Essays in Labor Economics and Political Economy

by

Annalisa Scognamiglio

M.Sc. Economics and Finance, University of Naples Federico II (2009)
M.A. Economics, University of Naples Federico II (2008)
B.A. Economics, University of Naples Federico II

ARCHIVES
MASSACHUSETTS INSTITUTE OF TECHNOLOGY
SEP 24 2014
LIBRARIES

Submitted to the Department of Economics
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

September 2014

© 2014 Annalisa Scognamiglio. All rights reserved.

The author hereby grants to MIT permission to reproduce and distribute publicly paper and electronic copies of this thesis document in whole or in part.

Author .... Signature redacted
Department of Economics
August 15, 2014

Certified by .... Signature redacted
David Autor
Professor of Economics
Thesis Supervisor

Certified by .... Signature redacted
Benjamin Olken
Professor of Economics
Thesis Supervisor

Accepted by .... Signature redacted
Nancy Rose
Charles P. Kindleberger Professor of Applied Economics
Chairman, Departmental Committee on Graduate Studies

Essays in Labor Economics and Political Economy

by

Annalisa Scognamiglio

Submitted to the Department of Economics
on August 15, 2014, in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Abstract

This thesis consists of three empirical contributions to the applied microeconomics literature.

The first chapter shows that there is substantial geographical variation in the use of cesarean sections in Italy. Such variation is not driven by medical need and higher cesarean rates are achieved by performing the procedure on less and less appropriate patients. I find no evidence that high-use areas develop higher ability in performing cesareans. Finally, by using both panel data analysis and instrumental variables, I show that there is no significant relation between risk-adjusted cesarean rates and maternal and neonatal mortality. The combined evidence in this chapter suggests that lowering cesarean rates would likely affect less appropriate patients, would not have negative spillovers in terms of quality of the procedure and would not affect neonatal nor maternal mortality.

The second chapter studies the response of sickness absences to changes in the replacement rate for sick leave. In June 2008 a national law modified both the strength of monitoring and the monetary cost of sick leaves for public sector employees. Using administrative data I show that absenteeism largely decreased following the reform. I identify the effects of an increase in the monetary cost of an absence using a differences in differences strategy that exploits variation in changes to the replacement rate for sick leave. Under the assumption that changes in monitoring had the same proportional impact on absenteeism within the same institutions, I estimate that a 1 percentage point decrease in the replacement rate reduces absenteeism by 1%.

The last chapter investigates the effect of diffusion of organized crime on local economies by examining a legal institution that operated in Italy between 1956 and 1988. The law allowed Public Authorities to force mafiosos to resettle to another town. Using variation in the number of resettled mafia members across destination provinces in a differences-in-differences setting, I find no conclusive evidence on the effect of the policy on crime or homicides, while there is a very robust positive impact on employment in the construction sector. This result is consistent with mafia exploiting these new locations mainly for money laundering and corruption.

Thesis Supervisor: David Autor
Title: Professor of Economics

Thesis Supervisor: Benjamin Olken
Title: Professor of Economics

Contents

List of Tables

List of Figures

Acknowledgements

I would like to thank my thesis supervisors David Autor and Benjamin Olken for the support they gave me throughout the PhD and for the countless discussions about my projects. I would like to thank the Economics faculty at MIT for all they taught me. In particular, I would like to thank professors Joshua Angrist, Daron Acemoglu and David Autor for having introduced me to Labor Economics and for the great passion they communicate with their teaching. I would like to thank the staff at MIT for all their help with various practical matters. I would like to thank the Labor Economics group at MIT for creating such a great research environment and all the participants to the Labor Lunch meetings for the feedback they gave me on my projects. I'm grateful to the Marco Fanno Foundation for the financial support during the first two years at MIT and to all the MIT undergraduate students that I had the pleasure to meet as a teaching assistant. I would like to thank professors Antonio Acconcia, Tullio Jappelli, Riccardo Martina, Marco Pagano and Marco Pagnozzi from University of Naples Federico II for having introduced me to Economics and for their encouragement in deciding to pursue a PhD, and all my friends in Cambridge and in Naples. Finally, I want to thank my family and, in particular, my sister for having always supported me with her positivity.

