivity y_i by the expected input contribution in order to derive a signal z_i of the effort exerted by the worker

$$z_i = \frac{y_i}{\frac{g(a_i)-1}{\ln g(a_i)}} = \frac{g(a_i)^{\eta_i} \ln g(a_i)\; e_i}{g(a_i) - 1} > 0 \tag{1.4}$$

Taking logs we get

$$\ln z_i = \ln e_i + \phi(\eta_i, a_i) \tag{1.5}$$

where noise $\phi(\eta_i, a_i)$ is a function of both hens' age a_i and the idiosyncratic shock η_i

$$\phi(\eta_i, a_i) = \ln \left\{ \frac{g(a_i)^{\eta_i} \ln g(a_i)}{g(a_i) - 1} \right\} \tag{1.6}$$

Let $f_i = \ln(e_i)$ and $v_i = \ln(z_i)$. The principal computes

$$\mathbb{E}\left\{f_i|\mathbf{v}\right\} = b(v_i - \bar{v}) + \bar{v} \tag{1.7}$$

where $b = \frac{Cov(z_i, e_i)}{Var(z_i)} < 1$. In case the noise $\phi(\eta_i, a_i)$ was normally distributed, the conditional expectation above would be the most accurate estimate of f_i. Simulations in Table 1.B.1 and Figure 1.B.1 show that this is indeed a reasonable assumption. Nonetheless, even when that is not the case and $\phi(\eta_i, a_i)$ was not normally distributed, the above expression for $\mathbb{E}\left\{f_i|\mathbf{v}\right\}$ would still return the predictor of f_i which minimizes the squared sum of prediction errors.

Following the conceptual framework in the chapter, the probability for a given worker to keep the job is an increasing and concave function of her expected level of effort, of which f_i is a monotonic transformation. We thus have

$$q\left[\mathbb{E}\left\{f_i|\mathbf{v}\right\}\right] = q[\ b(v_i - \bar{v}) + \bar{v}\ ] \tag{1.8}$$

with $q'(\cdot) > 0$ and $q''(\cdot) < 0$.

Notice that, since $b < 1$, the probability of keeping the job increases with both the individual signal v_i and any coworkers' signal v_{-i}. Furthermore, consistently with the empirical analysis, it can be shown that, given the expected idiosyncratic random shock $\mathbb{E}(\eta_i) = \frac{1}{2}$, signals v_i are also increasing with observable input quality $g(a_i)$.

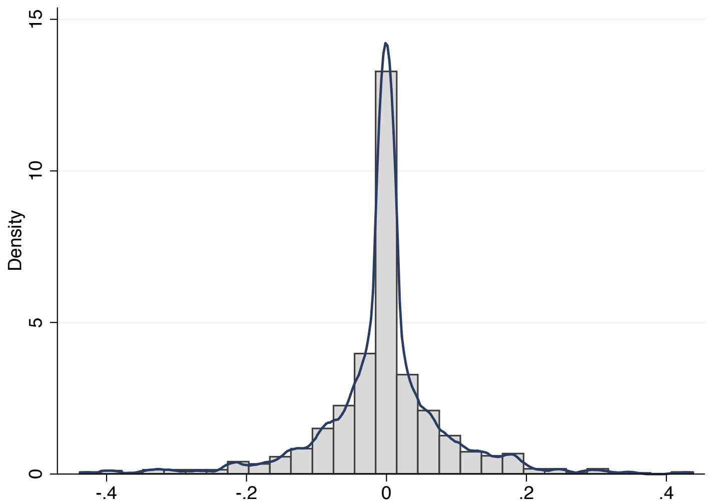
This is because, given the idiosyncratic unobservable component in input quality η_i, the principal cannot perfectly net out the input contribution to output. As a result, even observable increases in input quality increase the value of the signal the principal uses to calculate the expected level of effort exerted by the worker.

TABLE 1.B.1: SIMULATED DISTRIBUTIONS

Variable	N	Mean	St. Dev.	Min	Max
η_i	1000	0.51	0.288	0	1
a_i	1000	54.222	19.776	20.005	89.895
$g(a_i)$	1000	0.837	0.163	0.363	1
$\phi(\eta_i, a_i)$	1000	0.002	0.085	-0.476	0.386

Notes. The Table reports summary statistics for the distributions used in the simulation exercise. In order to match the conceptual framework, η_i is generated as independently and uniformly distributed on the $[0, 1]$ interval. The hens' age variable a_i is calibrated to the data and generated as independently and uniformly distributed on the $[20, 90]$ interval. Following the results in Table 1.3 and assuming $e_i = 1$, the input quality variable is set as equal to $g(a_i) = 0.04a_i - 0.0004a_i^2$. The noise variable $\phi(\eta_i, a_i)$ is defined as in equation 6 of Appendix B.

FIGURE 1.B.1: SIMULATED DISTRIBUTION OF $\phi(\eta_i, a_i)$



Notes. The figure plots the distribution of $\phi(\eta_i, a_i)$ as derived from the values of η_i, a_i and $g(a_i)$ reported in Table 1.B.1, together its the smoothed kernel density.

Chapter 2

MAKING DO WITH WHAT YOU HAVE: CONFLICT, FIRM PERFORMANCE AND INPUT MISALLOCATION IN PALESTINE

Joint with Michele Di Maio, University of Naples "Parthenope"

2.1 Introduction

There is robust evidence of a negative relationship between conflict and aggregate economic activity (Alesina et al. 1996; Collier et al. 2003; Blattman and Miguel 2010). Yet, our understanding of the microeconomic mechanisms behind such aggregate effects is still scarce. Specifically, there is a lack of empirical evidence on how conflict affects the backbone of the economy, namely the firm. Which firm-level outcomes are impacted by violent conflicts? What are the actual mechanisms behind these effects?

Providing the answers to these questions is challenging for three main reasons. First, violent conflicts usually take place in developing countries, where micro-level data on firms' activities are often unavailable, with the conflict itself making firm-level data collection even harder (Ksoll et al. 2014). Second, the identification of the effect of conflict on firms' performance crucially relies on the (often low) accuracy of the data used to measure conflict exposure. Finally, conflicts are often short-run and geographically localized. As a result, identification lacks of credible sources of variation in the intensity of conflict.

In this chapter, we study the operations of firms and their outcomes in the Occupied Palestinian Territories (OPT) during the Second Intifada.[1] The Israeli-Palestinian conflict has some unique features that make it particularly suitable for the analysis of the effects of a violent conflict on the operations of firms. First, establishment-level data for a representative sample of firms in the OPT are available for the entire period. Second, the conflict has been characterized by meaningful time and geographical variation in violence, with detailed information being available since its very beginning. Third, it is a conflict that - with different ups and downs - can be considered as long term and low-intensity when compared to other conflicts. This implies that - differently from what happens in countries affected by extremely violent conflicts and genocide episodes - the economy never collapsed in either the West Bank or the Gaza Strip during the Second Intifada, even if its functions were severely affected.

In providing an explanation to the relationship between violent conflicts and aggregate economic activity, we focus on one precise mechanism. We think about conflict as possibly affecting the functioning and accessibility of the markets where firms buy their production inputs and/or sell their final goods. If that's the case, the demand for inputs should change accordingly, with those firms which find it harder to access the market for one specific input using that input less intensively in production. We develop this intuition within the conceptual framework proposed by Hsieh and Klenow (2009). In their formalization of the economy, firms in the same sector are endowed with the same production technology. In absence of distortions, they all use inputs in the same proportions, while differences in total factor productivity determine the size of the firm. The presence of firm-level distortions in the accessibility of markets changes the marginal product of inputs, and the allocation of production factors across firms. It follows that heterogeneity arises within sectors in the proportions in which firms combine their inputs.

The model guides us in the empirical analysis and interpretation of results. In par-

[1]The Occupied Palestinian Territories include the West Bank and the Gaza Strip. The Second Intifada is a period of intensified violence which took place between 2000 and 2006. Section 2.2 provides extensive background information on the Israeli-Palestinian conflict and the Second Intifada in particular.

ticular, it illustrates how within-sector differences in the production choices of firms which are differentially exposed to conflict can be informative of the relative extent of conflict-induced distortions in the accessibility of markets.

We take these considerations to the data by combining establishment-level information from the OPT for the years 1999 to 2006 with information on conflict-related Palestinian fatalities. Taking the latter as a proxy for conflict intensity, we compare the outcomes and operations of firms in the same sector over time across districts experiencing differential changes in conflict intensity. We are thus able to net out both overall time trends and unobserved time-invariant sources of heterogeneity in firms' operations at the district level, possibly correlated with conflict intensity. Comparing establishments within the same 2-digit sector, we find that a one standard deviation increase in the yearly number of Palestinian fatalities in the establishment's district of location to be associated with a significant 6 to 9% in the firm's value of output. Our conceptual framework guides us in investigating to what extent such fall in output value is the result of conflict-induced distortions in accessibility of markets for inputs. While the total value of materials as relative to other production inputs does not vary systematically with conflict exposure, we find that firms operating in high conflict environments employ a lower value of imported materials with respect to that of domestically produced materials. In other words, firms which are differentially more exposed to conflict tend to substitute domestically produced materials for imported ones. We find the conflict to induce distortions in the accessibility of markets for imported material inputs which are more than three times bigger than the ones for markets for domestically produced materials, and significantly higher than those for labor and capital markets. Aggregate foreign trade figures further validate this finding.

The validity of our interpretation of the empirical results rests on the credibility of the proposed conceptual framework and its assumptions. We explicitly question these assumptions and undertake a number of robustness checks. First, we investigate whether there is any evidence of within-sector differences in production choices of firms which are unrelated to conflict exposure. In particular, we are interested in ruling out the possibility that such heterogeneity is correlated with firm size, i.e. that production functions are non-homothetic. Using data from the no-conflict period, we identify those sectors for which the assumption of homothetic production functions finds support in the data. We can thus show that our results are unchanged if we focus on such sample. Therefore, evidence is in favor of the hypothesis that the observed changes in production technology are due to distortions within the supply side of the economy rather than endogenous to a fall in demand. Second, we make sure that our results are not driven by systematic differences in firm-level prices.

We also explore the possible sources of conflict-induced distortions. We consider the role of external and internal mobility restrictions, and increased operating costs. We find suggestive evidence that days of border closures, transportation obstacles and transaction costs can be the relevant factors affecting the accessibility of markets for imported inputs. Furthermore, heterogeneity at the sector level shows that conflict-induced distortions are larger for firms operating in those sectors which were more intensive in imported materials and had higher average output value in the years prior to the Second Intifada, i.e. in the absence of conflict. Evidence thus shows that conflict affects disproportionally more the most productive sectors of the economy, suggesting the possibility of negative long-term effects on the Palestinian economy.

Our study builds upon and contributes to several strands of the literature. The first refers to those studies which investigate the effects of violent conflict on economic performance. The literature on the economics of conflict has mostly focused on household consumption, education, gender inequality, health and individual psychology.[2] The economic consequences of conflict and terrorism have been investigated at the macroeconomic level by estimating its impact on aggregate investment and output. Evidence robustly shows that violent conflict is associated with output fall (Cerra and Saxena 2008; Chen et al. 2008), lower investment (Fielding 2003; Eckstein and Tsiddon 2004) and lower growth (Alesina et al. 1996; Ades and Chua 1997; Collier 1999). A few studies investigate the effect of a violent conflict at the micro level, looking at outcomes such as: firm stocks (Abadie and Gardeazabal 2003; Guidolin and La Ferrara 2007), investment (Deininger 2003; Pshisva and Suarez 2010; Singh 2013), firm exit (Camacho and Rodriguez 2013), and entrepreneurship (Ciarli et al. 2010). In particular, Collier and Duponchel (2013) use data from a 2006 firm survey in four districts in Sierra Leone to study the effect of conflict intensity on firm size and revenues. They find that conflict reduces firm-level number of employees and their income. They suggest two channels through which civil war may negatively affect the demand for firms' output: an increase in unit cost due to the technical regress caused by the war-related physical destruction,

[2] See Blattman and Miguel 2010 for a survey of the literature.

and a decline in demand driven by the reduction in household income. Due to data limitations, they cannot directly test these predictions and only provide indirect evidence to support their view. Ksoll et al. (2014) use detailed firm-level export data to investigate the impact of ethnic violence in Kenya - which escalated after the 2007 presidential elections - on exporting firms operating in the floriculture sector. They find that violence negatively affected export volumes and revenues through an increase in workers' absence. Etkes and Zimring (2014) study the effect of the Israeli-imposed blockade of Gaza in 2007-2010 and find that it decreased the welfare of Palestinian households in Gaza up to 27% on average. They argue that the result is driven by the blockade-induced reallocation of workers across sectors and fall in productivity. They also show that the trade exposure of the sector matters: reliance on imported inputs is correlated with a decline in sector productivity while the share of exporting does not. Finally, Klapper et al. (2013) focus on civil unrest in Côte d'Ivoire following the coup dâětat in 1999, and investigate its impact on firm performance. Using census data for the period 1998-2003, they find that the conflict led to a drop in firm productivity, with the decrease being significantly larger for firms owned by or employing foreign individuals. Moreover, they find that the negative effect on TFP is relatively higher in import oriented industries. As for the channels, they suggest that results may be driven by the increase in the operating costs (including the cost of imported inputs) rather than by demand-side effects.

This chapter improves over the existing literature on the microeconomics of conflict along three dimensions. First, while the majority of previous studies have considered only one sector or some specific group of firms, we build our study sample starting from a representative sample of the whole population of establishments in the manufacturing sector. Second, our detailed establishment-level data allow us to look at a wide range of firm-level figures, including total and per-worker output value and input usage. Third, we specifically investigate one precise mechanism behind our main negative result on output value, namely conflict-induced distortions in the functioning and accessibility of markets for imported material inputs. We also provide suggestive evidence of the sources of distortions.

We also contribute to the empirical literature on factor misallocation. Starting with the seminal work of Wasmer and Weil (2004), several contributions have investigated how market frictions and distortions can affect aggregate output and productivity. A number of studies focus on capital market distortions (Buera et al. 2011; Banerjee and

Duflo 2014; Midrigan and Xu 2014), while others address the specific impact of labor and size-dependent policies (Hopenhayn and Rogerson 1993; Guner et al. 2008). More generally, Restuccia and Rogerson (2008) show how differences in the prices faced by individual producers in the United States can result in sizeable decreases in aggregate output and total factor productivity. Hsieh and Klenow (2009) compare the relative extent of aggregate factor misallocation across India, China and the United States, and investigate its negative effect on aggregate output. We contribute to this literature by identifying conflict as a determinant of factor misallocation. In the case of the Israeli-Palestinian conflict, we find evidence of conflict-induced distortions in the access to the market for imported materials, suggesting them to be responsible to some extent for the aggregate output value losses in the OPT.

Given the salience of our results on imported inputs, our study relates to the literature which links international trade and firms' performance. Several theoretical papers have emphasized the importance of trade in intermediate inputs in generating productivity gains resulting from better access to superior inputs and technology (Ethier 1982; Melitz 2003; Kugler and Verhoogen 2009; Kasahara and Lapham 2013; Novy and Taylor 2014). These predictions are confirmed by robust empirical evidence. Schor (2004), Amiti and Konings (2007), Kasahara and Rodrigue (2008) and Topalova and Khandelwal (2011) use establishment-level data and find that trade liberalization episodes in Brazil, Chile, India and Indonesia led to productivity increases in domestic firms through access to (cheaper and better) imported inputs. Our results corroborate this view, as conflict is found to negatively affect output value through its distortionary effect on imported inputs market access, forcing establishments to substitute imported inputs with domestically produced ones.

Finally, our study contributes to the literature on the effect of the Second Intifada on the Palestinian economy. Previous contributions have analyzed the impact of the conflict on a number of different economic outcomes: labor market (Miaari and Sauer 2011; Cali and Miaari 2013; Abrahams 2015), asset prices (Zussman et al. 2008) and child labor (Di Maio and Nandi 2013). While several reports have discussed the aggregate economic impact of the Second Intifada on the Palestinian economy (see for instance World Bank 2004), there are no empirical estimates of such effect at the micro level. To the best of our knowledge, ours is the first contribution to provide evidence of the effect of the Second Intifada on the behavior of Palestinian firms in both the West Bank and the Gaza Strip.

The rest of the chapter is organized as follows. In Section 2.2, we provide an overview of the Israeli-Palestinian conflict, focusing in particular on the period of the Second Intifada. We present our conceptual framework and derive testable empirical implications in Section 2.3. In Section 2.4, we describe the dataset and the main variables of interest. In Section 2.5, we present the empirical strategy, our results and the evidence on the main mechanism. Section 2.6 concludes.

2.2 Background: The Israeli-Palestinian Conflict and the Second Intifada

The Israeli-Palestinian conflict dates back to 1948, making it one of the longest and most politically relevant violent conflict in the world. In 1967, the Six-Day War ended with the Israeli occupation of the West Bank and the Gaza Strip, previously part of Jordan and Egypt respectively. In the following years, the conflict went through different phases, each characterized by different levels of violence. Between 1967 and 1993, Israel held the West Bank and the Gaza Strip under military rule. The Israeli occupation led in 1987 to an unarmed but violent and widespread Palestinian uprising. The so-called First Intifada came to an end in 1993, when the Oslo Accord created the Palestinian National Authority (PNA), and gave it limited control over some civilian matters (e.g. education, health and taxation) in both the West Bank and the Gaza Strip. The Israeli authorities maintained control over some strategic issues such as security, border controls and foreign trade between the Occupied Palestinian Territories (OPT) and Israel, Jordan and Egypt.

The years immediately after the Oslo Accord were characterized by a reduction in violent episodes on both sides. This relatively peaceful period came to an end in September 2000, with the beginning of the so-called Second Intifada.[3] The Second Intifada (also called the Al-Aqsa Intifada) has been a period of intensified violence between the occupying Israeli Defense Forces (IDF) and the Palestinians.[4] This phase of the conflict has been characterized by numerous violent events on both sides, including Palestinian

[3] For a thoughtful discussion about the causes of the Second Intifada see Pressman (2003).

[4] For a detailed description of the different periods of violence during the Second Intifada see Jaeger and Paserman (2008).

attacks in Israel, assassination of Palestinians leaders in Palestine and demolitions of Palestinian houses by the IDF. Since the beginning of the Second Intifada, there have been frequent and ongoing clashes in the OPT between Palestinians and the IDF that have often culminated with some killings. The causes of these clashes were the most varied, ranging from communication misunderstandings between Palestinian civilians and IDF at the checkpoints, to skirmishes between young Palestinians throwing stones and the IDF, up to actual armed fighting between Palestinian militants and the Israeli Army (Sletten and Pedersen 2003). Given that the Second Intifada has been essentially a period of violent resistance of different sectors of the Palestinian population against the Israeli occupying force, it not surprising that violence has been highly asymmetrical. Between 2000 and 2006, Palestinians killed 234 Israeli civilians and 226 IDF personnel in the OPT while the IDF caused more than four thousand Palestinian fatalities, with the majority of the killed being non-combatants (B'TSELEM 2007, Ajluni 2003). The conflict situation persisted during the whole period, but the intensity of violence varied substantially over time and space in both the West Bank and the Gaza Strip, with also periods of relative calm in different areas. Even if long-term, the low-intensity of the conflict implied that the Palestinian economy never completely collapsed, as opposed to what often happens to countries experiencing genocide episodes or interstate wars.[5]

In order to enhance security and control in the OPT during Second Intifada, the IDF also severely scaled up the restrictions on the mobility of goods and people within the OPT as well as across the borders with Israel, Jordan and Egypt.[6] Internal and external movement and access restrictions have been a key constraint to Palestinian economic development (e.g. World Bank 2010 and UNCTAD 2011). On the one hand, internal movement restrictions imposed by Israeli authorities stifle economic activity by raising transaction costs, the cost of doing business and increasing uncertainty (World Bank 2007b).[7] On the other hand, the effects of external closures have been quite dramatic for the Palestinian economy, its foreign trade and labor market (PCBS 2001, United

[5]Nonetheless, continuous exposure to conflict-related violence have been shown to have negative consequences on health (Mansour and Rees 2012), education (Brück et al. 2014), and psychological well-being (Mataria et al. 2009) of the Palestinians.

[6]According to the Israeli Army, this system has been devised as a security measure to protect its citizens (both in Israel and inside Israeli settlements in the West Bank) from surges, or expected surges, in the Israeli - Palestinian conflict (Miaari and Sauer 2011; IDF Military Advocate General 2012.)

[7]In 2000, nearly 60 percent of firms made a relevant share of their sales outside of their home city; by 2006, this had fallen to around 40 percent (World Bank 2007b).

Nations 2002, World Bank 2004, World Bank 2007b).[8] Since there are no ports or airports in the OPT, import and export goods need to travel through Israel, Jordan or Egypt. Israel currently controls all trade access routes, so that Palestinian trade flows heavily depend on the state of the conflict with Israel, which decides the imposition of closures and other restrictions.

Israeli security measures have imposed extremely high transaction costs on the Palestinian economy: they limit producers' access to imported inputs required for production and the maintenance of the capital stock and - by increasing uncertainty - inflate the cost of imported inputs and reduce output (World Bank 2008).[9] The negative impact of this situation is likely to be very sizable considering that the Palestinian economy is highly dependent on foreign trade, which constitutes about 80% of its gross domestic product, and in particular on trade with Israel which represents more than 80% of the total value of trade (UNCTAD 2006). On top of physical restrictions to the mobility of goods and people, the conflict was also shown to have a meaningful impact on the operating costs of firms in the OPT. 24% of firms in the West Bank and Gaza report political instability as the biggest obstacle to their operations, right after macroeconomic instability at 30%, and before transportations at 9% (World Bank 2007c).

There is no established ending date for the Second Intifada. However, violence decreased substantially after 2006. The results of the 2006 elections caused a *de facto* division of OPT into a Fatah-controlled West Bank and a Hamas-controlled Gaza Strip. In retaliation to Hamas, Israel imposed a complete blockade on the Gaza Strip in 2007. The West Bank and the Gaza Strip - which until then had similar economic and political institutions and very similar trends in prices and consumption - started to diverge in both economic and political terms (Etkes and Zimring 2014).

[8] While closures were intended to be a security measure, they had negative impact on the labor market, child labor and school attendance (Miaari and Sauer 2011; Di Maio and Nandi 2013).

[9] The procedure for clearing Palestinian goods through Israeli ports and controlled border crossings is long and extremely complicated. Israel requires that Palestinian trucks use the back-to-back system according to which all goods need to be unloaded from and re-loaded again onto trucks at checkpoints after the security check. Mikuriya (2009) notes that: *"The reality at the border of the Palestine Authority is very different from the normal customs landscape."*

2.3 Conceptual Framework

Conflict is likely to affect firms' behavior through different channels. In particular, it can affect firm's operations and outcomes by generating or exacerbating existing firm-level distortions in the accessibility of markets, and thus the marginal product of inputs and their relative demand. Measuring the impact of the conflict on the latter, we can thus quantify the amount of distortions induced by the conflict.

In our conceptual framework, distortions affect the ratio between the value of inputs used in production. If conflict makes it more difficult to access the market for final goods, such distortion acts like a tax on the value of the final product, thus reducing firm size: the demand for all inputs will decrease accordingly, and their marginal product will increase. However, the distortions the conflict generates (or exacerbates) may be heterogeneous across inputs. Indeed, the conflict can affect access conditions to some input markets disproportionally more. In this case, differential distortions across inputs will differentially affect their marginal product: for each pair of inputs, a larger distortion for one input will lead to a decrease in its demand and an increase in its marginal product relative to the other. Input value ratios will change accordingly. Therefore, if conflict has a differential impact on input distortions, input value ratios will be systematically different for firms operating in a conflict environment. The way we think about firm-level distortions and factor misallocation is close to Hsieh and Klenow (2009). We build upon their formalization of the economy to provide the conceptual framework for our analysis.

Let the aggregate final output in the economy be produced by a single representative firm which produces a single final good Y with price P. Good Y is produced using using a Cobb-Douglas production technology having as inputs the output Y_s from all S sectors in the economy, i.e.

$$Y = \Pi_{s=1}^{S} Y_s^{\theta_s} \tag{2.1}$$

with $\sum_{s=1}^{S} \theta_s = 1$. Taking the price P of the final good as given, cost minimization implies $P_s Y_s = \theta_s PY$ for all s. This set of S first order conditions determines the allocation of demand across sectors.

Production in each sector s is carried out by a single representative firm which aggregates M_s differentiated input products by means of a CES (Constant Elasticity of Substitution) production function. Each input for sector s is supplied by a firm i producing output Y_{si} and operating under monopolistic competition. Production in each sector s is thus given by

$$Y_s = \left(\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{2.2}$$

with $\sigma > 1$. Each input-supplier firm i operating in sector s produces by means of a Cobb-Douglas production function using as inputs capital, labor and materials. The production function of firm i is given by

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{\beta_s} M_{si}^{1-\alpha_s-\beta_s} \tag{2.3}$$

so that the output value of the firm is given by[10]

$$P_{si} Y_{si} = P_{si} A_{si} K_{si}^{\alpha_s} L_{si}^{\beta_s} M_{si}^{1-\alpha_s-\beta_s} \tag{2.4}$$

We measure output and input distortions faced by firm i using τ_{Yi} and τ_{Xi} respectively, where Y is firms' output and X is one of the different production inputs (capital, labor and materials). Inputs are traded in a centralized market, with firms taking prices as given and equal to w for labor, R for capital, and z for materials. The firm i maximizes profits as given by

$$(1 - \tau_{Yi}) P_{si} Y_{si} - w(1 + \tau_{Li}) L_{si} - R(1 + \tau_{Ki}) K_{si} - z(1 + \tau_{Mi}) M_{si} \tag{2.5}$$

The single representative firm for sector s takes the price P_s a given. Cost minimization determines the allocation of sector-level demand Y_s across the firms operating in sector s. The first order conditions imply

$$Y_{si} = Y_s \left(\frac{P_{si}}{P_s} \right)^{-\sigma} \Leftrightarrow P_{si} = P_s \left(\frac{Y_s}{Y_{si}} \right)^{\frac{1}{\sigma}} \tag{2.6}$$

for each firm i in sector s. Given product differentiation, in monopolistic competition each firm enjoys a certain degree of market power, so that P_{si} is endogenous to Y_{si}.

[10]Note that, with respect to Hsieh and Klenow (2009), we include materials as input. In the empirical analysis, we also further differentiate between imported and domestically produced materials. The proposed Cobb-Douglas production function and the input value ratio expressions we derive can be extended accordingly to accommodate for the two material inputs, each one having its own factor share parameter.

Since P_s and Y_s are exogenous to firm i and determined by the sector-level allocation, we can substitute $P_{si} = P_s\left(Y_s/Y_{si}\right)^{\frac{1}{\sigma}}$ in the firm's profits expression in equation 2.5 and maximize with respect to each input. From the corresponding first order conditions we get

$$K_{si} = \frac{\sigma-1}{\sigma}\alpha_s\frac{P_{si}Y_{si}}{R(1+\tau_{Ki})}(1-\tau_{Yi})$$

$$L_{si} = \frac{\sigma-1}{\sigma}\beta_s\frac{P_{si}Y_{si}}{w(1+\tau_{Li})}(1-\tau_{Yi}) \tag{2.7}$$

$$M_{si} = \frac{\sigma-1}{\sigma}(1-\alpha_s-\beta_s)\frac{P_{si}Y_{si}}{z(1+\tau_{Mi})}(1-\tau_{Yi})$$

Equation 2.7 clearly shows that output and input distortions have a different impact on the demand for each input and their marginal product. An increase in output distortion τ_{Yi}, such as lack of access to the market for final goods, proportionally decreases the demand for *all* inputs and increases their marginal product. While the firm becomes smaller, input relative marginal products and demand do not change. On the contrary, an increase in the distortion faced by input X (τ_{Xi}), such as lack of access to the input X market, reduces the demand for that input *disproportionally more* and increases its marginal product.

Rearranging 2.7, we obtain the following expressions for the ratios of input values

$$\frac{RK_{si}}{wL_{si}} = \frac{\alpha_s}{\beta_s}\frac{1+\tau_{Li}}{1+\tau_{Ki}}$$

$$\frac{RK_{si}}{zM_{si}} = \frac{\alpha_s}{1-\alpha_s-\beta_s}\frac{1+\tau_{Mi}}{1+\tau_{Ki}} \tag{2.8}$$

$$\frac{wL_{si}}{zM_{si}} = \frac{\beta_s}{1-\alpha_s-\beta_s}\frac{1+\tau_{Mi}}{1+\tau_{Li}}$$

These equations provide a number of useful results for our analysis. First, they show that input value ratios are invariant with respect to output distortion τ_{Yi}, but not to input distortions τ_{Xi}. Moreover, they are also invariant with respect to the firm-level price P_{si}.

This implies that they do not depend on the competition environment faced by the firm. As a result, for any market structure of each sector s, we can infer firm-level conflict-induced distortions by comparing input value ratios across firms which are differentially exposed to conflict. Indeed, any systematic relationship between conflict intensity and input value ratios across firms in the same sector would provide evidence of conflict-induced relative input distortions. For example, if the input value ratio between capital and labor $\left(\frac{RK_{si}}{wL_{si}}\right)$ was systematically higher for firms in conflict areas, this would indicate that conflict increases relatively more firm-level distortions in labor with respect to capital as measured by $\left(\frac{1+\tau_{Li}}{1+\tau_{Ki}}\right)$.

As a final step, we derive firm i's output value. As in Hsieh and Klenow (2009), the optimal firm-level output price under monopolistic competition is a constant mark-up over the marginal cost of production. The price is given by

$$P_{si} = \frac{\sigma}{\sigma-1}\frac{1}{A_{si}(1-\tau_{Yi})}\left[\frac{R(1+\tau_{Ki})}{\alpha_s}\right]^{\alpha_s}\left[\frac{w(1+\tau_{Li})}{\beta_s}\right]^{\beta_s}\left[\frac{z(1+\tau_{Mi})}{1-\alpha_s-\beta_s}\right]^{1-\alpha_s-\beta_s} \tag{2.9}$$

An increase in any firm-level distortion increases the optimal firm-level price. Using the within-sector demand allocation condition in equation 2.6, we can rewrite input levels as a function of P_{si} only and derive the firm-level demand of inputs given sector-level production and prices. Substituting into equation 2.4, we have that output value for firm i in sector s can be finally be written as

$$P_{si}Y_{si} = \frac{\sigma}{\sigma-1}\frac{1}{1-\tau_{Yi}}\left[\frac{1+\tau_{Ki}}{\alpha_s}\right]^{\alpha_s}\left[\frac{1+\tau_{Li}}{\beta_s}\right]^{\beta_s}\left[\frac{1+\tau_{Mi}}{1-\alpha_s-\beta_s}\right]^{1-\alpha_s-\beta_s}(RK_{si})^{\alpha_s}(wL_{si})^{\beta_s}(zM_{si})^{1-\alpha_s-\beta_s} \tag{2.10}$$

2.4 Data

For the purpose of this chapter, we combine several different data sources.[11] Throughout the empirical analysis, we measure conflict intensity using the yearly number of Palestinians fatalities caused by the IDF at the district level. Data on fatalities are col-

[11] For more details on the study sample, variables definition and additional data on the aggregate level please refer to the Data Appendix 2.7.

lected and distributed by the Israeli NGO B'TSELEM (B'TSELEM 2007). They are based on a number of sources and validated by several cross-checks. These data are considered to be accurate and reliable by both the Israelis and the Palestinians and have been previously used by other scholars studying the Israeli-Palestinian conflict (see for instance Jaeger and Paserman 2008, Mansour and Rees 2012 and Brück et al. 2014). While previous studies have considered other measures of conflict intensity, the number of conflict-related Palestinian fatalities provides the most accurate description of conflict intensity in the OPT during the Second Intifada.[12] The B'TSELEM dataset provides a rich set of information, such as age, gender and place of residence of the killed, the date, place, and a description of the circumstances of the event. This allows us to count in each year the number of fatalities in each of the 16 Palestinian districts (i.e. governorates).[13] In our empirical analysis, we also use the number of closure days, i.e. days in which the movements of labor and goods between the OPT (the West Bank and the Gaza Strip) and Israel as well as between the West Bank and Gaza Strip are completely banned. During closure days, all permits previously issued to residents of the OPT for purposes of work, trade, or medical treatment are invalid. Our data on closure days of the border between Israel and the OPT are also provided by B'TSELEM.

The establishment-level data we use belong to the Palestinian Industry Survey (IS), a yearly representative survey of Palestinian establishments in the manufacturing sector designed and administered by the Palestinian Central Bureau of Statistics (PCBS 2007). In addition to the information contained in the publicly available version of the dataset, we were confidentially given the district of location of each establishment. Moreover, we have information on the ISIC 2-digit sector the establishment belongs to. We are thus able to map each of the surveyed establishments in each of the 16 Palestinian districts and explore the relationship between our firm-level variables of interest within and between both sectors and districts over time for the years 2000 to 2006. In our analysis, we also consider establishment-level data from 1999, i.e. before the Second Intifada

[12]Other measures used in the literature include: number of Palestinian houses demolished (Benmelech et al. 2015); the number of border closure days (Di Maio and Nandi 2013); the number of IDF check points in the OPT (Cali and Miaari 2013).

[13]These were established after the signing of the Oslo Accords, together with the division of the Israeli-occupied territories into the West Bank and the Gaza Strip. Governorates in the West Bank are: Jenin, Tubas, Tulkarm, Nablus, Qalqilya, Salfit, Ramallah and Al-Bireh, Jericho, Jerusalem (including Israeli annexed East Jerusalem), Bethlehem and Hebron. Governorates in Gaza Strip are: North Gaza, Gaza, Deir al Balah, Khan Yunis and Rafah.

started, which we use for comparison between the no-conflict and the conflict period. Our final sample comprises 14,287 establishment observations spanning 8 years (out of an initial sample of 16418).[14] The main variables we use in the empirical analysis are output value, the value of capital and labor, and the value of materials used during the year. We also have data on the value of imported and domestically produced materials, respectively. Furthermore, we use the total amount of labor to compute output value per worker and average wage at the establishment level. Finally, we use the number of family workers and proprietors as a fraction of total amount of labor as additional controls.

Table 4.1 shows the summary statistics of the variables used in the empirical analysis. An average number of 35 Palestinians fatalities per district per year are recorded in the period 2000-2006. The standard deviation is equal to 42, meaning that we have considerable variation across the 112 district-year observations. As for the establishment-level data, we observe meaningful variation across establishments in the variables of interest and, in particular, in output value and input value ratios. Figure 2.1 provides some additional information on Palestinian firms. The data shows that more than 80% of establishments have less than 6 employees and an output value of less than 400,000 NIS (approximately 50,000 USD). This indicates that - as in most of the countries in the region - the largest part of Palestinian manufacturing production is carried out by small and medium enterprises (SMEs). As for the sector of activity, 75% of the establishments in the sample operate in the following five sectors: *Fabricated metal products, except machinery and equipment* (22%); *Furniture* (15%); *Food products and beverages* (14%); *Other non-metallic mineral products* (14%); *Wearing apparel and dressing, and dyeing of fur* (12%). Establishments appear to be in general evenly distributed across districts, even if some of the smallest sectors are clustered in specific districts.

Finally, we also use firm-level data from the World Bank Enterprise Survey (World Bank 2006). The sample consists of 401 formal sector enterprises located in both the West Bank (52%) and Gaza (43%). Surveyed enterprises belong to the manufacturing sector, construction, transport, and selected service sectors with more than five employees. Despite its cross-sectional nature, the World Bank survey has information on the city/town where each of the 228 enterprises in the West Bank is located. We use these data to complement the information in the Industry Survey in the investigation of the

[14]Data issues and sample derivation are described in detail in the Data Appendix 2.7.

sources of firm-level distortions.

2.5 Empirical Analysis

2.5.1 Conflict and Output Value

We begin by investigating the relationship between conflict intensity and economic outcomes at the aggregate level. Figure 2.2 plots the value of Palestine GDP over time between 2000 and 2006, together with the total number of Palestinians fatalities caused by IDF. Real GDP falls by 20% between 2000 and 2002, mirroring the steep increase in the number of Palestinian fatalities over the period. A downward trend in the number of fatalities in the period thereafter is instead associated with an increase in GDP, with the latter reaching its 2000 values in 2004. Figure 2.3 shows that similar inversely related trends can be observed between conflict intensity real aggregate output value as computed using the data from the Industry Survey. The Figure plots the weighted sum of establishments' output value over time together with Palestinians fatalities in the same period. Establishment-level output values are aggregated after adjusting its value using yearly 2-digit sector-level deflators. The evolution of total output value is close to the one previously observed for GDP, and still inversely related to conflict intensity as measured by the total number of Palestinian fatalities.

Establishment-level data allow to investigate further the negative aggregate relationship between conflict intensity and economic outcomes. As a first step, we compute the median of the distribution of the number of fatalities in the 112 district-year pairs. We then split the sample of surveyed establishments into a *high conflict* and a *low conflict* subsample according to the year of interview and district of location. The top graph in Figure 2.4 shows the distribution of output value for all establishments in the two subsamples, averaging out the overall sample mean. The entire distribution for establishments exposed to high conflict is shifted leftwards with respect to the one for the low conflict ones.[15] Perhaps more importantly, the same pattern holds when we average out 2-digit sector means and focus on within-sector variability, as shown in the bottom graph of Figure 2.4. While clear and intriguing, evidence from the previous figures

[15]Evidence from Abrahams (2015) suggests that relocation of firms within the OPT is not an issue for the validity of our results.

needs to be interpreted with caution. Firms surveyed in high conflict years can be systematically different from those surveyed in low conflict years. Additionally, surveyed firms located in districts where conflict intensity is systematically higher may not be comparable to those located in other districts.

We address these issues in a systematic way by combining together cross-district and time variation in the number of fatalities and looking at establishment-level figures across districts experiencing differential changes in conflict intensity. Exploiting both sources of variability at the same time, we can net out a large fraction of unobservable determinants of establishment-level outcomes, possibly correlated with conflict intensity. For this purpose, it is necessary to rely on meaningful variation in the number of fatalities both across and within districts over time. Figure 2.5 provides a graphical representation of our identifying source of variation. In each map, districts are classified according to the quintile they belong to in the distribution of fatalities in a given year, and of the change in the number of fatalities over two-year time spans. Looking at the top maps, we see that there is large cross-district variation in the number of fatalities. At the same time, the three bottom maps show that there is also meaningful variation in the number of fatalities within each district over time. In particular, differential changes in conflict intensity across districts constitute a source of variability which does not seem to overlap with the cross-sectional one. This is confirmed by Figure 2.6 which plots the average number of Palestinians fatalities over time across two subsamples of districts. The continuous line refers to those 25% of districts which recorded the highest number of fatalities in the 2002 peak fatalities year, while the dash line shows the same figure for all other districts. Once again, conflict intensity is shown to exhibit meaningful variation over time, with changes being different across the two groups of district.

As a preliminary analysis of the relationship between conflict intensity and output value, we compare average output value figures across high and low conflict districts over time for the same subgroups as identified in Figure 2.6. Table 2.2 shows estimates of establishment-level means of log of output value across the two subsamples for the years 1999 and 2002. As shown in the first row, prior to the Second Intifada average output value was already significantly 28% lower in high conflict districts. Conflict is associated with a decrease of output value in both areas, but significantly so only for high conflict districts. As a result, the output value gap across areas widens in 2002, reaching 73%. Difference-in-difference estimates reveal such widening to be significant at the 5% level.

We can investigate these figures more systematically by implementing the following regression specification

$$\ln\left(P_{si}Y_{si}\right)_{gt} \;=\; \delta_t + \gamma_g + \varphi_s + \beta\, \mathit{fatalities}_{gt} + \mathbf{Z}'_{isgt}\,\boldsymbol{\rho} + u_{isgt} \qquad (2.11)$$

where $\ln(P_{si}Y_{si})_{gt}$ is the log of output value of firm i in sector s surveyed in year t and located in district g. The variable $\mathit{fatalities}_{gt}$ is the number of Palestinians fatalities in year t in district g, measured in standard deviation units from the district-year distribution. This allows to make coefficient estimates directly interpretable as the increase in the dependent variable associated with a one standard deviation increase in $\mathit{fatalities}_{gt}$. Year and district fixed effects are captured by δ_t and γ_g respectively. The former allow to net out systematic differences across establishments surveyed in different years, while the latter controls for time-invariant differences across firms located in different districts. We also include 2-digits sector fixed effects φ_s, which allows us to investigate within-sector variability in the dependent variable of interest. $\mathbf{Z}_{isgt}$ is a vector of establishment-specific controls, such as the fraction of family workers and the one of proprietors over the total number of employees. Finally, u_{isgt} captures any residual idiosyncratic determinant of (log of) output value. The coefficient of interest β captures systematic differences in output value across establishments which are differentially exposed to conflict.

Table 2.3 shows coefficient estimates from the above regression specification. Standard errors are clustered along both sector-year and district-year categories. This allows the residuals u_{isgt} belonging to establishment observations located in the same district and year to be correlated, and the same for the residuals belonging to establishment surveyed in the same year and operating in the same sector.[16] Column 1 shows the estimate for the coefficient of the *fatalities* variable from a simple regression specification where that is the only included regressor, thus mirroring the distribution results in the top graph of Figure 2.4. A one standard deviation increase in the number of fatalities in the district is associated with a 12.6% decrease in establishment's output value, significant at the 5% level. When district and year averages are netted out (column 2), the magnitude of

[16]The number of clusters is above 50 in both dimensions, so that the cluster-robust estimates of the variance-covariance matrix of residuals are reliable.

the coefficient decreases to 7.3%, but significant at the 1% level. Sector fixed effects are included in column 3, with the point estimate now being equal to 6.3% and significant at the 10% level. Next, we include as controls the fraction of family workers and that of proprietors over the total number of employees. Indeed, small family businesses are expected to be different from other establishment, and may also be differentially represented across districts experiencing differential changes in conflict intensity. Results from column 4 show that a one standard deviation increase in the number of fatalities in the district is now associated with a 9% drop in output value, significant at the 1% level. As expected, both control variables are negatively associated with output value. In the last column, we allow for sector-specific trends and include the full set of sector-year fixed effects ϕ_{st}. Estimates turn out to be unchanged in terms of both magnitude and significance.