Chapter 1

Cesarean Sections: Use or Abuse?

1.1 Introduction

The cesarean section rate in Italy is much higher than in other European countries and in the United States, and it has been increasing dramatically over the past three decades. Furthermore, there is considerable geographical variation in the use of cesarean sections: the unadjusted cesarean section rate in Campania, a region in Southern Italy, is above 60% while the lowest rate is recorded in the Autonomous Provinces of Bolzano and Trento in the North where it is around 25%. Even within the South some areas use cesareans at higher rates than others.

The literature on geographical variation in the use of cesarean sections has mostly focused on the United States (Baicker *et al.* (2006), Chandra and Staiger (2014), Currie and MacLeod (2013)). However, Italy represents a very interesting case because of its extremely high rates: in 2011 the highest cesarean rate in the United States, reached in New Jersey, was 40%, way below the 60% reached in Campania in Italy.

Such geographical variation and the extremely high levels of cesarean rates reached in some areas have recently attracted the attention of policy makers. The Department of Health initiated an investigation in 2012 in order to evaluate and punish abusive adoption of this procedure. Performing unnecessary cesarean sections has potential negative consequences on maternal and neonatal health. Furthermore, cesarean sections are more costly than vaginal deliveries. Given that the Italian healthcare sector is characterized by universal public insurance, and it is mostly funded through taxation, cutting unnecessary costs can help to reduce distortionary taxation and to allocate tax revenues in more efficient ways. Reducing the use of cesareans is an explicit goal set by the government in the 2012 National Health Plan.

This paper aims to contribute to this debate by analyzing the relationship between variation in cesarean rates and patients' suitability, ability in performing the procedure and maternal and neonatal mortality. I show that cesareans are performed on less and less appropriate patients and I test whether increases in cesarean rates have positive effects on ability in performing cesareans. Even though the marginal patients are not appropriate for the procedure, lowering cesareans rates might have negative effects on the quality of cesareans for the inframarginal patients. I find that the quality of cesareans does not increase with cesarean rates. Finally, I assess the relation between risk-adjusted cesarean rates and maternal and neonatal mortality using both panel data analysis and instrumental variables and I find no evidence that cesarean rates affect these outcomes.

In particular, following a standard empirical approach in this literature (e.g. Baicker *et al.* (2006)), I estimate a logistic model for the probability of delivery via cesarean section that includes a rich set of patient-level controls for risk-factors and area fixed effects and then build a measure of patients' suitability to the cesarean section as the estimated predicted probability of cesarean excluding the area fixed effects. The area-specific risk-adjusted cesarean rates are obtained by retrieving the estimated area fixed effects and computing the predicted probability of a cesarean at the average level of risk. A regression of the appropriateness measure on the logarithm of the area risk-adjusted cesarean rate shows that a 1% increase in the risk-adjusted cesarean rate corresponds to a 6.7 percentage points decrease in the appropriateness measure. By using time-varying measures of appropriateness and risk-adjusted cesarean rates, I show that a within-area increase in cesarean rates is associated with a decrease in appropriateness. These results suggest that high cesarean rates do not emerge from an increase in the use of cesarean sections all across the board but rather that the marginal patients become less appropriate as the risk-adjusted cesarean rate increases.

Even though cesareans are performed on less and less appropriate patients, areas characterized by higher risk-adjusted cesarean section rates might develop higher productivity in performing cesarean sections. I test this hypothesis by relating the probability of having complications following a cesarean section with the area risk-adjusted cesarean rate for the sub-sample of women that received a previous cesarean section. The probability of a repeat cesarean is about 94%. This fact helps to isolate the effect of ability in performing a cesarean section from compositional effects. I find that a 10 percentage points increase in risk-adjusted cesarean section rates corresponds to an about 3 percentage points increase in the probability of complications for repeat cesareans. This result is confirmed when I use an alternative strategy that relies only on within-region variation.

The last step in the analysis is to examine the relationship between maternal and neonatal mortality and area risk-adjusted cesarean rates. A simple OLS regression shows a large negative relation between cesarean rates and neonatal mortality while no relation is found for maternal mortality. With the inclusion of area fixed effects, however, the coefficient drops by more than half and becomes insignificant. No significant relation is found in a cross-sectional regression where the areas' risk-adjusted cesarean rates are instrumented with the fraction of female gynecologists.

The fact that physicians work down the patients' suitability curve is consistent with the view that the rise in cesarean rates is not driven by changes in patients' risk-factors but rather by financial incentives for doctors and hospitals (Gruber and Owings (1996), Gruber *et al.* (1999)), changes in patients' preferences and fear of malpractice lawsuits (Dubay *et al.* (1999)), but not implied by it. For instance, physicians driven by financial incentives might be uniformly more aggressive. The results in this paper suggest instead that non-medical motives change physicians' behavior at the margin, i.e. the threshold level of risk after which a cesarean is performed decreases as the cesarean rate increases.

Baicker *et al.* (2006) study the variation in the use of cesarean section across counties in the United States and find a negative relationship between average appropriateness and risk-adjusted cesarean rates and no significant correlation between mortality and cesarean rates. My contribution relative to Baicker *et al.* (2006) is two-fold: I propose a strategy to test whether ability in performing cesareans increases with cesarean rates and an instrumental variable strategy for the identification of the causal effect of cesarean rates on mortality outcomes. Furthermore, I focus on Italy where, as discussed above, cesarean rates reach much higher levels.

This is not the first paper to highlight the high levels of cesareans and the geographical variation in the use of cesareans in Italy. For instance, Francese *et al.* (2012) explore the impact of supply factors, pricing policies and political economy factors on regional variation in the use of cesarean sections, and Cavalieri *et al.* (2013) analyze the impact of DRG tariff differentials on the risk-adjusted cesarean section rates for first-time mothers during the period 2009-2011and find that hospitals respond to financial incentives. To the best of my knowledge, however, this is the first study that highlights the negative relation between area use rates and patients' suitability in Italy, and that proposes a way to assess the effects on both quality of the procedure and mortality outcomes.

The rest of the paper proceeds as follows: section 1.2 documents the geographical variation and the upward trends in cesarean rates. Section 1.3 discusses potential explanations for the rise in cesarean sections. Section 1.4 analyzes the relation between patients' suitability and regional variation in risk-adjusted cesarean rates. Section 1.5 shows the relation between cesarean rates and ability in performing c-sections. Section 1.6 relates risk-adjusted cesarean rates to maternal and neonatal mortality, and section 1.7 concludes.

1.2 Geographical Variation and Trends in Cesarean Section Rates

The rate of cesarean section in Italy has been increasing substantially over time. Figure 1-1 shows the time series of cesarean section rates from 1980 to 2012. In 1980 there were about 11 cesarean sections per 100 live births, but such number doubles by 1990 and keeps increasing over time, reaching a peak of about 40 cesarean sections per 100 live births in 2007. An upward trend in the use of cesarean sections has been recorded in several countries. However, as shown in figure 1-2, the rate of cesarean sections is higher in Italy than in other OECD countries. For instance, the cesarean rate in Italy is 15 percentage points higher than in Spain, and about 7 percentage points higher than in the United States.

The increase in the use of cesarean sections, however, was not homogeneous across geographical areas. The evolution of unadjusted cesarean rates over time across Italian regions highlights substantial variation across geographical areas in both the levels and the trends. In the early 1980s cesarean rates in the Southern regions are comparable to those in the Northern and Central regions, but they evolve on steeper trends. By 1996 the lowest cesarean rate among the Southern regions, i.e. 28.2 in Calabria, is about 3 percentage points higher than the highest rate among the Northern regions. Campania shows the most impressive rise in cesarean rates: from 8.5% in 1980 to about 62% in 2011. Just in the decade between 1990 and 2000 the cesarean rate increases in Campania from 20% to more than 50%. Figure 1-3 shows that, even though cesarean rates are very high in all Southern regions, there is sizable variation with a 20 percentage points difference between the highest (Campania) and the lowest (Calabria) in 2010.