These results show that conflict exposure is negatively associated with firm output value.[17] We cannot interpret our point estimate as capturing the causal effect of conflict on firm output value. Indeed, there could be observable and unobservable time-varying factors which could lead to both a fall in the output value of firms and to an increase in conflict. At the same time, any negative shock on firm performance and output value may decrease the demand for labor and thus the opportunity cost of fighting (Dube and Vargas 2013). While these concerns cannot be ruled out, our focus is on a different mechanism. Consistently with our conceptual framework, we explore the extent to which the relationship we find between conflict exposure and firm output value can be explained by the distortions that the conflict generates in the accessibility and functioning of markets for inputs, which affect the production choices of firms. In what follows, we thus focus on the supply side of the economy and look for systematic differences in input usage across establishments which are differentially exposed to conflict.

[17] Our data do not allow us to separately look at establishment-level output level and prices. We provide a more detailed empirical discussion on the role of output prices in Section 2.5.3, where we also address similar concerns related to input prices and provide evidence in favor of our interpretation of results. Also, notice that the conceptual framework suggests that our estimates are only a lower bound of the relationship between conflict and output level. Indeed, equation 2.9 in Section 2.3 shows that, when firms enjoy a certain degree of market power, any increase in output or input distortion will result in higher firm-level output prices. It follows that, if conflict increases distortions, only a more than proportional decrease in output quantity would generate the negative result we find on output value.

2.5.2 The Mechanism: Conflict-Induced Changes in Input Usage

Our conceptual framework indicates that within-sector differences in input value ratios are informative of the relative amount of input distortions faced by the firms. We now exploit this feature of the model in the investigation of our establishment-level data. Taking logs of equation 2.8, we get

$$\ln\left(\frac{RK_{si}}{zM_{si}}\right) = \ln\left(\frac{\alpha_s}{1-\alpha_s-\beta_s}\right) + \ln\left(\frac{1+\tau_{Mi}}{1+\tau_{Ki}}\right)$$

$$\ln\left(\frac{wL_{si}}{zM_{si}}\right) = \ln\left(\frac{\beta_s}{1-\alpha_s-\beta_s}\right) + \ln\left(\frac{1+\tau_{Mi}}{1+\tau_{Li}}\right) \tag{2.12}$$

$$\ln\left(\frac{RK_{si}}{wL_{si}}\right) = \ln\left(\frac{\alpha_s}{\beta_s}\right) + \ln\left(\frac{1+\tau_{Li}}{1+\tau_{Ki}}\right)$$

For every pair of inputs (X^1_{si}, X^2_{si}) with corresponding prices (p_1, p_2), we can thus investigate conflict-induced relative input distortions by implementing the following regression specification

$$\ln\left(\frac{p_1X^1_{si}}{p_2X^2_{si}}\right)_{gt} = \delta_t + \gamma_g + \varphi_s + \lambda_{12}\,\mathit{fatalities}_{gt} + \mathbf{Z}'_{isgt}\,\boldsymbol{\rho} + \varepsilon_{isgt} \tag{2.13}$$

where $p_1X^1_{si}$ and $p_2X^2_{si}$ are the value of input X^1 and X^2 respectively for firm i operating in sector s surveyed in time t and located in district g, while $\mathit{fatalities}_{gt}$ is the number of Palestinians fatalities in year t in the same district. The set of parameters φ_s captures 2-digit sector-specific differences in production technologies, matching the sector-specific factor shares in the conceptual framework. We again exploit cross-district and time variation in conflict intensity by including the full set of year and district fixed effects, δ_t and γ_g, thus allowing for overall time trends and netting out time-invariant differences across districts. Notice that these fixed effects would also average out systematic differences in factor prices across establishments in different years, districts or sectors.[18] Finally, $\mathbf{Z}_{isgt}$ is a vector of establishment-specific controls such as

[18]This implies that results would be robust to deviations from our conceptual framework where prices are assumed to be the same for all firms. We discuss the role of prices more in detail in Section 2.5.3.

the fraction of family workers and fraction of proprietors over the total number of employees and ϵ_{isgt} is the error term. The coefficient of interest λ_{12} captures systematic differences in the corresponding input value ratio across firms which are differentially exposed to conflict.

Table 2.4 reports in each row the corresponding estimates of λ from the above specification separately for each of the input value ratios. Column 1 shows estimates from a specification where only year, district and sector fixed effects are included, together with our main variable of interest $\textit{fatalities}_{gt}$. Rows (a) to (c) consider the input value ratios of capital, labor and materials. Input value ratios between the three inputs are found not to differ systematically for firms operating in high conflict environments, with estimates of the λ coefficient being close to zero and insignificant. Conflict seems instead to affect the relative use of material inputs. In rows (d) to (h), we consider separately imported materials M^f and domestically produced materials M^d. As shown in row (d), a one standard deviation increase in the number of fatalities is found to be associated with a 1.2 increase in the value of domestically produced materials used in production relative to imported ones, with the estimate being significant at the 1% level. By the same token, the value of capital and labor with respect to imported materials increases significantly with conflict intensity (rows (e) and (f)), while the ratio of capital and labor value over the value of domestically produced materials decreases significantly (rows (g) and (h)). All estimates are significant at the 1% level. In column 2, the fraction of family workers and that of proprietors are added as controls. In column 3, the full set of district-year fixed effects ϕ_{st} is included to allow for sector-specific trends. Finally, for consistency with Table 2.3, column 4 reports estimates from the sample of firms for which we have data on output value.[19] Estimates for all input value ratios are stable across all specifications.

The above results show that the within-district and within-sector variation over time in the input value ratios used by Palestinian establishments is systematically correlated to conflict intensity. We interpret this as evidence that conflict induces distortions which are differential across inputs: the relative value of imported materials is systematically lower for firms exposed to high conflict environments, indicating that firms suffer dis-

[19]As discussed in the Data Appendix 2.7, information on output value is not available for a subset of establishments in the study sample. These are not systematically differentially represented in given years or districts, nor systematically different in terms of observables.

proportionally higher distortions in imported materials with respect to others inputs. Moreover, since the relative value of domestically produced materials is systematically higher for these same firms - while the relative value of total materials is not - we infer that conflict distortions lead firms to substitute domestically produced materials for imported ones.

As we have seen, our conceptual framework provides a theoretical link between input value ratios and the relative amount of distortions (see equation 2.8). We use this result and the coefficient estimates of λ in Table 2.4 to derive the relative sizes of input distortions τ associated with a one standard deviation increase in the number of Palestinians fatalities. Following equation 2.12, we have that, for every pair of inputs (X^1, X^2), the relative amount of distortions induced by a one-standard deviation increase in conflict intensity is given by

$$\exp\left(\hat{\lambda}_{12}\right) = \frac{1 + \tau_{X_i^2}}{1 + \tau_{X_i^1}} \tag{2.14}$$

Corresponding estimated relative input distortion values are reported in Table 2.5, together with 95% confidence intervals.[20] We can thus compare the relative size of distortions across inputs. Notice that, as shown in equation 2.14, a zero estimate of the coefficient λ of the *fatalities* variable from equation 2.13 is associated with an implied relative input distortions ratio of one, indicating no differential conflict-induced input distortions for the corresponding inputs. If instead λ is estimated to be negative (positive), the corresponding relative input distortions would be lower (higher) than one. This means that conflict induces more distortions in the input at the denominator (numerator) with respect to the one at the numerator (denominator). Results in rows (a) to (c) show that conflict does not induce differential distortions in capital with respect to labor, or in the two with respect to materials overall. However, as shown in row (d), a one standard deviation increase in conflict intensity is associated with a significant 3.5 increase in the relative distortions faced by firm in accessing imported materials with respect to domestically produced ones. As shown in rows (e) and (f), conflict-induced distortions in imported materials are 1.7 and 1.6 significantly higher when compared to those in capital and labor. Conversely, rows (g) and (h) indicate that distortions in domestically

[20]Consistent estimates of standard errors are derived accordingly from the standard error coefficient estimates in Table 2.4.

produced materials are significantly lower with respect to those for capital and labor.[21]

These results show that, during the Second Intifada, the conflict significantly distorted input usage of Palestinian establishments. In particular, those firms which were differentially more exposed to conflict substituted imported material inputs with domestically produced ones. The two inputs are likely to be different in their productivity, and thus to have different factor share parameters in the production function. Indeed, evidence from the trade literature shows how access to imported inputs increases firm productivity (Schor 2004; Amiti and Konings 2007; Kasahara and Rodrigue 2008; Topalova and Khandelwal 2011). These results indicate that the substitution of imported material inputs with domestically produced ones can be identified as one of the mechanisms responsible for the larger fall in output value of firms operating in high conflict environments.

One possible concern is that our results are capturing systematic differences related to firms' localization. Firms located closer to the border gates are likely to be more intensive in imported material inputs with respect to other establishments in the same sector. By the same token, districts near the border with Israel may experience higher variation in the number of Palestinian fatalities over the period. We condition on the role of distance from the border by saturating the input value ratio regression specifications with a full set of year fixed effects interacted with a measure of the road distance of the district capital from the closest entry passage.[22] Corresponding estimated relative input distortions are reported in Table 2.6. Point estimates are very similar to those reported in Table 2.5. This suggests that our results are not confounded by firms' localization.

[21]Notice that our estimates do not address issues related to workforce composition, which may also change. One argument could be that conflict exposure may induce a change in the relative supply of skilled versus unskilled workers and thus a change in the composition of labor input despite the relative overall demand of labor being unchanged. As we discuss later in Section 2.5.3, this effect may operate for instance through the impact of border closures, which prevents Palestinian workers from commuting to Israel. However, any change in workforce composition would generate the effect we find on the relative use of imported vs. domestically produced materials only it if made labor more complementary to domestically produced materials than to imported ones. This is unlikely to be the case, as those workers whose relative supply increases - those who commute to Israel and are stuck in the OPT in conflict times - are instead more likely to be complementary to imported inputs.

[22]Since we do not have the geographical coordinates of the firm's location, we proxy the distance of the firm from the gate using the district capital under the assumption that firms are more likely to be located close to the largest urban center of the district.

Evidence Supporting the Mechanism: Conflict and Foreign Trade

Our results indicate that the relative demand for imported material inputs decreases with conflict intensity. Our suggested mechanism would thus find empirical support in the evidence that conflict intensity is associated with changes in aggregate Palestinian foreign trade, and imports in particular.

Foreign trade is an important determinant of the Palestinian economy, as the latter is highly dependent upon imported goods and services. During the Second Intifada, the total value of Palestinian imports is recorded to be 6 to 8 times the total value of its export, with the negative balance of trade being equal to 40 to 50% of GDP at its current value. Moreover, while Palestinian imports from Israel represent around 70% of the total value of imports in the period, Palestinian exports to Israel represent instead the 90% of total value of exports.[23] Still, volumes are such that trade with the rest of the world appears to be more balanced with respect to trade with Israel, as shown in Figure 2.7.

The empirical evidence shows that the evolution of Palestinian foreign trade during the Second Intifada is correlated with conflict intensity. Figure 2.8 shows aggregate real trade figures for Palestine for the years 2000 to 2006, together with the total number of Palestinians fatalities. Imports clearly decrease with the rise of conflict intensity between 2000 and 2002, reaching their minimum in 2002, which is the conflict peak year. Import values rise in the period thereafter. However, export levels do not experience a comparable change in levels. Indeed, the net balance of trade reaches its maximum in 2002, tracking the evolution of fatalities over the period. This shows that, while total Palestinian foreign trade decreases during the Second Intifada, the value of imports decreased disproportionally much more with the rise of conflict intensity with respect to the value of exports.[24] Indeed, evidence from the Industry Survey shows that firms' external sales do not change significantly for firms being differentially exposed to conflict during the period of interest.

[23] See the Data Appendix 2.7 for data sources and methodology. Also, note that trade with the OPT represents instead for Israel only a small share of its foreign trade.

[24] Recent contributions in the literature have explored the link between foreign trade and conflict. Berman and Couttenier (2015) shows that external income shocks are important determinants of the intensity and geography of civil conflicts. In the case of the OPT, Cali and Miaari (2015) suggest that, while changes in export levels in the 1990s are positively correlated with conflict intensity during the Second Intifada, changes in the level of imports are not.

Not only the aggregate value of exports and imports changed with the conflict, but possibly also their composition. Figure 2.9 and 2.10 show export and import trade composition in 1999 and 2002 respectively. The figures show that export composition does not experience any meaningful change in conflict years. On the contrary, import share are shown to change substantially. In particular, the data show that the sectors that suffer the largest reduction are: *Miscellaneous manufacturing articles*, *Manufactures goods (classified by materials)* and *Machinery and transportation equipments*. As expected, given the overall import reduction and their more inelastic demand, the sectors that increase instead their share of total imports are *Mineral fuel and lubricants* and *Food and live animals*. These results suggest that the conflict had a differential effect across sectors. We explore this possibility more in detail in Section 2.5.5.

The little change we observe in export levels and composition are particularly important, as they suggest that the external demand of firms in the OPT did not experience meaningful changes during the Second Intifada (as compared to imports). This rules out the possibility that the changes in firms' input usage are driven by changes in external demand, as the latter does not correlate with conflict intensity.

2.5.3 Robustness Checks

Non-homothetic Production Functions and Demand-side Effects

The validity of our interpretation of empirical results rests on the assumptions of Hsieh and Klenow (2009). In particular, the model assumes homothetic production functions. While firms in the same sector can be heterogeneous in terms of total factor productivity, this assumption ensures that - in absence of distortions - they will all use inputs in the same proportion. This implies that within-sector differences in input value ratios which relate systematically to conflict exposure can be interpreted as evidence of the relative amount of distortions induced by the conflict in the accessibility of markets for inputs. This allows us to identify a precise supply-side mechanism for the observed fall in output value in high conflict areas.

This is not necessarily the case if we allow for non-homothetic production functions. In this case, demand-side effects could explaining the changes in input value ratios. Indeed, when differences in factor shares are systematically correlated with firm's output, conflict-induced changes in demand can lead to changes in input usage. In particular, if firms with lower output were to employ relatively more domestically produced materials with respect to foreign produced ones, the observed increase in the relative amount of domestically produced materials in production could entirely be driven by output fall, with possibly no role played by conflict-induced distortions in the accessibility of markets.[25]

With non-homothetic production functions, in absence of distortions firm size should be correlated with input value ratios. We can test for the significance of this relationship in our context using data from the year 1999, thus prior to the start of the Second Intifada. Figure 2.13 panel (a) plots the relationship between the log of the ratio between the value of domestically produced materials and foreign produced ones over the log of output value in the year 1999, averaging out sector-level means. Substantial heterogeneity is observed across firms for any given level of output value. Furthermore, the line fitting the scatterplot is downward sloping, with the corresponding coefficient being significant at the 5% level. This means that, prior to the start of the conflict and within sectors, firms with higher output value employed relatively less domestically produced materials with respect to foreign produced ones. As specified above, such result can threaten the validity of our reasoning, and suggest that demand-driven mechanisms may be at work. However, the relationship appears to be not economically significant: one standard deviation increase in the log of imported vs domestic materials input value ratio is associated with a decrease in the log of output value of less than 10% of a standard deviation. Further analysis of the data reveals that in 1999 the relationship between input value ratio and output value is non-significant for 15 out of the 25 sectors (to which 903 out of the 1336 surveyed establishments belong to). Figure 2.13 panel (b) confirms that for these sectors the two variables are orthogonal one to the other, indicating that the homothetic assumption holds in this restricted sample. It is worth noticing that the sample includes the three most conflict-affected sectors and the two largest sectors in the Palestinian economy. Finally, we estimate relative input distortion values using observations belonging to this restricted sample, where the homotheticity assumption finds support in the data. Point estimates and 95% confidence intervals are reported in Table 2.9. Results are almost exactly the same as the ones we found previously in Table 2.5.

[25]Moreover, if firms with lower output were to employ relatively more domestically produced materials with respect to foreign produced ones, a negative shock on output value would lead firms to employ a higher fraction of domestically produced materials, and at the same time possibly lower the demand for labor and thus decrease the opportunity cost of fighting and increase conflict (Dube and Vargas 2013).

Under the assumption that the within-sector relationship between factor shares and output value remained constant over time, this suggest that our findings are not driven by the fact that in some sectors production functions could be non-homothetic. Evidence is thus supportive of the mechanism we posit: the effect on input value ratios operates through conflict-induced distortions within the supply side of the economy rather than through the demand side of the economy.

Output and Input Prices

As we noted before, our analysis of the relationship between output value and conflict intensity does not take establishment-level prices explicitly into account. In our conceptual framework, prices should increase following an increase in any output or input distortions. This implies that the negative effect we find on output value would be in fact only a lower bound for the effect on output level. From an empirical point of view, notice that time, sector and district fixed effect in our regression specification already control for overall price trends and differences in average prices across establishment operating in different sectors or located in different districts. When sector-year fixed effects are included, even sector-specific trend in prices are controlled for. In what follows, we show that the residual correlation between conflict and establishment-level output and input prices does not confound our results.

Despite not having establishment-level prices, we have information on the evolution of prices at the sector level. If any relationship exists between the evolution of sector-level prices and conflict, this should emerge when looking at those sectors which are clustered in specific districts. We thus identify in the data those sectors which are most geographically localized. The 70% of establishments operating in manufacture of tobacco products surveyed in the Industry Survey are located in the district of Jenin, while 70% of establishments operating in manufacture of leather products are located in Hebron. In Hebron are also located 43% of establishment manufacturing basic metals. We check for the possibility that establishment-level output prices vary at the district-year level by asking - for these district-clustered sectors - whether the Producer Price Index (PPI) tracks the evolution of Palestinian fatalities in the same district. Figure 2.14 shows the evolution of PPI in these three sectors over time, together with the evolution of fatalities in the corresponding district. We do not find evidence of a negative relationship between prices and conflict intensity over time in any of these cases. We can thus likely rule out the possibility that the decrease in output value we observe for firms operating in high conflict environments is due to a decrease in prices. If anything, and in accordance with our conceptual framework, evidence suggests that the decrease in firms' output value is due to a decrease in output which more than offsets any increase in output price.

Similarly, our interpretation of the results on relative input distortions rests on the assumption of no differences in relative factor prices faced by firms which are differentially exposed to conflict. Again, despite the fact that part of the across-establishments variation in factor prices is already controlled for by the included sets of fixed effects, we cannot completely rule out the possibility that there are still differences in relative factor prices associated to conflict intensity.

Our conceptual framework clarifies whether and how changes in factor prices may confound our results. On the one hand, the conflict could lead to an increase in the price of imported input materials by making access the corresponding market more difficult to achieve. However, given the demand for imported materials, this effect would go against the relative distortionary effect we found (i.e. the reduction in the imported vs domestic inputs value ratio), as the value of imported materials used in production would increase. On the other hand, conflict could have an ambiguous effect on the price of domestically produced inputs. Under perfect competition, the latter are rewarded according to their marginal revenues. Conflict increases output price and increases the demand for domestically produced material inputs, thus reducing their marginal product. The price of domestically produced input materials would then go up only if the increase in output price were to more than offset the decrease in the input marginal product.

In order to shed light on this last issue, we can investigate the only domestic input for which we have establishment-level factor prices, namely labor. We divide the total value of labor $w_{si}L_{si}$ by the total amount of labor L_{si}, and replace the log of the resulting average wage at the establishment level as outcome in equation 2.15. Table 2.10 reports parameter estimates from the corresponding regression specification. Controlling for year, district and sector fixed effects, an increase in one standard deviation in the number of fatalities is found to be associated with a 7% decrease in average wages, significant at the 5% level. Parameter estimates are robust to the inclusion of the fraction of family workers and that of proprietors as controls in column 2, which are, as reasonable to expect, negatively associated with average wage. The full set of sector-year fixed effects is included in column 3, while the sample is restricted to only observations for which we have data on output value in column 4. Estimates are stable and equally significant across specifications. Our results are consistent with the results in the previous literature showing that conflict during the Second Intifada negatively affected the monthly earnings of Palestinian workers (Mansour 2010; Miaari and Sauer 2011; Di Maio and Nandi 2013). This is because border closures created an excess supply of labor within the OPT, while internal mobility restrictions prevented labor from relocating across districts (Miaari and Sauer 2011; Abrahams 2015).[26] To conclude, the negative relationship we find between average wage and conflict intensity is reassuring, as the prices of locally available inputs (i.e., labor) decrease more for establishments operating in high conflict environments. All else equal, this would decrease the value of locally available inputs in production, while results show that it increases. Our estimates of the effect of conflict on relative input distortions are thus likely to be only a lower bound for their true values.

2.5.4 The Sources of Distortions

Results from the previous section show how firms located in districts which are differentially more exposed to conflict substitute domestically produced materials for imported ones in production. We attribute these changes to conflict-induced distortions in the functioning and accessibility of markets for imported materials, which lead firms to change their relative demand for inputs. In what follows, we explore several possible sources of distortions.

As we discussed in Section 2.2, one of the distinctive features of the Israeli-Palestinian conflict is the use of external border closures and internal mobility restrictions as a security measure by the IDF to control the border gates of entry and exit between Israel and the OPT. During closure days, movements of workers and import and export of goods

[26]The relationship between conflict and wages may operate both ways: lower wages decrease the opportunity cost of rioting for the Palestinians, thus possibly increasing conflict (Dube and Vargas 2013). However, results on input value ratios show that the relative demand for labor does not change with conflict exposure. Therefore, there does not seem to be any link between the change in wages and the finding of substitution between domestically produced and imported materials which may drive a spurious correlation between conflict and material input usage.

are interrupted. It follows that border closures could be one source of conflict-induced distortions and input misallocation documented in the previous section. Conceptually, border closures can be framed as a negative shock to the accessibility of foreign markets, which apply to the whole OPT. As shown in Section 2.5.2 Table 2.6, the magnitudes of the estimated distortions induced by the conflict do not change if we allow for differential effects of any year-specific shock according to distance from the border as captured by the interaction of the latter with year fixed effects in our regression specification. Still, in order to shed light on the impact of border closures per se, we can include as regressor the interaction of the yearly number of closure days with the road distance of district capital from the closest entry passage. In other words, we allow the effect of border closures on input usage to be heterogeneous according to distance from the border.[27] Table 2.7 reports the estimated coefficients of the variables of interest from the proposed augmented specification. Compared to the baseline results in Table 2.4, the coefficients of the *fatalities* variable are slightly higher in magnitude, but the difference is not significant. Perhaps more importantly, the coefficient of the interaction variable is also significant: we find the impact of border closures to be systematically higher for firms located farther away from the border with Israel. Indeed, accessibility of markets for imported materials is likely to be even more difficult the more the travel distance to the border. Therefore, results from Table 2.7 indicate that the closures of borders exacerbates the impact of conflict on relative input distortions: the higher the number of closure days and the more distant is the firm from the entry gates, the more firms substitute domestic inputs for foreign ones. This suggests that part of the effect of conflict on output value is related to the increased difficulties of importing associated with closure of borders. Furthermore, evidence shows that, while the relationship between fatalities and input usage is not differential across West Bank and Gaza, the differential impact of border closure according to distance from the border is there only in the West Bank.[28] This is consistent with the Gaza Strip being much smaller in size than the West Bank, so that the impact of border closure does not vary according to distance.

[27]As in the robustness exercise in Section 2.5.2, the distance variable accounts for the fact that firms closer to entry gates could be systematically different from other firms in terms of production choices and importing behavior.

[28]Results are available from the authors upon request. In order to test for differential effect of the variables of *fatalities* and the border closure across West Bank and Gaza, we interact both variables with a dummy equal to one if the establishment belongs to the West Bank.

In order to shed further light on the sources of distortions in accessibility of markets for imported material inputs, we can gather additional evidence from the World Bank Enterprise Survey (World Bank 2006). The corresponding dataset provides information for 401 enterprises located in the West Bank and Gaza. For those located in the West Bank, information on the exact city or town of location is also available. Similarly to what we have before at the district level, we can thus merge the World Bank (2006) data with the B'TSELEM (2007) data on Palestinians fatalities, and derive the number of fatalities in 2006 in the town where the firm is located. Despite the fact that we are using data from a cross-section of enterprises and only for the year 2006, we are confident that the extensive information in the survey coupled with finer variation in fatalities can shed light on the sources of distortions during the Second Intifada. Our analysis is based on a difference-in-difference strategy, checking whether the relationship between conflict intensity and firm outcomes is systematically different for importing firms as opposed to non-importing firms. We thus implement the following regression specification

$$y_{ig} \; = \; \alpha + \beta \, m_{ig} + \gamma \, \mathit{fatalities}_g + \delta \, \mathit{fatalities}_g \times m_{ig} + \mathbf{X}'_{ig} \, \boldsymbol{\theta} + \mathbf{Z}'_g \, \boldsymbol{\psi} + v_{ig} \quad (2.15)$$

where y_{ig} is the outcome variable of interest for firm i located in city/town g, m_{ig} is a dummy equal to one if the firm reports to import any good or service, and $\mathit{fatalities}_g$ is the number of Palestinians fatalities in city/town g. $\mathbf{X}_{ig}$ is a vector of pre-determined firm-level variables, such as sales and employment in 2003 and the year in which the firm began operating. $\mathbf{Z}_g$ is a vector of city/town level controls. The coefficient δ captures whether the relationship between conflict intensity and firm-level outcomes is systematically different according to importing status.

We focus first on what the firms report to be main obstacles to their operations, on a scale from 1 to 4. Table 2.8 shows the estimated coefficients from the above regression specification. Consistently with the previous results on the differential effect of border closures, Panel A shows how the score attached to custom and trade regulations as obstacle is differentially and systematically higher for importing firms operating in high conflict localities. Panel B shows that the same pattern holds when we consider the score attached to transportation as obstacle to firm operations. This is consistent with the evidence on the salience of internal mobility restrictions within the OPT. Barriers have been shown to increase the traveling time within the OPT and the cost of doing business (UNCTAD 2011; World Bank 2007a; World Bank 2007b).[29]

Evidence in Panel C is particularly interesting. Estimates show that importing firms in high conflict localities pay 4 to 6 percentage points more of their inputs before delivery. This suggests that the uncertainty related to conflict is disproportionally more salient for transactions on foreign markets with respect to local markets. This is consistent with the hypothesis that exposure to conflict shapes the terms of the contract between the firm and foreign suppliers, decreasing the bargaining power of the former. This increases the operating costs that the firm faces when accessing the market for foreign produced inputs, possibly explaining the changes in input usage that we documented in the previous section.

2.5.5 Sector-level Heterogeneity and Long-term Effects

Until now, we have studied the contemporaneous impact of conflict on production choices and firm performance. In fact, conflict-induced distortions are also likely to have long-term effects. In order to study them, one would ideally follow the same firm over time, and investigate whether the firms which are more affected by conflict are the most productive ones. Unfortunately, existing data sources do not provide information for the same firms over time. We can nonetheless recover the panel dimension by taking the sector as our unit of analysis, and explore the heterogeneous effect of the conflict across sectors.

We start by ranking 2-digit sectors according to the size of conflict-induced relative distortions in imported and domestically produced materials. We run the following regression specification:

$$\ln\left(\frac{z^d M^d_{si}}{z^f M^f_{si}}\right)_{gt} = \delta_t + \gamma_g + \varphi_s + \lambda^s_{M^d M^f}\, \textit{fatalities}_{gt} \times \varphi_s + \mathbf{Z}'_{isgt}\,\boldsymbol{\lambda} + \varepsilon_{isgt} \quad (2.16)$$

[29] Cali and Miaari (2013) find that internal checkpoints have a significant negative effect on employment, wages, and days worked per month and a positive effect on the number of hours per working day. Abrahams (2015) finds instead that the effect of mobility restrictions are spatially differentiated: core locations benefit while peripheral locations suffer in terms of employment. While these results suggest an important role played by internal mobilty restrictions, the existing data suffer from serious limitation: data are missing for the most violent year (2002) and for all districts in the Gaza Strip for all years. This implies that it is not possible to precisely quantify the role of internal mobility restriction in our framework using those data.

where $z^d M^d$ is the value of domestically produced materials consumed during the year t by firm i operating in sector s and located in district g, and $z^f M^f$ is the corresponding value for imported materials. The only difference with respect to the previously adopted specification is that we now interact 2-digit sector fixed effects with the $\textit{fatalities}_{gt}$ variable. This allows us to investigate the effect of conflict intensity on the relative distortions for imported vs. domestically produced material inputs separately for each sector, as captured by the set of parameters $\lambda^s_{M^f M^d}$. As before, we can derive the sector-specific implied relative input distortions as

$$\exp\left(\hat{\lambda}^s_{M^d M^f}\right) = \frac{1 + \tau^s_{M_i^f}}{1 + \tau^s_{M_i^d}} \tag{2.17}$$

Table 2.11 shows the top and bottom 2-digit sectors as ranked in terms of the conflict-induced distortions they suffer. Most affected sectors are: *Manufacture of motor vehicles, trailers and semitrailers*, *Manufacture of coke, refined petroleum products and nuclear fuel* as well as *Manufacture of chemicals and chemical products*. At the opposite side of the spectrum, the least affected sector is *Other mining and quarrying*.

Sectoral differences in the effect of the conflict are related to their intensity in imported material usage. Figure 2.11 plots the estimated coefficient for the implied input distortions from the previous regression against the average imported materials value intensity in each sector in 1999, i.e. before the outbreak of the Second Intifada.[30] The results show a positive relationship between the extent of conflict-induced distortion and imported materials value intensity in 1999, as confirmed by the line fitting the relationship between the two. This suggests that sectors which are more intensive in imported materials are also those which have been more affected in terms of relative input distortions, making them substitute imported materials with domestically produced ones relatively more. Perhaps more importantly, these same sectors are found to be the most productive ones. Figure 2.12 plots the implied material distortions against the average output value in each sector in 1999. The results show that those sectors which are more vulnerable to the negative impact of the conflict are those which had higher output value before the conflict started. This means that the conflict impacts the most those

[30]We compute the average imported materials value intensity in each sector by dividing the total value of imported materials employed in production over total output value at the establishment level (and taking logs).

sectors with the highest productivity as measured by average output value, indicating the possibility of negative long-term effects on the Palestinian economy.

2.6 Concluding Remarks

Firms are the main engine of economic development. The analysis of their behavior during conflict times is essential to explain the response of aggregate economic outcomes to events such as uprisings, violent conflicts and wars. Moreover, learning about the microeconomic effects of conflicts is crucial for the design and implementation of successful economic recovery policies.

In this chapter, we have documented the negative effect of the Second Intifada on total and per-worker output value of Palestinian establishments. Furthermore, the conceptual framework adopted here has made it possible to explore one specific mechanism responsible for the effect we have found on output value. We have shown that conflict distorts input usage of Palestinian establishments, inducing them to substitute domestically produced materials for imported ones. Distortions within the supply side of the economy thus contribute to explain the larger fall in output value of firms operating in high conflict environments.

Even though this is not the first study to explore the effect of the conflict on firms' activity, our study contributes to the literature along several dimensions. First, and differently from most of previous contributions, we investigated the effects of conflict using a representative sample of manufacturing firms. Second, this is first contribution to focus on the effect of conflict on individual firm's output value, highlighting the role of input distortions in affecting the choice of inputs in production as the relevant mechanism. In this respect, this is the first study to provide a detailed description and evidence on how firms adapt their production activity to a conflict environment, and thus to identify conflict as a possible additional source of distortion and input misallocation.

The evidence we have discussed and the results we obtained in this chapter suggest several other potentially important questions to be explored. How do international trade and development interact during a violent conflict? Are the most productive firms within sectors also those who suffer the most from conflict? What are the short and long term consequences of such differential losses on economic development? Answering these questions will motivate our future research.

Tables and Figures

TABLE 2.1: SUMMARY STATISTICS

	Obs.	Mean	St. Dev.	Min	Max
Palestinians Killed by IDF (District × Year)	112	35.044	42.010	0	210
Log of Output Value	11397	11.741	1.511	0	19.656
Log of Output Value per Worker	11397	10.297	1.165	-2.303	18.023
Log of Value of Capital	14221	10.138	1.942	0.693	18.531
Log of Value of Labor	10243	10.492	1.24	5.994	16.746
Log of Value of Materials	14160	11.308	2.045	3.932	18.769
Log of Value of Local Materials	14160	8.826	3.138	0	18.785
Log of Value of Imported Materials	14160	6.456	4.801	0	18.688
Fraction of Family Workers	14284	0.167	0.247	0	1
Fraction of Proprietors	14284	0.444	0.324	0	1
Log of Value of Capital/Materials	14100	-0.553	1.816	-13.169	6.828
Log of Value of Labor/Materials	10183	-0.856	1.361	-8.593	4.185
Log of Value of Capital/labor	10197	0.223	1.67	-10.786	6.161
Log of Value of Imported/Local Materials	14160	-2.37	6.345	-18.112	18.405
Log of Value of Capital/Imported Materials	14100	3.687	4.645	-12.855	17.751
Log of Value of Capital/Local Materials	14100	1.322	3.198	-13.155	17.231
Log of Value of Labor/Imported Materials	10183	3.117	4.69	-6.367	16.544
Log of Value of Labor/Local Materials	10183	1.046	2.96	-8.699	15.451
Log of Average Wage	10243	8.955	0.779	3.932	12.145

Notes. The table shows summary statistics for the variables used in the empirical analysis. Establishment-level value variables are in Israeli New Sheqel (NIS) (Sources: Industry Survey, Palestinian Bureau of Statistics, B'TSELEM).

TABLE 2.2: LOG OF OUTPUT VALUE 1999-2002

	High Conflict Districts	Other Districts	*Column Difference*
1999	11.496	11.777	-0.281*
	(0.125)	(0.073)	(0.145)
2002	10.994	11.723	-0.728***
	(0.155)	(0.067)	(0.169)
Row Difference	-0.502**	-0.055	-0.447**
	(0.200)	(0.099)	(0.223)

Notes. (* p-value< 0.1; ** p-value<0.05; *** p-value<0.01) The table reports average Log of Output Value in Israeli New Sheqel (NIS) for surveyed establishments in years 1999 and 2002, dividend into subgroups according to their location district. High conflict districts are those 25% of districts with the highest numbers of Palestinians killed by IDF in 2002. Row and column differences between averages and standard errors are reported, with results from a *t-test* of difference in means across subgroups. *Difference-in-difference* estimate with standard errors is reported as well (Sources: Industry Survey, Palestinian Bureau of Statistics, B'TSELEM).

TABLE 2.3: CONFLICT AND OUTPUT VALUE

	Log of Output Value, $\ln(PY)$				
	(1)	(2)	(3)	(4)	(5)
fatalities	-0.126**	-0.073***	-0.063*	-0.089***	-0.086***
	(0.049)	(0.024)	(0.036)	(0.033)	(0.033)
$\frac{\text{Family Workers}}{\text{Total}}$				-1.522***	-1.533***
				(0.100)	(0.097)
$\frac{\text{Proprietors}}{\text{Total}}$				-2.713***	-2.717***
				(0.112)	(0.112)
District FE	N	Y	Y	Y	Y
Year FE	N	Y	Y	Y	n.a.
Sector FE	N	N	Y	Y	n.a.
Sector $\times$ Year FE	N	N	N	N	Y
Observations	10042	10042	10042	10039	10039
R^2	0.007	0.035	0.156	0.434	0.443

Notes. (* p-value< 0.1; ** p-value<0.05; *** p-value<0.01) Standard Errors are clustered along both sector-year and district-year categories. Dependent variable is log of Output Value in Israeli New Sheqel (NIS). Main independent variable is number of Palestinians killed by IDF in the year and district where surveyed establishment is located (measured in standard deviation units) (Sources: Industry Survey, Palestinian Bureau of Statistics, B'TSELEM).

TABLE 2.4: INPUT DISTORTIONS - REGRESSION COEFFICIENTS

		Coefficient of *fatalities* variable			
		(1)	(2)	(3)	(4)
(a)	$\ln RK_{si}/zM_{si}$	0.005	0.008	0.006	0.008
		(0.043)	(0.044)	(0.046)	(0.043)
(b)	$\ln wL_{si}/zM_{si}$	0.025	0.024	0.010	0.016
		(0.039)	(0.037)	(0.040)	(0.031)
(c)	$\ln RK_{si}/wL_{si}$	-0.018	-0.015	-0.000	0.003
		(0.040)	(0.039)	(0.041)	(0.034)
(d)	$\ln z^d M^d_{si}/z^f M^f_{si}$	1.216***	1.234***	1.243***	1.296***
		(0.272)	(0.270)	(0.270)	(0.307)
(e)	$\ln RK_{si}/z^f M^f_{si}$	0.523***	0.538***	0.551***	0.570***
		(0.122)	(0.119)	(0.127)	(0.141)
(f)	$\ln wL_{si}/z^f M^f_{si}$	0.471***	0.466***	0.484***	0.507***
		(0.138)	(0.140)	(0.150)	(0.179)
(g)	$\ln RK_{si}/z^d M^d_{si}$	-0.690***	-0.692***	-0.690***	-0.727***
		(0.171)	(0.171)	(0.164)	(0.181)
(h)	$\ln wL_{si}/z^d M^d_{si}$	-0.668***	-0.668***	-0.662***	-0.672***
		(0.184)	(0.182)	(0.182)	(0.199)
	$\frac{\text{Family Workers}}{\text{Total}}$	N	Y	Y	Y
	$\frac{\text{Proprietors}}{\text{Total}}$	N	Y	Y	Y
	Sector FE	Y	Y	n.a.	n.a.
	Year FE	Y	Y	n.a.	n.a.
	District FE	Y	Y	Y	Y
	Sector $\times$ Year FE	N	N	Y	Y

Notes. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01) The table reports estimates of the coefficient of the *fatalities* variable. Standard Errors are clustered along both sector-year and district-year categories. Dependent variable is log of ratio of Input Values in Israeli New Sheqel (NIS). Main independent variable is number of Palestinians killed by IDF in the year and district where surveyed establishment is located (measured in standard deviation units). RK_{si} is value of capital; zM_{si} is value of materials; wL_{si} is value of labor; $z^f M^f_{si}$ is value of imported materials; $z^d M^d_{si}$ is value of domestically produced materials; . Estimates in column (4) are derived after excluding observations with no data on output value (Sources: Industry Survey, Palestinian Bureau of Statistics, B'TSELEM).

TABLE 2.5: INPUT DISTORTIONS - IMPLIED RELATIVE VALUES

		Implied Relative Distortion			
		(1)	(2)	(3)	(4)
(a)	$(1+\tau_M)/(1+\tau_K)$	1.005	1.008	1.006	1.008
		[0.919;1.090]	[0.920;1.095]	[0.916;1.096]	[0.923;1.093]
(b)	$(1+\tau_M)/(1+\tau_L)$	1.025	1.024	1.010	1.016
		[0.948;1.103]	[0.950;1.098]	[0.931;1.089]	[0.955;1.078]
(c)	$(1+\tau_L)/(1+\tau_K)$	0.982	0.985	1.000	1.003
		[0.905;1.059]	[0.910;1.060]	[0.919;1.080]	[0.936;1.071]
(d)	$(1+\tau_{M^f})/(1+\tau_{M^d})$	3.375	3.434	3.465	3.655
		[1.578;5.172]	[1.616;5.252]	[1.634;5.295]	[1.459;5.852]
(e)	$(1+\tau_{M^f})/(1+\tau_K)$	1.687	1.713	1.736	1.768
		[1.283;2.090]	[1.314;2.112]	[1.302;2.169]	[1.279;2.256]
(f)	$(1+\tau_{M^f})/(1+\tau_L)$	1.602	1.593	1.623	1.660
		[1.168;2.036]	[1.156;2.030]	[1.147;2.099]	[1.079;2.241]
(g)	$(1+\tau_{M^d})/(1+\tau_K)$	0.501	0.501	0.502	0.484
		[0.334;0.669]	[0.333;0.668]	[0.340;0.663]	[0.312;0.655]
(h)	$(1+\tau_{M^d})/(1+\tau_L)$	0.513	0.513	0.516	0.511
		[0.328;0.698]	[0.330;0.696]	[0.332;0.700]	[0.312;0.710]
	$\frac{\text{Family Workers}}{\text{Total}}$	N	Y	Y	Y
	$\frac{\text{Proprietors}}{\text{Total}}$	N	Y	Y	Y
	Sector FE	Y	Y	n.a.	n.a.
	Year FE	Y	Y	n.a.	n.a.
	District FE	Y	Y	Y	Y
	Sector $\times$ Year FE	N	N	Y	Y

Notes. The table reports implied relative distortion values as derived using coefficient estimates from Table 4, together with 95% Confidence Intervals. Standard Errors are clustered along both sector-year and district-year categories. τ_K is average distortion level for capital; τ_M is average distortion level for materials; τ_L is average distortion value for labor; τ_{M^f} is average distortion value for imported materials; τ_{M^d} is average distortion value for domestically produced materials. Estimates in column (4) are derived after excluding observations with no data on output value (Sources: Industry Survey, Palestinian Bureau of Statistics, B'TSELEM).