1.3 Potential Explanations for the Trends in Cesarean Rates

Upward trends in cesarean section rates have been observed in several countries. For instance, in the United States the cesarean section rate has increased from about 22% in 1990 to 30% in 2005. The medical literature (e.g. Ecker and Frigoletto (2007)) has suggested several factors that can explain the observed rise in cesarean section rates: technological changes that make cesarean deliveries less risky, e.g. the development of new anesthetic techniques, the introduction of modern antibiotics and the creation of neonatal intensive care units, and the diffusion of diagnostic techniques that increase the likelihood of a pregnancy being identified as benefiting from a cesarean delivery, e.g. the development of pre-delivery diagnostic techniques for the fetus. The reduction in the use of forceps, following studies that highlighted the risks for the fetuses, also contributes to the rise in cesarean sections. Compositional changes of the mothers, e.g. the increase in mothers' age and obesity, and changes in preferences, e.g. the change in the risk threshold that are considered acceptable, also play a role in the rise of cesarean sections.

The factors highlighted above can help explain the upward trend in Italy as well. Figure 1-4 shows that average mothers' age at delivery has increased over time. However, the increase in the South and the Islands, where cesarean rates increased the most, is smaller than in other areas. Furthermore, there have been dramatic social and economic changes over the past decades in Italy that might have determined changes in preferences toward type of delivery. For instance, the share of women with college degree has increased from 4.9% in 1993 to 12.3% in 2012, and female labor force participation has increased from about 42% in 1993 to 53.5% in 2012. As shown in figure 1-5, the fertility rate has also been changing dramatically over the past decades, and its evolution followed different patterns across areas. The fertility rate has been decreasing over time in Southern Italy whereas it exhibits a U-shaped evolution in Northern and Central Italy. This fact might contribute to the differences in the evolution of cesarean rates across these broad areas. Indeed, there is a negative correlation between cesarean rates and fertility rates within provinces, robust to the inclusion of region by year fixed effects. It is hard, however, to argue for a causal interpretation, as omitted variable bias is likely to be present in this context. Other potential factors explaining the fast rise in cesarean rates are the use of repeat cesarean and the existence of spillovers effects, for which an increase in cesarean rates is self-reenforcing over time - e.g. as cesarean rates increase, the option for a cesarean section is perceived as more and more "natural" by both mothers and physicians.

The economic literature has focused on changes in physicians' behavior as a potential explanation for the rise in cesarean section rates. In particular, the literature has mostly looked at two potential factors influencing physician practice:

1. Malpractice lawsuits: the increased fear of malpractice lawsuits, often alleging a failure to perform timely cesarean delivery, might induce physicians to opt for cesarean sections. There is, however, conflicting evidence on this matter. For instance, Dubay *et al.* (1999) find a positive relation between malpractice premiums and the use of cesarean sections whereas Baicker and Chandra (2005) and Kim (2007) find no evidence of an impact of malpractice fear on the use of cesarean sections. Malpractice lawsuits are on the rise in Italy as well. DiMarzo (2012) reports that between 1994 and 2008 the number of claims filed annually against hospitals and medical practitioners increased from 3,150 to almost 30,000.

2. Incentive effects of the payment system: if the net financial benefit of performing a cesarean section is higher than for a vaginal delivery, providers have incentives to induce demand for the former rather than the latter. Gruber and Owings (1996) hypothesize that the fall in fertility rates represents a negative income shock for physicians and find that providers substitute from vaginal deliveries to cesarean sections, characterized by a higher reimbursement, to compensate for the decrease in volumes. Gruber *et al.* (1999) compare privately insured patients with Medicaid patients and find a positive impact of tariff differentials on the probability of cesarean delivery.

In line with this literature, an additional factor that can help explain the rise in cesarean rates in Italy is the introduction in 1992-1993 of dramatic changes to both the organizational structure and the reimbursement system of the National Health System. With the laws 502/1992 and 517/1993, the Italian National Health System goes from being a highly centralized system to a decentralized system, both in terms of organization and of funding for the provision of healthcare services. More powers are given to the Regions, together with the responsibility for balancing the budgets. The Local Health Authorities go from being operational units subject to the control of the municipalities to corporations. The relationship between public insurance and private providers, previously based mostly on bilateral agreements for the provision of healthcare services, is fully reorganized. Finally, the funding system changes toward increasing competition among hospitals, by introducing the reimbursement system based on the DRGs and allowing public for fee services - i.e. public providers can practice as private professionals using the facilities of the public hospitals. The introduction of several fundamental changes at once and the potential for complementarities in these changes makes it difficult to identify the causal impact of each of them. Furthermore, the trends in the use of cesarean sections across provinces start diverging already before the introduction of the reform. So, even though the reform had an impact on the use of cesarean sections, it is difficult to capture.