TABLE 2.6: INPUT DISTORTIONS - IMPLIED RELATIVE VALUES: ROBUSTNESS
ROAD DISTANCE OF DISTRICT CAPITAL FROM CLOSEST ENTRY PASSAGE

		Implied Relative Distortion			
		(1)	(2)	(3)	(4)
(a)	$(1+\tau_M)/(1+\tau_K)$	0.996	0.999	0.999	1.000
		[0.919;1.073]	[0.920;1.079]	[0.915;1.082]	[0.928;1.073]
(b)	$(1+\tau_M)/(1+\tau_L)$	1.007	1.004	0.991	0.997
		[0.918;1.097]	[0.919;1.089]	[0.901;1.081]	[0.933;1.061]
(c)	$(1+\tau_L)/(1+\tau_K)$	1.001	1.007	1.021	1.024
		[0.931;1.071]	[0.937;1.076]	[0.946;1.095]	[0.959;1.089]
(d)	$(1+\tau_{M^f})/(1+\tau_{M^d})$	3.234	3.300	3.334	3.441
		[1.584;4.884]	[1.618;4.982]	[1.639;5.030]	[1.398;5.484]
(e)	$(1+\tau_{M^f})/(1+\tau_K)$	1.655	1.686	1.709	1.720
		[1.261;2.048]	[1.293;2.080]	[1.287;2.130]	[1.241;2.199]
(f)	$(1+\tau_{M^f})/(1+\tau_L)$	1.571	1.560	1.605	1.625
		[1.195;1.947]	[1.179;1.941]	[1.188;2.022]	[1.114;2.135]
(g)	$(1+\tau_{M^d})/(1+\tau_K)$	0.513	0.513	0.513	0.500
		[0.351;0.676]	[0.350;0.676]	[0.356;0.670]	[0.327;0.673]
(h)	$(1+\tau_{M^d})/(1+\tau_L)$	0.515	0.513	0.513	0.515
		[0.335;0.695]	[0.337;0.689]	[0.335;0.690]	[0.318;0.713]
	$dt_{\text{passage}} \times$ Year FE	Y	Y	Y	Y
	$\frac{\text{Family Workers}}{\text{Total}}$	N	Y	Y	Y
	$\frac{\text{Proprietors}}{\text{Total}}$	N	Y	Y	Y
	Sector FE	Y	Y	n.a.	n.a.
	Year FE	Y	Y	n.a.	n.a.
	District FE	Y	Y	Y	Y
	Sector $\times$ Year FE	N	N	Y	Y

Notes. The table reports implied relative distortion values (together with 95% Confidence Intervals) as derived from estimating the input value ratio regression, including as regressors the full set of year dummies interacted with the road distance of the district capital from the closest entry passage as measured in 10km units. Standard Errors are clustered along both sector-year and district-year categories. τ_K is average distortion level for capital; τ_M is average distortion level for materials; τ_L is average distortion value for labor; τ_{M^f} is average distortion value for imported materials; τ_{M^d} is average distortion value for domestically produced materials; τ_{O^e} is average distortion value for imported oil and fuel; τ_{O^l} is average distortion value for domestically produced oil and fuel. Estimates in column (4) are derived after excluding observations with no data on output value (Sources: Industry Survey, Palestinian Bureau of Statistics, B'TSELEM).

TABLE 2.7: INPUT DISTORTIONS, FATALITIES AND BORDER CLOSURES - REGRESSION COEFFICIENTS

	(1)	(2)	(3)	(4)
PANEL A	Dependent Variable: $\ln z^d M_{si}^d / z^f M_{si}^f$			
fatalities	1.263***	1.279***	1.290***	1.340***
	(0.247)	(0.247)	(0.246)	(0.289)
closure days $\times$ dt_{passage}	0.010**	0.010**	0.010**	0.009*
	(0.004)	(0.004)	(0.004)	(0.005)
PANEL B	Dependent Variable: $\ln RK_{si} / z^f M_{si}^f$			
fatalities	0.547***	0.562***	0.575***	0.591***
	(0.115)	(0.112)	(0.120)	(0.135)
closure days $\times$ dt_{passage}	0.005**	0.005**	0.005**	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
PANEL C	Dependent Variable: $\ln wL_{si} / z^f M_{si}^f$			
fatalities	0.499***	0.492***	0.515***	0.536***
	(0.116)	(0.119)	(0.127)	(0.156)
closure days $\times$ dt_{passage}	0.006**	0.006**	0.006***	0.006**
	(0.002)	(0.002)	(0.002)	(0.003)
PANEL D	Dependent Variable: $\ln RK_{si} / z^d M_{si}^d$			
fatalities	-0.713***	-0.715***	-0.713***	-0.749***
	(0.157)	(0.157)	(0.151)	(0.171)
closure days $\times$ dt_{passage}	-0.005*	-0.005*	-0.005*	-0.005*
	(0.002)	(0.002)	(0.002)	(0.003)
PANEL E	Dependent Variable: $\ln wL_{si} / z^d M_{si}^d$			
fatalities	-0.694***	-0.694***	-0.690***	-0.695***
	(0.169)	(0.166)	(0.166)	(0.188)
closure days $\times$ dt_{passage}	-0.006**	-0.006**	-0.006**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
$\frac{\text{Family Workers}}{\text{Total}}$	N	Y	Y	Y
$\frac{\text{Proprietors}}{\text{Total}}$	N	Y	Y	Y
Sector FE	Y	Y	n.a.	n.a.
Year FE	Y	Y	n.a.	n.a.
District FE	Y	Y	Y	Y
Sector $\times$ Year FE	N	N	Y	Y

Notes. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01) The table reports estimates of the coefficient of the *fatalities* variable and the interaction of the yearly number of days of border closure with the road distance of the district capital from the closest entry passage as measured in 10km units. Standard Errors are clustered along both sector-year and district-year categories. Dependent variable is log of ratio of Input Values in Israeli New Sheqel (NIS). Main independent variable is number of Palestinians killed by IDF in the year and district where surveyed establishment is located (measured in standard deviation units). RK_{si} is value of capital; zM_{si} is value of materials; wL_{si} is value of labor; $z^f M_{si}^f$ is value of imported materials; $z^d M_{si}^d$ is value of domestically produced materials. Estimates in column (4) are derived after excluding observations with no data on output value. The variable *closure days* captures the yearly number of days of border closure, while dt_{passage} measures road distance of the district capital from the closest entry passage as measured in 10km units (Sources: Industry Survey, Palestinian Bureau of Statistics, B'TSELEM).

TABLE 2.8: SELF-REPORTED OBSTACLES TO FIRMS' OPERATIONS

	(1)	(2)	(3)	(4)	(5)
PANEL A	Dep. Variable: Customs and Trade Regulations as Main Obstacle				
fatalities	-0.227***	-0.247***	-0.101	-0.016	-0.042
	(0.05)	(0.05)	(0.10)	(0.09)	(0.09)
$Importer$	0.287	0.355	0.336	0.393	0.309
	(0.34)	(0.34)	(0.32)	(0.30)	(0.30)
fatalities $\times$ $Importer$	0.249***	0.237***	0.246***	0.234***	0.292***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
PANEL B	Dep. Variable: Trasportation as Main Obstacle				
fatalities	-0.254***	-0.257***	-0.144*	-0.062	-0.075
	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)
$Importer$	0.255	0.305	0.304	0.386	0.393
	(0.34)	(0.34)	(0.33)	(0.31)	(0.28)
fatalities $\times$ $Importer$	0.296***	0.288***	0.293***	0.258***	0.301***
	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)
PANEL C	Dep. Variable: Percentage of Inputs Paid Before Delivery				
fatalities	-0.013	-0.003	-0.009	-0.010	-0.013
	(0.02)	(0.01)	(0.02)	(0.03)	(0.03)
$Importer$	0.110	0.100	0.107	0.090	0.090
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
fatalities $\times$ $Importer$	0.039**	0.041***	0.041***	0.051***	0.062***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
Population 1997	N	Y	Y	Y	Y
Sales in 2003	N	N	N	Y	Y
Employment in 2003	N	N	N	Y	Y
Year Started	N	N	N	Y	Y
Other Controls	N	N	N	N	Y
District FE	N	N	Y	Y	Y
Observations	10042	10042	10042	10039	10039
R^2	0.007	0.035	0.156	0.434	0.443

Notes. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01) Standard Errors are clustered along both sector-year and district-year categories. Dependent variable in Panel A is whether customs and trade regulations are reported as obstacles to the operations of the firm on a 1 to 4 scale. Dependent variable in Panel B is whether transportations are reported as obstacles to the operations of the firm on a 1 to 4 scale. Dependent variable in Panel C is the share of inputs and services that the firm reports to pay before delivery. Main regressors are: number of Palestinians killed by IDF in the year and locality where surveyed establishment is located (measured in standard deviation units), dummy for whether the firm reports a positive share of imported inputs in production, and the interaction between the two (Sources: World Bank Enterprise Survey 2006, B'TSELEM).

TABLE 2.9: INPUT DISTORTIONS AND HOMOTHETIC PRODUCTION FUNCTIONS
IMPLIED RELATIVE VALUES: RESTRICTED SAMPLE

		Implied Relative Distortion			
		(1)	(2)	(3)	(4)
(a)	$(1+\tau_M)/(1+\tau_K)$	1.027	1.030	1.022	1.013
		[0.930;1.124]	[0.931;1.129]	[0.918;1.126]	[0.917;1.109]
(b)	$(1+\tau_M)/(1+\tau_L)$	1.060	1.059	1.046	1.038
		[0.964;1.156]	[0.966;1.152]	[0.946;1.147]	[0.963;1.112]
(c)	$(1+\tau_L)/(1+\tau_K)$	0.988	0.990	0.995	1.000
		[0.887;1.088]	[0.896;1.084]	[0.897;1.093]	[0.921;1.078]
(d)	$(1+\tau_{M^f})/(1+\tau_{M^d})$	3.480	3.545	3.536	3.627
		[1.435;5.524]	[1.491;5.599]	[1.498;5.574]	[1.356;5.898]
(e)	$(1+\tau_{M^f})/(1+\tau_K)$	1.719	1.750	1.744	1.760
		[1.256;2.182]	[1.299;2.200]	[1.265;2.223]	[1.273;2.247]
(f)	$(1+\tau_{M^f})/(1+\tau_L)$	1.645	1.648	1.659	1.680
		[1.079;2.212]	[1.077;2.219]	[1.061;2.256]	[1.038;2.321]
(g)	$(1+\tau_{M^d})/(1+\tau_K)$	0.493	0.493	0.492	0.485
		[0.315;0.672]	[0.314;0.671]	[0.321;0.664]	[0.301;0.670]
(h)	$(1+\tau_{M^d})/(1+\tau_L)$	0.507	0.506	0.513	0.515
		[0.298;0.716]	[0.301;0.711]	[0.307;0.719]	[0.301;0.729]
	$\frac{\text{Family Workers}}{\text{Total}}$	N	Y	Y	Y
	$\frac{\text{Proprietors}}{\text{Total}}$	N	Y	Y	Y
	Sector FE	Y	Y	n.a.	n.a.
	Year FE	Y	Y	n.a.	n.a.
	District FE	Y	Y	Y	Y
	Sector $\times$ Year FE	N	N	Y	Y

Notes. The table reports implied relative distortion values (together with 95% Confidence Intervals) as derived from estimating the input value ratio regression over the restricted sample of observations belonging to sectors where no significant relationship between material value ratio and output value is found in 1999. Standard Errors are clustered along both sector-year and district-year categories. τ_K is average distortion level for capital; τ_M is average distortion level for materials; τ_L is average distortion value for labor; τ_{M^f} is average distortion value for imported materials; τ_{M^d} is average distortion value for domestically produced materials; τ_{O^e} is average distortion value for imported oil and fuel; τ_{O^l} is average distortion value for domestically produced oil and fuel. Estimates in column (4) are derived after excluding observations with no data on output value (Sources: Industry Survey, Palestinian Bureau of Statistics, B'TSELEM).

TABLE 2.10: CONFLICT AND WAGES

	Log of Wages, $\ln(W/L)$			
	(1)	(2)	(3)	(4)
fatalities	-0.070**	-0.072**	-0.079**	-0.076**
	(0.035)	(0.035)	(0.035)	(0.034)
$\frac{\text{Family Workers}}{\text{Total}}$		-2.014***	-2.015***	-2.032***
		(0.071)	(0.071)	(0.084)
$\frac{\text{Proprietors}}{\text{Total}}$		-2.250***	-2.242***	-2.224***
		(0.081)	(0.081)	(0.075)
Sector FE	Y	Y	n.a.	n.a.
Year FE	Y	Y	n.a.	n.a.
District FE	Y	Y	Y	Y
Sector $\times$ Year FE	N	N	Y	Y
Observations	8891	8891	8891	7302
R^2	0.156	0.443	0.459	0.476

Notes. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01) Standard Errors are clustered along both sector-year and district-year categories. Dependent variable is log of average wage in Israeli New Sheqel (NIS) as derived by dividing the total wage bill by the total number of employees. Main independent variable is number of Palestinians killed by IDF in the year and district where surveyed establishment is located (measured in standard deviation units). Estimates in column (4) are derived after excluding observations with no data on output value (Sources: Industry Survey, Palestinian Bureau of Statistics, B'TSELEM).

TABLE 2.11: SECTOR RANKING BY DISTORTION IN MATERIALS

Most Affected

Rank	*ISIC code*	*Sector name*
1	(34)	Manufacture of motor vehicles, trailers and semitrailers
2	(23)	Manufacture of coke, refined petroleum products and nuclear fuel
3	(21)	Manufacture of paper and paper products
4	(37)	Recycling
5	(24)	Manufacture of chemicals and chemical products

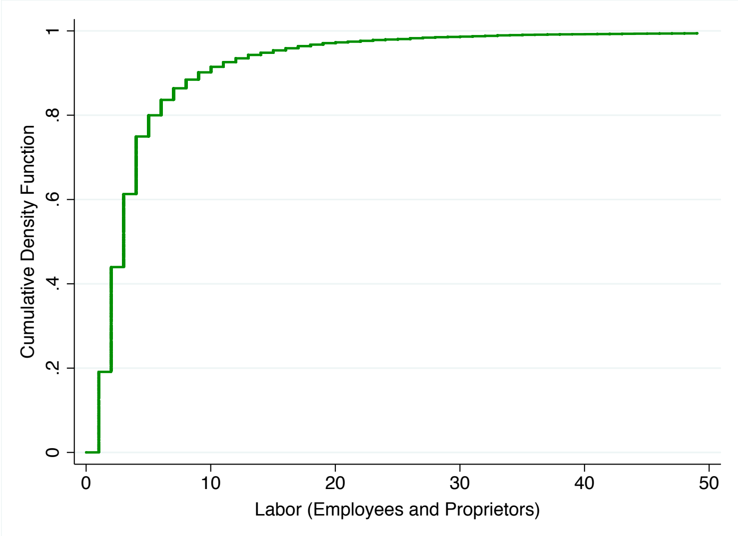
Least Affected

Rank	*ISIC code*	*Sector name*
25	(20)	Manufacture of wood and of products of wood and cork, except furniture; articles of straw and plaiting materials
24	(36)	Manufacture of furniture; manufacturing n.e.c.
23	(35)	Manufacture of other transport equipment
22	(32)	Manufacture of radio, television and communication equipment and apparatus
21	(14)	Other mining and quarrying

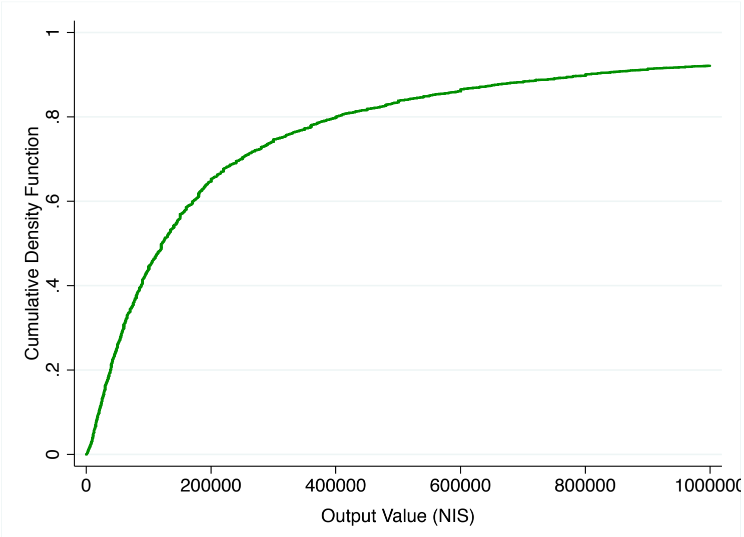
Notes. The table reports most and least affected 2-digits sectors as defined by deriving sector-level average distortions for domestically produced materials vs. imported materials (Sources: Industry Survey, Palestinian Bureau of Statistics, B'TSELEM).

FIGURE 2.1: LABOR AND OUTPUT

a) Distribution of Employment

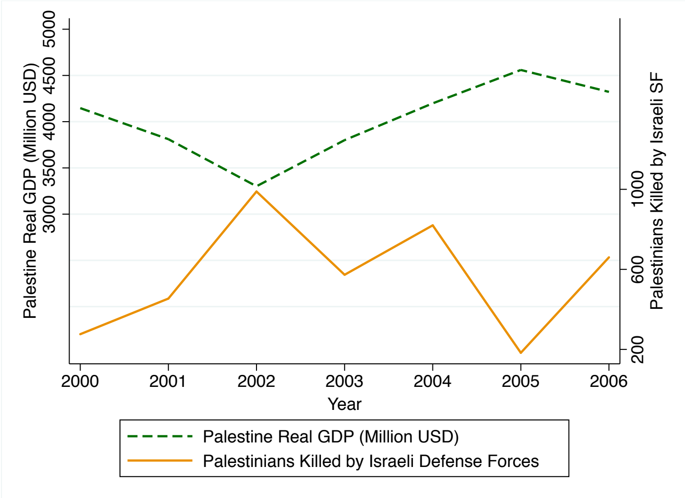


b) Distribution of Output Value



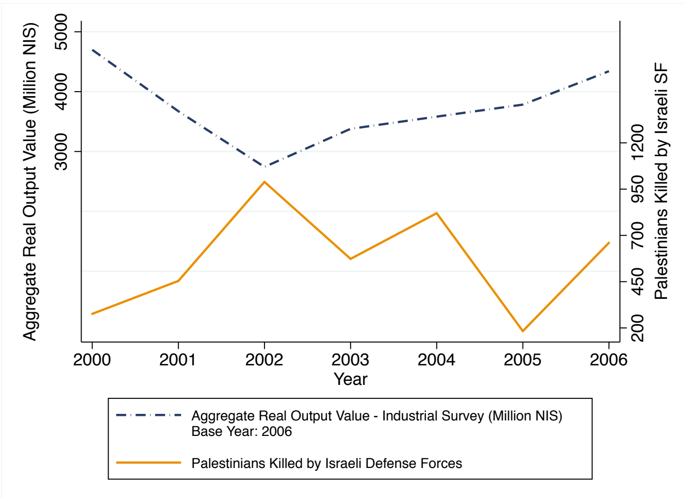
Notes. The top and bottom figures show distribution of number of workers and value of output for Palestinian firms (Sources: Palestinian Central Bureau of Statistics; B'TSELEM).

FIGURE 2.2: CONFLICT AND PALESTINIAN GDP



Notes. The top and bottom figures show the evolution of current and real Palestine GDP (Million USD) respectively over time, together with the evolution of the total number of Palestinians killed by IDF (Sources: Palestinian Central Bureau of Statistics; B'TSELEM).

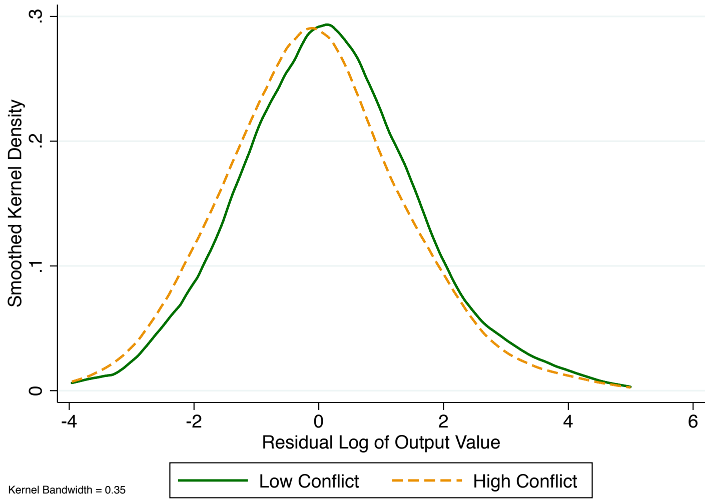
FIGURE 2.3: CONFLICT AND AGGREGATE OUTPUT VALUE



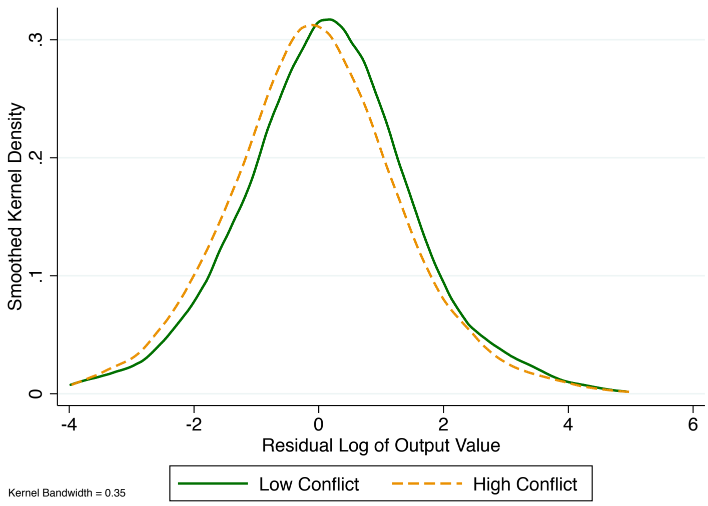
Notes. The top and bottom figures show the evolution of the total current and real value of production in Israeli New Sheqel (NIS) respectively over time, as derived from the Industry Survey. The figures also plot the evolution of the total number of Palestinians killed by IDF in the same years (Sources: Industry Survey, Palestinian Central Bureau of Statistics; B'TSELEM).

FIGURE 2.4: CONFLICT AND OUTPUT VALUE

a) Output Value (Log of)



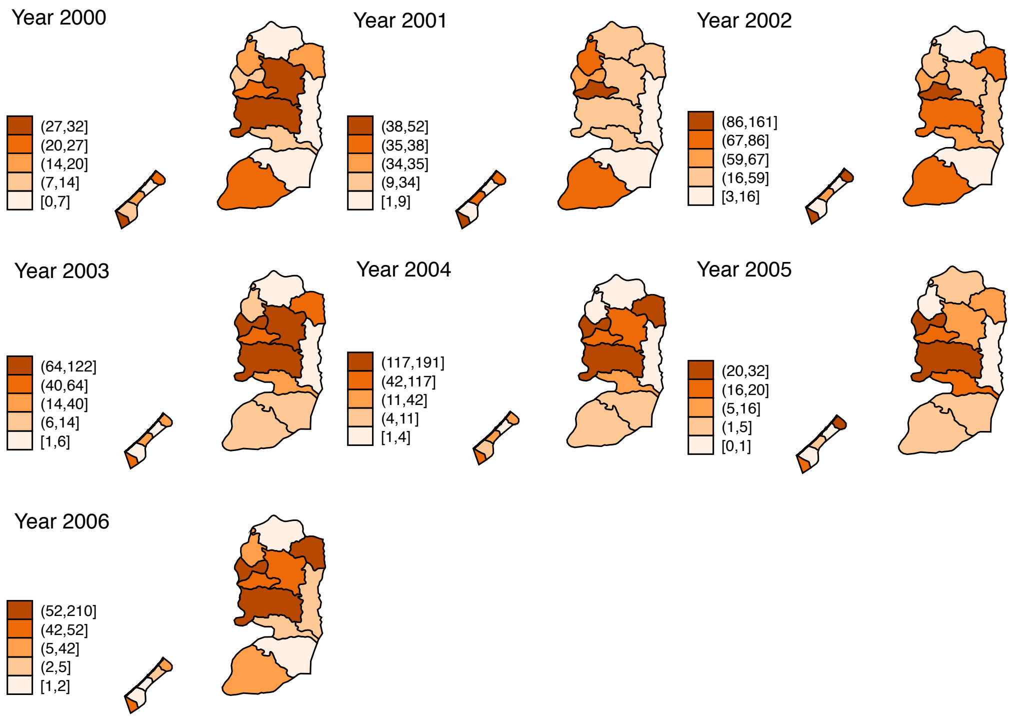
b) Output Value (Log of, within sector)



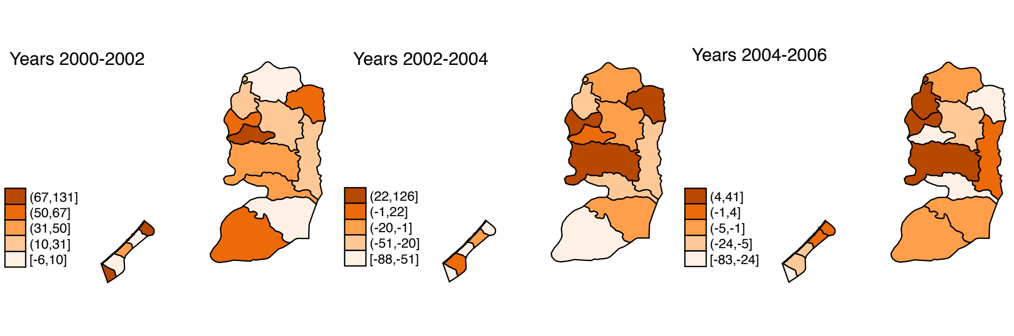
Notes. The top figure shows the distribution of residual Log of Output Value in Israeli New Sheqel (NIS) for firms located in high and low conflict areas respectively. High conflict area comprises those districts and years with a total number of Palestinians killed by IDF higher than the median. Low conflict area comprises all other districts-years. The bottom figure shows the distribution of within-sector residual Log of Output Value in the two areas (Sources: Industry Survey, Palestinian Central Bureau of Statistics; B'TSELEM).

FIGURE 2.5: CROSS-DISTRICT AND TIME CONFLICT VARIABILITY - MAPS

a) Cross-district Variability

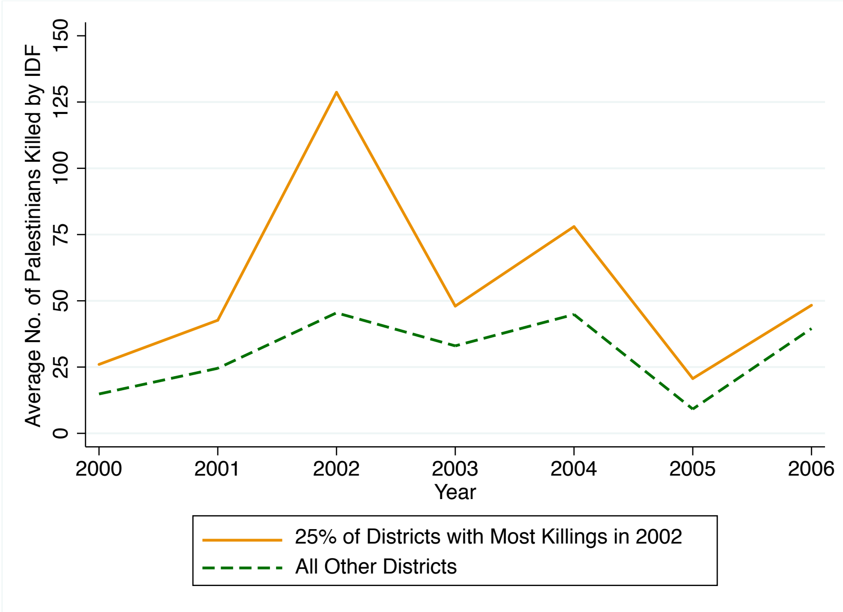


b) Within-district Variability



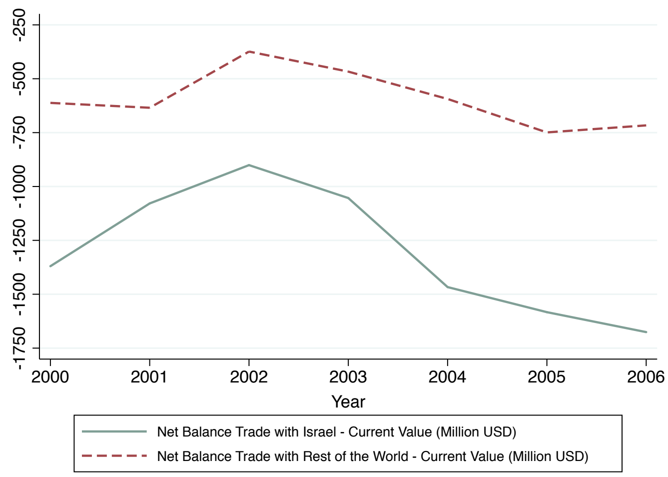
Notes. The maps show the distribution of the number of Palestinians killed by IDF across districts in given years and its changes over given time spans. In each map, districts are colored according to the quintiles they belong to in the distribution of levels and changes respectively (Sources: B'TSELEM).

FIGURE 2.6: CROSS-DISTRICT AND TIME CONFLICT VARIABILITY



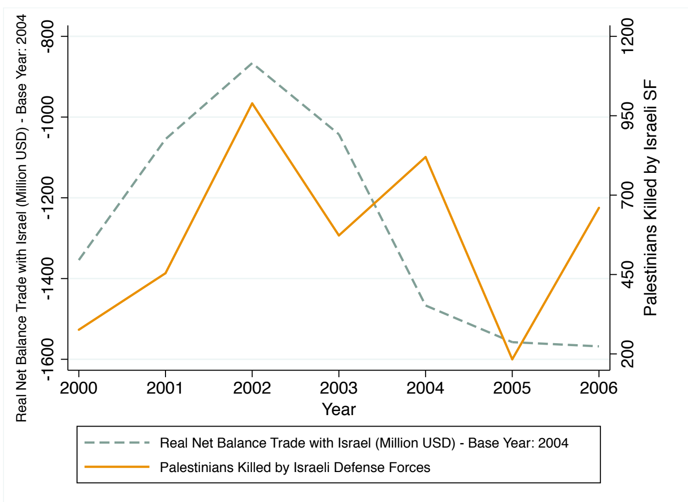
Notes. The figure plots the average number of Palestinians killed by IDF over time in districts as divided according to the number of fatalities in 2002 (Sources: B'TSELEM).

FIGURE 2.7: NET BALANCE OF TRADE PER GROUP OF COUNTRIES



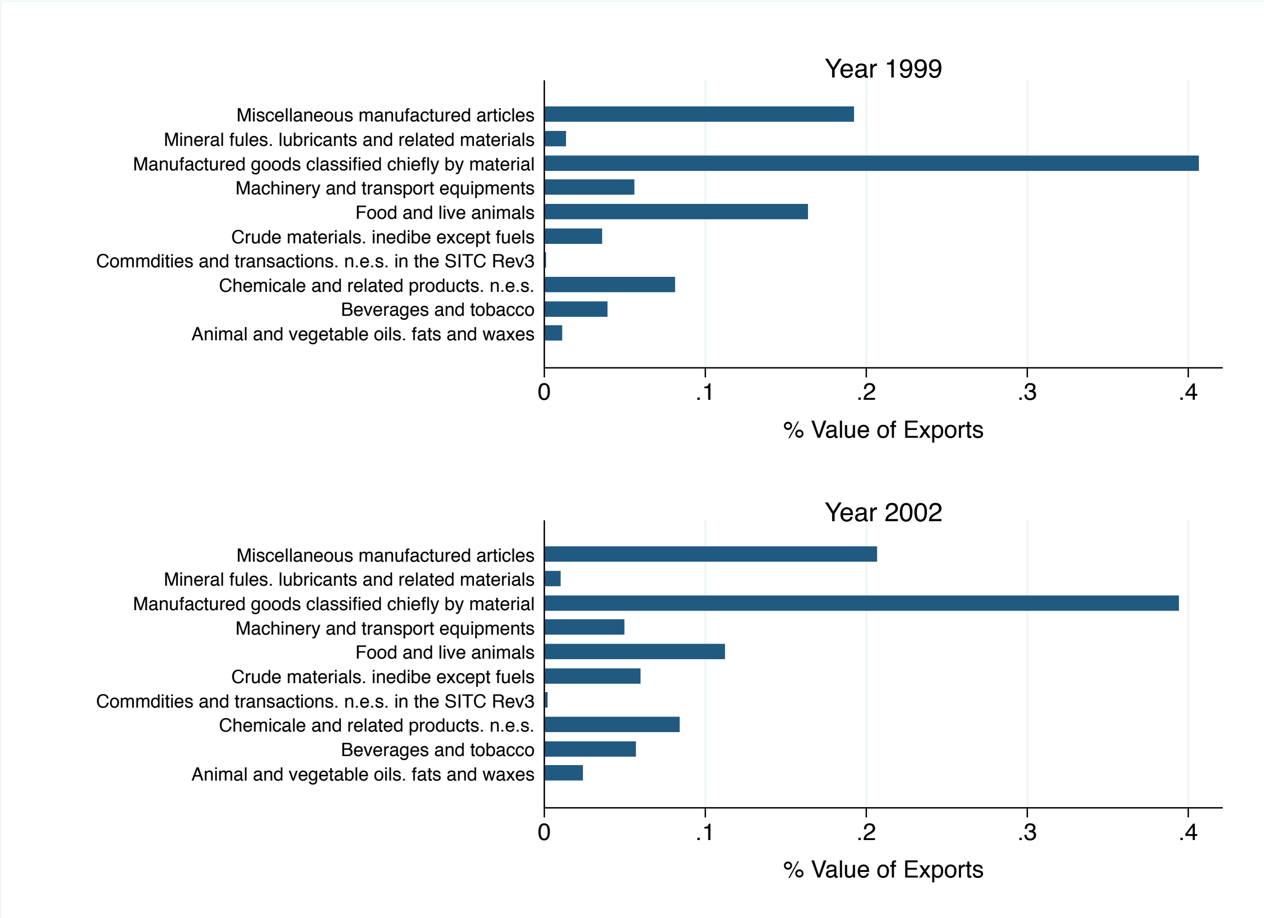
Notes. The figure plots the evolution of the Net Balance of Trade with Israel and Rest of the World separately over time (Sources: Palestinian Central Bureau of Statistics).

FIGURE 2.8: CONFLICT AND VALUE OF TRADE



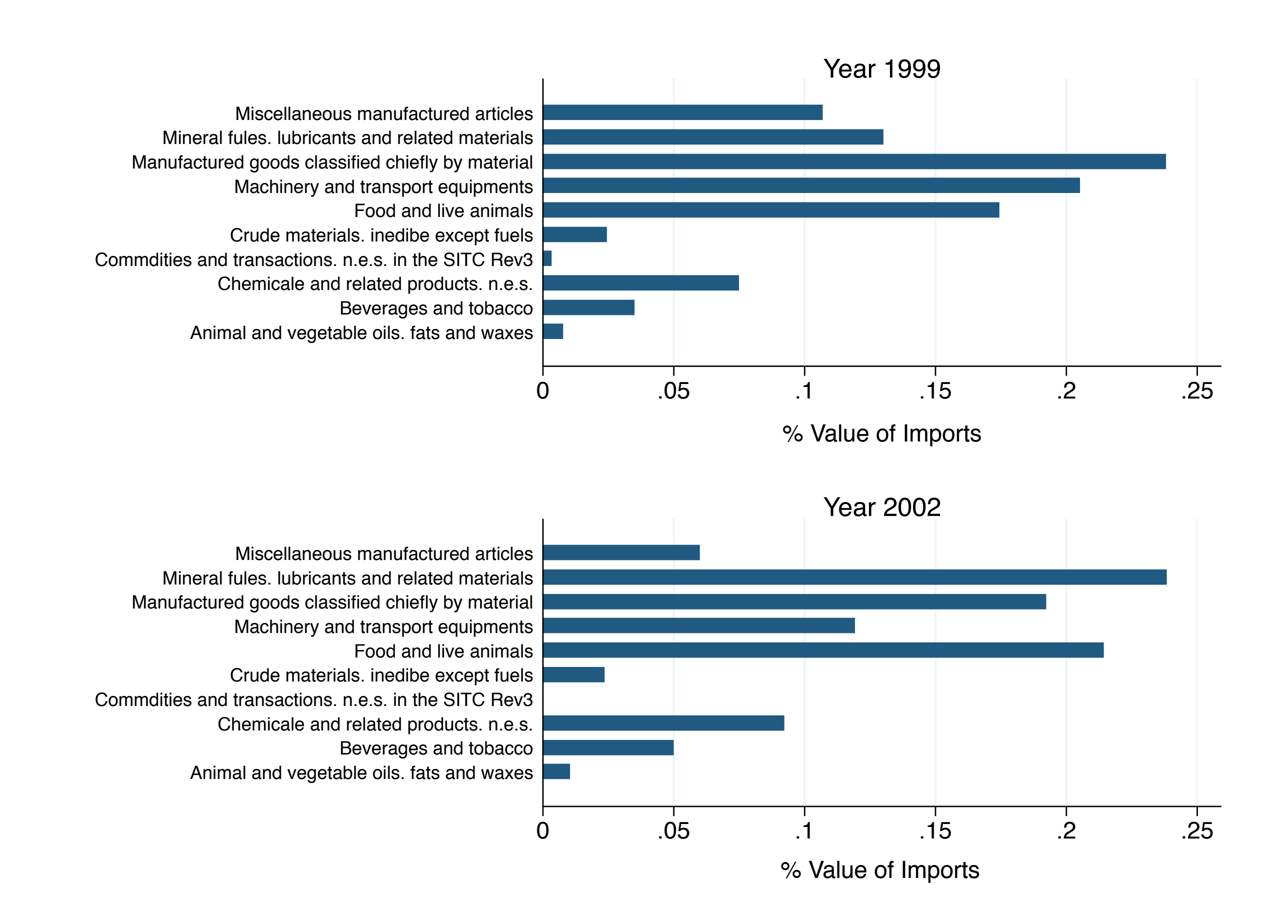
Notes. The figures plot the evolution of the total real value of Imports, Exports and Net Balance Trade over time, together with the evolution of total number of Palestinians killed by IDF (Sources: Palestinian Central Bureau of Statistics; B'TSELEM).

FIGURE 2.9: TRADE COMPOSITION: EXPORTS



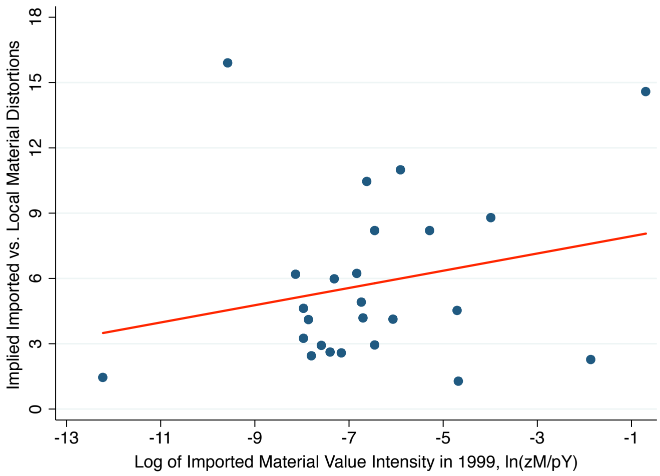
Notes. The figures plot the export composition (sector share over total export) in 1999 and 2002 (Sources: Palestinian Central Bureau of Statistics; B'TSELEM).

FIGURE 2.10: TRADE COMPOSITION: IMPORTS



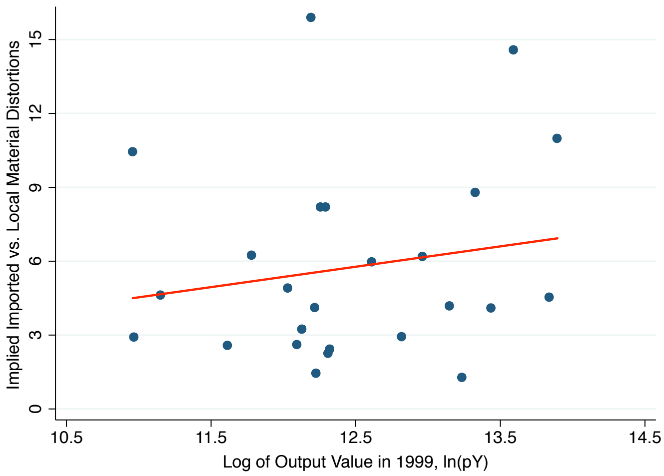
Notes. The figures plot import composition (sector share over total import) in 1999 and 2002 (Sources: Palestinian Central Bureau of Statistics; B'TSELEM).

FIGURE 2.11: SECTOR-LEVEL DISTORTIONS AND IMPORTED MATERIAL INTENSITY



Notes. The figure plots 2-digits sector-level average distortions for domestically produced materials vs. imported materials against average imported material intensity as measured in 1999. Sectors for which conflict distorted the domestically vs. imported materials input ratio the most are those with the higher imported material intensity in 1999 (Sources: Industry Survey, Palestinian Central Bureau of Statistics; B'TSELEM).

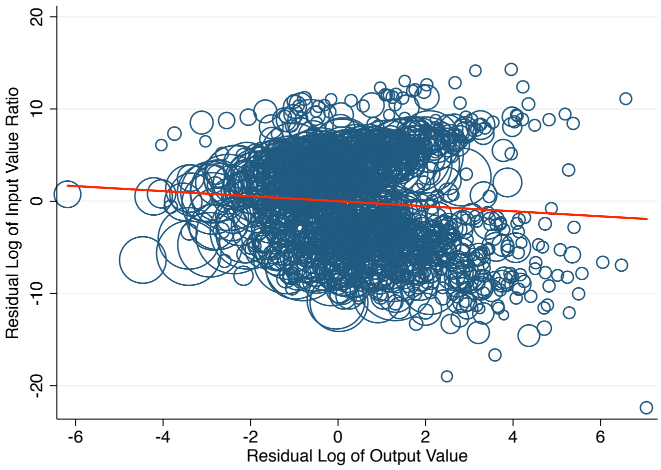
FIGURE 2.12: SECTOR-LEVEL DISTORTIONS AND OUTPUT VALUE



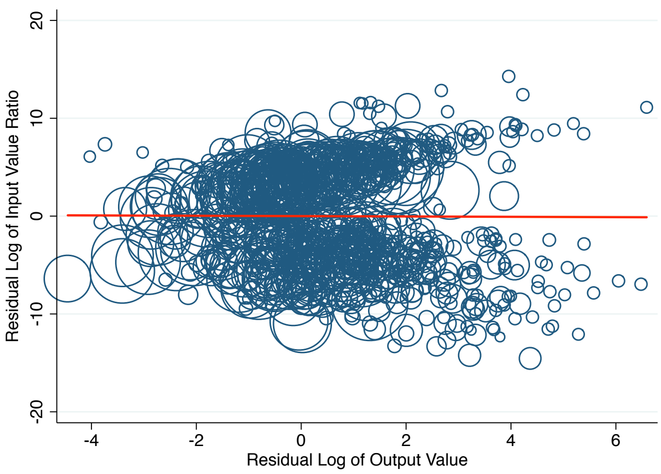
Notes. The figure plots 2-digits sector-level average distortions for domestically produced materials vs. imported materials against average output value as measured in 1999. Sectors for which conflict distorted the domestically vs. imported materials input ratio the most are those with the higher output value in 1999 (Sources: Industry Survey, Palestinian Central Bureau of Statistics; B'TSELEM).