The discussion above suggests that the increase in cesarean sections experienced in Italy and especially in some areas might be driven by reasons other than growing medical need. Geographical variation in the use of cesarean section is thus likely the result of such non-medical factors affecting different areas in different ways. The analysis that follows focuses on understanding the implications of the importance of non-medical factors in terms of physician behavior and patients' outcomes.

1.4 Geographical Variation in the Use of Cesarean Section and Patients' Appropriateness

Section 1.2 documents substantial variation in the use of cesarean sections across geographical areas in Italy. A large literature in medicine documents the existence of geographical variation in the use of intensive health treatments, unrelated to outcomes, and has often explained it with a "flat of the curve medicine" argument - i.e. physicians use high-intensity procedures up to to the point in which the marginal product is zero. The economics literature has offered alternative explanations for the observed facts. For instance, Chandra and Staiger (2007) test a Roy model with productivity spillovers for the use of surgical procedures for the treatment of heart attacks and find higher returns from surgery for most appropriate patients in high-intensity areas, while there is no relationship between overall outcomes and area intensity. Several papers focus specifically on geographical variation in the use of cesarean section. Baicker *et al.* (2006) show that there is sizable variation in the use of cesarean sections across counties in the US. They further show that the average appropriateness of patients decreases with the area's risk-adjusted cesarean rate while there is no significant relation with maternal and neonatal mortality.

This section analyzes the relation between patients' suitability and geographical variation in the use of cesarean sections in Italy. In particular, I test whether there is a negative relation between appropriateness and risk-adjusted regional cesarean section rates among the women that received a cesarean section. This allows one to identify whether physicians in high-use areas perform cesarean sections on increasingly less suitable patients.

1.4.1 Microdata - Survey on Health Condition and Healthcare Utilization

The patient level data is obtained from the 2004/2005 Survey on Health Conditions and Healthcare Utilization. The survey provides a full account of individual health, healthcare use, demographics and socio-economic status and has an additional section about pregnancy, childbirth delivery and breast-feeding which is filled in by all women in the sample that had a baby in the previous five years. The 2004-2005 survey includes 50,474 households for a total of 128,040 individuals. The pregnancy/childbirth delivery section is filled in by 5,812 women. Table 1.1 reports the fraction of births via cesarean. Among all births 35% happen via cesarean section, 63% of which are scheduled cesarean sections (column (1), table 1.1). Column (2) restricts the sample to women with no previous cesarean section. Among them the fraction of women receiving a cesarean section is substantially lower and equal to 26%, and only 13% of mothers with no previous cesarean section have a scheduled cesarean. Table 1.2 shows that there is substantial variation across geographical areas in the use of cesarean sections, both in the full sample of births and in the sub-sample of mothers that did not have previous cesarean sections. The fraction of cesarean births is 15 percentage points higher in the South and the Islands than in the North. The gap is smaller in the sub-sample of mothers that did not have previous cesarean births, but it is still sizable - i.e. the fraction of cesarean births in the South and the Islands is 11 percentage points higher than that in the North.

1.4.2 Empirical Strategy and Results

Following the literature (Baicker *et al.* (2006), Chandra and Staiger (2007)), I estimate a logistic model for the probability of receiving a cesarean section that includes a rich set of patient-level controls and region fixed effects:

$$\Pr\left(\mathrm{CS}_{ij}=1\,|\,X_{ij}\,,\theta_j\right)=\mathrm{F}\left(\theta_0+\theta_j+\beta X_{ij}\right) \tag{1.1}$$

where i indexes a patient, θ_j are region fixed effects and $\mathrm{F}(.)$ is the logistic distribution. Table 1.3 gives summary statistics and a description of all the variables included as controls. The measure of appropriateness used in the analysis below is built as the predicted probability of receiving a cesarean section net the region fixed effects, $Appropriateness_{ij}=\mathrm{F}\left(\hat{\theta}_0+\hat{\beta}X_{ij}\right)$. The estimated region fixed effects are used to build regional risk-adjusted cesarean section rates, $RACR_j=\mathrm{F}\left(\hat{\theta}_0+\hat{\theta}_j+\hat{\beta}\overline{X}\right)$, where $\overline{X}$ is the vector of the controls' means. The variation in the cesarean rates across regions is not explained by differences in the distribution of risk-factors but rather the risk-adjusted rates for some regions are higher than the corresponding unadjusted rates, i.e. cesarean rates in some areas are higher than what the model would predict given the distribution of patients' characteristics. This means that the regional variation in cesarean rates is driven by factors others than patients' characteristics, e.g. supply factors, physician practice style etc, but it does not tell us much about the model that drives the increases in cesarean rates.

In order to test whether doctors walk down the distribution of patients' observable appropriateness, I correlate the area risk-adjusted cesarean rates with average appropriateness of patients that receive a cesarean section. If doctors in high-use areas perform cesarean sections on less appropriate patients we should observe a negative relationship between average appropriateness and risk-adjusted cesarean rates. Figure 1-6 shows that average appropriateness for cesarean births is lower in regions with higher risk-adjusted cesarean rates. Notice that this is not a mechanical relationship. As discussed in Baicker *et al.* (2006), both a positive relationship and a zero relationship can arise. For instance, if doctors in high-use areas are uniformly more aggressive and perform more cesarean sections for all appropriateness levels we would find no correlation. A simple example can help to understand the logic. Suppose that there are only two observable types of patients, A and B, and two regions, 1 and 2. For simplicity assume that in both regions patients are evenly distributed across the two types. Type-A patients are more likely to need a cesarean section than type-B patients. In particular, 20% of type-A patients and 10% of type-B patients need a cesarean. Region 1 has exactly these proportions, while region 2 performs cesareans on 40% of type-A patients and 20% of type-B patients. The average predicted probability of a cesarean delivery among cesarean births is the same in the two regions, but the risk-adjusted cesarean rate in region 2 is higher.

In the same spirit I test whether the marginal cesarean birth has lower appropriateness than the average cesarean birth. The estimating equation is

$$Appropriateness_{ij} = \alpha + \beta \cdot \log(RACR_j) + \epsilon_{ij} \tag{1.2}$$

and the sample is restricted to cesarean births only. The coefficient β in equation 1.2 measures the difference between the predicted probability of a cesarean section for the marginal cesarean birth and the average cesarean birth. A negative β means that doctors perform cesareans on less and less appropriate patients as the cesarean rate increases.

Table 1.4 reports the coefficient estimates for model 1.2. The appropriateness measure and the regional risk-adjusted cesarean section rates in column (1) in table 1.4 are obtained as described above, while column (2) refers to births via scheduled cesarean. This means that the appropriateness measure and the risk-adjusted cesarean rates are obtained from model 1.1 using a dummy variable that equals one for scheduled cesarean and zero for vaginal births as well as unscheduled cesarean births. Panel A, B and C in table 1.4 respectively use the samples of all birth-weights, low birth-weights - i.e. birth-weight at or below 2.5kg, and normal birth-weights - i.e. birth-weight above 2.5kg. The relationship between appropriateness and regional risk-adjusted cesarean rates is negative in all sub-samples. A 1% increase in the regional risk-adjusted cesarean section rate corresponds to a 6.7 percentage points decrease in appropriateness for normal birth-weights, and to a 20 percentage points decrease in appropriateness for the sub-sample of low birth-weights. The point estimates are smaller and less precise when considering scheduled cesarean sections (column (2) in table 1.4) but there is still a sizable negative relationship between appropriateness and scheduled cesarean rates, suggesting that, as the rate of scheduled cesarean sections increases, doctors schedule cesareans for less appropriate women.