FIGURE 2.13: WITHIN-SECTOR HETEROGENEITY IN TECHNOLOGY AND OUTPUT VALUE

a) All Sectors

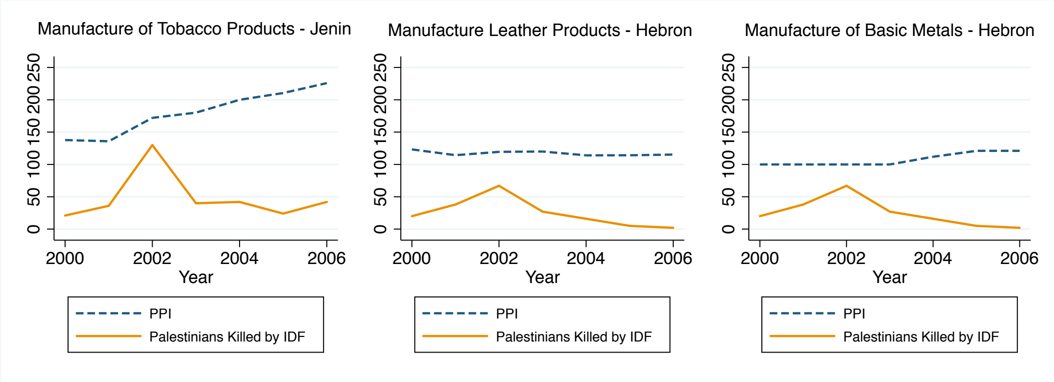


b) Restricted Sample



Notes. The top and bottom figures plot the within-sector residual log of the ratio between the value of domestically produced materials and imported materials used over the residual log of output value for firms in 1999. Circle size correspond to the observation's weight in the sample. The top figure shows the relationship of interest using all available observations, while the bottom figure considers only those sectors for which the relationship between the two variables is non-significant (Sources: Palestinian Central Bureau of Statistics).

FIGURE 2.14: PRODUCER PRICE INDEX AND CONFLICT



Notes. The figures plot the evolution of Producer Price Indexes for selected 2-digit sectors clustered in one particular district over time, together with the total number of Palestinians killed by IDF in the same district (Sources: Palestinian Central Bureau of Statistics; B'TSELEM).

2.7 Data Appendix

This appendix contains a detailed description of the study sample and the variables used in the empirical section.

2.A.1 Industry Survey 1999-2006

Establishment-level variables are derived using micro data from the Industry Survey (IS) for the years 1999 to 2006, provided by the Palestinian Central Bureau of Statistics. Implemented since 1994, together with other economic surveys, it aims at providing a detailed description of the Palestinian economy. The sample of the IS in each year is a single-stage stratified random sample, meaning a systematic sample in which the establishment constitutes the primary sampling unit (PSU). Three levels of strata are used to arrive at an efficient representative sample (i.e. economic activity, size of employment and geographical levels). Survey responses are typically higher than 90%. The sampling weight of the establishment is the reciprocal of the sampling probability of that establishment. Weights are adjusted to compensate for non-responses. In the released version of the IS dataset we employ, we also have information on the district of location of each surveyed establishment.

We build our final dataset by combining IS data from each of the considered years. We end up with a final sample of 16418 observations, with sum of sampling weights equal to 113912. Inspecting the distribution of each one of the variables of interest, we notice the variables referring to fixed assets to have implausible peaks corresponding to values lower than 5. Fixed assets variables are: book value of assets at the beginning of the year; value of imported, new and second-hand assets purchased during the year; value of internally produced assets; value of capital additions and improvements; value of written-off and losses; value of assets sold during the year; capital depreciation during the year; book value of assets at the end of the year. We thus group together those 1788 observations (10.89% of the final sample) for which *all* of the capital information variables assume values lower than 5. Establishments in this subsample do not appear to be systematically different from others in terms of year of the survey or district of location. However, they are found to employ a significantly lower amount of labor and being attributed lower sampling weights. We exclude these observations from our analysis, trading off the national representativity of the employed restricted sample for the reliability of information on capital. Furthermore, surveyed establishments are given the option to choose the currency to use in reporting value information. While the vast majority of establishments (13903 of the remaining sample) choose to report information in Israeli New Sheqel (NIS), 275 establishments report information in Jordanian Dinnar and 109 establishments in US Dollars. We do not have information on currency used for 343 establishments. Using yearly information on exchange rates, we thus convert Jordanina Dinnars and US Dollars values to NIS, while eliminating observations belonging to establishments with no currency information. Again, these are not systematically differentially represented in given years or districts. Our final sample of analysis thus contains 14287 observations, divided by year as follows: 1778 (1999), 1530 (2000), 1439 (2001), 1497 (2002), 1689 (2003), 2251 (2004), 2155 (2005), 1948 (2006).

Output Value. We consider the reported total value of output produced during the year.

A total number of 2890 establishments (20.23% of the study sample) do not provide this information. These are not systematically differentially represented in given years or districts. Nonetheless, when studying input values and distortions, we thus show the robustness of results when restricting the sample to those observations for which we have information on the value of output. When taking logs, we take the natural logarithm after augmenting all variable values by 1.

Aggregate Output Value. The current aggregate output value is computed by calculating the weighted sum of establishment-level output value separately in each year, using the provided sampling weights. The real value is computed by first deflating establishment-level output values using 2-digit sector Producer Price Index values for each year (base year 1996), and then calculating the weighted sum of deflated establishment-level output value.

Output Value per Worker. We divide the reported total value of output produced during the year by the total amount of labor as defined by the total number of employees plus proprietors. When taking logs, we take the natural logarithm after augmenting all variable values by 1.

Value of Capital. Similarly to Hsieh and Klenow (2009), we take the average of the book value of fixed assets at the beginning and end of the year. When taking logs, we take the natural logarithm after augmenting all variable values by 1.

Value of labor. We derive the total value of labor by adding up the total value of salaries for administrative, operative, other, and home employees. We also add the value of other benefits and payments in kind. When taking logs, we take the natural logarithm after augmenting all variable values by 1.

Value of Materials. When considering total value, we take the reported value of materials consumed during the year. We also consider separately the value of domestically and foreign produced materials consumed during the year, and, within those, the reported value of oil and fuel. When taking logs, we take the natural logarithm after augmenting all variable values by 1.

Fraction of Family Workers and Proprietors. We divide the number of family workers and the number of proprietors by the total amount of labor as defined by the total number of employees plus proprietors.

Input Value Ratios. For each one of the ratio, we divide the total value of one input by the other, with both values augmented by 1. We then take the natural logarithm of the resulting value.

Imported Materials Value Intensity. We divide the total value of foreign produced materials consumed during the year by the value of output produced during the year, with both values augmented by 1. We then take the natural logarithm of the resulting value.

Average Wage. We divide the total value of labor by the total amount of labor as defined by the total number of employees plus proprietors. When taking logs, we take the natural logarithm after augmenting all variable values by 1.

2.A.2 Conflict Variables

Fatalities. Data on fatalities contains all Palestinian fatalities caused by the IDFs during the Second Intifada. These data are collected by the Israeli NGO B'TSELEM and are considered accurate and reliable by both the Israelis and the Palestinians (Mansour and Rees 2012).

Data on all (Israeli and Palestinian) fatalities related to the Second Intifada are available at http://www.btselem.org, accessed on March 1, 2014. The B'TSELEM website lists the name of the fatality, the person's age and gender, place of residence, the date and place of death, and a description of the circumstances of the event. The website reports all the fatalities occurred in relation to the conflict, namely: 1) Palestinians killed by IDF; 2) Palestinians killed by Israeli civilians; 3) Israeli civilians killed by Palestinians; 4) Israeli security force personnel killed by Palestinians; 5) Foreign citizens killed by Palestinians; 6) Foreign citizens killed by IDF and 7) Palestinians killed by Palestinian. Using the available information for each fatality, we construct our main conflict variable as the total number of all Palestinians killed by IDFs (IDF) in each district throughout each year. As it clearly emerges from the descriptions of the events, the situations in which Palestinian fatalities happened are the most varied. For this reason, Palestinians killed by IDF are categorized in three groups, as follows: 1) *took part in the hostilities* - these are persons who were participating directly in hostilities at the time they were killed (for example, a person on the way to fire a rocket, to shoot soldiers, or detonate an explosive belt in the midst of civilians, during the action itself, and on returning from the action); 2) *did not take part in the hostilities* - these are persons who were not participating directly in hostilities at the time they were killed; 3) *unknown if took part in the hostilities* - in some cases, B'TSELEM was unable to collect sufficient information, or the existing information was insufficient to determine whether the person participated directly in the hostilities, and if so, what was the nature of the person's involvement. Palestinian subject of targeted killing, i.e. persons whom the Defense Force deliberately killed in the framework of a targeted-killing operation, were recorded in a separate list. The decision to kill them was based on confidential intelligence that B'TSELEM is unable to examine, making it impossible for the organization to determine with certainty whether the person took part in the hostilities. The classification of the different Palestinian fatalities is based on the principles of international humanitarian law, which distinguishes between combatants and civilians and between an attack carried out by state agents and attacks carried out by independent organizations or private individuals. As a rule, Palestinians in the West Bank and the Gaza Strip are classified as civilians, in part because Palestinian combat there is not carried out by an organized army of a sovereign state. However, the lists distinguish between civilians who took part in hostilities, and thus lost the protection given to civilians not involved in the hostilities, and civilians who were completely uninvolved in the hostilities. The information on Palestinian fatalities is based on B'TSELEM's investigation into the circumstances of the death in each case. As part of the investigation, B'TSELEM collects eyewitness testimony; gathers medical documents and photographs; and cross-checks its information with IDF Spokesperson announcements, information appearing on websites and blogs of armed Palestinian organizations, information gathered by Palestinian and international human rights organizations, and media reports. B'TSELEM emphasizes that publication of the name of a person among the list of fatalities or mention that the person was a civilian or, alternatively, was killed while taking part in hostilities does not indicate that the agent causing the death violated the law and does not prove this person's innocence (http://www.btselem.org/statistics/casualties_clarifications). We create our $fatalities_{gt}$ variable by counting the total number of fatalities recorded in the B'TSELEM database as Palestinians killed by IDF in year t and district t. In most specification, we rescale the variable and divide it by its standard deviation in the distribution of fatalities per district-year.

Border Closures. Data are provided by B'TSELEM at `http://www.btselem.org`, accessed on March 1, 2014. Figures were provided by the IDF Spokesperson's Office on August 7, 2011 and by the Israeli Ministry of Defense on December 6, 2009. We use these data to construct or variable *closures* as the monthly number of closure days, i.e. the number of days during which the IDF imposed comprehensive closure of the borders between the OPT and Israel and between the West Bank and the Gaza Strip in each year.

2.A.3 Other Variables

Gross Domestic Product. Data on real and current value of Palestine GDP over the years 2000 to 2006 are provided by the PCBS in the *National Accounts* subsection of the *Statistics* section of their website (`http://www.pcbs.gov.ps/`), accessed on March 1, 2014.

Producer Price Index. Yearly Producer Price Index numbers by classes in Palestine for years 1999 to 2006 (base year 1996) are elaborated by the PCBS using Producer Price Index Survey, 1999 - 2006.

Aggregate Value of Trade. Data on total value of Palestian Imports and Exports over the years 2000 to 2006 are provided by the PCBS in the *Foreign Trade* subsection of the *Statistics* section of their website (`http://www.pcbs.gov.ps/`), accessed on March 1, 2014. We derive real figures by using price deflators as derived by combining information on real and current GDP from the same source. Yearly information on the value of Palestinian Net Trade Balance are derived by subtracting the value of Imports from the value of Exports in each year.

Chapter 3

ETHNICITY, MIGRATION AND CONFLICT: EVIDENCE FROM CONTEMPORARY SOUTH AFRICA

Joint with Giorgio Chiovelli, University of Bologna

3.1 Introduction

Civil war is closely related with poor economic performance. Understanding its determinants is regarded as crucial in the challenge for world development (Blattman and Miguel 2010). Conflict commonly manifests itself through ethnic markers. Ethnic traits stand out as a salient technology for either or both the generation and expression of social tensions. Indeed, the empirical evidence shows the probability of conflict outbreak and conflict incidence to be strongly correlated with measures of historical ethnic distribution (Montalvo and Reynal-Querol 2005, 2010; Desmet et al. 2012; Esteban et al. 2012). However, it is still unknown whether migration flows involving ethnically diverse communities have any impact on conflict prevalence. In this chapter, we study the extent to which changes over time in ethnic distribution correlate with contemporaneous changes in conflict incidence.

We focus on the history of contemporary South Africa. Starting in the 1950s, apartheid segregation laws regulated the ethnic composition of local districts. The repeal of apartheid legislation in the early 1990s restored free internal mobility of blacks within the country while democratization in 1994 ended the white minority rule in favor of the newly enfranchised black majority. Throughout this period, black-dominated parties and unions were struggling violently amongst themselves to benefit from the transition and dominate the new institutional scenario. The top panel in Figure 3.1 plots the total number of armed confrontations between organized groups recorded in South Africa from 1989 to 2004. Non-state conflict events refer to struggles between black-dominated groups, while one-side conflict events are those in which the Government is involved.[1] Violence between black groups reached its peak in 1993, with almost 500 confrontations recorded in the country as a whole. It then decreased sharply after democratization in 1994, and died out almost completely since 2000. By the same token, the bottom panel in Figure 3.1 is taken from Reed (2013) and plots the internal migration rates in South Africa from 1955 to 1999.[2] The number of moves per person-year spiked in 1991, the same year the last legal impediment to mobility (the Group Areas Act) was repealed. Migration rates remained as high as 9% in the years to follow. In this chapter, we link these two facts in studying the relationship between ethnicity and conflict. In particular, we explore the extent to which the struggle between black organized groups over the period manifested itself through ethnic markers. Indeed, we relate migration-driven changes in local districts' ethnic composition to the concurrent changes in conflict incidence and find the number of conflict events to be positively correlated with contemporaneous measures of within-black ethnolinguistic polarization.[3]

Several theoretical contributions in the literature explore the relationship between ethnic diversity and conflict. Horowitz (1985) first noticed that conflicts seem to arise in societies where a large ethnic minority faces another ethnic majority.[4] Modeling social confrontation and its relationship with measures of heterogeneity in general, Esteban and Ray (1994, 1999) argue that polarized societies, characterized by internally homo-

[1]Source: Geo-referenced Event Dataset of the Uppsala Conflict Data Program (UCDP-GED v1.5), Department of Peace and Conflict Research, Uppsala University. The data are described in details in the Data section.

[2]Source: South Africa Migration and Health Survey (SAMHS)

[3]We use the polarization index used in Reynal-Querol (2002) and Montalvo and Reynal-Querol (2005, 2010), which falls within the class of measures proposed by Esteban and Ray (1994). The index formula is presented and discussed in Section 4.

[4]Collier (2001) and Collier and Hoeffler (2004) further develop and empirically test this hypothesis. Horowitz himself extensively studied South Africa as a case study of a society divided along ethnic lines.

geneous but externally very distant groups, are more prone to experience conflict. In the specific case of ethnicity, ethnic lines may become salient in conflict as they allow for separation of individuals into groups that are homogenous under one trait (ethnicity), but significantly different in their economic characteristics. Indeed, Esteban and Ray (2008, 2011a) explore the role of intra-group synergies in conflict effort that arise when ethnic groups are characterized by high within-group economic inequality. Caselli and Coleman (2013) rationalize instead the salience of ethnic trait in conflicts framing it as a technological device which prevents indiscriminate access to the expected gains of the winning group. Finally, Esteban and Ray (2011b) develop an extensive theory of conflict which highlights the role of different distribution measures. Indeed, together with Esteban et al. (2012), they show both theoretically and empirically the informativeness of the polarization measure with regard to conflict severity to be positively related to the *degree of publicness* of the disputed *prize*. We conceptualize the struggle within the black majority in South Africa through the end of apartheid as a dispute for political power in the new institutional scenario, both at the local and national level. Such prize is intrinsically public in nature. We thus refer to these last contributions as the theoretical foundation for our focus on the polarization measure.[5]

For the purpose of this chapter, we combine geo-referenced information on conflict with South Africa Census data. As a preliminary analysis, we exploit cross-district variation in ethnic composition before the fall of apartheid in 1991 and find a positive correlation between ethnolinguistic polarization within the black majority and the number of recorded armed confrontations between black-dominated organized groups. As a first contribution of this study, and despite their primarily political nature, we thus provide a qualification of these conflicts as expressed through ethnic markers. Then, we exploit the most distinguished feature of this setting: time variation in the ethnic distribution at the local district level. Mainly driven by the migration flows following the repeal of apartheid segregation laws, substantial time variation allows us to combine data from 1991 and 1996 and show the change in polarization at the district level to be positively strongly and significantly correlated with the change in the number of conflict events per year. We implement a first-difference specification which rules out unobserved differences in time-invariant determinants of conflict incidence across districts. The point

[5] For an overview of the debate over the use of alternative ethnolinguistic distribution measures in the empirical analysis see also Alesina et al. (2003) and Desmet et al. (2009).

estimate of the coefficient of interest is stable across specifications. Evidence suggests an increase in the within-black polarization index of one cross-district standard deviation to be associated with an increase in the number of conflict events per district of more than the 1991 national average. Moreover, conditioning on the total number of conflict events in 1989-1990 still yields highly significant results.

The relationship we find using a first-difference approach can potentially be driven by unobserved factors which affect the evolution of both ethnic composition and conflict in the same way, generating a spurious correlation between the two. For example, unobserved geographic characteristics may be correlated with both changes in ethnic diversity and the evolution of conflict (Michalopoulos 2012). We examine the severity of this issue by looking at the relationship of interest within clusters of neighboring districts. In the spirit of matching methods, we control for common trends at the cluster level. We thus exploit only residual variability in both within-black ethnolinguistic polarization and conflict incidence and still find evidence of a positive relationship between the two. Finally, we specifically focus on internal migration as the main source of variability for the change in districts' ethnic composition. Individuals' migration choice and location decision may potentially be endogenous to the evolution of conflict. In the presence of more than two groups, mapping the outcomes of individual decision problems into systematic changes in the polarization index is theoretically challenging.[6] We thus implement an instrumental variable strategy where we use pairwise distance between districts to predict the location decision of internal migrants. This because, once the migration decision is taken, distance from the origin is a strong determinant of ultimate location choice (Kok et al. 2003). In a simulation exercise, we use distance-based predicted location probabilities to re-allocate an exogenously given fraction of migrants from each ethnolinguistic group from each district to the rest of South Africa, independently from conflict levels and changes. The resulting predicted change in the district-level polarization index is thus used as instrument for the actual one, ruling out identification threats from both endogenous location decisions of internal migrants and other sources of changes in ethnic distribution, such as disease prevalence. 2SLS point estimates are higher than previous ones, highlighting the role played by internal migra-

[6]Esteban and Ray (1994) provide a series of examples to intuitively show the absence of a partial order for increasing polarization. The same arguments prevent establishing even a partial map between migration flows and changes in the polarization measure.

tion and confirming the existence of a strong link between within-black ethnolinguistic polarization and number of violent confrontations between black-dominated organized groups.

This chapter contributes to the empirical literature studying relationship between ethnic polarization and conflict incidence. Such exploration was first carried out by Montalvo and Reynal-Querol (2005). More recently, Desmet et al. (2012) investigate the explanatory power of diversity measures as computed at different levels of the ethnolinguistic world tree. Most of the existing studies exploit variation at the cross-country level and make use of time-invariant distribution indices, drawn from historical and encyclopedic sources of ethnic diversity.[7] One contribution of this study is that we employ contemporaneous ethnolinguistic group populations from Census data in the computation of our time-varying index of ethnic polarization at the local district level. In particular, we draw information from South Africa Censuses on languages spoken and validate them using the *Ethnologue* linguistic database (Lewis 2009).[8] We also use information on districts' socio-economic characteristics, drawn from Census data, in order to show the robustness of results in reduced form.

Finally, we contribute to a growing body of the literature that studies conflict at a more disaggregated level, such as local communities and individuals themselves. Within these, Michalopoulos and Papaioannou (2011) use information on spatial distribution of African ethnicities before colonization and find contemporary civil conflict incidence to be concentrated in the historical homeland of partitioned ethnicities. Rohner et al. (2013) use individual, county and district-level data from Uganda to investigate the social and economic consequences of ethnic conflicts. Dube and Vargas (2013) exploit variation in the international price of several agricultural commodities and look at the differential effect on violent conflict across municipalities in Colombia. Besley and Reynal-Querol (2014) look instead into conflict persistence in Africa having fine geographical grids as units of observation. Finally, Harari and La Ferrara (2013) study

[7]One exception is Novta (2013), who studies theoretically and empirically the relationship between municipal-level ethnic composition and the spread of civil conflict in Bosnia.

[8]Detailed information about this procedure is available in the data section. Notice that, with this approach, we trade off the possible drawbacks from the use of potentially endogenous administrative boundaries with the advantages of deriving a time-variant measure of ethnic polarization to employ in our analysis at the sub-national level. The *Ethnologue* database has been already used as source of ethnolinguistic information in Alesina et al. (2003), Desmet et al. (2009), Desmet et al. (2012) and Esteban et al. (2012).

instead the impact of negative climate shocks on conflict incidence using within-year variation at the local level.

The chapter is organized as follows. In Section 2, we provide a short overview of the history of contemporary South Africa. Section 3 introduces the relevant concepts, variables and measures, coupled with the data we use. The empirical strategy and results are presented in Section 4. Section 5 concludes.

3.2 Historical Background: South Africa and the End of Apartheid

Since the end of World War II until 1994, South Africa was ruled under *apartheid* regime. Apartheid - meaning *apartness* in Afrikaans - was a form of government based on physical separation of blacks and whites achieved through racial discrimination and political disenfranchisement of the black majority. Divisions along racial lines were thought to be the fundamental organizing principle for the allocation of all resources and opportunities, the basis of all spatial demarcation, planning and development and the boundary for all social interactions (Posel 2001). Under apartheid, economic activity was based on the exploitation of black cheap labor force in order to ensure high returns to white-owned capital investments (Clark and Worger 2011). By the same token, white workers and farmers were given protection from the competition of their black counterparts.

An extensive legislation implementing racial segregation was put in place after the election of the National Party (NP) into government in 1948. The Population Registration Act (1950) formalized the racial classification system through identifying four different races living in the South Africa. Blacks were further classified into native ethnicities on the basis of the first language they spoke. The Bantu Authorities Act (1951) and Bantu Resettlement Act (1954) established ten black ethnicity-based *homeland* reserve areas, known as *Bantustan*: Transkei and Ciskei (Xhosa ethnicity), Bophuthatswana (Tswana), Venda (Venda), Gazankulu (Tsonga), Lebowa (Sotho), Qwaqwa (Sotho), KwaZulu (Zulu), KaNgwane (Swazi) and KwaNdebele (Sotho). The long-term objective of the law was to let the homelands become independent territories.[9] Political

[9]Over time, the government granted various degrees of self-government to the Bantustans, ranging

separation was achieved with the Promotion of Bantu Self-Government Act (1959), which implied the *de iure* disenfranchisement of blacks from white South Africa. In less than thirty years, approximately 3.5 million blacks were obliged to move to the homelands the government assigned to the different ethnolinguistic groups (Clark and Worger 2011). A number of legislative acts, such as the Group Areas Act, implemented and guaranteed re-settlement of blacks and influx controls. The Bantustans became densely populated areas with low levels of service delivery, infrastructure and employment (Kok et al. 2003). Figure 3.2 presents the map of Bantustans in South Africa as defined by the apartheid legislation as of 1986.

The apartheid system began to collapse in the mid-1980s mainly due to the internal contradictions and conflicting effects of the same implemented policies. Exploitation and control of black labor force revealed itself as costly and hardly compoundable with the enforcement of physical separation of races and ethnicities. Moreover, twenty-five countries (USA and UK among them) set a trade embargo in the late 1980s, following the 1977 UN Resolution 418 on a mandatory arms embargo. At the same time, opposition parties started to organize. Together with the black Africa National Congress (ANC) - a multiethnic party established in 1912 - and the Pan-Africanist Congress (PAC) founded in 1953, the Zulu-based Inkatha Freedom Party (IFP) was formed in 1980s and the multiracial United Democratic Front (UDF) was created in 1983. Opposition to apartheid was not homogeneous and parties were not cohesive. Black political parties engaged in conflicts for two main reasons. First, there was no agreement on how to put an end to the apartheid experience. Second, there was no consensus on how a new post-apartheid South Africa should be ruled.

Among the others, confrontation between the ANC/UDF and IFP was the harshest. The IFP was the KwaZulu governing party, drawing support from the traditional Zulu chiefly structures in the province, and running on a strongly conservative political platform closely aligned with large business interests in the province (Carver 1996). On the other hand, the basis of support for both the UDF and ANC was mainly the urban youth and working class, with their political goal being the establishment of a non-racial unitary state in contrast with traditional chief power. As a result, the ANC and

from independent state-nation - as in Transkei, Bophuthatswana, Venda, and Ciskei between 1977 and 1981 - to limited self-government - as in KwaZulu, Lebowa, Gazankulu, Qwaqwa, KaNgwane and KwaNdebele.

IFP had divergent views on the future role of Bantustans, the consequences of international embargoes, and the eradication of local traditional power. Moreover, the apartheid government took advantage of divisions within the black opposition in its struggle to retain power. Indeed, the independentist goals of the IFP and its opposition to ANC were seconded if not supported by the apartheid establishment (Clark and Worger 2011).[10]

In the late 1980s, the government decided to repeal the Pass Law and to free ANC leaders like Nelson Mandela and other black leaders with the aim of freezing the protests and starting to negotiate. Between 1990 and 1991, the Natives' Land Act, the Population Registration Act and the Group Areas Act were repealed and free mobility of blacks within South Africa was restored. As previously shown in the bottom panel of Figure 3.1, internal (especially inter-provincial) migration rates spiked. The relative economic deprivation of Bantustans acted as a centrifugal force. Indeed, Kok et al. (2003) use data on migrants from the 1996 Census to show the substantial contribution to migration of former homelands. Moreover, Bouare (2002) identifies relative GDP as one of the most important determinants of inter-provincial moves, together with the relative number of reported crimes.[11]

Negotiations taking place in 1991-1992 were everything but smooth: while Mandela and de Klerk (NP) were signing official agreements, fightings kept going on. Free elections were held in 1994, with Mandela becoming the first black president of the Republic of South Africa. The struggles between black-dominated groups weakened but continued in the following years. A number of competing explanations have been put forward among both academics and activists: political competition, ethnic mobilization, underlying social and economic deprivation, and the role of powerful local leaders who relied on the use of violence in their struggle to retain power. Carver (1996) argues that the violence after 1994 was motivated by the willingness to eliminate pockets of support for the minority party in any given area. One example of this would be the 1995 Christmas Day massacre at Shobashobane, in the south east of KwaZulu-Natal. On that occasion, 19 ANC members were murdered by a group of about 600 Inkatha Freedom

[10]Results from our empirical analysis are qualitatively the same when we control for measures of the intensity of governmental repression. These additional results are available from the authors upon request.

[11]It is here worth noticing that existing contributions, like Kok et al. (2003), use post-migration data from the 1996 Census to derive predictors of former migration decisions between 1991 and 1996. This constitutes a serious limitation to their study. Indeed, the authors themselves argue that their analysis could not find entirely satisfactory explanations for the observed internal migration trends.

Party members in an attack to an ANC enclave within an almost exclusively pro-IFP territory.

3.3 The Data: Concepts and Measurement

The database for the analysis is built through combining several different data sources. The fundamental geographical unit for the within-country empirical analysis is the Magisterial District (MD), a sub-provincial territorial unit defined by the judicial system under the administration of the Department of Justice and Constitutional Development.[12] The map of South Africa in Figure 3.3 shows the district boundaries. These are still informed by the pre-1994 demarcations of the self-governing states and the Republic of South Africa territory. This makes them particularly valuable as units of comparative analysis on a small-scale geographical basis, as all other administrative divisions have been subject to frequent re-demarcations after democratization in 1994. Partly because of this, MDs have been used as unit of analysis in the economics and natural science literature (Case and Deaton 1999; Hoffman and Todd 2000).

3.3.1 Ethnic Polarization

Ethnolinguistic information is drawn from the 1991 and 1996 Census of South Africa[13] (Statistics South Africa 1991, 1998). These allow for separate identification of individuals belonging to different ethnolinguistic groups according to the first language they speak. The native African groups in the database are Swazi, Xhosa, Zulu, Sotho, Tswana, Tsonga and Venda.[14] For each MD, we count the total number of individuals in each group and compute the relative share of each group within the black majority.

[12] South Africa is currently divided into 9 provinces and 354 MDs. 298 of these were surveyed in the 1991 Census of the Republic of South Africa, as the remaining ones were part of independent Bantustans.

[13] Access to the 10% sample Census data for both years was kindly provided by DataFirst Research Unit at the University of Cape Town.

[14] Desmet et al. (2012) show how to make use of the genealogical relationship between world languages in the construction of distribution indexes. In line with their approach, we use information contained in the *Ethnologue* linguistic database (Lewis 2009) assuming all languages at the same level to be as equally distant from the proto-languages of their respective families. We build our measure considering black ethnolinguistc groups in South Africa which correspond to level 11 in the world language tree.

Throughout the analysis, we employ the *binary* version of the polarization index implemented in Reynal-Querol (2002) and Montalvo and Reynal-Querol (2005, 2010), which falls within the class of measures proposed by Esteban and Ray (1994). The ethnolinguistic polarization within the black majority is computed as

$$ELP_{Within-Black} = 1 - \sum_{i=1}^{N} \left(\frac{1/2 - \pi_i}{1/2} \right)^2 \pi_i \tag{3.1}$$

where π_i is the within-black share of group i and N is the number of groups. The index value ranges between 0 and 1, with the maximum value being reached in presence of two groups of the same size. The index combines information on both the number of groups and their relative size, returning a distribution measure linked to the generation of social tension between equally distant groups (Esteban and Ray 1994). In the presence of more than two groups, the index value decreases monotonically with the number of groups if they are all of the same size. It is worth here noticing that, when groups have different sizes, changes in the population size of a given group do not map systematically into changes in the polarization index. Esteban and Ray (1994) provide a series of examples in this respect.

3.3.2 Conflict

The measure of conflict incidence is derived from the Geo-referenced Event Dataset of the Uppsala Conflict Data Program (UCDP-GED v1.5).[15] Assembled by the Department of Peace and Conflict Research at Uppsala University, it provides geo-referenced information on organized violence in Africa between 1989 and 2010, detailing different categories - state-based conflict, non-state conflict and one-sided violence.[16] The data

[15] Department of Peace and Conflict Research, Uppsala University. The dataset is available at `http://www.ucdp.uu.se/ged/data.php`. See Melander and Sundberg (2011) for the last data presentation. See Eck (2012) for a complete discussion of the UCDP-GED database and its comparison with the Armed Conflict Location Events Dataset (ACLED). The UCPD-GED geocoding and precision is there concluded to be far superior to ACLED's and found particularly suitable for the study of conflict at the sub-national level.

[16] *State-based* conflict is defined as a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths in a year in the period (1989-2010). *Non-state* conflict refers to the use of armed force between two organised armed groups, neither of which is the government of a

are disaggregated spatially and temporally down to the level of individual events of fatal violence. For each conflict event, information is given on date of the event, place of the event (with coordinates), actors participating and estimates of fatalities. A conflict event is recorded in the database if it caused at least 1 death and it involved actors engaged in a nationwide conflict which caused at least 25 deaths in a year in the period (1989-2010).

We measure the yearly incidence of armed confrontations between black-dominated organized groups in South Africa at the MD level by counting the number of related geo-referenced conflict events in each MD per year. These amount to all non-state conflict events.[17]

3.3.3 Socio-economic and Geographical Controls

We aggregate further information for the surveyed territories at the MD level from Census 1991 and 1996, checking for consistency across waves. Moreover, we use data on population, rural population, number of individuals reporting no education, number of unemployed individuals, number of individuals out of the labor force and number of South African citizens.[18]

In addition to conflict and Census data, we use three additional data sources. Following Michalopoulos and Papaioannou (2013, 2014), we use NOOA (2012) night-time light satellite images data for 1992 (the first available year) and 1996 as a proxy for economic conditions in South Africa at the MD level.[19]. Consistently with their approach, we average night-time light density across 30-second grid areas (approximately 1 square kilometer) within the same MD. In line with the existing literature, we also make use

state, which results in at least 25 battle-related deaths in a year in the period. *One-sided violence* refers to the use of armed force by the government of a state or by a formally organised group against civilians which results in at least 25 deaths in a year in the period (Sundberg et al. 2010).

[17]In the study of the relationship between ethnic polarization and conflict, the literature has used conflict data from the Peace Research Institute Oslo (PRIO) Montalvo and Reynal-Querol 2005, 2010; Esteban et al. 2012). This is mainly due to the cross-countries analysis and large time span (1945 to 2010) these studies usually consider. Non-state and one-sided conflicts are there considered as outcomes to test robustness of results.

[18]In our regression specification we use the logarithm of these variables, augmenting all values by 0.01 when some of them are equal to zero. Results go through other variables specification and level shift.

[19]For an extensive discussion of these data and their validity as a proxy for economic conditions in the african territories see Michalopoulos and Papaioannou (2014, 2013) See also Doll et al. (2006) and Sutton et al. (2007). In our regression specifications, consistently with Michalopoulos and Papaioannou (2014, 2013), we augment the night-time light satellite measure by 0.01 before taking its logarithm. Results are unaltered with respect to other or no level shift.

of geographical variables as controls. In our cross-sectional specification we include use a MD-level measure of terrain ruggedness(data from Nunn and Puga (2012)). The measure is computed by averaging 30-second grid area observations belonging to the same MD.[20] The terrain slope index from Global Aero-ecological Zones (GAEZ) data (IIASA/FAO 2012) is created by averaging 5-minute by 5-minute (approximately 9 km by 9 km) grid-cells observations within the same MD. Finally, area accessibility from GAEZ is computed as estimated travel time to nearest city with 50,000 or more inhabitants in year 2000.

3.4 Empirical Strategy and Results

3.4.1 Preliminary Analysis

More than 2,000 non-state conflict events are geo-referenced in MDs of South Africa in the UCDP-GED dataset in the period 1989-1996.[21] ANC and IFP confronted each other in more than 85% of events. As for the others, within the most numerous are those where the United Democratic Front (UDF) is involved against the IFP, and the ANC Greens faction against the ANC Reds faction. An average number of 1.2 non-state conflict events per MD is recorded in 1991, with cross-district variation being larger than four times the national mean. Overall, conflict prevalence decreases after democratization in 1994. The average is 0.1 in 1996, but with a cross-district variation of 0.7.[22]

Table 3.1 shows the population sizes of the African native ethnolinguistic groups in South Africa according to the 1991 and 1996 Census. Together with nationwide stocks, the table reports the differences in the population of each ethnolinguistic group between 1991 and 1996. MDs in those Bantustans which were already granted independence are not covered by the 1991 Census of the Republic of South Africa. The inclusion of former independent Bantustan territories in the 1996 Census generates a dramatic increase in the population stocks of the corresponding ethnolinguistic groups. In the fourth column, the same overall differences are computed looking only at those

[20]Data are available at `http://diegopuga.org/data/rugged/`.

[21]Table 3.A.1 in the Appendix reports the total number of one-sided conflict events involving the Government and non-state conflict events per year in MDs in South Africa recorded in the UCDP-GED dataset, together with the estimated total number of deaths.

[22]Summary statistics for the derived sample are reported in Table 3.A.2 of the appendix.

294 districts which are part of both the 1991 and 1996 Census. We find evidence of a substantial inflow into these territories of individuals belonging to ethnicities previously segregated in the independent Bantustans. At the extreme, the Tswana group population increases by more than 30%.

On top of migration inflows from independent Bantustans, we find evidence of substantial internal mobility.[23] According to 1996 Census data, 2.5 millions blacks moved from one MD to another in between 1991 and 1996. Figure 3.4 shows the change in the population share of the three biggest ethnolinguistic groups at the district level in between 1991 and 1996, plotted against the share of black population in 1991. It is worth noticing that the most relevant changes do not seem to be concentrated in those districts where the share of blacks in 1991 was either negligible or close to one.[24]

As suggested by the above figures, the negligible change in average within-black polarization between 1991 and 1996 hides substantial variability over time across districts. The time difference goes from a minimum of -0.89 to a maximum of one, spanning almost the entire support of admissible values. Remarkably, the standard deviation of the overtime chenge in the polarization index is as high as half of its 1991 cross sectional standard deviation.

About 32% of conflict events recorded in 1991 takes place in the 25% of districts with the highest level of within-black polarization. More importantly, the relationship appears to be stronger when within-province variability in conflict incidence is considered. The 25% of districts with the highest within-black polarization have on average 0.66 conflicts more than the province average, as opposed to the 0.48 less recorded in the 25% of districts with the lowest within-black polarization.

3.4.2 Cross-sectional Estimates, 1991

We start the regression analysis by exploiting cross-district variation in both within-black polarization and conflict in 1991. We thus compare the incidence of conflict in

[23]Using data from the South Africa Migration and Health Survey (SAMHS), Reed (2013) studies internal migration patterns amongst the black population of South Africa in the second half of the twentieth century. He reports non-negligible migration rates even before the repeal of the Pass Law in 1986. Nonetheless, migration rates spike in 1991 and after, and estimates are very similar to the one we obtain using data from Statistics South Africa (1998). Indeed, SAMHS data are recognized by Reed (2013) to compare favorably to Census data.

[24]Figure 3.A.1 in the Appendix carries further exploration of migration patterns.

1991 across districts characterized in the same year by different levels of within-black polarization, in the search of a systematic relationship between the two variables. We adopt the following linear regression specification

$$conf_{ip91} = \gamma_p + \beta \, ELP_{WB\ ip91} + \mathbf{Z}'_{ip}\omega + \mathbf{X}'_{ip91}\varphi + u_{ip91} \qquad (3.2)$$

where $conf_{ip91}$ is the number of non-state conflict events recorded in district i in province p in 1991. $ELP_{WB\ ip91}$, computed as discussed in Section 4, is the within-black polarization index in the same district in 1991, while Z_{ip} is a set of time-invariant district geographical characteristics (ruggedness, slope index and accessibility). X_{ip91} is the vector of time-varying demographic and economic controls, capturing time-variant district characteristics in 1991 (log of population, black population, rural population, number of individuals reporting no education, number of unemployed, number of individuals out of the labor force and number of South Africa citizens). γ_p captures province fixed effects, netting out average differences across provinces. The residual u_{ip91} captures instead those unobserved factors which affect conflict incidence.

Table 3.2 provides the corresponding results. Throughout all specifications, an Ordinary Least Squares (OLS) estimation with province fixed effects is run on the available 1991 sample. Given the possible endogeneity of within-black polarization to conflict intensity, we start by providing results from a regression with no additional controls in the first column. The results show a positive and significant relationship between the within-blacks polarization index and number of conflict events at the district level.[25] An increase of one cross-district standard deviation of the within-black polarization index is associated with 0.8 more conflict events per year in 1991, more than half of the national average. Columns (2) and (3) include additional controls such as population, black population, and the Night-time Lights measure as proxy for local economic activity (all in logs).[26] Both the magnitude and significance of the coefficient of interest turn

[25]We performed the same estimations using a Poisson model specification which takes into account the count nature of our dependent variable. Results are substantially unchanged and available from the authors upon request. Finally, as a further check, we use the logarithm of the number of conflict events (augmented by 0.01) as outcome in all specifications and find highly consistent results.

[26]Notice that the inclusion of population stocks allows to look at the relationship of interest keeping population constant, thus being analogous to the use of the number of conflict events per capita as dependent variable. Indeed, replacing the latter as outcome yields equally significant results.

out to be almost unaffected. Column (4) reports estimation results after further including geographic controls such as indexes of ruggedness, terrain slope and accessibility. The coefficient of interest remains unchanged in both magnitude and significance with respect to columns (2) and (3). Results in column (5) show the results from the full specification including as controls a number of economic covariates such as the log of rural population, number of unemployed individuals and number of individuals reporting no education. The coefficient of the within-blacks polarization is now lower in magnitude and significant only at the 11% level. Nonetheless, we find results to be consistent with the hypothesis of the observed non-state conflict events to be qualifiable as expressed along ethnic lines. These findings are in line with the cross-country literature relating ethnic polarization to conflict as discussed in Section 2.

3.4.3 First-difference Estimates, 1991-1996

The restoration of free internal mobility of blacks after 1991 largely accounts for time variation in ethnolinguistic group population shares per district. Together with initial cross-district variation, it opens the way for the implementation of a first-difference strategy which looks at the evolution of both within-black ethnolinguistic polarization and non-state conflict, net of district-specific time-invariant characteristics. In other words, it is possible to compare the evolution of conflict across districts experiencing differential changes in ethnic composition, and test whether the observed change in within-black polarization systematically correlates with the change in non-state conflict incidence.

We combine the available information from both 1991 and 1996 and adopt the following specification

$$\Delta conf_{i96-91} = \delta + \beta \, \Delta ELP_{WB \; i96-91} + \Delta \mathbf{X}'_{i96-91}\varphi + \Delta u_{i96-91} \tag{3.3}$$

where $\Delta conf_{i96-91}$ is the change in the number of recorded non-state conflict events in district i in between year 1991 and 1996, while $\Delta ELP_{WB \; i96-91}$ is the corresponding change in the within-blacks polarization index. The proposed first-difference specification allows to cancel out both observable and unobservable time-invariant characteristics at the district level. The effect of nationwide events (such as democratization in 1994) and general time trends are instead captured by the constant term δ. As before, X_{it} is the vector of time-varying demographic and economic controls in year t (population, blacks, night-time light, rural, etc.). The difference residual Δu_{i96-91} captures those unobserved changes and factors which affect the change in conflict incidence.

Results are reported in Table 3.3. All specifications are implemented over the sample of districts for which Census data are available for both 1991 and 1996. The first column provides the results from the simple regression specification. Notice that the negative estimate of the constant term is consistent with the general decrease in conflict prevalence with the first democratic elections in 1994. More importantly, the estimated coefficient of the ethnolinguistic polarization is highly significant. The point estimate more than doubles the obtained from the 1991 cross-sectional analysis.[27] An increase in one cross-district standard deviation in the within-black ethnolinguistic polarization measure is now associated with 2 more conflict per district, more than the 1991 national average. Changes in ethnic composition at the district level are thus found to be informative of the evolution of conflict. Column (2) and (3) show that the results are robust to the inclusion of time-variant economic controls. The coefficient of interest remains significant and relatively stable.[28]

Column (4) provides estimation results assuming heteroskedastic difference residuals and estimating Eicker-Huber-White robust standard errors (White 1980). This allows to take into account heterogeneity in the variability of the first-difference residuals in the computation of the standard errors used for inference. The coefficient of interest is still significant at the 10% level. In column (5), we take into account cross-sectional dependence of first-difference residuals and follow Conley (1999) in allowing for non-zero correlation when coordinate distance between districts' centroids is less than 1 degree latitude and/or 1 degree longitude (approximately 110 km). The estimate of our coefficient of interest retains significance at the 10% level. The same holds when spatial spillovers are directly taken into account by including as regressor the average change

[27]We produced estimates from a non linear specification. Results are still positive and significant using a fixed-effects Poisson model. These are available from the authors upon request. As before, we also use the logarithm of the number of conflict events (augmented by 0.01) as outcome in all specifications and still find consistent results.

[28]Table 3.A.3 in the Appendix shows how estimates of the coefficient of the within-black ethnolinguistic polarization measure in the first-difference specification remains highly significant when controlling separately for the changes of each within-black group shares. None of the latter individually thus seem to be responsible for the relationship we find in the baseline specification.

in within-black ethnolinguistic polarization in neighboring districts $\overline{\Delta ELP}_{WB\ j96-91}$. Assuming heteroskedastic difference residuals, the point estimate of the coefficient of interest is somewhat lower than before, but still significant at the 10% level. The average change in within-black ethnolinguistic polarization in neighboring district is also found to be highly correlated with the change in conflict incidence, with the corresponding coefficient being significant at the 5% level.

Finally, column (7) reports instead the results from a specification which augments the first-difference one by including the number of non-state conflict events in the 1989 and 1990. Given the general decrease in the number of conflict events over the period, we want to test whether the systematic relationship we find between within-black polarization and conflict incidence is robust to conditioning on a measure of pre-1991 conflict incidence.[29] The coefficient of the latter is negative and highly significant. This means that the observed decrease in the number of conflict events in between 1991 and 1996 was higher in those districts with a high number of conflicts in 1989 and 1990. More importantly, we still find evidence of a systematic relationship between within-black polarization and conflict incidence. The estimated coefficient is highly significant. Together with the negative estimate of the pre-1991 conflict measure coefficient, the decrease in the point estimate of the change in within-black polarization suggests the existence of a negative relationship between the latter and conflict incidence in 1989-1990.

3.4.4 First-difference with Cluster-specific Trends

One possible concern with the above results is that these can be driven by the presence of unobserved factors which affect the evolution of both ethnic composition and conflict in the same way, generating a spurious correlation between the two. For example, those districts where polarization increased in 1991-1996 might be systematically different from others in terms of geographic characteristics (Michalopoulos 2012). The same factors might have been on their own responsible for the change in the incidence of conflict within the black majority, generating a spurious correlation between changes in

[29] Given the adopted linear regression model specification, the estimator of the parameter in column (7) is inconsistent and not directly comparable with the ones from the simple first-difference specification. The inclusion of a lag as a regressor in the first-difference model does not allow to net out district-level time-invariant unobservable characteristics. We intentionally compromise on the consistency of our estimator in order to check whether our results are robust to a partial solution to the problem of mean-reversion and convergence.

ethnic composition and conflict.

We study the extent to which these issues are likely to affect the results by looking at the evolution of within-black polarization and conflict within clusters of neighboring districts. Similarly to the neighbors-pair fixed-effects analysis in Acemoglu et al. (2012), our argument is that districts located next to each other are highly comparable in terms of both observable and unobservable characteristics. As a result, when looking at the relationship of interest within clusters of neighboring districts, it is possible to net out those common unobserved sources of heterogeneity and time-varying omitted variables, possibly correlated with the evolution of both polarization and conflict incidence. Only residual variability in the variables of interest is therefore exploited for identification.

We define as *treated* those districts $g \in M$ where our polarization measure *decreased more than average* in 1991-1996. We then keep their neighboring *non-treated* districts $f \in N(g)$, and drop treated districts with no non-treated neighboring districts. We obtain a sub-sample of 227 out of the initial 294 districts.[30] For each treated district $g \in M$ and its non-treated neighbors $f \in N(g)$, we focus on 1991-1996 differences and consider the following model

$$\begin{aligned} \Delta conf_{g96-91} &= \delta + \gamma_g + \beta\, \Delta ELP_{WB\ g96-91} + \Delta \mathbf{X}'_{g96-91}\varphi + \Delta\varepsilon_{g96-91} \qquad g \in M \\ \Delta conf_{f96-91} &= \delta + \gamma_g + \beta\, \Delta ELP_{WB\ f96-91} + \Delta \mathbf{X}'_{f96-91}\varphi + \Delta\varepsilon_{f96-91} \quad f \in N(g) \end{aligned} \tag{3.4}$$

where, as before, $\Delta conf_{i96-91}$ is the change in the number of recorded non-state conflict events in district i in between year 1991 and 1996, while $\Delta ELP_{WB\ i96-91}$ is the change in the within-blacks polarization index (with $i = g, f$). Time trends are still controlled for by δ. γ_g captures cluster-specific trends, controlling for unobservable determinants of evolution of conflict in 1991-1996, possibly related with change in polarization over the period. In other words, we include a dummy for each cluster of districts, taking value one for all treated and non-treated observation in the cluster. X_{it}

[30]Following the proposed definition, the final subsample contains 105 treated and 122 non-treated districts.

is the vector of time-variant district characteristics in year t (population, blacks, night-time light, rural, etc.). The difference residual $\Delta\varepsilon_{i96-91}$ captures those idiosyncratic unobserved changes and factors which affect the change in conflict incidence, net of cluster-specific trends.

In the final restricted sample, each non-treated district is possibly neighbor of more than one treated district. Thus, there exist several different ways to group districts into clusters. We implement a bootstrap-type procedure where we run a series of regressions, matching in each repetition each non-treated district to a single treated district. The results deliver an empirical distribution of parameter estimates $\hat{\beta}$ which can be used for inference.[31].

Results are shown in Table 3.4. Column (1) reports the estimate of the coefficient of interest when only the logarithm of total black population, total population and the night-time satellite light variables are included as controls. Netting out cluster specific trends and exploiting only within-cluster residual variability, we still find a significant relationship between the change in within-black ethnolinguistic polarization and the evolution of conflict. The corresponding point estimate is highly significant and somewhat larger than the one obtained before. The full set of other time-variant economic controls is included in column (2), with results being substantially unchanged. A full set of third-degree polynomials of covariates is included in column (3). We do this in order to control for non-linear discontinuities at the border, which may themselves be correlated with the outcome variable (Acemoglu et al. 2012). The point estimate is still highly significant, even if lower in magnitude.

Given the restricted sample, we attach to these estimates only a local interpretation. Nonetheless, results are largely consistent with the ones derived in the previous section. If anything, the presence of unobserved omitted factors which are systematically correlated with both the change in within-black polarization and conflict incidence seem to downward bias our initial first-difference estimate of the parameter of interest.

However, exploiting differential changes in ethnic composition across neighboring districts can still be problematic. Internal migration is the primary source of variation for

[31]The focus on clusters instead of pairs of neighboring districts and the implementation of the suggested bootstrap-type procedure differs from Acemoglu et al. (2012) Our approach avoids duplicating observations as required by their neighbors-pair fixed-effects strategy, and delivers standard errors for inference without building up and estimating the parameters of the variance-covariance matrix of residuals as required by their random-effects strategy.

the change in ethnic composition at the district level in between 1991 and 1996. According to 1996 Census data, migration across contiguous districts represent a high fraction of total district-level moves in the period. Focusing on the districts in our sample, Table 3.5 shows, for each ethnic group, the average number of moves towards neighboring districts as a fraction of total outmigration in 1991-1996. On average, 35% of Xhosa movers from a given district are estimated to relocate in neighboring districts. The same percentage is 28% for movers from the Zulu ethnic group. The relocation of internal migrants in neighboring districts and the differential changes in ethnic composition that follow could possibly be endogenous to the evolution of conflict. The purpose of the next section is to address this issue in a systematic way.

3.4.5 Internal Migration and Instrumental Variable Strategy

With the implementation of a first-difference identification strategy we compare districts which experienced different changes in the within-black polarization measure in between 1991 and 1996, and find heterogeneity along this dimension to be significantly correlated with the observed changes in the incidence of conflict within the black majority at the district level. Changes over time in the polarization measure occur when group population sizes change at different rates: if all ethnolinguistic group populations were changing at the same rate in all districts, the polarization measure would have not changed anywhere. Therefore, one concern for the validity of our empirical exercise is that the disproportional changes in the size of ethnolinguistic groups may themselves be driven by the change of conflict incidence.

We focus on internal migration as the main source of variability for the change in districts' ethnic composition. Conflict causes displacement of individuals and households. High non-state conflict incidence in 1991 could be framed as a *push* factor that positively affected individuals' propensity to migrate out of the district after 1991. By the same token, expectations about low non-state conflict incidence in 1996 can be conceptualized as a *pull* factor in the same framework. If agents' expectations were fulfilled, migration decisions would be endogenous to conflict incidence in both 1991 and 1996. Still, this does not necessarily imply that migration decisions are endogenous to the *changes* in conflict incidence over the period. Moreover, even if this was the case, our exercise would be invalidated only if the following two conditions are met. First, endogenous migration decisions need to map into endogenous disproportional changes in ethnolinguistic group population sizes. Second, the resulting changes in the ethnolinguistic polarization index need to be positively correlated with changes in conflict incidence. Both requirements are far from being immediately framed in a coherent narrative. Suppose that one given ethnic group has comparative advantages in armed confrontation. Individuals belonging to this group may thus migrate disproportionally more towards districts where conflict incidence is expected to increase. If expectations are fulfilled, we would observe positive changes in the size of the given group in those districts which experienced higher changes in conflict incidence. However, the same percentage change in the size of a given group does not map systematically into changes in the polarization index if the latter is heterogeneous across districts to begin with. This is even more the case in the presence of more than two groups as in our case. In this respect, Esteban and Ray (1994) show with a series of examples the intuition for the absence of a partial order for increasing polarization. Furthermore, Table 3.A.3 in the Appendix shows how changes in each within-black group shares cannot individually account for all the variability of the change in within-black ethnolinguistic polarization, whose coefficient estimates remain highly significant in the first-difference specification.

To investigate the issue, we implement an instrumental variable (IV) strategy where pairwise distance between districts is used to predict the location decision of internal migrants. We use information from the 1996 Census on surveyed individuals who declare to have moved in between 1991 and 1996 and to have been resident in a different district in 1991. Using the same data, Kok et al. (2003) provide evidence of a negative relationship between the number of migrants moving between two districts and pairwise distance between them. We exploit this feature and estimate a conditional logit model (Cameron and Trivedi 2005) for the location decision of migrants in the sample of the form

$$p_{ij} = \frac{e^{\beta \ distance_{ij}}}{\sum_{j \in S} e^{\beta \ distance_{ij}}} \tag{3.5}$$

where $distance_{ij}$ is the distance (in km) between district i and j in the set of South Africa districts S. We thus estimate the probability of each individual leaving district i after 1991 to be observed in district j in 1996 as predicted by the values of pairwise distance only.[32]

In a simulation exercise, we next assume that a fraction x of individuals from each ethnolinguistic group e leave each district $i \in S$ after 1991, and allocate them to districts $j \neq i$ using the estimated probabilities $\hat{p}_{ij}$ derived as above. The value of x is chosen by matching it with the total district-level outflow rate of blacks who located in any other district over the relevant period, equal to 8.66%.[33] We thus compute predicted population stocks for each black ethnolinguistic group in each district i in 1996 as

$$\widehat{N}_{e,i,1996} = N_{e,i,1991}(1-x) + \sum_{j \in S} \hat{p}_{ji}\, x N_{e,j,1991} \tag{3.6}$$

The predicted population share are next used to construct a predicted within-black ethnolinguistic polarization index for 1996 using the same formula as in section 4. We then take the difference between our predicted ethnolinguistic polarization in 1996 and the actual one in 1991 in order to obtain the predicted change in polarization between 1991 and 1996, $\Delta\widetilde{ELP}_{WB,i}$. Notice that, by forcing x to be the same for all ethnic groups in all districts, we rely on $\hat{p}_{ji}$ only in the generation of predicted time variability in the change in the polarization index. Our predicted value for the change in within-black ethnolinguistic polarization is the one which would be observed in case a given exogenous fraction of individuals in each ethnic group in each district were to leave after 1991 and locate in another district according to what predicted by distance only. Indeed, individual reallocation probabilities are computed as independent from conflict levels and their changes at both origin and destination, and assigned to each fictitiously displaced individual. We use this prediction as a source of exogenous variation for the actual change in polarization observed in the data, ruling out the potential endogeneity of individuals' migration decisions. Furthermore, focusing on predicted internal migration allows to validate the latter as the main mechanism for the change in districts' ethnic composition and rule out other potentially endogenous sources of disproportional changes in ethnic group population sizes, such as disease (specifically HIV) prevalence.

[32]Conditional Logit estimation results are available from the authors upon request.

[33]Focusing on the 294 districts in our sample, we calculate the total number of individuals moving from one MD to another in between 1991 and 1996 as recorded in the 1996 Census. We then divide this number by the total number of individuals belonging to any black ethnolinguistic group living in any of the 294 districts surveyed in the 1991 Census of the Republic of South Africa.

Results from both the first and the second-stage regressions are reported in Table 3.6. Conditional on the other variables included as controls, the *F-statistics* for the significance test of the instrument in the first-stage regression are safely above 10 in all specifications. The instrument appears strong enough in producing a relevant shift in the actual value of the change in the within-black polarization index. For consistency with the previous analysis, we start by including only the total number of blacks, total population and night-time satellite light value in logs as controls in the first column. The point estimate of the coefficient of interest is significant at the 10% level and more then doubles the one obtained in Table 3.3, suggesting the presence of a downward bias in previous estimates from endogenous migration decisions. An increase in within-black polarization of one 1991 cross-district standard deviation is now associated with 4.5 more conflict events, almost four times the 1991 national average. However, results from a Hausman test do not allow to reject the hypothesis of both the first-difference and the IV estimators being consistent (Hausman 1978). In the second column, we allow first-difference residuals to be heteroskedastic and estimate Eicker-Huber-White robust standard errors (White 1980). The estimate of the within-black polarization coefficient are significant at the 5% level.[34] The same pattern of significance is observed when conditioning on the full set of economic controls in column (3) and (4), with the point estimate being somewhat lower in magnitude.

Results from the implemented instrumental variable strategy confirm the existence of a positive relationship between within-black ethnolinguistic polarization and non-state conflict incidence in the data. Ruling out potential threats from both the endogeneity of individual migration decisions and other sources of differential changes in ethnic group populations sizes yields a much bigger point estimate of the effect of interest. The downward bias in the first-difference specification might indeed be caused by heterogeneous exposure and/or resistance of ethnic groups to diseases, which could be possibly negatively correlated with the change in within-black polarization, but positively correlated with the change in conflict incidence. However, given the spatial heterogeneity of

[34]Eicker-Huber-White robust standard errors may be lower than conventional ones. Angrist and Pischke (2010) show that this can be the case whenever lower variance of the residual is associated with covariate values far from the mean of the covariate distribution. In our case, given that the mean of the predicted change in polarization is close to zero, this would mean that those districts which are assigned by our instrument to experience the smallest change in polarization also have higher variability in the first-difference residuals of the change in conflict.

internal migration flows we observe in the data, we cannot exclude differences in magnitude to be attributable to the local interpretation of the instrumental variable estimate of the parameter we wish to identify (Angrist et al. 1996).

Exclusion Restriction and Falsification Tests

One possible concern with the proposed instrumental variable approach is that, despite the role played by internal migration patterns as estimated using pairwise distances, the predicted change in polarization is still a function of local ethnic distribution in 1991. The latter may not be uncorrelated with unobserved district-level characteristics, which may themselves affect the evolution of conflict incidence in the following year. Additionally, the ethnic distribution in 1991 could have been strategically manipulated by the apartheid rulers or the very same ethnic groups in order to shape the evolution of conflict in the years to follow. In both cases, if the variability in the change of polarization induced by the proposed instrument were to come from the variation in ethnic composition at the MD level in 1991, the exclusion restriction would be violated.

In order to address this concern, we plot in Figure 3.5 the relationship between the change in conflict incidence 1991-1996 and the initial level of polarization across districts in 1991, together with the line fitting the relationship between the two. The figure shows the absence of any relationship between the two variables. Nonetheless, our instrument is also a function of ethnic composition in other districts, with this relationship being stronger for closer districts. In Figure 3.6, we explore the relationship between the change in conflict incidence 1991-1996 and the average level of polarization in neighboring districts in 1991. As before, we find no significant relationship between ethnolinguistic polarization in neighboring districts and the evolution of conflict in the following years. Given the highly non-linear nature of our instrument, we also plot the change in conflict incidence between 1991 and 1996 over the initial within-black share of each ethnic group in 1991, and the average share of each ethnic group in neighboring districts. All plots are depicted in Figures 3.A.2 and 3.A.3 in the Appendix. No meaningful relationships are detectable. We take evidence from these results altogether as reassuring: the absence of any relationship between ethnic composition in 1991 and the evolution of conflict in the following years speaks in favor of our exclusion restriction.

Another way to address the same concern is to show that the variation induced by the instrument relies on predicted internal migration patterns, and does not overlap with the one due to 1991 polarization values. We thus implement a falsification test where we use the within-black polarization index in the MD in 1991 as instrument for its actual change in between 1991 and 1996. The idea of the test is straightforward: if the variability we exploit in our original strategy were to be driven by the initial distribution of ethnic groups, results from this falsification test - where predicted migration is not playing any role - would be similar to the previous ones. Results are reported in Table 3.7. Conditional on the other variables included as controls, within-black polarization index in 1991 is found to be a strong negative predictor of the change in polarization. This is due to the mechanical negative correlation that arises when regressing the predicted change in polarization over the level of polarization in the previous period, as the latter appears in the former with a negative sign. Nonetheless, second-stage regression results for the coefficient of interest are insignificant in all specifications.

We repeat the same exercise in Table 3.8, but using now as instrument the average level of polarization in neighboring districts in 1991. No significant relationship is here found in the first stage. Both the initial level of polarization in the district and the one in neighboring districts are used as instruments in Table 3.9. Despite the strong first stage, we again find no significant relationship in the second stage.

Again, we interpret these results altogether as validating our original instrumental variable strategy. We there rely on a non-trivial source of variation which stems out of internal migration moves, as the variability in the endogenous regressor induced by measures of ethnic distribution in 1991 does not relate systematically with the evolution of conflict in the following years. Internal migration flows are thus found to be the relevant mechanism for the generation of changes in within-black polarization index which mattered for the evolution of conflict in the period.[35]

As a final check, we investigate whether the change in ethnolinguistic polarization is systematically related with any pre-existing trend in conflict incidence. We argue this is unlikely to be the case, as the years between 1991 and 1996 exhibit an overall decrease in conflict incidence following democratization in 1994. Nonetheless, given that our conflict data are available since 1989, we can replace as outcome the change in

[35]We also use 1980 Census data and replicate the falsification test using the within-black polarization at the district level in 1980. Apartheid legislation was still fully in place in the period, as the Pass Law was only repealed in 1986. Using observations for the 279 districts available in the sample, we find within-black polarization in 1980 to have no predictive power for its change in between 1991 and 1996.

conflict incidence between 1989 and 1991 in our first-difference specification. Results are reported in Table 3.10. By construction, the first stage regression results are identical to those belonging to our main IV specification. Second stage estimates are instead non-significant. This allows us to conclude that the relationship we found between the change in ethnic polarization between 1991 and 1996 does not capture a general trend in the evolution of conflict, and its relationship with the latter is indeed specific of the period under investigation.

3.5 Conclusions

This chapter studies the extent to which conflict incidence correlates over time with contemporaneous measures of ethnic distribution. The history of contemporary South Africa in 1991 through 1996 carries with it substantial variation in the variables of interest. Combining Census data with geo-referenced information on conflict, we show the incidence of violent struggles amongst black-dominated organized groups during the fall of apartheid to be positively correlated with within-black ethnolinguistic polarization. We thus provide a qualification of these conflicts as expressed through ethnic markers, despite their primarily political nature. Time variability along both dimensions allows to investigate the relationship of interest after clearing out the impact of unobserved time-invariant characteristics at the local level. A one cross-district standard deviation increase in within-black polarization is found to be associated with an increase in the number of conflict events of more than the 1991 national average. Findings are robust to several additional checks. Comparing the evolution of within-black polarization and conflict within clusters of neighboring districts still yields highly significant results. The same holds when focusing specifically on the internal migration channel. We simulate migration patterns and the resulting changes in ethnic distribution using location probabilities as predicted by pairwise distance between districts. Instrumental variable point estimates are still positive and bigger than first-difference ones, validating internal migration as the main source of variability for the changes in ethnic distribution which mattered for the evolution of conflict.[36]

[36]Results are confirmed when the estimated number of deaths in non-state conflicts per MD is used as measure of conflict incidence, and a measure of the intensity of governmental repression is controlled for. These findings are not for publication and are available from the authors upon request.

The approach and empirical results in this chapter contribute to disclose the potential of the use of micro-level data in the study of social conflict and its determinants. On one hand, migration-driven changes in the ethnic distribution at the local level are here revealed to be informative of conflict prevalence. The exploration of how this interacts with displacement caused by conflict itself constitutes a fruitful avenue for future research. On the other hand, the specificities of the South Africa setting can be further investigated in order to study the effect of democratization on conflict. Evidence from this chapter suggests the heterogeneity and divisions within the newly enfranchised majority to interact with nationwide institutional changes and still inform conflict incidence at the local level even after democratization in 1994. The need for a theoretical and empirical investigation of this argument motivates our future research agenda.

Tables and Figures

TABLE 3.1: ETHNIC GROUP POPULATION SIZES

	TOTAL POPULATION		DIFFERENCE 1996-1991	
	1991 Census 298 MDs	1996 Census 354 MDs	Overall	Study Sample 294 MDs
Xhosa	2,493,382	7,206,005	4,712,623	77,370
Zulu	8,416,125	9,216,413	800,288	163,555
Sotho	6,414,684	7,378,473	963,789	234,038
Swazi	943,989	1,017,233	73,244	45,365
Tswana	1,437,660	3,299,902	1,862,242	463,044
Tsonga	1,450,874	1,757,589	306,715	82,791
Venda	116,533	876,546	760,013	2,296

Notes. The Table shows the total ethnic group population sizes in our sample in 1991 and 1996, together with the overall difference and the difference using only all districts for which information is available in both 1991 and 1996 samples (Sources: Statistics South Africa 1991, 1998).

TABLE 3.2: 1991 CROSS-SECTIONAL ESTIMATION

	Total Number of Non-state Conflict Events 1991				
	(1)	(2)	(3)	(4)	(5)
ELP_{WB}	2.399**	2.464**	2.444**	2.381**	1.888
	(1.07)	(1.09)	(1.10)	(1.10)	(1.17)
Blacks (log)		-0.046	-0.029	-0.257	-0.348
		(0.42)	(0.43)	(0.47)	(0.52)
Population (log)		0.367	0.312	0.518	0.226
		(0.52)	(0.55)	(0.59)	(3.89)
Night-time Lights (log)			0.038	0.018	-0.014
			(0.12)	(0.13)	(0.13)
Rural Population (log)					0.001
					(0.13)
No Education (log)					0.325
					(1.64)
Unemployed (log)					1.203
					(0.74)
Constant	-0.425	-3.973	-3.414	-1.032	0.607
	(0.74)	(3.19)	(3.66)	(4.57)	(5.28)
Province Fixed Effects	Y	Y	Y	Y	Y
Geographic Controls	N	N	N	Y	Y
Other Economic Controls	N	N	N	N	Y
Observations	294	294	294	291	291
R^2	0.180	0.185	0.185	0.199	0.214

Notes. Standard errors in parenthesis. The table reports Ordinary Least Squares coefficients estimates from the 1991 cross-sectional specification. The unit of observation is a MD in South Africa for which information is available in 1991. The dependent variable is the total number of non-state conflict events coded in the MD in 1991 in the UCDP-GED dataset. ELP_{WB} is the district-level within-black polarization measure. Other controls are defined as in the data section (Sources: Statistics South Africa 1991, 1998; Nunn and Puga 2012; IIASA/FAO 2012; NOOA 2012).

TABLE 3.3: FIRST-DIFFERENCE ESTIMATION

	Change in Total No. of Non-state Conflict Events 1991-1996						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔELP_{WB}	5.924***	5.562***	5.178***	5.178*	5.178*	4.758*	4.107***
	(1.59)	(1.63)	(1.66)	(2.96)	(3.04)	(2.79)	(1.41)
Non-state Conf 89-90							-0.273***
							(0.03)
$\overline{\Delta ELP}_{WB\ j}$						7.692	
						(3.58)	
Δ Blacks (log)		-0.276	-0.325	-0.325	-0.325	-0.354	-0.228
		(0.43)	(0.45)	(0.27)	(0.26)	(0.34)	(0.38)
Δ Population (log)		0.019	5.366	5.366	5.366	2.885	-0.796
		(0.75)	(4.80)	(6.70)	(5.10)	(6.34)	(4.11)
Δ Night-time Lights (log)		-0.277	-0.239	-0.239	-0.239	-0.246	-0.129
		(0.16)	(0.16)	(0.25)	(0.29)	(0.25)	(0.13)
Δ Rural Population (log)			-0.682***	-0.682***	-0.682***	-0.677***	-0.378**
			(0.22)	(0.26)	(0.29)	(0.26)	(0.19)
Δ No Education (log)			-1.011	-1.011	-1.011	0.142	0.540
			(1.75)	(1.94)	(1.43)	(1.78)	(1.49)
Δ Unemployed (log)			-0.113	-0.113	-0.113	-0.037	-0.112
			(0.83)	(0.61)	(0.68)	(0.61)	(0.70)
Constant	-1.068***	-0.882***	-3.718*	-3.718**	-3.718*	-3.589**	-1.290
	(0.28)	(0.30)	(1.91)	(1.80)	(1.89)	(1.75)	(1.63)
Other Economic Controls	N	N	Y	Y	Y	Y	Y
Observations	294	294	294	294	294	294	294
R^2	0.045	0.058	0.096	0.096	0.096	0.112	0.354

Notes. Standard errors in parenthesis. The table reports first-difference coefficients estimates. The unit of observation is a MD in South Africa for which information is available in both periods. The dependent variable is the change in total number of non-state conflict events coded in the MD in between 1991 and 1996 in the UCDP-GED dataset. ΔELP_{WB} is the district-level change in within-black polarization measure. $\overline{\Delta ELP}_{WB\ j}$ is the average change in neighboring districts. *Non-state Conf 89-90* is the total number of conflict events coded in the MD in 1989-1990. Other controls are defined as in the data section (Sources: Statistics South Africa 1991, 1998; NOOA 2012). (1), (2), (3) are first-difference estimates assuming homoskedastic difference residuals; those in (4) and (6) are first-difference estimates assuming heteroskedastic difference residuals; in (5) we allow for cross-sectional dependence in the structure of difference residuals (Conley 1999) allowing for non-zero correlation when coordinate distance between districts' centroids is less than 1 degree latitude and/or 1 degree longitude (approximately 110 km). Those in (7) are estimates from the first-difference model augmented with the measure of pre-1991 conflict incidence, assuming homoskedastic difference residuals.

TABLE 3.4: FIRST-DIFFERENCE WITH CLUSTER-SPECIFIC TRENDS

	Change in Total No. of Non-state Conflict Events		
	(1)	(2)	(3)
ΔELP_{WB}	6.08***	6.36***	5.26***
	(1.83)	(1.98)	(1.51)
Other Economic Controls	N	Y	Y
Polynomial of Controls	N	N	Y
Observations	227	227	227
Repetitions	200	200	200

Notes. Empirical standard errors in parenthesis. The table reports coefficients estimates and standard errors from a first-difference specification with cluster-specific trends. A restricted sample of *treated* districts are kept from the initial sample, together with their neighboring *control* districts (see text for details). A bootstrap-type procedure is implemented, where at each repetition every control district is randomly matched to a single treated district and coefficients from the first-difference specification with cluster-specific trends are estimated. The total number of blacks and total population, and night-time satellite light value in logs are used as controls in (1), while all economic controls are included in (2). Specification (3) is augmented with a 3rd order polynomial of controls (Sources: UCDP-GED v1.5; Statistics South Africa 1991, 1998; NOAA 2012).

TABLE 3.5: MIGRATION ACROSS DISTRICT BOUNDARIES

	% of Moves towards Neighboring Districts		
	Districts of Origin	Mean	St. Dev.
Xhosa	266	34.7	33.5
Zulu	229	28.3	30
Sotho	238	33.2	28.3
Swazi	116	29	34.5
Tswana	162	32.7	34.4
Tsonga	128	31.1	32.1
Venda	77	31.9	37.5

Notes. The Table shows separately for each ethnic group the percentage of movers in between 1991 and 1996 which are estimated to relocate in neighboring districts with respect to the one of origin. (Sources: Statistics South Africa 1998).

TABLE 3.6: INSTRUMENTAL VARIABLE ESTIMATION

	(1)	(2)	(3)	(4)
1st Stage	Change in Polarization Measure ΔELP_{WB}			
$\Delta\widetilde{ELP}_{WB}$	0.244***	0.244***	0.249***	0.25***
	(0.06)	(0.06)	(0.06)	(0.06)
F-stat	17.13	17.13	17.60	17.60
robust *F-stat*		14.82		16.07
2nd Stage	Change in Total Number of Non-state Conflict Events			
$\Delta\widehat{ELP}_{WB}$	13.438*	13.438**	12.074*	12.074**
	(7.10)	(5.85)	(6.95)	(5.28)
Δ Blacks (log)	-0.121	-0.121	-0.117	-0.117
	(0.46)	(0.26)	(0.50)	(0.28)
Δ Population (log)	0.361	0.361	2.640	2.640
	(0.83)	(0.76)	(5.54)	(6.15)
Δ Night-time Lights (log)	-0.252	-0.252	-0.243	-0.243
	(0.16)	(0.24)	(0.16)	(0.24)
Constant	-0.969***	-0.969***	-2.822	-2.822
	(0.32)	(0.29)	(2.12)	(1.75)
Economic Controls	N	N	Y	Y
Observations	294	294	294	294

Notes. Standard errors in parenthesis. The table reports first-stage and second-stage instrumental variable estimates of the first-difference baseline model. The unit of observation is a MD in South Africa for which information is available in both periods. The dependent variable is the change in the total number of non-state conflict events coded in the MD in between 1991 and 1996 in the UCDP-GED dataset. ELP_{WB} is the district-level within-black polarization measure. The total number of blacks and total population, and night-time satellite light value in logs are used as controls in both the first and second stage in (1) and (2), while all other economic controls are included in (3) and (4). First-difference residuals are assumed to be homoskedastic in columns (1) and (3), and heteroskedastic in (2) and (4), where Eicker-Huber-White robust standard errors (White 1980) are estimated (Sources: UCDP-GED v1.5; Statistics South Africa 1991, 1998; NOOA 2012).

TABLE 3.7: INSTRUMENTAL VARIABLE FALSIFICATION (I)

Instrument: Within-black Polarization in 1991

	(1)	(2)	(3)	(4)
1st Stage	Change in Polarization Measure ΔELP_{WB}			
$ELP_{1991,WB}$	-0.159***	-0.159***	-0.156***	-0.156***
	(0.03)	(0.03)	(0.03)	(0.03)
F-stat	30.52	30.52	28	28
2nd Stage	Change in Total Number of Non-state Conflict Events			
$\Delta\widehat{ELP}_{WB}$	2.862	2.862	3.461	3.461
	(5.25)	(5.72)	(5.45)	(5.16)
Δ Blacks (log)	-0.329	-0.329	-0.377	-0.377
	(0.44)	(0.22)	(0.47)	(0.30)
Δ Population (log)	-0.098	-0.098	6.045	6.045
	(0.78)	(0.65)	(5.16)	(6.51)
Δ Night-time Lights (log)	-0.286	-0.286	-0.238	-0.238
	(0.16)	(0.27)	(0.16)	(0.25)
Constant	-0.853***	-0.853***	-3.942	-3.942
	(0.30)	(0.25)	(2.00)	(1.87)
Economic Controls	N	N	Y	Y
Observations	294	294	294	294

Notes. Standard errors in parenthesis. The table reports first-stage and second-stage instrumental variable estimates of the first-difference baseline model. The unit of observation is a MD in South Africa for which information is available in both periods. The dependent variable is the change in the total number of non-state conflict events coded in the MD between 1991 and 1996 in the UCDP-GED dataset. ELP_{WB} is the district-level within-black polarization measure. The total number of blacks and total population, and night-time satellite light value in logs are used as controls in both the first and second stage in (1) and (2), while all other economic controls are included in (3) and (4). First-difference residuals are assumed to be homoskedastic in columns (1) and (3), and heteroskedastic in (2) and (4), where Eicker-Huber-White robust standard errors (White, 1980) are estimated (Sources: UCDP-GED v1.5; Statistics South Africa, 1991, 1998; NOOA, 2012).

TABLE 3.8: INSTRUMENTAL VARIABLE FALSIFICATION (II)

Instrument: Average Within-black Polarization in Neighboring Districts in 1991

	(1)	(2)	(3)	(4)
1st Stage	Change in Polarization Measure ΔELP_{WB}			
$\overline{ELP}_{-i\ 1991,WB}$	-0.042	-0.042	-0.034	-0.033
	(0.04)	(0.03)	(0.04)	(0.03)
F-stat	1.21	2.05	0.73	1.35
2nd Stage	Change in Total Number of Non-state Conflict Events			
$\Delta\widehat{ELP}_{WB}$	-18.736	-18.736	-18.581	-18.581
	(33.28)	(28.43)	(42.36)	(36.50)
Δ Blacks (log)	-0.752	-0.752	-1.044	-1.044
	(0.86)	(0.86)	(1.40)	(1.36)
Δ Population (log)	-1.037	-1.037	14.758	14.758
	(1.75)	(1.75)	(17.83)	(16.95)
Δ Night-time Lights (log)	-0.355	-0.355	-0.227	-0.227
	(0.23)	(0.38)	(0.21)	(0.30)
Constant	-0.615	-0.615	-6.806	-6.806
	(0.54)	(0.42)	(6.02)	(5.58)
Economic Controls	N	N	Y	Y
Observations	294	294	294	294

Notes. Standard errors in parenthesis. The table reports first-stage and second-stage instrumental variable estimates of the first-difference baseline model. The unit of observation is a MD in South Africa for which information is available in both periods. The dependent variable is the change in the total number of non-state conflict events coded in the MD between 1991 and 1996 in the UCDP-GED dataset. ELP_{WB} is the district-level within-black polarization measure. The total number of blacks and total population, and night-time satellite light value in logs are used as controls in both the first and second stage in (1) and (2), while all other economic controls are included in (3) and (4). First-difference residuals are assumed to be homoskedastic in columns (1) and (3), and heteroskedastic in (2) and (4), where Eicker-Huber-White robust standard errors (White, 1980) are estimated (Sources: UCDP-GED v1.5; Statistics South Africa, 1991, 1998; NOOA, 2012).

TABLE 3.9: INSTRUMENTAL VARIABLE FALSIFICATION (III)

Instruments: Within-black Polarization in 1991 and
Average Within-black Polarization in Neighboring Districts in 1991

	(1)	(2)	(3)	(4)
1st Stage	Change in Polarization Measure ΔELP_{WB}			
$ELP_{1991,WB}$	-0.324***	-0.324***	-0.316***	-0.316***
	(0.04)	(0.06)	(0.04)	(0.06)
$\overline{ELP}_{-i\ 1991,WB}$	0.270	0.270	0.268	0.269
	(0.05)	(0.07)	(0.05)	(0.07)
F-stat	28.76	15.72	27.03	15.38
2nd Stage	Change in Total Number of Non-state Conflict Events			
$\Delta\widehat{ELP}_{WB}$	6.323	6.323	6.264	6.264
	(3.96)	(5.72)	(4.08)	(5.52)
Δ Blacks (log)	-0.261	-0.261	-0.293	-0.293
	(0.43)	(0.20)	(0.45)	(0.25)
Δ Population (log)	0.052	0.052	4.937	4.937
	(0.76)	(0.63)	(4.95)	(6.41)
Δ Night-time Lights (log)	-0.275	-0.275	-0.240	-0.240
	(0.16)	(0.25)	(0.16)	(0.25)
Constant	-0.891***	-0.891***	-3.577**	-3.577**
	(0.30)	(0.25)	(1.94)	(1.83)
Economic Controls	N	N	Y	Y
Observations	294	294	294	294

Notes. Standard errors in parenthesis. The table reports first-stage and second-stage instrumental variable estimates of the first-difference baseline model. The unit of observation is a MD in South Africa for which information is available in both periods. The dependent variable is the change in the total number of non-state conflict events coded in the MD between 1991 and 1996 in the UCDP-GED dataset. ELP_{WB} is the district-level within-black polarization measure. The total number of blacks and total population, and night-time satellite light value in logs are used as controls in both the first and second stage in (1) and (2), while all other economic controls are included in (3) and (4). First-difference residuals are assumed to be homoskedastic in columns (1) and (3), and heteroskedastic in (2) and (4), where Eicker-Huber-White robust standard errors (White, 1980) are estimated (Sources: UCDP-GED v1.5; Statistics South Africa, 1991, 1998; NOOA, 2012).

TABLE 3.10: INSTRUMENTAL VARIABLE FALSIFICATION (IV)

Dependent Variable: Change in Total Number of Non-state Conflict Events 1989-1991

	(1)	(2)	(3)	(4)
1st Stage	Change in Polarization Measure ΔELP_{WB}			
$\Delta\widetilde{ELP}_{WB}$	0.244***	0.244***	0.249***	0.25***
	(0.06)	(0.06)	(0.06)	(0.06)
F-stat	17.13	17.13	17.60	17.60
2nd Stage	Change in Total Number of Non-state Conflict Events 1989-1991			
$\Delta\widehat{ELP}_{WB}$	-3.982	-4.506	-4.080	-4.080
	(6.12)	(4.54)	(4.96)	(3.84)
Δ Blacks (log)	0.202	0.191	0.273	0.273
	(0.40)	(0.21)	(0.43)	(0.25)
Δ Population (log)	0.026	0.003	-2.223	-2.223
	(0.71)	(0.89)	(4.69)	(4.73)
Δ Night-time Lights (log)	0.046	0.044	0.032	0.032
	(0.14)	(0.26)	(0.14)	(0.26)
Constant	0.100	0.106	0.671	0.671
	(0.27)	(0.17)	(1.82)	(1.86)
Economic Controls	N	N	Y	Y
Observations	294	294	294	294

Notes. Standard errors in parenthesis. The table reports first-stage and second-stage instrumental variable estimates of the first-difference baseline model. The unit of observation is a MD in South Africa for which information is available in both periods. The dependent variable is the change in the total number of non-state conflict events coded in the MD between 1989 and 1991 in the UCDP-GED dataset. ΔELP_{WB} is the district-level change in within-black polarization measure between 1991 and 1996. The total number of blacks and total population, and night-time satellite light value in logs are used as controls in both the first and second stage in (1) and (2), while all other economic controls are included in (3) and (4). First-difference residuals are assumed to be homoskedastic in columns (1) and (3), and heteroskedastic in (2) and (4), where Eicker-Huber-White robust standard errors (White, 1980) are estimated (Sources: UCDP-GED v1.5; Statistics South Africa, 1991, 1998; NOOA, 2012).

FIGURE 3.1: CONFLICT AND MIGRATION IN CONTEMPORARY SOUTH AFRICA

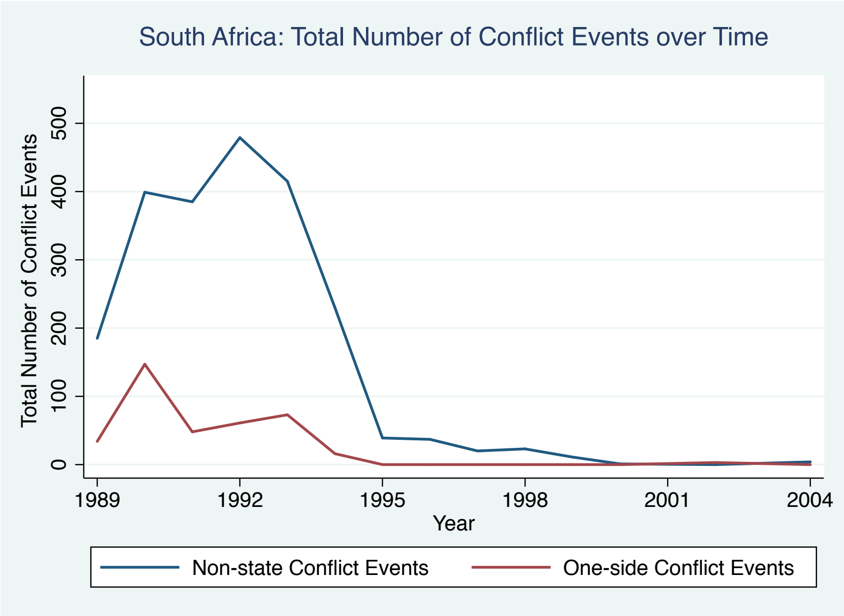


Figure 1a. The figure plots the total number of conflict events in South Africa from 1989 to 2004. Non-state conflict events refer to struggles between black-dominated groups, while one-side conflict events are those in which the Government is involved. The data are described in details in the Data section (Source: UCDP-GED).

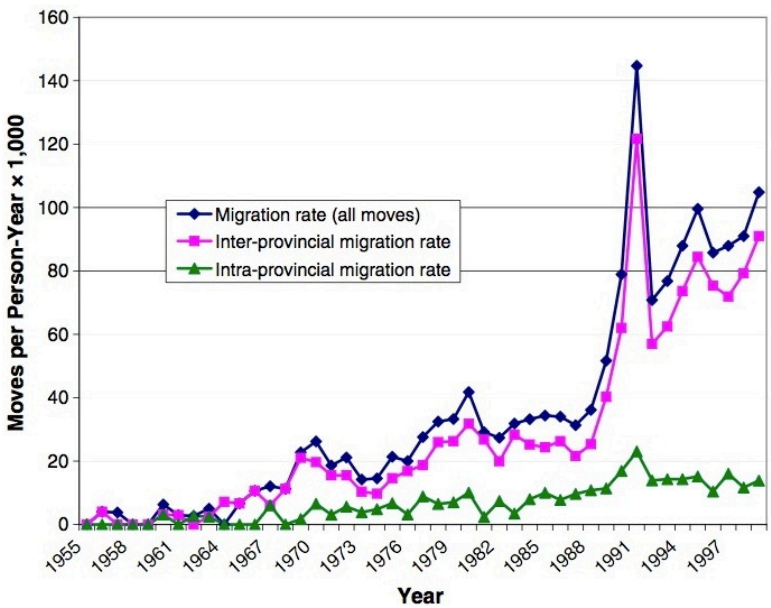
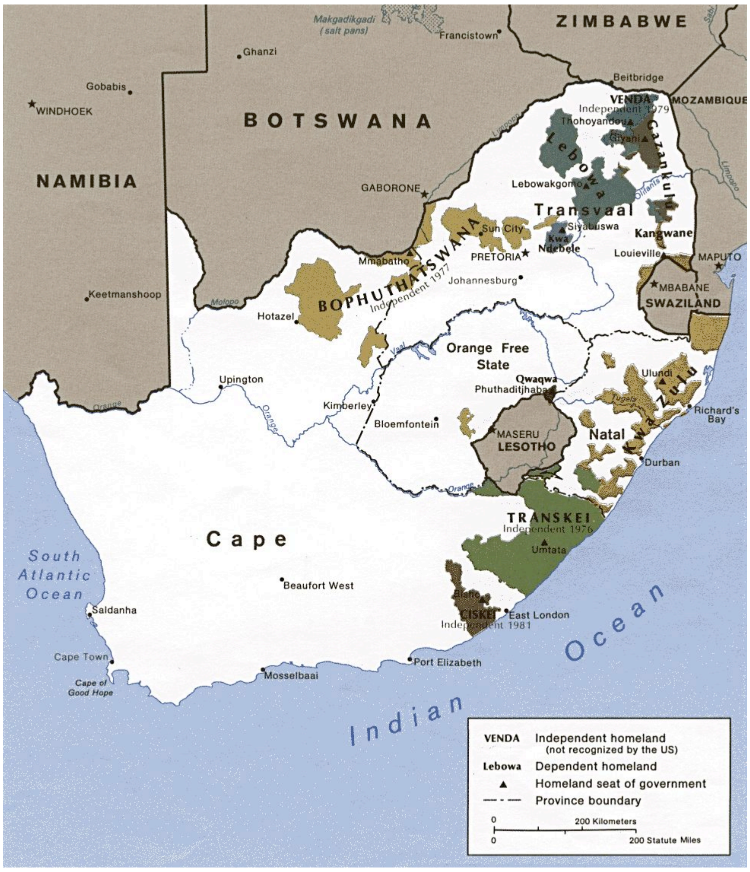


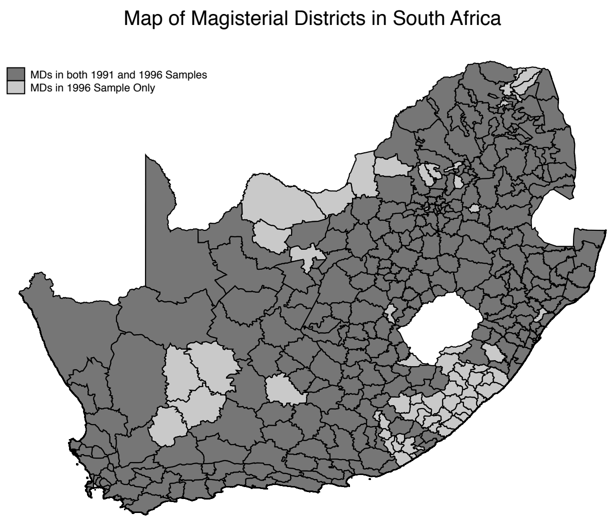
Figure 1b. The figure plots the migration rates in South Africa from 1955 to 1999. Source: South Africa Migration and Health Survey (SAMHS), Reed 2013.

FIGURE 3.2: MAP OF BANTUSTANS



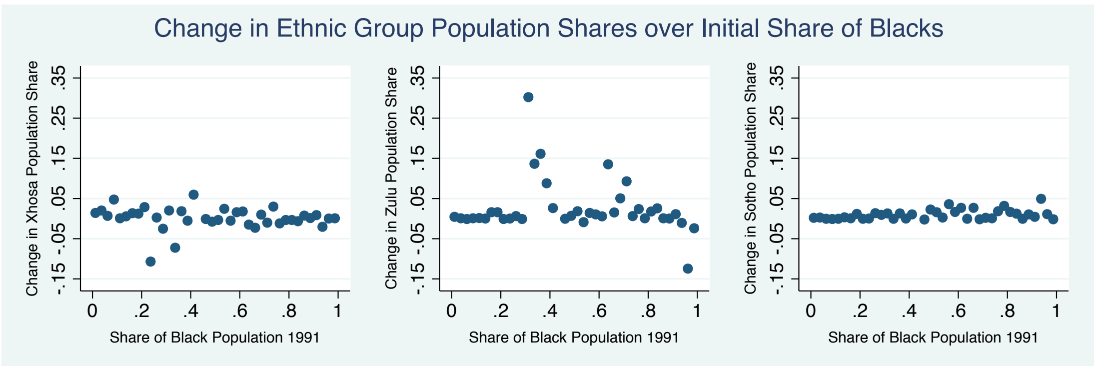
Notes. Map of Bantustans in South Africa as of 1986 (produced by the U.S. CIA. Source: University of Texas at Austin 1986).

Figure 3.3: Map of Magisterial Districts in South Africa



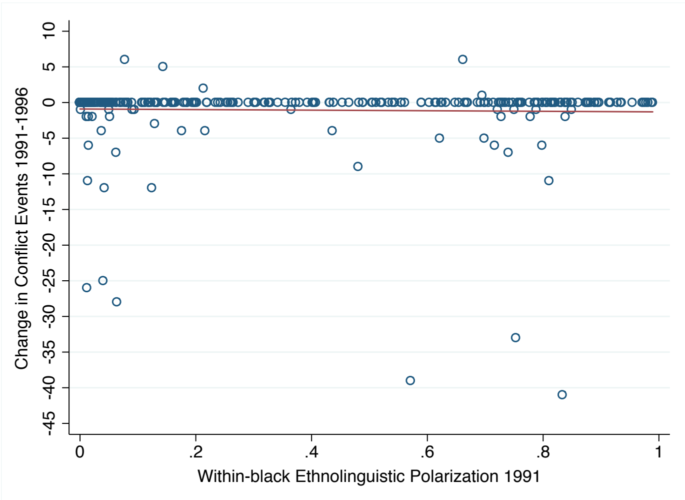
Notes. Map of Magisterial Districts in South Africa, indicating in dark grey those we for which information can be retreived from both the 1991 and 1996 Census (Statistics South Africa 1991, 1998). Those Bantustans which were already granted independence are not covered by the 1991 Census of the Republic of South Africa (Source: authors' elaboration using Stata).

Figure 3.4: Ethnic Group Populations per District: Changes 1991-1996



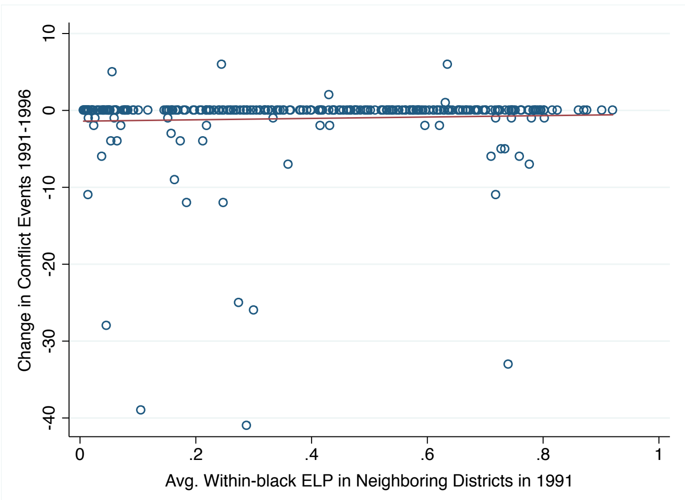
Notes. The figure shows the change in population share of each ethnolinguistic group at the district level plotted over the initial share of blacks. Observations are districts for which we are able to retrieve information consistently from both 1991 and 1996 Census (Source: Statistics South Africa 1991, 1998). This excludes districts in the apartheid homelands which were granted independence and were no longer part of the Republic of South Africa. Observations are averaged per bins of share of blacks of size 2.5%.

FIGURE 3.5: CHANGE IN CONFLICT AND INITIAL POLARIZATION



The figure plots the change in the total number of non-state conflict events between 1991 and 1996 over the levels of within-black ethnolinguistic polarization in the same district in 1991 (Source: UCDP-GED; Statistics South Africa 1991, 1998).

FIGURE 3.6: CHANGE IN CONFLICT AND INITIAL POLARIZATION IN NEIGHBORING DISTRICTS



The figure plots the change in the total number of non-state conflict events between 1991 and 1996 over the average levels of within-black ethnolinguistic polarization in neighboring district in 1991 (Source: UCDP-GED; Statistics South Africa 1991, 1998).

3.6 Appendix

TABLE 3.A.1: ONE-SIDED AND NON-STATE CONFLICT EVENTS: 1989-1998

	Gov. Repression		Non-state Conflicts	
Year	Conflict Events	Est. Deaths	Conflict Events	Est. Deaths
1989	34	54	185	226
1990	147	195	399	1243
1991	48	49	385	657
1992	61	61	479	665
1993	73	67	415	643
1994	16	14	230	444
1995	0	0	39	143
1996	0	0	37	156
1997	0	0	20	30
1998	0	0	23	44
1999	0	0	11	19
2000	0	0	1	0
2002	3	2	0	0
2004	0	0	4	0
2010	1	1	0	0

Notes. The Table shows the total number of One-sided and Non-state conflict events per year in South Africa recorded in the geo-referenced Event Dataset of the Uppsala Conflict Data Program (UCDP-GED v1.5) which we are able to map into MDs, together with the estimated total number of deaths.

TABLE 3.A.2: SUMMARY STATISTICS

PANEL A: YEAR 1991

Variable	Mean	St. Dev.	Min	Max	N
Non-state Conflict Events	1.271	5.192	0	41	303
ELP_{WB}	0.368	0.336	0	0.989	296
Blacks	72.418	110.795	0	972.838	299
Population	103.67	156.61	3.04	1546.067	299
Rural Population	44.876	76.325	0	419.321	299
No Education	29.879	37.919	1.136	253.145	299
Unemployed	7.194	15.502	0.034	189.362	299
Night-time Lights	4.133	12.79	0	63	354
Accessibility	2.04	0.762	1	4	351
Ruggedness	2.249	1.448	0.237	6.538	354
Slope Index	73.009	22.623	13	99	351

PANEL B: YEAR 1996

Variable	Mean	St. Dev.	Min	Max	N
Non-state Conflict Events	0.105	0.692	0	6	354
ELP_{WB}	0.34	0.332	0	0.997	350
Blacks	87.97	109.609	0	896.042	354
Population	114.63	139.528	3.557	902.861	354
Rural Population	53.123	73.148	0	404.352	354
No Education	21.674	23.123	0.929	137.231	354
Unemployed	13.403	20.166	0.214	189.748	354
Night-time Lights	4.816	13.26	0	63	354

PANEL C: DIFFERENCE 1991-1996

Variable	Mean	St. Dev.	Min	Max	N
Non-state Conflict Events	-1.044	4.9	-41	6	298
ELP_{WB}	0.002	0.177	-0.889	0.997	294
Blacks	3.541	69.902	-665.71	338.236	298
Population	2.752	78.429	-788.692	347.736	298
Rural Population	-2.697	40.793	-224.642	175.135	298
No Education	-10.822	23.11	-195.972	52.845	298
Unemployed	4.695	12.893	-118.249	78.861	298
Night-time Lights	0.785	3.15	-15	29	298

Notes. Data for Blacks, Population, Rural Population, No Education, Unemployed, Not Economically Active and Citizens of South Africa are in thousands. All variables are discussed in Section 3 (Sources: UCDP-GED v1.5, Statistics South Africa 1991, 1998; Nunn and Puga 2012; IIASA/FAO 2012; NOOA 2012).

TABLE 3.A.3: FIRST-DIFFERENCE ESTIMATION: WITHIN-BLACH GROUP SHARES AS CONTROLS

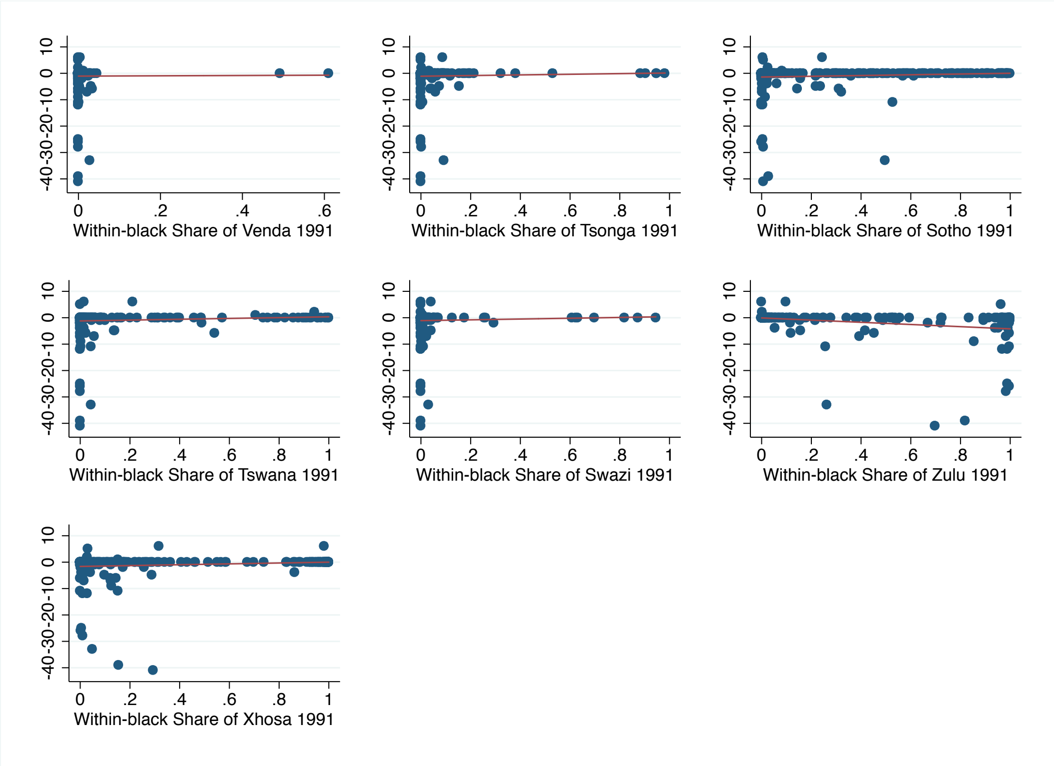
	Change in Total No. of Non-state Conflict Events 1991-1996						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔELP_{WB}	6.499***	4.961***	5.403***	5.362***	5.174***	5.215***	5.234***
	(1.68)	(1.64)	(1.78)	(1.68)	(1.66)	(1.68)	(1.66)
Δ Sh. Xhosa$_{WB}$	10.865***						
	(3.40)						
Δ Sh. Zulu$_{WB}$		-13.569***					
		(4.31)					
Δ Sh. Sotho$_{WB}$			-1.503				
			(4.22)				
Δ Sh. Swazi$_{WB}$				-7.346			
				(9.80)			
Δ Sh. Tswana$_{WB}$					-1.648		
					(4.64)		
Δ Sh. Tsonga$_{WB}$						1.114	
						(7.38)	
Δ Sh. Venda$_{WB}$							32.563
							(46.68)
Δ Blacks (log)	-1.299**	-0.323	-0.441	-0.342	-0.342	-0.325	-0.328
	(0.54)	(0.44)	(0.55)	(0.45)	(0.45)	(0.45)	(0.45)
Δ Population (log)	4.485	5.612	5.312	5.213	5.265	5.347	5.301
	(4.73)	(4.73)	(4.81)	(4.81)	(4.82)	(4.81)	(4.81)
Δ Night-time Lights (log)	-0.240	-0.229	-0.242	-0.237	-0.237	-0.239	-0.242
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
Δ Rural Population (log)	-0.682***	-0.704***	-0.684***	-0.681***	-0.679***	-0.683***	-0.685***
	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
Δ No Education (log)	-1.267	-1.285	-1.018	-0.937	-1.037	-1.022	-0.904
	(1.73)	(1.73)	(1.76)	(1.76)	(1.76)	(1.76)	(1.76)
Δ Unemployed (log)	0.077	0.056	-0.090	-0.165	-0.120	-0.114	-0.111
	(0.82)	(0.82)	(0.83)	(0.83)	(0.83)	(0.83)	(0.83)
Constant	-3.314*	-4.042**	-3.631*	-3.696*	-3.731*	-3.722*	-3.839**
	(1.88)	(1.88)	(1.93)	(1.91)	(1.91)	(1.91)	(1.92)
Other Economic Controls	Y	Y	Y	Y	Y	Y	Y
Observations	294	294	294	294	294	294	294
R^2	0.127	0.126	0.096	0.098	0.096	0.096	0.097

Notes. Standard errors in parenthesis. The table reports first-difference coefficients estimates. The unit of observation is a MD in South Africa for which information is available in both periods. The dependent variable is the change in total number of non-state conflict events coded in the MD in between 1991 and 1996 in the UCDP-GED dataset. ΔELP_{WB} is the district-level change in within-black polarization measure. For each black ethnolinguistic group, ΔSh. *Group*$_{WB}$ is the change in the within-black share of that group. Other controls are defined as in the data section (Sources: Statistics South Africa 1991, 1998; NOOA 2012). All estimates are derived assuming homoskedastic difference residuals.

FIGURE 3.A.1: ETHNIC GROUP POPULATIONS PER DISTRICT: CHANGES 1991-1996

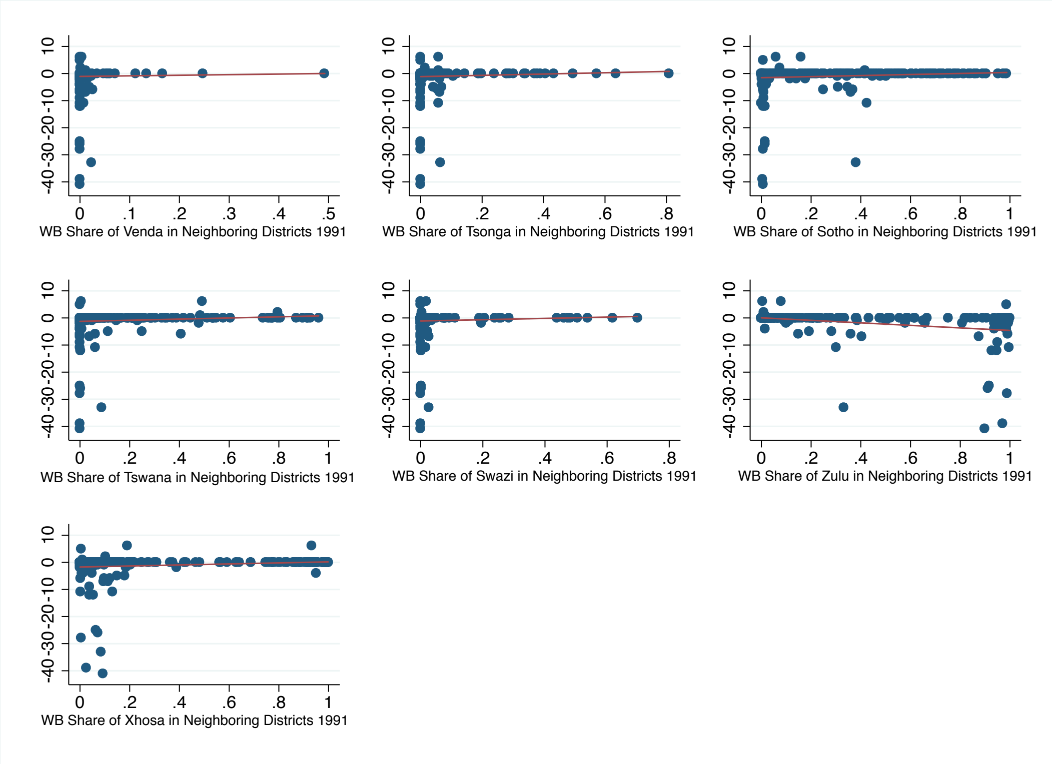
Notes. The top graphs in the figure show the change in population share of each of the three biggest ethnolinguistic groups at the district level plotted over the initial share of each group. The bottom graphs plot instead the changes for the two biggest groups, Xhosa and Zulu, over the population share of the other in 1991. Observations are districts for which we are able to retrieve information consistently from both 1991 and 1996 Census (Source: Statistics South Africa 1991, 1998). This excludes districts in the apartheid homelands which were granted independence and were no longer part of the Republic of South Africa. Observations are averaged per bins of share of blacks of size 2.5%. Taking these figures and Figure 4 together, a few patterns emerge. Districts where the population share of the Zulu ethnolinguistic group grew the most between 1991 and 1996 are those were both the Zulu population share and the share of blacks in 1991 were large but not close to one. According to the bottom graphs, the Xhosa population share was very low in 1991 in these same districts. The Zulu group population seems thus to increase more than proportionally in those districts with a relevant presence of non-black population, and where the Zulu themselves were already a large share of the population. Similarly, looking at changes in the Xhosa population shares, these seem to be disproportionally more positive in those districts where the Zulu group population share was low in 1991, and more negative otherwise. Again, the most important changes in absolute terms seem to be observed where non-black population shares were positive in 1991.

FIGURE 3.A.2: CHANGE IN CONFLICT AND INITIAL WITHIN-BLACK SHARES



The figure plots the change in the total number of non-state conflict events between 1991 and 1996 over the within-black share of each ethnolinguistic group in 1991 (Source: UCDP-GED; Statistics South Africa 1991, 1998).

FIGURE 3.A.3: CHANGE IN CONFLICT AND INITIAL WITHIN-BLACK SHARES IN NEIGHBORING DISTRICTS



The figure plots the change in the total number of non-state conflict events between 1991 and 1996 over the average within-black share of each ethnolinguistic group in neighboring districts in 1991 (Source: UCDP-GED; Statistics South Africa 1991, 1998).

Chapter 4

CRIME PROTECTION INVESTMENT SPILLOVERS: THEORY AND EVIDENCE FROM THE CITY OF BUENOS AIRES

4.1 Introduction

Crime rates exhibit high variation over time and space. Economic and social characteristics only account for a small fraction of such variation. Starting with Glaeser et al. (1996), several contributions have focused on social interactions among criminals as the unobserved source of the variability documented in the data (Zenou 2003). Indeed, when the individual decision to become a criminal positively depends on the criminal choice of others, multiple equilibria arise. As a result, crime rates may be highly heterogeneous across otherwise identical locations. Following these insights, a number of recent studies have investigated the extent to which the criminal choices of individuals positively relate to each other (Ballester et al. 2010; Patacchini and Zenou 2012; Liu et al. 2012; Damm and Dustmann 2014).

Nonetheless, the choices of potential victims are likely to be equally interdependent. In particular, individuals undertake investment in protection technologies in order to decrease their victimization probabilities. To the extent to which these choices are positively correlated, spillovers on the side of potential victims can potentially be as important as social interactions mechanisms on the side of criminals in generating multiple equilibria and thus explaining the high spatial and time variability of crime rates. Furthermore, when investment decisions are decentralized, the extent to which externalities are internalized determines the scope for government intervention. Questioning the size and sign of externalities in this context is thus crucial for the design and implementation of successful policies aimed to maximize the total welfare of potential victims.

The purpose of this chapter is to theoretically explore and empirically identify spillovers among potential victims from investment in observable property crime protection technologies. The size and sign of spillovers of this origin is undetermined a priori. Given the stock of active criminals, when protection devices are observable, investors exert a negative externality on non-investors as criminal activity is diverted towards unprotected targets (Clotfelter 1978; Cook 1986; Cook and MacDonald 2011; Vollaard and van Ours 2011; Gonzalez-Navarro 2013; van Ours and Vollaard 2014). However, the higher the number of protected individuals, the lower is the probability for an active criminal of successfully committing an offense. Following the decrease in expected returns from criminal activity, the crime supply side may respond accordingly, leading to a reduction of criminals which generates a positive externality on non-investors (Shavell 1991; Ayres and Levitt 1998).[1]

I develop these arguments in a novel theoretical framework. The model builds upon Ehrlich (1996, 2010) in the formalization of the market for offenses. Similarly to frictional labor market models, a *victimization function* captures likely deviations from the perfectly competitive set-up, and governs the matching between active criminals and potential victims. Spillovers within the victim side of the market arise as trading externalities, and their sign and size depend on the responsiveness of equilibrium victimization probabilities to overall protection investment.

I take these issues to the data by focusing on burglary protection technologies, and using originally collected data from the City of Buenos Aires. Geo-referenced household-level data allow to explore the extent to which neighbors' choices concerning investment in protection relate to each other. Answers to specifically targeted questions in the survey allow to consider investment in private security, special door locks, bars,

[1]When protection devices are unobservable, positive externalities are likely to prevail, as shown by Ayres and Levitt (1998) in their study of Lojack.

armor plating, alarms, CCTV cameras, outdoor lighting and staying at home not to leave the house alone.

As a preliminary result, I find both burglary victimization rates and protection investment levels to vary substantially within the City area, with the two being unconditionally positively correlated. More importantly, I find evidence of significant spatial clustering of observable burglary protection technologies. Looking at the degree of analogy between the protection investment schedule of neighbors, I find that close neighbors are significantly more likely to implement the same investment schedule with respect to neighbors located farther apart. Such positive correlation between close neighbors' protection investment decisions is attributable to negative spillovers from protection investment, which increase the victimization probabilities of unprotected individuals and thus their likelihood to invest in protection themselves. Nonetheless, both sorting of individuals with the same propensity to invest in protection and differences in idiosyncratic location characteristics at the within-neighborhood level may confound the results.

In the second part of the empirical analysis, I tackle the causal question explicitly and ask whether neighbors' investment in protection has any impact on household's investment decisions. In order to achieve identification, I exploit within-neighborhood variation in close neighbors' investment status as induced by their knowledge of crimes occurred sufficiently far from their house. Information about others' victimization experiences can be framed as a shock to the agent's information set, leading to beliefs update and changes in her optimal protection investment decisions. Indeed, information about any crime episode involving friends, relatives, acquaintances or others is shown to be strongly and positively correlated with individual household's protection investment.

Variation in the neighbors' reported information about crimes occurred sufficiently far away can be used as a source of exogenous variation for neighbors' investment status under a set of relatively weak and partially testable assumptions. In particular, once the individual household's reported information is controlled for, neighbors' knowledge of any crime episode is assumed to be as good as randomly assigned, and to have no direct effect on individual household's investment decisions. In this respect, I investigate the potential confounding effects of information sharing and overlapping peer groups among neighbors, and further take them into account by controlling for the household's reported information and beliefs. Hence, only residual variability in neighbors' information is used for identification. The proposed strategy shares the same framework of some recent advances in the empirical network literature on peer effects, which exploit the variation within higher-order links as a source of exogenous variation for behavior of first-order links in order to achieve identification (Bramoullé et al. 2009; Calvó-Armengol et al. 2009; De Giorgi et al. 2010; Blume et al. 2011).

I find that the protection investment of neighbors significantly affects household's investment decisions. Instrumenting neighbors' investment status with a dummy capturing whether they report information about any crime involving friends, relatives, acquaintances and others occurred at least 20 blocks away, I find neighbors' investment in cameras and alarms to positively and significantly affect the likelihood of a given household to invest in the same protection technology. The decision of one neighbor to install monitored alarms is found to significantly increase the probability of a given household of doing the same by around 20 percentage points. The same effect is about 10 percentage points for CCTV cameras, while no effect is found for special door locks, bars, outdoor lighting and the cumulate protection investment score. In particular, further investigation reveals that the relationship between neighbors' cumulate protection and own investment appears to be non-linear. Neighbors' cumulate investment is positively correlated with own investment when the former is lower, but the opposite holds for higher values of average cumulate neighbors' protection investment. The weakness of the corresponding first stage prevents instead from identifying the effect for other protection technologies such as private security guards, armor plating and unmonitored alarms.

In light of the theoretical argument formalized in the model, evidence is in favor of the hypothesis that protection investment of neighbors brings about negative externalities as it increases the victimization probabilities of unprotected individuals, thus raising the scope for protection. Neighbors' investment in protection thus causally increases the protection investment levels of a given household. This indirectly suggests that the supply of burglary is relatively inelastic to the fraction of protected individuals, or perceived to be so by potential victims.

This chapter contributes to the existing literature on the economics of crime along several dimensions. First, I provide a novel theoretical framework which builds upon and puts together the insights from several existing studies. In doing this, I disclose the potential from introducing elements of friction in the classical model of the market for offenses, possibly opening the way to further studies investigating the origin and consequences of these frictions. Second, to the best of my knowledge and differently from standard victimization surveys, the data collected for this project are the first to provide extensive information on household burglary protection investment. When combined with geo-referenced information on household location, these allow to answer an entirely new set of research questions. Indeed, the results from the empirical analysis highlight the relevance of externalities among potential crime victims in their belief updating process and protection investment decisions. I thus regard this study as complementary to those exploring social interaction mechanisms among criminals, enhancing our knowledge of crime and its determinants.

The rest of the chapter is organized as follows. The theoretical model is presented in Section 4.2. Section 4.3 introduces the setting and shows the first set of empirical results. The effect of neighbors' investment on own investment decisions is investigated in Section 4.4. Section 4.5 concludes.

4.2 Crime and Protection in a Frictional Market Model

The salience of spillovers from investment in observable property crime protection technologies can be better assessed through the lenses of a theoretical model of frictional market for offenses. As in Ehrlich (1996, 2010), observed crime rates can be rationalized in a market context as equilibrium results. The supply side of this market is shaped by the choice of criminals, who decide whether or not to become active through balancing the benefits and costs of engaging in criminal activities (Becker 1968). The demand for crime is instead determined by the decision of potential victims, who choose whether or not to invest in protection in face of its cost and their victimization probabilities.

In this framework, a crime event is nothing but a trading episode. Nonetheless, this market is supposedly far from being considered as perfectly competitive. Unobserved heterogeneity, frictions, information imperfections are likely to be increasing the cost of trading. As for frictional labor market models (Pissarides 2000), it is possible to capture such features altogether through the definition of a Constant-Returns-to-Scale (CRS) *victimization function*

$$v(\gamma, \lambda) = \gamma^{\mu}\lambda^{1-\mu} \tag{4.1}$$

with $\mu \in (0, 1)$, where λ is the number of unprotected individuals as a fraction of the population of potential victims, and γ is the normalized fraction of active criminals.[2] For simplicity, the protection investment decision is thought of as a binary choice. The victimization function plays the same role of the matching function in frictional labor market models. It returns the total number of matches using as inputs the number of active criminals and the number of unprotected individuals: trading and thus crime occurs whenever one match is realized. Market frictions prevent trading opportunities from being cleared with probability one. Whenever one active criminal more and one unprotected potential victim more appear in this market, the probability for them to match and thus for a crime to occur is strictly lower than one.

Individual victimization and matching probabilities can be defined accordingly. The individual probability for an unprotected potential victim to match with an active criminal and thus be victimized is given by

$$q(\gamma, \lambda) = \frac{\gamma^{\mu}\lambda^{1-\mu}}{\lambda} = \left(\frac{\gamma}{\lambda}\right)^{\mu} \tag{4.2}$$

By the same token, the individual probability for an active criminal to match with an unprotected potential victim is given by

$$h(\gamma, \lambda) = \frac{\gamma^{\mu}\lambda^{1-\mu}}{\gamma} = \left(\frac{\lambda}{\gamma}\right)^{1-\mu} \tag{4.3}$$

Market tightness shapes individual victimization probabilities as frictions are responsible for the generation of trading externalities. The decision of each agent is thus not independent from the choice of others. Consider first the protection decision of potential victims. A population of agents of mass one makes a binary investment choice. Each agent chooses $a_i \in \{0, 1\}$, where $a_i = 1$ if the observable protection investment is undertaken, and zero otherwise. Agent i maximizes her payoff function

$$u_i = a_i(w - K) + (1 - a_i)\{q(\gamma, \lambda)[w - L_i] + [1 - q(\gamma, \lambda)]w\} \tag{4.4}$$

where w is individual wealth, K is the cost of protection investment and L_i is the individual loss from victimization. If the agent invests in protection, she keeps all her

[2] The fraction of active criminals is normalized as a fraction of population of potential victims, whose mass is equal to one.

wealth with probability one, but needs to pay the investment cost. If no protection investment is undertaken, with probability $q(\gamma, \lambda)$ the agent is victimized and suffers the corresponding loss. Otherwise, she keeps her entire wealth at no cost. Heterogeneity on this side of the market is shaped through the differences in the losses L_i from victimization, distributed according to a cumulative distribution function $H(\cdot)$. It follows that the agent decides to invest in protection ($a_i = 1$) if the expected loss exceeds the cost of the investment, meaning

$$\left(\frac{\gamma}{\lambda}\right)^{\mu} L_i \geq K \tag{4.5}$$

Notice that, given the stock of active criminals γ, a higher fraction of protected individuals (smaller λ) increases the likelihood of each agent to invest in protection. This is because observable protection by some potential victims diverts criminals' attention towards the rest of unprotected individuals.[3] Following Shavell (1991), this can be labeled as the *diversion effect* of individual protection investment. Given the above equation and knowing the distribution of L_i, it is possible to identify the agent who is indifferent between investing or not, and define the equilibrium fraction of unprotected individuals λ^* implicitly as

$$\lambda^* = H\left[K\left(\frac{\lambda^*}{\gamma}\right)^{\mu}\right] \tag{4.6}$$

It is worth noticing that the equilibrium fraction of unprotected individuals diminishes with the stock of active criminals γ and increases with the protection investment cost as captured by K.

At the same time, agents from an exogenously given population of potential criminals decide whether or not to become active as captured by a binary choice variable $g_j \in \{0, 1\}$.[4] Each agent j maximizes

$$w_j = g_j\left[h(\gamma, \lambda)(\hat{L} - R)\right] + (1 - g_j)r_j \tag{4.7}$$

where $\hat{L}$ are expected gains from property crime as equal to the expected loss of unpro-

[3]The problem of a social planner willing to maximize the sum of payoffs of potential victims and the resulting equilibrium solution are developed in Appendix A Section 1.

[4]The existence an of exogenously given population of potential criminals can be rationalized as in Di Tella et al. (2010) by the presence of labor market frictions which prevents individuals with an earning potential lower than a given threshold to enter the labor market. These same individuals consider to become criminals in order to avoid starvation.

tected potential victims, meaning $\hat{L} = \mathbb{E}(L_i|a_i = 0)$. R is the payoff value of the cost of crime, meaning the probability of getting caught times the corresponding loss. r_j captures instead the payoff value of a given outside option, possibly also capturing ethic considerations. Heterogeneity is in this case shaped through such outside option value r_j, which is modeled as distributed according to a cumulative distribution function $G(\cdot)$. Similarly to potential victims, criminals decide to become active ($g_j = 1$) whenever

$$\left(\frac{\lambda}{\gamma}\right)^{1-\mu} (\hat{L} - R) \geq r_j \tag{4.8}$$

so that, given the fraction of unprotected individuals, the equilibrium fraction of active criminals can be defined implicitly by

$$\gamma^* = G\left[\left(\frac{\lambda}{\gamma^*}\right)^{1-\mu} (\hat{L} - R)\right] \tag{4.9}$$

Notice that the equilibrium fraction of active criminals increases with the expected gains from crime $\hat{L}$ and diminishes with its cost as captured by R. More importantly, it diminishes when the fraction of unprotected individuals λ is lower, provided that changes $\hat{L}$ are small enough. In other words, investment in protection has a *deterrence effect*, which reduces the profitability for criminals to become active (Shavell 1991).

The two equilibrium equations are determined simultaneously in the definition of the overall model equilibrium as

$$\begin{aligned} \lambda^* &= H\left[K\left(\frac{\lambda^*}{\gamma^*}\right)^{\mu}\right] \\ \gamma^* &= G\left[\left(\frac{\lambda^*}{\gamma^*}\right)^{1-\mu} (\hat{L} - R)\right] \end{aligned} \tag{4.10}$$

An equilibrium always exists in this setting.[5] The simultaneous determination of λ^* and γ^* carries with it the non-trivial interaction between the diversion and deterrence effect of investment in observable protection technologies. Given the stock of

[5]Notice that the above define a continuous mapping from a convex compact subset of the euclidean space $\mathbb{R}^2$ to itself, $f : [0, 1]^2 \to [0, 1]^2$. A fixed point exists by Brouwer fixed point theorem.

active criminals, when a given agent decides to invest in protection, the victimization probabilities of other unprotected individuals increase because of the diversion effect. However, the same investment choice also diminishes the returns from criminal activities, and thus the fraction of active criminals in virtue of the deterrence effect. These two effects jointly determine the change in victimization probabilities of other potential victims, and their likelihood to invest in protection themselves as captured by equation (5).[6] If the equilibrium fraction of active criminals was highly elastic to the fraction of unprotected individuals, the deterrence effect would be prevalent. Investment by some potential victims would wipe out criminals and decrease victimization probabilities of other unprotected individuals, diminishing the likelihood to invest in protection themselves. In this case, investment in observable protection technologies would have positive spillovers. The opposite would hold if the equilibrium fraction of active criminals was relatively stable and inelastic to the fraction of unprotected individuals. The diversion effect would prevail in this case, with investment by some potential victims increasing the victimization probabilities of other unprotected individuals. The likelihood of the latter to invest in protection themselves would increase accordingly.

4.3 Burglary in the City of Buenos Aires

Results from the previous section suggest the sign and size of spillover effects among potential victims from investment in observable crime protection technologies not to be uniquely identified by theory. The question of interest is thus investigated empirically using household-level data from the City of Buenos Aires. I focus on one specific crime category, *burglary*, defined by the illegal entry into a building for the purposes of committing an offense. The analysis aims at providing evidence of a systematic relationship between burglary protection investment of neighbors, with the final goal of testing the hypothesis of non-zero spillover effects.

The City of Buenos Aires (*Capital Federal*) counts approximately 3 millions inhabitants and 1.4 million dwellings.[7] The household-level data for the analysis belong to an original survey designed and administered in the fall of 2013 in collaboration with the Research Lab on Crime, Institutions and Policies (LICIP) at Universidad Torcuato

[6]The formal theoretical argument is developed in Appendix A Section 2.

[7]2010 Argentina Census (INDEC)

Di Tella. The main body of the questionnaire is based on a previously designed survey (*Encuesta Larga*) administered by LICIP in 8 waves between 2006 and 2010. The final sample counts 1192 interviewed households. I geo-referenced the data and located each of the interviewed households in the Buenos Aires City map. Figure 4.1 shows the City map together with the location of interviewed households as indicated by the green dots. The thick shaded lines coincide with the administrative boundaries of the 48 neighborhoods in the City.

Interviewed household members are asked a number of questions concerning their victimization experiences. In particular, 144 out of the 1192 households (12.1%) report to have suffered from burglary or burglary attempt in the 5 years before the interview. Furthermore, the survey was specifically designed in order to draw extensive information about the household's burglary protection investment behavior. In particular, households are asked whether they hire private security, have any special door locks, bars, armor plating, monitored and non-monitored alarms, CCTV cameras or outdoor lighting installed and whether any household member permanently stays at home not to leave the house alone. Nine investment dummy variables taking value one when the specific investment is undertaken can be defined accordingly. Moreover, in order to capture the household's cumulate protection investment, I define a *protection investment score* taking integer values from 0 to 9 and equal to the sum of the previously defined dummies. The percentages of interviewed households undertaking each investment is shown in Table 4.1, together with the summary statistics for all the variables used in the empirical analysis.

Using the same data, Figure 4.2 plots the burglary victimization rates and average protection investment scores per *Comuna* in the City. The *Comunas* are the basic units of decentralized political and administrative management below the City level, each one corresponding to one or more administrative neighborhoods. Each *comuna* is colored according to the quintile it belongs to in the distribution of the corresponding variable. Substantial variability in both burglary victimization rates and average protection investment scores is observed across *comunas* within the City area. Moreover, the two variables appear to be correlated. Figure 4.3 plots one against the other. Fitting a linear relationship between the two, the *p-value* of the corresponding coefficient estimate turns out to be equal to 0.044. In what follows, I will investigate whether and how spillovers among potential victims are at least partially responsible for the spatial variability of protection investment within the City.

4.3.1 Spatial Clustering

Are close neighbors significantly more or less likely to implement the same burglary protection investment schedule? Is there any evidence of spatial clustering of observable protection investment in the City of Buenos Aires? In a framework similar to Bayer et al. (2008) in their exploration of labor market referrals, I consider all pairs of households located in the same administrative neighborhood. I then ask whether households located close enough have a systematically more similar burglary protection investment schedule with respect to households living in the same neighborhood but farther apart. The validity of this approach rests on the use of the set of household pairs living in the same neighborhood but farther apart as comparison group for immediate neighboring household pairs. It follows that results can thus be ascribed to spillover effects only to the extent to which sorting of individuals with the same propensity to implement a given protection investment schedule does not occur within the neighborhood boundaries. Also, idiosyncratic location characteristics at the within-neighborhood level could still be driving a spurious correlation between the investment schedules of close neighbors. Both issues will be addressed later in the chapter, in the search of direct evidence of non-zero spillover effects.

A grid of cells of 450m edge is superimposed over the Buenos Aires City map. Figure 4.4 shows a detail of the Buenos Aires City map around the *Recoleta* neighborhood, together with households' location and the superimposed cell grid. The final sample is composed by all pairs of household located in the same neighborhood. Households located within the same cell are labeled as *close neighbors*.[8]

Starting from the nine burglary protection investment dummy variables defined above,

[8]The choice of a specific edge size is motivated as follows. Given the sample of all household pairs living in the same neighborhood, increasing the cell size automatically increases the number of household pairs defined as close neighbors, which can be thought of as treated units. This decreases the minimum detectable effect for a given power, sample size and significance level (Duflo et al. 2008). By the same token, the assumption of absence of sorting within neighborhood and across cells is less likely to hold as cell size increases. I thus chose the edge size so to let the within-neighborhood average number of blocks per cell be at most 10% of the total number of blocks in the neighborhood. At the resulting 450m edge cell size, an average number of 11 blocks are contained into one cell, with the smallest administrative neighborhood (*San Telmo*) containing 85 blocks. As shown in Table 4.4, results are robust to reasonable changes in edge size.

for each household pair (i, j) in neighborhood b it is possible to define an *investment similarity score* variable $siminv_{ijb}$ taking integer values from 0 to 9. The variable captures the degree of similarity between households' investment schedule. Its value is defined by counting the number of investment dummy variables which take the same value for both households in the pair. If none of the nine variables take the same value, the burglary protection investment schedule of the two households is completely different and the investment similarity score variable takes value 0. If all nine dummy variables take the same value, the two households in the pair implement exactly the same protection investment schedule, and the investment similarity score variable takes value 9. Values 1 to 8 correspond to intermediate cases.

Table 4.2 shows the frequencies of each value taken by $siminv_{ijb}$ in the whole sample of household pairs located in the same neighborhood. The total number of pairs of surveyed households located in the same administrative neighborhood is equal to 24985. Over 50% of the household pairs in the sample have an investment similarity score taking values 7 or 8, while only 3 pairs refer to households implementing a completely different investment schedule. Figure 4.5 provides a graphical representation of how geographical proximity relate to these numbers. The fraction of close neighbors over the total number of household pairs is estimated separately for each value taken by the investment similarity score, together with the corresponding 95% confidence interval. The figure reveals a clear pattern in the data. Indeed, a higher fraction of close neighbors is found within those household pairs with higher investment similarity scores, suggesting that immediate neighboring households have a more similar protection investment schedule with respect to households located in the same administrative neighborhood, but farther apart.

This pattern is investigated more rigorously through implementing the following regression specification

$$siminv_{ijb} = \gamma_b + \beta\, close_{ijb} + \mathbf{X}'_{ijb}\, \delta + u_{ijb} \tag{4.11}$$

where $siminv_{ijb}$ is the protection investment similarity score defined as above for the household pair (i, j) in neighborhood b, while $close_{ijb}$ is a dummy equal to 1 if i and j are located in and belong to the same cell. γ_b is neighborhood fixed effect which controls for average differences in household pairs' similarity across neighborhoods. $\mathbf{X}_{ijb}$ is a vector of pair's demographic and economic characteristics. Residual determinants of investment similarity are captured by u_{ijb}. The coefficient of interest β captures whether close neighbors have a systematically different propensity to implement the same burglary protection investment schedule with respect to neighbors located farther apart.[9]

Point estimates for β are reported in Table 4.3. Given that one household belongs to more than one pair in the final dataset, consistently with Bayer et al. (2008), bootstrapped standard errors are computed and used for inference in most specification. Column 1 reports the estimate of the coefficient of interest from a simple regression of the investment similarity score over the close neighbors dummy and neighborhood fixed effects. The point estimate is significant at the 1% level. Close neighbors are shown to be significantly more likely to implement the same burglary protection investment schedule with respect to the average household pair in the same neighborhood. The point estimate is 0.166, equal to the 2.3% of the score mean and 11% of its standard deviation. In column 2 to 5, I progressively include the vectors of pair-level controls.[10] The point estimate slightly decreases, but keeps being significant at the 1% level.

Results can be interpreted in light of the theoretical model presented above. Investment by close neighbors in one specific observable protection device increases the victimization probability of a given household and thus its likelihood to make the same investment. This generates a higher degree of similarity between the investment schedule of close neighbors, and implicitly suggests the relative supply of burglars in the city to be relatively inelastic to the fraction of investors in the average location (or perceived to be so by potential victims). Nonetheless, the same observed pattern could arise if sorting of individuals with the same propensity to implement a given protection investment schedule occurs at the cell level, or if idiosyncratic cell characteristics independently shape the investment schedules of close neighbors in the same way (correlated effects). The need to rule out these alternative explanations motivates the second part of the empirical analysis in Section 4.4.

[9]The same analysis is performed also using neighborhood (or reference group) definition different from the administrative neighborhood one. As shown in Table 4.4, using police districts yields qualitatively and quantitatively similar results.

[10]The full set of included controls is specified in the table notes.

Robustness

Robustness of results is explored further in Table 4.4. In the first column, I include individual household fixed effects for each pair member. The generalized regression specification is

$$siminv_{ijb} = \lambda_{ib} + \lambda_{jb} + \beta\, close_{ijb} + u_{ijb} \tag{4.12}$$

Fixed effects should be thought of as capturing the households' idiosyncratic propensity to implement the investment schedule of neighbors. If individuals were sorting across cells within neighborhood according to such propensity, we would mistakenly consider proximity to be responsible of a spurious correlation generated by sorting (Bayer et al. 2008). Moreover, the inclusion of individual household fixed effects allows to correct residuals estimates $\hat{u}_{ijb}$ for a potential source of non-independence between them when the same household belongs to different pairs. The resulting point estimate in column 1 is now equal to 0.067, but still significant at the 1% level.

The issue of possibly correlated residuals can be further explored by testing the robustness of results with respect to alternative standard errors estimation techniques. Results from clustering standard errors at the neighborhood level are shown in column 2 of Table 4.4. The estimate of the coefficient of interest is still significant at the 5% level. Finally, in the estimation of the variance-covariance matrix of residuals, we can allow their correlation to be non-zero whenever two observations have one pair household member in common. Following Fafchamps and Gubert (2007a,b), we can thus implement a dyadic standard errors estimation which allows for $\mathbb{E}(u_{ijb}u_{gkb}) \neq 0$ whenever i or j is equal to either g or k. Column 3 shows the point estimate of interest in this case to be still significant at the 1% level.

Column 4 in Table 4.4 reports the same estimate of the coefficient of interest, but exploiting variation within the boundaries of police districts instead of administrative neighborhoods. The point estimate is still significant at the 1% level and now equal to 0.105. Finally, columns 5 and 6 reports estimate under alternative grid cell size definitions, with edges equal to 350m and 400m respectively. Results are found to be comparable to previous ones in terms of both magnitude and significance.

4.4 Protection Investment Spillovers

Evidence from the previous section suggests that immediate neighbors have a systematically more similar burglary protection investment schedule with respect to neighbors living farther apart. However, it remains silent on whether protection investment of neighbors has any causal effect on individual household's investment decisions. I thus implement an alternative identification strategy where I exploit within-neighborhood variation in close neighbors' investment status, and look for a systematic relationship of the latter with a given household's investment choice.

In the same framework of Miguel and Kremer (2004) in their study of externalities from deworming treatment in Kenya, I implement the following regression specification

$$y_{ib} = \psi_b + \lambda_d \, N^y_{dib} + \phi_d \, N_{dib} + \mathbf{Z}'_{ib} \, \theta + v_{ib} \tag{4.13}$$

where y_{ib} is dummy variable indicating the protection investment status of household i in neighborhood b. The nine investment variables and the overall protection investment score are studied separately. N_{dib} is the total number of surveyed households within distance d from household i, while N^y_{dib} is the number of those among them who undertook the investment under investigation, meaning those for which $y = 1$. In the case of the overall protection investment score, N^y_{dib} equals the cumulate investment of surveyed neighbors. $\mathbf{Z}_{ib}$ is a vector of household-level demographic and economic controls, while the fixed effects ψ_b capture average differences across neighborhoods. The coefficient of interest λ_d captures spillovers from protection investment of close neighbors. More specifically, $\lambda_d \neq 0$ reveals systematic differences between households located in the same neighborhood and with the same number of surveyed immediate neighbors, but differing in the number of the latter who invest in a given protection technology.

Estimation of the above equation using Ordinary Least Squares (OLS) is likely to deliver a biased estimate of the coefficient of interest. First, the above equation defines the investment choice of all households simultaneously, yielding to problems of the same family of those identified by Manski (1993) in the estimation of endogenous peer effects. Second, as outlined before, within-neighborhood sorting of individuals with the same propensity of investing in a given protection technology can potentially generate a spurious positive correlation between the investment status of immediate neighbors.

Third, the same would be true if idiosyncratic location characteristics at the within-neighborhood level are independently pushing the investment choices of neighbors in the same direction. Fourth, the inclusion of both spatial lags and neighborhood fixed effects yields a mechanical downward bias in OLS estimates of the same nature of the Nickell-Hurwicz bias in short time series (Nickell 1981; Guryan et al. 2009; Plümper and Neumayer 2010).[11]

In order to overcome these problems, I exploit the variation in the protection investment status of close neighbors as induced by their reported information about crimes suffered by their friends, relatives, acquaintances and others. The questionnaire specifically asks the respondent to list these crimes, if any, together with the category and whether they occurred at least 20 blocks away from the respondent's house. Crime at such a high distance from the interviewed household can be thought of as orthogonal to the protection investment of the given household and its neighbors. Such statement is supported by the empirical evidence in the economics of crime literature showing no significant spatial displacement of crime beyond the neighborhood boundaries after an exogenous increase in police presence (Draca et al. 2010; Di Tella and Schargrodsky 2004).

Information about crimes involving one's contacts and others can be framed as a shock to the agent's information set. New, updated information on crime and its probability to occur is likely to induce variation in the agent's protection investment decisions. I thus implement an Instrumental Variable (IV) strategy and use within-neighborhood variation in the number of surveyed close neighbors reporting information about any crime occurred at least 20 blocks away N^v_{dib} as a source of exogenous variation for the number of surveyed close neighbors who invest in protection N^y_{dib}. In the regression specification I include the full set of neighborhood fixed effects and control for whether the household has itself information about any crime episode. The validity of this approach rests on the satisfaction of few well identified assumptions. First, conditional on the included controls, the number of surveyed close neighbors reporting information about any crime occurring sufficiently far away needs to be a strong predictor of the

[11]Notice also that N^y_{dib} refers to surveyed close neighbors. Therefore, it is only an estimate of the intensity of protection adoption within the immediate neighborhood. As long as the survey sampling design is such that the number of surveyed close neighbors is randomly assigned to households, the problem can be conceptualized as one of *random measurement error* in the regressor of interest, which would result in attenuation bias in the estimate of the coefficient of interest.

number of the former investing in the specific technology under investigation. Second, neighbors' reported knowledge of crime episodes has to be as good as randomly assigned to each given household, and have no direct effect on the investment schedule of the latter.

Table 4.5 shows OLS estimates of the coefficients from a series of regressions of the number of surveyed close neighbors reporting information about any crime occurred at least 20 blocks away N^v_{dib} over a number of variables capturing household's demographic and economic characteristics, controlling for the total number of surveyed neighbors N_{dib} and neighborhood fixed effects. Close neighbors are defined as those who are located within a distance d of 150m from the given household. Results show the neighbors' knowledge of any crime episodes occurred far away not to be systematically related to given household's characteristics. All coefficients of interest turn out to be negligible and/or non-significant at standard significance level. Remarkably, in the first column, a non-significant coefficient estimate indicates that the number of neighbors reporting any information about crimes occurred far away is orthogonal to a given household's knowledge of the same.[12] Moreover, no systematic relationship is found in the last column, when we look at respondent's beliefs on crime using a dummy equal to one if crime is considered to be a very serious issue, which is likely to be a relevant determinant of protection investment behavior. All this is particularly reassuring, as it shows that potential confounding effects of information sharing and overlapping of peer groups among neighbors are not a concern in this setting.

Results in Table 4.5 speak in favor of the exclusionary restriction, i.e. the assumption of no direct effect of neighbors' reported knowledge of crimes on household's information and protection investment decisions. Furthermore, no systematic relationship is found when we look at the other variables, suggesting the proposed instrument to be as good as randomly assigned. A significant coefficient is estimated when the probability for the respondent of being married, being a college graduate and the household's dwelling to be a flat is considered, but the point estimate is negligible in magnitude. When all variables are used as explanatory variables at the same time, results from an *F-test* of joint significance show that the hypothesis of all coefficients being jointly zero cannot be rejected (*p-value* of 0.498). Nonetheless, all these variables will be pro-

[12]In order to take care of the mechanical Nickell-Hurwicz-type bias outlined before, the sample is here restricted to households who are at most 310m distant from each other.

gressively included as controls in the main empirical analysis in order to evaluate the robustness of results and improve on estimates' precision.

Table 4.6 shows OLS estimates of λ_d from equation (13) for the nine different observable protection investments under investigation (private security, special door locks, bars, armor plating, monitored and non-monitored alarms, CCTV cameras, outdoor lighting and permanently stay at home), together with the results for the overall protection investment score. Standard errors are clustered at the neighborhood level. Point estimates are negative in most specifications, from the one which only includes the total number of surveyed close neighbors and neighborhood fixed effects as controls (column 1) to the ones which include demographic and economic controls (column 2 and 3 respectively), respondent's beliefs about crime (column 4) and dwelling type characteristics (column 5). All the variables investigated in Table 4.5 are used as demographic or economic controls. Within the latter, I also include the dummy variables capturing ownership of specific durable goods, as listed in the bottom panel of Table 4.1. Together with the dummy of whether house is a flat, controls for dwelling type characteristics include distance from the closest police station. OLS estimates are negative and significant when looking at the propensity of a given household to invest in special door locks and non-monitored alarms given the neighbors' composition of the same. As discussed above the size and sign of OLS estimates need to be interpreted with caution.

Two-stage Least Squares (2SLS) estimation results are shown in Table 4.7. Estimates are restricted only to those protection investment variables for which the proposed instrument is found to be relevant enough, meaning it induces meaningful variation in the endogenous variable of interest. In this respect, the table displays the value of the *F-statistic* for the test of significance of the instrument in the first stage regression, which is indeed safely above 10 in all specifications. Results are ordered as in Table 4.6 in columns 1 to 5, with standard errors being clustered at the neighborhood level. Additionally, in column 6, we follow Conley (1999) and implement a Generalized Method of Moments (GMM) estimation using the same instrument, but allowing for spatial correlation of residual determinants of protection investment among households located within $150m$ one from the other. A positive and significant effect is found when monitored alarms and CCTV cameras are considered: one close neighbor more shifting from being a non-investor to be an investor increases the probability for a given household of doing the same of 19 and 10 percentage points respectively. The estimate is significant at the 1% level. Note that the 2SLS estimates are invariant to the inclusion of controls, and in particular the measure of household's beliefs towards crime in column 4. Moreover, taking spatial correlation into account still yields estimates which are significant at the 5% level, as reported in column 6. Non-significant effects are found instead when the other technologies are considered, meaning special door locks, bars and outdoor lighting. No effect is found also for the cumulate investment of neighbors as captured by the overall protection investment score.

The same pattern arise qualitatively when the definition of close neighbors is changed according to their distance from the given household, as shown in Table 4.8. The table reports as before 2SLS estimates of the parameter of interest for each protection investment variable as derived from the fully saturated regression specification. Each column corresponds to a different definition of close neighbors depending on the distance d from the given household. As reasonable to expect, the positive and significant effects of neighbors' investment in monitored alarms and CCTV cameras decreases in magnitude when the definition of close neighbors becomes broader.

In order to shed further light on the result of no effect for cumulate investment, Figure 4.6 plots the individual household's protection investment score over the average investment score of surveyed close neighbors. The relationship between the two appears to be non-linear, with own cumulate protection being positively related to neighbors' investment score when the latter takes smaller values, and negative otherwise. The same pattern arise when considering alternative definitions of neighbors according to distance from the given household, as shown in Figure 4.7. This suggests that high levels of cumulate neighbors' protection investment may actually exert a positive externalities on a given household, decreasing its victimization probability and thus its likelihood of investing in protection itself. However, this result is only tentative and cannot be interpreted causally.

Overall, results from this section give to the previous result of spatial clustering of burglary protection investments a causal interpretation. Given household's information and beliefs, investment by neighbors is found to significantly increases the likelihood of investing in protection for the average household. In light of the model, this is due to the perceived increase in household's victimization probability, implicitly suggesting the burglary supply to be relatively inelastic to the intensity of protection in the average location, or perceived to be so by potential victims.

4.5 Conclusions

This chapter explores both theoretically and empirically the extent to which observable crime protection investment of potential victims relate to each other. In theory, the impact of a marginal investment decision on the likelihood of other individuals to invest in protection themselves is far from being unambiguous. On one side, observable protection by some agents divert criminals' activity towards other unprotected targets. On the other side, it diminishes returns to engage in criminal activity and therefore the stock of active criminals. The ultimate sign and size of protection on victimization probability of other potential victims and thus their likelihood to acquire protection is thus an empirical question.

These issues are explored theoretically in a model of frictional market for offenses. Externalities among potential victims arise as trading externalities and the sources of spillovers' ambiguity is identified by theory. The issue is then taken to the data using geo-referenced household-level information from the City of Buenos Aires. Focusing on burglary protection investment decisions, close neighbors are shown to implement a more similar observable protection investment schedule than neighbors farther apart. Perhaps more importantly, exploiting within-neighborhood variation in close neighbors' reported information about crimes as a source of exogenous variation for their investment status, an Instrumental Variable identification strategy reveals the latter to have a significant impact on individual household's propensity to invest. This is true when looking at the likelihood of installing monitored alarms and CCTV cameras, while it seems not to be the case for other technologies. Finally, the investigation of the relationship between neighbors' and own cumulate investment is shown instead to be non-linear, with a positive effect on own investment when neighbors' cumulate protection investment is low, and a negative effect when the latter is higher.

The proposed evidence of non-zero spillover effects of protection investment calls for the need of investigating further the potential victims' side of the market for offenses. A clear understanding of its functioning and its explanatory power for the variability of equilibrium crime rates is crucial for rigorous design of crime reduction policies. When interpreted in light of the theoretical model, evidence indirectly suggests burglary supply to be relatively inelastic to the fraction of protected individuals, or perceived to be so by potential victims. Indeed, the model calls for the corresponding and compelling evidence on the supply side of the market for offenses. However, victimization is endogenous to protection investments, so that victimization information in the same data used in this chapter cannot be exploited for credible identification. More generally, information on burglars and burglary episodes is typically hard to find and compile. This is especially true for the City of Buenos Aires, where, according to our survey, police reporting of burglary events is around 40%. The need to overcome these challenges motivates my future research agenda for this project.

Tables and Figures

TABLE 4.1: SUMMARY STATISTICS

Variable	N	Mean	St. Dev.	Min	Max
Age	1185	47.973	15.243	18	90
Female	1192	0.548	0.498	0	1
Any HH member $<$ 18 years old	1192	0.297	0 .457	0	1
Married	1192	0.496	0.50	0	1
Owner	1192	0.569	0.495	0	1
College degree	1192	0.270	0.444	0	1
Self-employed	1192	0.352	0.478	0	1
Retired	1192	0.184	0.387	0	1
Unemployed	1192	0.049	0.217	0	1
Believes Crime is Very Serious Problem	1192	0.522	0.50	0	1
Dwelling is a flat	1192	0.522	0.50	0	1
Distance from closest Police Station (km)	1192	0.779	0.468	0.024	2.409
Reports any crime occurred $>$ 20 blocks away	1192	0.266	0.442	0	1
Number of Surveyed Neighbors within 150m	1192	2.804	4.716	0	26
Protection Investment Variables					
Private Security	1192	0.159	0.365	0	1
Special Door Locks	1192	0.176	0.381	0	1
Bars	1192	0.210	0.407	0	1
Armor plating	1192	0.065	0.246	0	1
Alarm, monitored	1192	0.097	0.297	0	1
Alarm, non-monitored	1192	0.048	0.213	0	1
CCTV Camera	1192	0.135	0.342	0	1
Outdoor Lighting	1192	0.050	0.219	0	1
Permanently Stays at Home	1192	0.367	0.482	0	1
Individual Protection Score (0-9)	1192	1.307	1.424	0	8
Durable Goods Ownership Dummies					
Cars	1192	0.327	0.469	0	1
Cable TV	1192	0.780	0.414	0	1
DVD Player	1192	0.513	0.50	0	1
Internet at Home	1192	0.641	0.480	0	1
Computers/Tablets	1192	0.608	0.488	0	1
Domestic Service	1192	0.138	0.345	0	1
Washing Machine	1192	0.372	0.484	0	1

TABLE 4.2: FREQUENCIES OF INVESTMENT SIMILARITY SCORE VALUES

Investment Similarity Score Value	Frequency	%
0	3	0.01
1	67	0.27
2	161	0.64
3	348	1.39
4	834	3.34
5	2105	8.43
6	3945	15.79
7	5615	22.47
8	7063	28.27
9	4844	19.39
Total	24985	100

Notes. Unit of observation is pair of households in the same administrative neighborhood.

TABLE 4.3: SPATIAL CLUSTERING OF BURGLARY PROTECTION INVESTMENT

	Investment Similarity Score				
	(1)	(2)	(3)	(4)	(5)
Close Neighbors	0.166***	0.161***	0.161***	0.156***	0.157***
(Same Cell)	(0.033)	(0.030)	(0.028)	(0.029)	(0.028)
NB Fixed Effects	Y	Y	Y	Y	Y
Demographic Controls		Y	Y	Y	Y
Economic Controls			Y	Y	Y
Dwelling Type Controls				Y	Y
Beliefs Controls					Y
Outcome mean	7.139	7.139	7.139	7.139	7.139
Observations	24985	24985	24985	24985	24985
R^2	0.135	0.136	0.141	0.143	0.1445

Notes. Unit of observation is pair of households belonging to the same administrative neighborhood. Outcome variable is investment similarity score defined as above. Dummies for demographic controls include: both interview household members above the median age, both female, both households with any member aged less than 18, both married, both couple households. Dummies for economic controls include: both house howlers, both primary schooling, both secondary schooling, both college graduates, both employees, both self-employed, both retired, both unemployed. Dummies for dwelling type controls include: both flats, both independent houses. Dummies for beliefs controls include: both interviewed household members consider the problem of crime in Buenos Aires very serious, both think crime has increased over the last year, both think crime has increased over the last 5 years. Bootstrapped SEs are computed using 200 repetitions. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01.)

TABLE 4.4: SPATIAL CLUSTERING OF PROTECTION INVESTMENT: ROBUSTNESS

	Investment Similarity Score					
	(1)	(2)	(3)	(4)	(5)	(6)
Close Neighbors	0.067***	0.166**	0.166***	0.105***	0.188***	0.188***
(Same Cell)	(0.021)	(0.079)	(0.021)	(0.030)	(0.033)	(0.032)
NB Fixed Effects	Y	Y	Y		Y	Y
Police District Fixed Effects				Y		
HHs Fixed Effects	Y					
Clustered SEs		Y				
Dyadic SEs			Y			
Outcome mean	7.139	7.139	7.139	7.139	7.139	7.139
Observations	24985	24985	24985	24985	24985	24985
R^2	0.697	0.135	0.135	0.149	0.135	0.135

Notes. Unit of observation is pair of households in the same administrative neighborhood. Outcome variable is investment similarity score defined as above. Column (5) and (6) provide results given an alternative definition of grid cell size, with edge equal to 350m and 400m respectively. Bootstrapped SEs are computed using 200 repetitions. Clustered SEs in Column (2) are clustered at the administrative neighborhood level. Dyadic SEs in Column (3) are from Fafchamps and Gubert (2007a,b). (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01.)

TABLE 4.5: NEIGHBORS' INFORMATION ABOUT CRIME EPISODES AND HOUSEHOLD CHARACTERISTICS

	Neighbors Reporting Any Crime Suffered by Friends, Relatives, Acquaintances, Others (N^v_{150ib})												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Reports any crime $>$ 20 blocks away	0.024												0.024
	(0.049)												(0.051)
Age		-0.001											0.000
		(0.001)											(0.002)
Female			0.049										-0.008
			(0.036)										(0.041)
Any HH member				0.003									0.019
Aged $<$ 18				(0.040)									(0.047)
Married					-0.070*								-0.010
					(0.036)								(0.043)
House Owner						0.043							0.023
						(0.037)							(0.043)
College Degree							0.069*						-0.006
							(0.042)						(0.048)
Self-employed								-0.042					0.018
								(0.038)					(0.045)
Retired									-0.036				-0.076
									(0.046)				(0.069)
Unemployed										-0.033			-0.101
										(0.083)			(0.125)
House is a Flat											0.076*		0.057
											(0.039)		(0.045)
Beliefs on Crime												-0.041	-0.034
												(0.036)	(0.041)
N_{150ib}	0.104***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.064***	0.063***	0.062***	0.064***	0.102***
	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)
Constant	-0.058	-0.007	-0.069	-0.044	0.005	-0.080	-0.058	-0.024	-0.034	-0.042	-0.050	-0.020	-0.061
	(0.198)	(0.215)	(0.203)	(0.203)	(0.203)	(0.205)	(0.202)	(0.203)	(0.203)	(0.202)	(0.202)	(0.203)	(0.227)
F-test p-value													0.498
Observations	460	1185	1192	1192	1192	1192	1192	1192	1192	1192	1192	1192	457
R^2	0.381	0.256	0.258	0.257	0.259	0.258	0.259	0.258	0.257	0.257	0.259	0.258	0.390

Notes. Standard Errors in parenthesis. Unit of observation is individual household. Each column show the coefficient from a regression of the number of surveyed neighbors reporting information about at least one crime episode occurred sufficiently far away over the corresponding household characteristic, the total number of surveyed neighbors and the full set of administrative neighborhood fixed effects. In columns 1 and 13 a restricted sample of observations at distance of at most 310m between them to avoid the Nickell-Hurwicz bias problems described in the chapter (Plümper and Neumayer 2010; Nickell 1981). $d = 150m$. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01.)

TABLE 4.6: OWN AND NEIGHBORS' PROTECTION INVESTMENT: OLS RESULTS

	Protection Investment in the Same Technology				
	(1)	(2)	(3)	(4)	(5)
Neighbors' Investment in:					
Private Security	-0.049	-0.053	-0.054	-0.053	-0.052
	(0.050)	(0.046)	(0.045)	(0.044)	(0.042)
Special Door Locks	-0.032**	-0.034**	-0.037**	-0.037***	-0.038***
	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)
Bars	-0.009	-0.005	-0.005	-0.005	-0.005
	(0.024)	(0.025)	(0.024)	(0.024)	(0.023)
Armor plating	-0.032	-0.041	-0.043	-0.042	-0.044
	(0.033)	(0.031)	(0.030)	(0.030)	(0.030)
Alarm, monitored	-0.001	-0.001	-0.003	-0.003	-0.001
	(0.033)	(0.032)	(0.033)	(0.033)	(0.033)
Alarm, non-monitored	-0.066**	-0.076***	-0.077***	-0.077***	-0.080***
	(0.031)	(0.022)	(0.020)	(0.020)	(0.022)
CCTV Camera	0.003	-0.003	-0.000	-0.000	-0.007
	(0.035)	(0.036)	(0.037)	(0.037)	(0.037)
Outdoor lighting	-0.048	-0.051*	-0.049	-0.049	-0.051
	(0.029)	(0.030)	(0.031)	(0.031)	(0.032)
Permanently Stays at Home	-0.014	-0.012	-0.015	-0.013	-0.020
	(0.015)	(0.016)	(0.015)	(0.014)	(0.015)
Overall Investment Score (0-9)	0.006	-0.005	-0.010	-0.009	-0.010
	(0.030)	(0.029)	(0.028)	(0.028)	(0.028)
Any Crime Victim Within HH's Contacts	Y	Y	Y	Y	Y
N_{150ib}	Y	Y	Y	Y	Y
NB Fixed Effects	Y	Y	Y	Y	Y
Demographic Controls		Y	Y	Y	Y
Economic Controls			Y	Y	Y
Beliefs Controls				Y	Y
Dwelling Type Controls					Y
Observations	1192	1185	1185	1185	1185

Notes. Standard Errors in parenthesis, clustered at the administrative neighborhood level. The table reports OLS estimates and SEs from the regressions of each row investment variable y over the corresponding number of surveyed neighbors who invest in the same technology, N^y_{150ib}. When considering the overall investment score, the cumulate investment of surveyed neighbors is considered. The total number of surveyed neighbors is controlled for in all specifications, together with the set of administrative neighborhood dummies and a dummy for whether the given household reports any crime suffered by friends, relatives, acquaintances or others occurred at least 20 blocks away. Demographic Controls include: age, age squared, dummies for female, whether there is any household member aged less than 18, married. Economic Controls include dummies for: house is owned, college degree, self-employed, retired, unemployed, durable goods ownership. Beliefs Controls include a dummy equal to one if interviewed household member thinks the problem of crime in the City is very serious. Dwelling Type Controls include dummy for whether house is a flat and distance from closest police station. $d = 150m$. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01.)

TABLE 4.7: THE EFFECT OF NEIGHBORS' PROTECTION INVESTMENT: IV RESULTS

	Protection Investment in the Same Technology					
	(1)	(2)	(3)	(4)	(5)	(6)
Neighbors' Investment in:						
Special Door Locks	0.080	0.075	0.038	0.036	0.032	0.032
	(0.056)	(0.060)	(0.067)	(0.067)	(0.065)	(0.065)
1st Stage F-stat	46.51	47.06	48.44	48.16	47.47	47.47
Bars	0.006	0.004	-0.019	-0.020	-0.012	-0.012
	(0.056)	(0.061)	(0.072)	(0.073)	(0.073)	(0.057)
1st Stage F-stat	42.38	42.38	43.03	43.30	43.03	43.03
Alarm, monitored	0.198***	0.204***	0.183**	0.186***	0.189***	0.189**
	(0.075)	(0.077)	(0.072)	(0.072)	(0.073)	(0.088)
1st Stage F-stat	44.62	44.49	46.38	46.38	46.38	46.38
CCTV Camera	0.112**	0.104**	0.108***	0.113***	0.106***	0.106**
	(0.044)	(0.041)	(0.037)	(0.039)	(0.041)	(.047)
1st Stage F-stat	46.24	46.24	46.79	46.65	46.79	46.79
Outdoor lighting	-0.028	-0.024	-0.026	-0.027	-0.025	-0.025
	(0.076)	(0.074)	(0.076)	(0.075)	(0.074	(0.070))
1st Stage F-stat	48.30	48.30	49.14	49.84	50.13	50.13
Overall Investment Score (0-9)	0.069	0.067	0.047	0.052	0.050	0.050
	(0.064)	(0.067)	(0.073)	(0.073)	(0.071)	(0.061)
1st Stage F-stat	45.70	44.89	42.90	42.38	42.64	42.64
Any Crime Victim Within HH's Contacts	Y	Y	Y	Y	Y	Y
N_{150ib}	Y	Y	Y	Y	Y	Y
NB Fixed Effects	Y	Y	Y	Y	Y	Y
Demographic Controls		Y	Y	Y	Y	Y
Economic Controls			Y	Y	Y	Y
Beliefs Controls				Y	Y	Y
Dwelling Type Controls					Y	Y
Observations	1192	1185	1185	1185	1185	1185

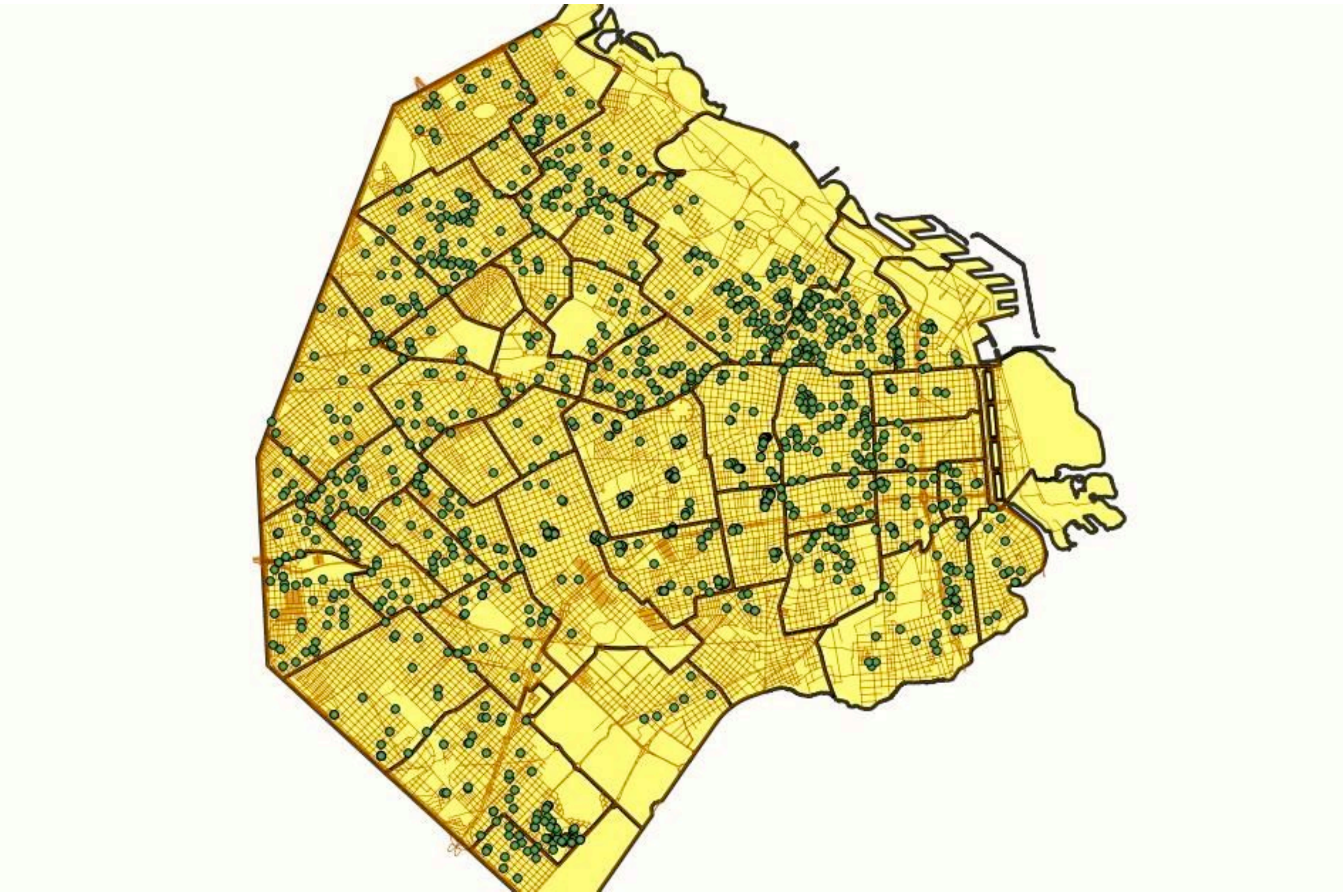
Notes. Standard Errors in parenthesis, clustered at the administrative neighborhood level. The table reports 2SLS estimates and SEs from the regressions of each row investment variable y over the corresponding number of surveyed neighbors who invest in the same technology, N^{y}_{150ib}. Instrument is the number of neighbors reporting any crime suffered by friends, relatives, acquaintances or others occurred at least 20 blocks away. When considering the overall investment score, the cumulate investment of surveyed neighbors is considered. *1st Stage F-stat* displays the value of the *F-statistics* for the test of significance of the instrument in the clustered first stage regression. The total number of surveyed neighbors is controlled for in all specifications, together with the set of administrative neighborhood dummies and a dummy for whether the given household reports itself any crime suffered by friends, relatives, acquaintances or others occurred at least 20 blocks away. Demographic Controls include: age, age squared, dummies for female, whether there is any household member aged less than 18, married. Economic Controls include dummies for: house is owned, college degree, self-employed, retired, unemployed, durable goods ownership. Beliefs Controls include a dummy equal to one if interviewed household member thinks the problem of crime in the City is very serious. Dwelling Type Controls include dummy for whether house is a flat and distance from closest police station. Column (6) reports GMM estimates allowing for non-zero correlation of residuals belonging to observations located within 150m one from the other (Conley 1999). $d = 150m$. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01.)

TABLE 4.8: THE EFFECT OF NEIGHBORS' PROTECTION INVESTMENT BY DISTANCE

	Protection Investment in the Same Technology				
	(1)	(2)	(3)	(4)	(5)
	$d = 100m$	$d = 200m$	$d = 300m$	$d = 400m$	$d = 500m$
Neighbors' Investment in:					
Special Door Locks	-0.051	0.004	0.010	0.030	0.015
	(0.143)	(0.069)	(0.074)	(0.062)	(0.048)
1st Stage F-stat	24.40	63.04	41.60	41.47	48.72
Bars	-0.028	-0.008	(0.009)	0.067	0.084
	(0.111)	(0.072)	(0.075)	(0.059)	(0.077)
1st Stage F-stat	22.18	25	12.88	18.06	12.74
Alarm, monitored	0.403***	0.155**	0.096***	0.067***	0.058***
	(0.152)	(0.071)	(0.030)	(0.024)	(0.022)
1st Stage F-stat	23.81	39.81	55.50	73.62	87.05
CCTV Camera	0.138*	0.083*	0.058	0.058*	0.036*
	(0.074)	(0.035)	(0.039)	(0.031)	(0.019)
1st Stage F-stat	30.58	70.56	84.82	90.63	121.66
Outdoor lighting	0.118	-0.008	-0.026	0.053	0.052
	(0.097)	(0.071)	(0.070)	(0.060)	(0.058)
1st Stage F-stat	32.60	32.15	46.92	36.97	20.07
Overall Investment Score (0-9)	0.142	0.013	0.006	0.048	0.035
	(0.089)	(0.087)	(0.068)	(0.044)	(0.034)
1st Stage F-stat	29.05	48.02	53.44	65.93	78.32
Any Crime Victim Within HH's Contacts	Y	Y	Y	Y	Y
N_{dib}	Y	Y	Y	Y	Y
NB Fixed Effects	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
Economic Controls	Y	Y	Y	Y	Y
Beliefs Controls	Y	Y	Y	Y	Y
Dwelling Type Controls	Y	Y	Y	Y	Y
Observations	1185	1185	1185	1185	1185

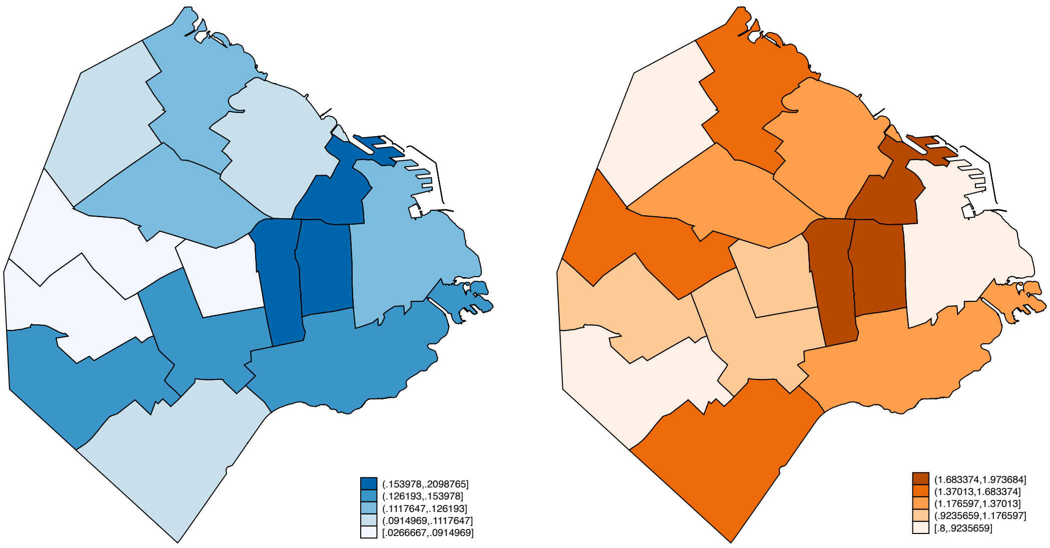
Notes. Standard Errors in parenthesis, clustered at the administrative neighborhood level. The table reports 2SLS estimates and SEs from the regressions of each row investment variable y over the corresponding number of surveyed neighbors who invest in the same technology, N^{y}_{dib}. Neighbors are defined differently across columns according to distance d. Instrument is the number of neighbors reporting any crime suffered by friends, relatives, acquaintances or others occurred at least 20 blocks away. When considering the overall investment score, the cumulate investment of surveyed neighbors is considered. *1st Stage F-stat* displays the value of the *F-statistics* for the test of significance of the instrument in the clustered first stage regression. The total number of surveyed neighbors is controlled for in all specifications, together with the set of administrative neighborhood dummies and a dummy for whether the given household reports itself any crime suffered by friends, relatives, acquaintances or others occurred at least 20 blocks away. Demographic Controls include: age, age squared, dummies for female, whether there is any household member aged less than 18, married. Economic Controls include dummies for: house is owned, college degree, self-employed, retired, unemployed, durable goods ownership. Beliefs Controls include a dummy equal to one if interviewed household member thinks the problem of crime in the City is very serious. Dwelling Type Controls include dummy for whether house is a flat and distance from closest police station. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01.)

FIGURE 4.1: BUENOS AIRES CITY MAP



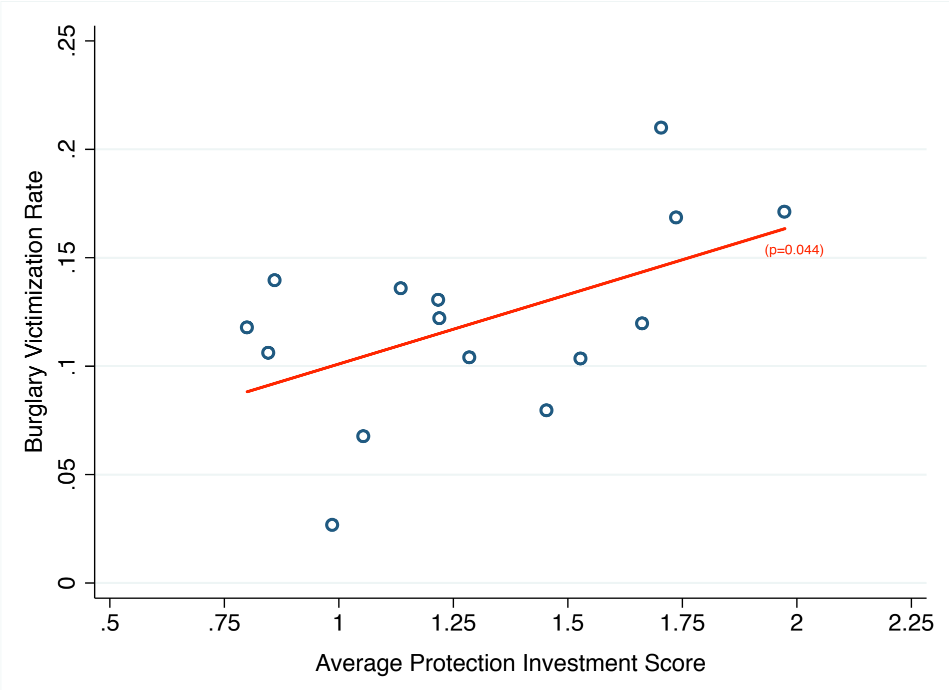
Notes. Map of the City of Buenos Aires with location of interviewed households.

FIGURE 4.2: BURGLARY VICTIMIZATION RATES AND AVERAGE PROTECTION SCORES



Notes. The maps display the burglary victimization rates (left) and the average protection investment scores (right) across *Comunas* in the City of Buenos Aires. In each map, *comunas* are colored according to the quintiles they belong to in the corresponding distribution.

FIGURE 4.3: BURGLARY VICTIMIZATION RATES AND AVERAGE PROTECTION SCORES

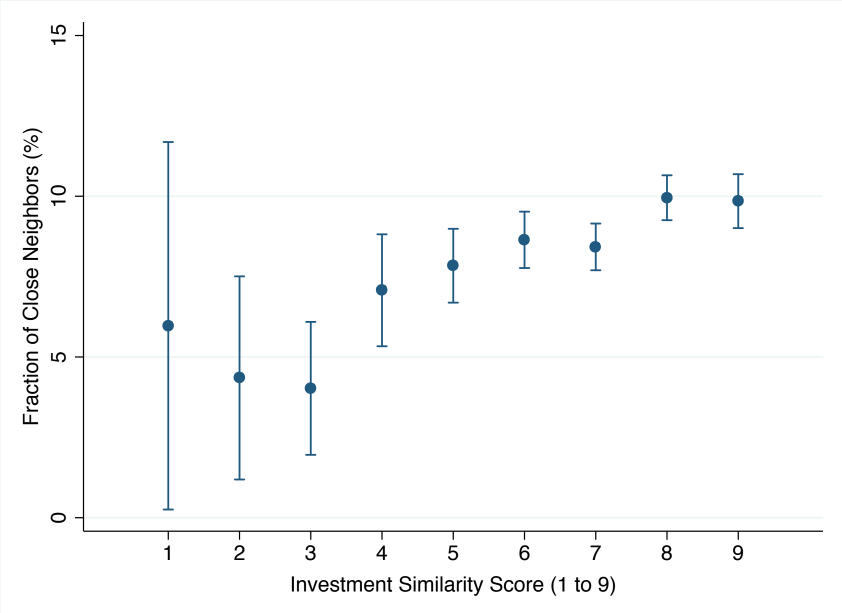


Notes. The figure plots burglary victimization rates against the average protection investment scores per *Comunas* in the City of Buenos Aires. The red line fits the linear relationship between the two variables (*p-value* in parenthesis).

FIGURE 4.4: CELL GRID AND ADMINISTRATIVE NEIGHBORHOODS' BOUNDARIES

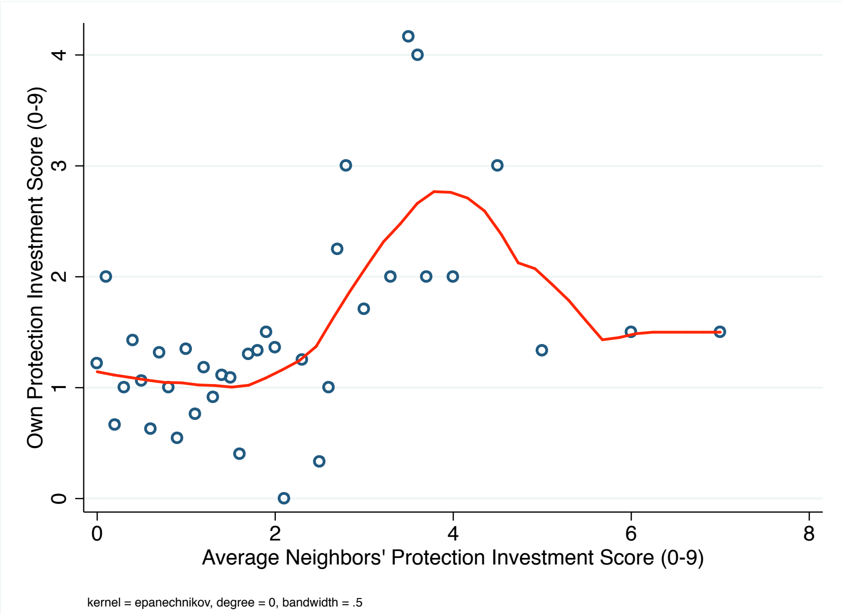
Notes. A detail of the Buenos Aires City map showing the *Recoleta* administrative neighborhood, households' location and the superimposed cell grid.

FIGURE 4.5: NEIGHBORS AND INVESTMENT SIMILARITY SCORE



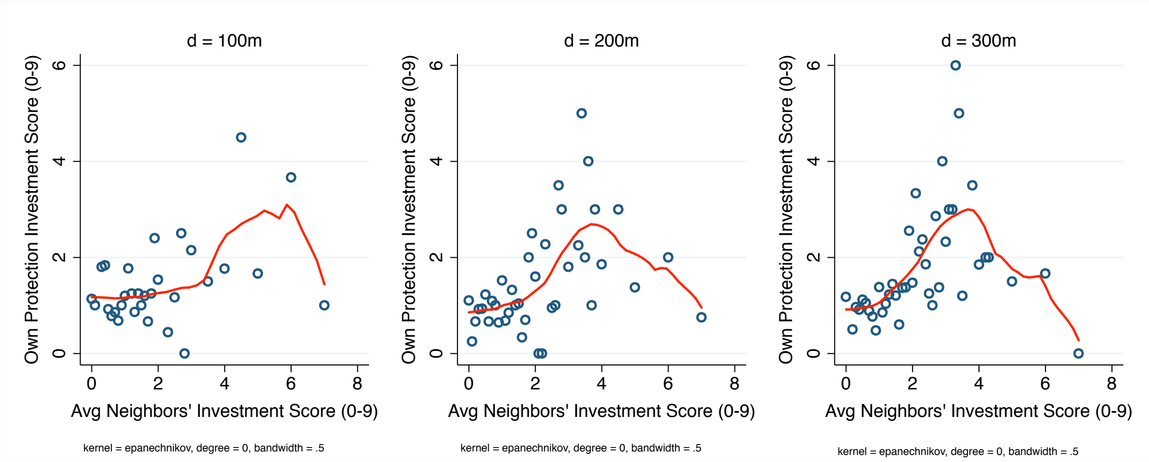
Notes. The figure plots the probability of two households in the sample of being close neighbors as estimated separately for each value of the protection investment similarity score for the pair, together with 95% confidence intervals.

FIGURE 4.6: OWN AND NEIGHBORS' PROTECTION INVESTMENT SCORE



Notes. The figure plots the smoothed average protection investment score of a given household per each bin of the average neighbors' protection investment score, with bin size being equal to 0.1 ($d = 150m$).

FIGURE 4.7: OWN AND NEIGHBORS' PROTECTION INVESTMENT SCORE BY DISTANCE



Notes. Each figure plots the smoothed average protection investment score of a given household per each bin of the average neighbors' protection investment score, with bin size being equal to 0.1. Each figure is derived considering a different definition of close neighbors according to their distance d from the given household.

4.6 Appendix

4.A.1 Social Planner Problem

Consider the problem of a social planner willing to maximize the sum of payoffs of potential victims $W = \sum_i u_i$. In doing this, the social impact of i's choice of protecting himself on other potential victims is taken into account. The solution is given by

$$\left(\frac{\gamma_i}{\lambda}\right)^{\mu} L_i \geq K + \mu\gamma^{\mu}\lambda^{-1-\mu} \int_0^{\dot{L}} L_i h(L_i) dL_i \tag{4.14}$$

where the second term on the RHS defines the social cost of the individual investment choice, equal to the marginal increase in the potential loss of unprotected individuals as given by the increase in their victimization probability following the investment of i. Note that $\dot{L}$ is the loss corresponding to the individual whose investment choice is regarded as indifferent by the social planner. Following the same procedure as above we derive $\dot{L}$ and thus compute the equilibrium fraction of unprotected individuals as implicitly defined by

$$\lambda^* = H\left[K\left(\frac{\lambda^*}{\gamma}\right)^{\mu} + \frac{\mu}{\lambda^*}\int_0^{\dot{L}} L_i h(L_i) dL_i\right] \tag{4.15}$$

Comparing this equilibrium solution to the decentralized one we can see that, given the number of active criminals γ, the socially efficient equilibrium fraction of unprotected individuals is higher than the one reached by the decentralized equilibrium.

4.A.2 The Sign of Spillover Effects

Starting from equation (5), consider the probability for agent i to invest in protection, meaning to choose $a_i = 1$. This is given by

$$Pr(a_i = 1) = Pr\left[\left(\frac{\gamma}{\lambda}\right)^{\mu} L_i > K\right] = 1 - H\left[K\left(\frac{\lambda}{\gamma}\right)^{\mu}\right] \tag{4.16}$$

From which it follows

$$\frac{\partial Pr(a_i = 1)}{\partial \lambda} = -K\mu \left(\frac{\lambda}{\gamma}\right)^{\mu} \left[\frac{1}{\lambda} - \frac{1}{\gamma}\frac{\partial \gamma}{\partial \lambda}\right] h \left[K\left(\frac{\lambda}{\gamma}\right)^{\mu}\right] \tag{4.17}$$

The middle term on the RHS of the above equation captures the tension between the *diversion* and *deterrence* effect. In case the fraction of active criminals γ was unresponsive to the change in the fraction of unprotected individuals ($\partial\gamma/\partial\lambda = 0$), the diversion effect would prevail, and the above derivative would be negative. As a result, investment by others would correspond to a decrease in the fraction of unprotected individuals, and thus an increase in the individual likelihood to protect herself for agent i.

Using the equilibrium equation for γ, we can apply the implicit function theorem and derive

$$\frac{\partial \gamma}{\partial \lambda} = \frac{g\left[\left(\frac{\lambda}{\gamma}\right)^{1-\mu}(\hat{L} - R)\right]\left(\frac{\lambda}{\gamma}\right)^{1-\mu}\left[\frac{1-\mu}{\lambda}(\hat{L} - R) + \frac{\partial \hat{L}}{\partial \lambda}\right]}{1 + g\left[\left(\frac{\lambda}{\gamma}\right)^{1-\mu}(\hat{L} - R)\right]\left(\frac{\lambda}{\gamma}\right)^{1-\mu}\frac{1-\mu}{\gamma}(\hat{L} - R)} \tag{4.18}$$

which is indeed positive provided that $\partial\hat{L}/\partial\lambda$ is negligible.

Bibliography

Abadie, A. and Gardeazabal, J. (2003). The Economic Costs of Conflict: A Case Study of the Basque Country. *American Economic Review*, 93(1):113–132.

Abrahams, A. (2015). Hard Traveling: Commuting Costs and Welfare in the Second Palestinian Uprising. Unpublished.

Acemoglu, D., García-Jimeno, C., and Robinson, J. A. (2012). Finding Eldorado: Slavery and long-run development in Colombia. *Journal of Comparative Economics*, 40(4):534–564.

Ades, A. and Chua, H. (1997). Thy neighbor's curse: regional instability and economic growth. *Journal of Economic Growth*, 2:279–304.

Ajluni, S. (2003). The Palestinian Economy and the Second Intifada. *Journal of Palestine Studies*, 32(3):64–73.

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., and Wacziarg, R. (2003). Fractionalization. *Journal of Economic Growth*, 8(2):155–94.

Alesina, A., Özler, S., Roubini, N., and Swagel, P. (1996). Political Instability and Economic Growth. *Journal of Economic Growth*, 1(2):189–211.

Amiti, M. and Konings, J. (2007). Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia. *American Economic Review*, 97(5):1611–1638.

Ammermueller, A. and Pischke, J.-S. (2009). Peer Effects in European Primary Schools: Evidence from the Progress in International Reading Literacy Study. *Journal of Labor Economics*, 27(3):315–348.

Angrist, J. and Pischke, J. (2009). *Mostly Harmless Econometrics*. Princeton University Press.

Angrist, J. D. (2014). The perils of peer effects. *Labour Economics*, 30(0):98 – 108.

Angrist, J. D., Imbens, G. W., and Rubin, D. B. (1996). Identification of Causal Effects Using Instrumental Variables. *Journal of the American Statistical Association*, 91(434):pp. 444–455.

Angrist, J. D. and Pischke, J. S. (2010). A Note on Bias in Conventional Standard Errors under Heteroskedasticity. Unpublished.

Arcidiacono, P., Kinsler, J., and Price, J. (2013). Productivity Spillovers in Team Production: Evidence from Professional Basketball. mimeo.

Ayres, I. and Levitt, S. D. (1998). Measuring Positive Externalities from Unobservable Victim Precaution: An Empirical Analysis of Lojack. *The Quarterly Journal of Economics*, 113(1):43–77.

Ballester, C., Calvó-Armengol, A., and Zenou, Y. (2010). Delinquent Networks. *Journal of the European Economic Association*, 8(1):34–61.

Bandiera, O., Barankay, I., and Rasul, I. (2005). Social Preferences and the Response to Incentives: Evidence from Personnel Data. *The Quarterly Journal of Economics*, 120(3):917–962.

Bandiera, O., Barankay, I., and Rasul, I. (2006). The Evolution of Cooperative Norms: Evidence from a Natural Field Experiment. *The B.E. Journal of Economic Analysis & Policy*, 5(2):1–28.

Bandiera, O., Barankay, I., and Rasul, I. (2007). Incentives for Managers and Inequality Among Workers: Evidence From a Firm-Level Experiment. *The Quarterly Journal of Economics*, 122(2):729–773.

Bandiera, O., Barankay, I., and Rasul, I. (2008). Social capital in the workplace: Evidence on its formation and consequences. *Labour Economics*, 15(4):724–748.

Bandiera, O., Barankay, I., and Rasul, I. (2009). Social Connections and Incentives in the Workplace: Evidence From Personnel Data. *Econometrica*, 77(4):1047–1094.

Bandiera, O., Barankay, I., and Rasul, I. (2010). Social Incentives in the Workplace. *Review of Economic Studies*, 77(2):417–458.

Bandiera, O., Barankay, I., and Rasul, I. (2013). Team Incentives: Evidence from a Firm Level Experiment. *Journal of the European Economic Association*, 11(5):1079–1114.

Banerjee, A. V. and Duflo, E. (2014). Do firms want to borrow more? testing credit constraints using a directed lending program. *The Review of Economic Studies*, 81(2):572–607.

Bayer, P., Ross, S. L., and Topa, G. (2008). Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes. *Journal of Political Economy*, 116(6):1150–1196.

Becker, G. S. (1968). Crime and Punishment: An Economic Approach. *Journal of Political Economy*, 76:169.

Benmelech, E., Berrebi, C., and Klor, E. (2015). Counter-suicide-terrorism: Evidence from house demolitions. *The Journal of Politics*.

Berman, N. and Couttenier, M. (2015). External shocks, internal shots: the geography of civil conflicts. Technical report.

Besley, T. and Reynal-Querol, M. (2014). The Legacy of Historical Conflict: Evidence from Africa. *American Political Science Review*, 108:319–336.

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

Bloom, N., Eifert, B., Mahajan, A., McKenzie, D., and Roberts, J. (2013). Does Management Matter? Evidence from India. *The Quarterly Journal of Economics*, 128(1):1–51.

Bloom, N., Mahajan, A., McKenzie, D., and Roberts, J. (2010). Why Do Firms in Developing Countries Have Low Productivity? *American Economic Review: Papers & Proceedings*, 100(2):619–23.

Bloom, N. and Van Reenen, J. (2007). Measuring and Explaining Management Practices Across Firms and Countries. *The Quarterly Journal of Economics*, 122(4):1351–1408.

Bloom, N. and Van Reenen, J. (2010). Why Do Management Practices Differ across Firms and Countries? *Journal of Economic Perspectives*, 24(1):203–24.

Bloom, N. and Van Reenen, J. (2011). *"Human Resource Management and Productivity"*, , volume 4 of *Handbook of Labor Economics*, chapter 19, pages 1697–1767. Elsevier.

Blume, L. E., Brock, W. A., Durlauf, S. N., and Ioannides, Y. M. (2011). Chapter 18 - Identification of Social Interactions. volume 1 of *Handbook of Social Economics*, pages 853 – 964. North-Holland.

Blume, L. E., Brock, W. A., Durlauf, S. N., and Jayaraman, R. (2013). Linear Social Interactions Models. NBER Working Papers 19212, National Bureau of Economic Research, Inc.

Bouare, O. (2002). Determinants of Internal Migration in South Africa. *Southern African Journal of Demography*, 8(1):23, 2001–2002.

Bramoullé, Y., Djebbari, H., and Fortin, B. (2009). Identification of peer effects through social networks. *Journal of Econometrics*, 150(1):41–55.

Brown, J. (2011). Quitters Never Win: The (Adverse) Incentive Effects of Competing with Superstars. *Journal of Political Economy*, 119(5):982 – 1013.

Brück, T., Di Maio, M., and Miaari, S. H. (2014). Learning the Hard Way: The Effect of Violent Conflict on Student Academic Achievement. IZA Discussion Papers 8543, Institute for the Study of Labor (IZA).

B'TSELEM (2007). Annual report: Human rights in the occupied territories. B'TSELEM.

Buera, F. J., Kaboski, J. P., and Shin, Y. (2011). Finance and Development: A Tale of Two Sectors. *American Economic Review*, 101(5):1964–2002.

Caeyers, B. (2014). Exclusion bias in empirical social interaction models: causes, consequences and solutions. CSAE Working Paper Series 2014-05, Centre for the Study of African Economies, University of Oxford.

Cali, M. and Miaari, S. H. (2013). The Labor Market Impact of Mobility Restrictions: Evidence from the West Bank. Policy Research Working Paper Series 6457, The World Bank.

Cali, M. and Miaari, S. H. (2015). Should I trade or should I go (to war)? Lessons from the Second Intifada. Hicn working paper 186.

Calvó-Armengol, A., Patacchini, E., and Zenou, Y. (2009). Peer effects and social networks in education. *Review of Economic Studies*, 76(4):1239–1267.

Camacho, A. and Rodriguez, C. (2013). Firm Exit and Armed Conflict in Colombia. *Journal of Conflict Resolution*, 57(1):89–116.

Cameron, A. C. and Trivedi, P. K. (2005). *Microeconometrics: Methods and Applications*. Cambridge University Press, New York.

Carver, R. (1996). *Kwazulu-Natal - Continued Violence and Displacement*. WRITENET.

Case, A. and Deaton, A. (1999). School Inputs and Educational Outcomes in South Africa. *The Quarterly Journal of Economics*, 114(3):pp. 1047–1084.

Caselli, F. and Coleman, W. J. (2013). On the Theory of Ethnic Conflict. *Journal of the European Economic Association*, 11:161–192.

Cerra, V. and Saxena, S. (2008). Growth Dynamics: The Myth of Economic Recovery. *American Economic Review*, 98(1):439–457.

Chen, S., Loayza, N. V., and Reynal-Querol, M. (2008). The Aftermath of Civil War. *The World Bank Economic Review*, 22(1):63–85.

Ciarli, T., Parto, S., and Savona, M. (2010). Entrepreneurship under Conflict in Afghanistan: Determinants and Motivations of Small Business Owners. Unpublished.

Clark, N. L. and Worger, W. H. (2011). *South Africa. The Rise and Fall of Apartheid*. Pearson, 2nd edition.

Clotfelter, C. T. (1978). Private security and the public safety. *Journal of Urban Economics*, 5(3):388–402.

Collier, P. (1999). On the Economic Consequences of Civil War. *Oxford Economic Papers*, 51(1):168–183.

Collier, P. (2001). Implications of Ethnic Diversity. *Economic Policy*, 16(32):127–166.

Collier, P. and Duponchel, M. (2013). The Economic Legacy of Civil War: Firm-level Evidence from Sierra Leone. *Journal of Conflict Resolution*, 57(1):65–88.

Collier, P., Elliott, V., Hegre, H., Hoeffler, A., Reynal-Querol, M., and Sambanis, N. (2003). *Breaking the Conflict Trap: Civil War and Development Policy (Policy Research Reports)*. World Bank; Oxford University Press.

Collier, P. and Hoeffler, A. (2004). Greed and Grievance in Civil War. *Oxford Economic Papers*, 56(4):563–595.

Conley, T. G. (1999). GMM Estimation with Cross Sectional Dependence. *Journal of Econometrics*, 92(1):1–45.

Cook, P. J. (1986). The demand and supply of criminal opportunities. *Crime and Justice*, 7:1–27.

Cook, P. J. and MacDonald, J. (2011). Public safety through private action: an economic assessment of bids. *The Economic Journal*, 121(552):445–462.

Cornelissen, T., Dustmann, C., and Schönberg, U. (2013). Peer Effects in the Workplace. IZA Discussion Papers 7617, Institute for the Study of Labor (IZA).

Coviello, D., Ichino, A., and Persico, N. (2014). Time allocation and task juggling. *American Economic Review*, 104(2):609–23.

Damm, A. P. and Dustmann, C. (2014). Does growing up in a high crime neighborhood affect youth criminal behavior? *American Economic Review*, 104(6):1806–32.

De Giorgi, G., Pellizzari, M., and Redaelli, S. (2010). Identification of Social Interactions through Partially Overlapping Peer Groups. *American Economic Journal: Applied Economics*, 2(2):241–75.

Deininger, K. (2003). Causes and Consequences of Civil Strife: Micro-level Evidence from Uganda. *Oxford Economic Papers*, 55(4):579–606.

Desmet, K., Ortuño Ortín, I., and Wacziarg, R. (2012). The Political Economy of Linguistic Cleavages. *Journal of Development Economics*, 97(2):322–338.

Desmet, K., Ortuño Ortín, I., and Weber, S. (2009). Linguistic Diversity and Redistribution. *Journal of the European Economic Association*, 7(6):1291–1318.

Di Maio, M. and Nandi, T. K. (2013). The effect of the Israeli-Palestinian conflict on child labor and school attendance in the West Bank. *Journal of Development Economics*, 100(1):107–116.

Di Tella, R., Galiani, S., and Schargrodsky, E. (2010). Crime Distribution and Victim Behavior during a Crime Wave. In *The Economics of Crime: Lessons for and from Latin America*, NBER Chapters, pages 175–204. National Bureau of Economic Research, Inc.

Di Tella, R. and Schargrodsky, E. (2004). Do police reduce crime? estimates using the allocation of police forces after a terrorist attack. *American Economic Review*, 94(1):115–133.

Doll, C. N., Muller, J.-P., and Morley, J. G. (2006). Mapping Regional Economic Activity from Night-time Light Satellite Imagery. *Ecological Economics*, 57(1):75 – 92.

Draca, M., Machin, S., and Witt, R. (2010). Crime displacement and police interventions: Evidence from londonÕs Òoperation theseusÓ. In *The Economics of Crime: Lessons for and from Latin America*, NBER Chapters, pages 359–374. National Bureau of Economic Research, Inc.

Dube, O. and Vargas, J. F. (2013). Commodity Price Shocks and Civil Conflict: Evidence from Colombia. *Review of Economic Studies*, 80(4):1384–1421.

Duflo, E., Glennerster, R., and Kremer, M. (2008). Using randomization in development economics research: A toolkit. In Schultz, T. P. and Strauss, J. A., editors, *Handbook of Development Economics*, volume 4, chapter 61, pages 3895–3962. Elsevier.

Eck, K. (2012). In Data We Trust? A Comparison of UCDP GED and ACLED Conflict Events Datasets. *Cooperation and Conflict*, 47(1):124–141.

Eckstein, Z. and Tsiddon, D. (2004). Macroeconomic consequences of terror: theory and the case of Israel. *Journal of Monetary Economics*, 51(5):971–1002.

Ehrlich, I. (1996). Crime, Punishment, and the Market for Offenses. *The Journal of Economic Perspectives*, 10(1):pp. 43–67.

Ehrlich, I. (2010). The Market Model of Crime: A Short Review and New Directions. In Benson, B. L. and Zimmerman, P. R., editors, *Handbook on the Economics of Crime*, chapter 1, pages 3–12. Edward Elgar.

Esteban, J., Mayoral, L., and Ray, D. (2012). Ethnicity and Conflict: An Empirical Study. *American Economic Review*, 102(4):1310–42.

Esteban, J. and Ray, D. (1994). On the Measurement of Polarization. *Econometrica*, 62(4):819–51.

Esteban, J. and Ray, D. (1999). Conflict and Distribution. *Journal of Economic Theory*, 87(2):379–415.

Esteban, J. and Ray, D. (2008). On the Salience of Ethnic Conflict. *American Economic Review*, 98(5):2185–2202.

Esteban, J. and Ray, D. (2011a). A Model Of Ethnic Conflict. *Journal of the European Economic Association*, 9(3):496–521.

Esteban, J. and Ray, D. (2011b). Linking Conflict to Inequality and Polarization. *American Economic Review*, 101(4):1345–74.

Ethier, W. J. (1982). National and International Returns to Scale in the Modern Theory of International Trade. *American Economic Review*, 72(3):389–405.

Etkes, H. and Zimring, A. (2014). Gains from trade: lessons from the gaza blockade 2007-2010. *Journal of International Economics*, forthcoming.

Fafchamps, M. and Gubert, F. (2007a). Risk Sharing and Network Formation. *American Economic Review*, 97(2):75–79.

Fafchamps, M. and Gubert, F. (2007b). The Formation of Risk Sharing Networks. *Journal of Development Economics*, 83(2):326–350.

Falk, A. and Ichino, A. (2006). Clean Evidence on Peer Effects. *Journal of Labor Economics*, 24(1):39–58.

Fielding, D. (2003). Modelling Political Instability and Economic Performance: Israeli Investment during the Intifada. *Economica*, 70(277):159–186.

Gifford, S. (1998). Limited Entrepreneurial Attention and Economic Development. *Small Business Economics*, 10(1):17–30.

Glaeser, E. L., Sacerdote, B., and Scheinkman, J. A. (1996). Crime and Social Interactions. *The Quarterly Journal of Economics*, 111(2):507–548.

Gonzalez-Navarro, M. (2013). Deterrence and geographical externalities in auto theft. *American Economic Journal: Applied Economics*, 5(4):92–110.

Gould, E. D. and Winter, E. (2009). Interactions between Workers and the Technology of Production: Evidence from Professional Baseball. *The Review of Economics and Statistics*, 91(1):188–200.

Graham, B. S. (2008). Identifying Social Interactions Through Conditional Variance Restrictions. *Econometrica*, 76(3):643–660.

Guidolin, M. and La Ferrara, E. (2007). Diamonds Are Forever, Wars Are Not: Is Conflict Bad for Private Firms? *American Economic Review*, 97(5):1978–1993.

Guner, N., Ventura, G., and Yi, X. (2008). Macroeconomic Implications of Size-Dependent Policies. *Review of Economic Dynamics*, 11(4):721–744.

Guryan, J., Kroft, K., and Notowidigdo, M. J. (2009). Peer Effects in the Workplace: Evidence from Random Groupings in Professional Golf Tournaments. *American Economic Journal: Applied Economics*, 1(4):34–68.

Harari, M. and La Ferrara, E. (2013). Conflict, climate and cells: A disaggregated analysis. CEPR Discussion Papers 9277, C.E.P.R. Discussion Papers.

Hausman, J. A. (1978). Specification Tests in Econometrics. *Econometrica*, 46(6):1251–71.

Hirshleifer, D. and Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(1-3):337–386.

Hjort, J. (2014). Ethnic divisions and production in firms. *The Quarterly Journal of Economics*, 129(4):1899–1946.

Hoffman, T. M. and Todd, S. W. (2000). A National Review of Land Degradation in South Africa: the Influence of Biophysical and Socioeconomic Factors. *Journal of Southern African Studies*, 26(4):743–758.

Hopenhayn, H. and Rogerson, R. (1993). Job Turnover and Policy Evaluation: A General Equilibrium Analysis. *Journal of Political Economy*, 101(5):915–38.

Horowitz, D. L. (1985). *Ethnic Groups in Conflict*. Berkeley: University of California Press.

Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and Manufacturing TFP in China and India. *The Quarterly Journal of Economics*, 124(4):1403–1448.

Ichino, A. and Maggi, G. (2000). Work Environment And Individual Background: Explaining Regional Shirking Differentials In A Large Italian Firm. *The Quarterly Journal of Economics*, 115(3):1057–1090.

IDF Military Advocate General (2012). Legal issues in judea and samaria: Movement and access restrictions. *Israel Defence Forces*.

IIASA/FAO (2012). *Global Agro-ecological Zones (GAEZ v3.0)*. available at http://www.gaez.iiasa.ac.at/ (accessed April 20, 2012), Laxenburg, Austria and FAO, Rome, Italy.

Ioannides, Y. M. and Topa, G. (2010). Neighborhood Effects: Accomplishments And Looking Beyond Them. *Journal of Regional Science*, 50(1):343–362.

Jaeger, D. A. and Paserman, M. D. (2008). The Cycle of Violence? An Empirical Analysis of Fatalities in the Palestinian-Israeli Conflict. *American Economic Review*, 98(4):591–1604.

Kahneman, D. (1973). *Attention and Effort (Experimental Psychology)*. Prentice Hall.

Kandel, E. and Lazear, E. P. (1992). Peer Pressure and Partnerships. *Journal of Political Economy*, 100(4):801–17.

Kasahara, H. and Lapham, B. (2013). Productivity and the decision to import and export: Theory and evidence. *Journal of International Economics*, 89(2):297 – 316.

Kasahara, H. and Rodrigue, J. (2008). Does the use of imported intermediates increase productivity? plant-level evidence. *Journal of Development Economics*, 87(1):106 – 118.

Klapper, L., Richmond, C., and Tran, T. (2013). Civil Conflict and Firm Performance. Evidence from Côthe d'Ivoire. Policy Research Working Paper Series 6640, The World Bank.

Kok, P., O'Donovan, M., Bouare, O., and Van Zyl, J. (2003). *Post Apartheid Patterns of Internal Migration in South Africa*. Human Sciences Research Council.

Ksoll, C., Macchiavello, R., and Morjaria, A. (2014). Guns and Roses: Flower Exports and Electoral Violence in Kenya. Unpublished.

Kugler, M. and Verhoogen, E. (2009). Plants and Imported Inputs: New Facts and an Interpretation. *American Economic Review: Papers & Proceedings*, 99(2):501–07.

Lee, L.-f. (2007). Identification and estimation of econometric models with group interactions, contextual factors and fixed effects. *Journal of Econometrics*, 140(2):333–374.

Lewis, M. P. (2009). *Ethnologue: Languages of the World, Sixteenth edition*. SIL international Dallas, TX, available at http://www.ethnologue.com/ (accessed March 11, 2012).

Liu, X., Patacchini, E., Zenou, Y., and Lee, L.-F. (2012). Criminal Networks: Who is the Key Player? Working Papers 2012.39, Fondazione Eni Enrico Mattei.

Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *Review of Economic Studies*, 60(3):531–42.

Mansour, H. (2010). The effects of labor supply shocks on labor market outcomes: Evidence from the Israeli-Palestinian conflict. *Labour Economics*, 17(6):930–939.

Mansour, H. and Rees, D. I. (2012). Armed conflict and birth weight: Evidence from the al-Aqsa Intifada. *Journal of Development Economics*, 99(1):190–199.

Mas, A. and Moretti, E. (2009). Peers at Work. *American Economic Review*, 99(1):112–45.

Mataria, A., Giacaman, R., Stefanini, A., Naidoo, N., Kowal, P., and Chatterji, S. (2009). The quality of life of palestinians living in chronic conflict: assessment and determinants. *The European Journal of Health Economics*, 10(1):93–101.

Melander, E. and Sundberg, R. (2011). Climate Change, Environmental Stress, and Violent Conflict: Tests Introducing the UCDP Georeferenced Event Dataset. Paper presented at the International Studies Association, March 16-19, Montreal, Canada.

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica*, 71(6):1695–1725.

Miaari, S. and Sauer, R. (2011). The labor market costs of conflict: closures, foreign workers, and Palestinian employment and earnings. *Review of Economics of the Household*, 9(1):129–148.

Michalopoulos, S. (2012). The Origins of Ethnolinguistic Diversity. *American Economic Review*, 102(4):1508–39.

Michalopoulos, S. and Papaioannou, E. (2011). The Long-Run Effects of the Scramble for Africa. NBER Working Papers 17620, National Bureau of Economic Research, Inc.

Michalopoulos, S. and Papaioannou, E. (2013). Pre-colonial Ethnic Institutions and Contemporary African Development. *Econometrica*, 81(1):113–152.

Michalopoulos, S. and Papaioannou, E. (2014). National Institutions and Subnational Development in Africa. *The Quarterly Journal of Economics*, 129(1):151–213.

Midrigan, V. and Xu, D. Y. (2014). Finance and misallocation: Evidence from plant-level data. *American Economic Review*, 104(2):422–58.

Miguel, E. and Kremer, M. (2004). Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities. *Econometrica*, 72(1):159–217.

Mikuriya, K. (2009). Keynote Address. Stakeholder conference for the palestinian revenue and customs economic development programme, Ramallah (Palestine), 24 - 25 May 2009.

Montalvo, J. and Reynal-Querol, M. (2005). Ethnic Polarization, Potential Conflict and Civil War. *American Economic Review*, 95(3):796–816.

Montalvo, J. and Reynal-Querol, M. (2010). Ethnic Polarization and the Duration of Civil Wars. *Economics of Governance*, 11(2):123–143.

Nickell, S. J. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica*, 49(6):1417–26.

NOOA (2012). *Version 4 DMSP-OLS Nighttime Lights Time Series*. available at http://www.ngdc.noaa.gov/dmsp/downloadV4composites.html (accessed April 20, 2012).

Novta, N. (2013). Ethnic Diversity and the Spread of Civil War. Unpublished.

Novy, D. and Taylor, A. M. (2014). Trade and Uncertainty. *NBER Working Paper 19941*.

Nunn, N. and Puga, D. (2012). Ruggedness: The Blessing of Bad Geography in Africa. *The Review of Economics and Statistics*, 94(1):20–36.

Patacchini, E. and Zenou, Y. (2012). Juvenile Delinquency and Conformism. *Journal of Law, Economics and Organization*, 28(1):1–31.

PCBS (2001). Impact of the israeli measures on the palestinian labour market.

PCBS (2007). Industry Survey 1999-2006. `www.pcbs.gov.ps`.

Pissarides, C. (2000). *Equilibrium unemployment theory*. MIT Press, Cambridge, Mass. [u.a.], 2. ed edition.

Plümper, T. and Neumayer, E. (2010). Model specification in the analysis of spatial dependence. *European Journal of Political Research*, 49(3):418–442.

Posel, D. (2001). What's in a Name? Racial Categorisations Under Apartheid and Their Afterlife. *Transformation*, 47:50–74.

Pressman, J. (2003). The Second Intifada: Background and causes of the Israeli Palestinian conflict. *Journal of Conflict Studies*, 23(2):114–148.

Pshisva, R. and Suarez, G. A. (2010). Capital crimes: kidnappings and corporate investment in Colombia. In Di Tella, R., Edwards, S., and Schargrodsky, E., editors, *The economics of crime: lessons for and from Latin America*, pages 63–97. University of Chicago Press.

Reed, H. E. (2013). Moving Across Boundaries: Migration in South Africa, 1950-2000. *Demography*, 50(1):71–95.

Restuccia, D. and Rogerson, R. (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic Dynamics*, 11(4):707 – 720.

Reynal-Querol, M. (2002). Ethnicity, Political Systems, and Civil Wars. *Journal of Conflict Resolution*, 46(1):29–54.

Rohner, D., Thoenig, M., and Zilibotti, F. (2013). Seeds of Distrust: Conflict in Uganda. *Journal of Economic Growth*, 18(3):217–252.

Sacerdote, B. (2001). Peer Effects With Random Assignment: Results For Dartmouth Roommates. *The Quarterly Journal of Economics*, 116(2):681–704.

Schor, A. (2004). Heterogeneous productivity response to tariff reduction. evidence from brazilian manufacturing firms. *Journal of Development Economics*, 75(2):373 – 396.

Shapiro, C. and Stiglitz, J. E. (1984). Equilibrium unemployment as a worker discipline device. *The American Economic Review*, 74(3):433–444.

Shavell, S. (1991). Individual precautions to prevent theft: Private versus socially optimal behavior. *International Review of Law and Economics*, 11(2):123–132.

Singh, P. (2013). Impact of Terrorism on Investment Decisions of Farmers: Evidence from the Punjab Insurgency. *Journal of Conflict Resolution*, 57(1):143–168.

Sletten, P. and Pedersen, J. (2003). Copying with conflict. Palestinian communities two years into the Intifada. Technical Report 2004:4, FAFO Report 408, Oslo, Norway.

Statistics South Africa (1991). *South African Census 1991 [dataset]. Version 1.1.* Pretoria: Statistics South Africa [producer]. Cape Town: DataFirst [distributor]. http://www.datafirst.uct.ac.za/ (accessed Februrary 3, 2012).

Statistics South Africa (1998). *South African Census 1996 [dataset]. Version 1.2.* Pretoria: Statistics South Africa [producer]. Cape Town: DataFirst [distributor]. http://www.datafirst.uct.ac.za/ (accessed Februrary 3, 2012).

Statistics South Africa (2007). *Using the 2001 Census: Approaches to Analysing Data*. Statistics South Africa, Pretoria.

Sundberg, R., Lindgren, M., and Padskocimaite, A. (2010). *UCDP GED Codebook Version 1.0-2011*. Department of Peace and Conflict Research, Uppsala University.

Sutton, P. C., Elvidge, C. D., and Ghosh, T. (2007). Estimation of Gross Domestic Product at Sub-national Scales Using Nighttime Satellite Imagery. *International Journal of Ecological Economics & Statistics*, 8(S07):5–21.

Terza, J. V., Basu, A., and Rathouz, P. J. (2008). Two-stage residual inclusion estimation: Addressing endogeneity in health econometric modeling. *Journal of Health Economics*, 27(3):531–543.

Topalova, P. and Khandelwal, A. (2011). Trade Liberalization and Firm Productivity: The Case of India. *The Review of Economics and Statistics*, 93(3):995–1009.

UNCTAD (2006). The palestinian war-torn economy: Aid, development and state formation. *UNCTAD/GDS/APP/2006/1*, United Nations Publications.

UNCTAD (2011). Report on unctad assistance to the palestinian people: Developments in the economy of the occupied palestinian territory. *TD/B/58/4*, United Nations Publications.

United Nations (2002). The impact of closure and other mobility restrictions on palestinian productive activities. *UN-Office of the United Nations Special Coordinator*.

University of Texas at Austin (1986). *South Africa: Black Homelands 1986*. Perry-Castañeda Library Map Collection, http://en.wikipedia.org/wiki/File:Southafricanhomelandsmap.png (accessed June 8, 2012).

van Ours, J. C. and Vollaard, B. (2014). The engine immobiliser: A non-starter for car thieves. *The Economic Journal*. forthcoming.

Vollaard, B. and van Ours, J. C. (2011). Does regulation of built-in security reduce crime? evidence from a natural experiment*. *The Economic Journal*, 121(552):485–504.

Wasmer, E. and Weil, P. (2004). The Macroeconomics of Labor and Credit Market Imperfections. *American Economic Review*, 94(4):944–963.

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica*, 48(4):817–38.

World Bank (2004). *Four Years. Intifada, closures and Palestinian economic crisis*. World Bank.

World Bank (2006). Enterprise Analysis Unit - World Bank Group. `www.enterprisesurveys.org`.

World Bank (2007a). Movement and access restrictions in the west bank: Uncertainty and inefficiency in the palestinian economy.

World Bank (2007b). West bank and gaza investment climate assessment: Unlocking the potential of the private sector. *Report No. 39109*.

World Bank (2007c). West Bank and Gaza Investment Climate Assessment: Unlocking the Potential of the Private Sector.

World Bank (2008). Implementing the palestinian reform and development agenda. *Economic monitoring report to the Ad Hoc Liaison Committee*.

World Bank (2010). The underpinnings of the future palestinian state: Sustainable growth and institutions. *Economic Monitoring Report to the Ad Hoc Liaison Committee*.

Zenou, Y. (2003). The Spatial Aspects of Crime. *Journal of the European Economic Association*, 1(2-3):459–467.

Zussman, A., Zussman, N., and Morten Orregaard, N. (2008). Asset Market Perspectives on the Israeli-Palestinian Conflict. *Economica*, 75(297):84–115.