As documented above, cesarean section rates were on the rise everywhere in Italy. However the growth rates exhibit cross-sectional variation. This allows me to construct a strategy that uses within-region variation to test whether an increase in the regional risk-adjusted cesarean rate corresponds to a decrease in appropriateness. I build time-varying measures of appropriateness and risk-adjusted cesarean section rates by following the procedure described above. In order to allow for changes in the responsiveness to risk factors over time, I estimate model 1.1 in section 1.4 separately for the different time periods. For instance, this allows for technological changes to affect the way different risk factors influence the probability of cesarean birth. The estimating equation to test this hypothesis is

$$Appropriateness_{ijt} = \alpha_j + \lambda_t + \beta \cdot \log\left(RACR_{jt}\right) + \epsilon_{ijt} \tag{1.3}$$

where y_{ijt} is the outcome for mother i in region j in time period t, α_j are region fixed effects and λ_t are time-period fixed effects. The areas' time-varying risk-adjusted cesarean rates are obtained by following the procedure in the previous section where model 1.1 is estimated separately on the two time periods, 1998-2002 and 2003-2005. Table 1.5 reports the estimates for equation 1.3: a 1% increase in within-region risk-adjusted cesarean rates is associated with a 20 percentage points decrease in the appropriateness measure. I interpret this finding as evidence of a decrease in the threshold level of patients' appropriateness after which cesarean sections are performed.

1.5 Regional Risk-Adjusted Cesarean Rates and Ability in Performing Cesarean Sections

Areas characterized by higher risk-adjusted cesarean section rates might develop higher productivity in performing cesarean sections. I test this hypothesis by relating the probability of having complications following a cesarean section with the areas risk-adjusted cesarean rates for the sub-sample of women that received a previous cesarean section. About 94% of the births following a cesarean birth happen via cesarean section. This fact helps isolating the effect of the ability in performing a cesarean section from compositional effects. Using the full sample of mothers would lead to a mechanical relation between the incidence of problems related to childbirth delivery, due to the fact that some problems are more likely to appear following a cesarean section. Restricting the attention to cesarean birth also presents some problems. Table 1.6 shows that, for the sub-sample of cesarean births, a 10 percentage points increase in the area's risk-adjusted cesarean rate corresponds to a 3 percentage points decrease in the probability of any problem occurring following childbirth delivery and to a 1.2 percentage points increase in the probability of healing problems. However, the compositional differences across areas in the group of cesarean births do not allow to isolate the effect of ability. As shown in the previous sections, patients' suitability decreases with the cesarean rate. The estimates in table 1.6 are thus the joint effect of decreased appropriateness and changes in ability. I restrict the sample to women with previous cesarean sections in order to reduce concerns related to mechanical effects and compositional differences across areas. Table 1.7 shows the relation between the probability of complications and the area's risk-adjusted cesarean rate, obtained by estimating linear probability models of outcomes on regional risk-adjusted cesarean rates and patient level controls. The outcome in column (1) in table 1.7 is a dummy variable that equals one if a mother experiences any complication following childbirth delivery. A 10 percentage points increase in the risk-adjusted cesarean rate corresponds to a 1.53 percentage points decrease in the probability of having any problem, but the estimate is very imprecise. The outcomes in columns (2) and (3) are dummy variables that equal one if a mother experiences respectively healing complications and gynecological problems following childbirth delivery. A 10 percentage points increase in risk-adjusted cesarean section rates corresponds to an about 3 percentage points increase in the probability of healing problems, while the relation between the incidence of gynecological problems and areas' risk-adjusted cesarean rates is small and insignificant. While the probability of receiving a cesarean section conditional on having received one before is very high everywhere, there is sizable geographical variation. Higher incidence of healing problems might thus be partly explained by the increase in the fraction of cesarean births. Controlling for the fraction of women receiving a cesarean section (not reported) changes the coefficients only marginally. These findings go against the hypothesis that areas that perform more cesarean sections have higher ability than low-cesarean rates areas. Table 1.8 shows the relation between bad outcomes and cesarean rates using only within region variation. The coefficients in table 1.8 are obtained by splitting the dataset in two time periods, 1998-2002 and 2003-2005, and estimating the following model

$$y_{ijt} = \alpha_j + \lambda_t + \beta RACR_{jt} + \epsilon_{ijt} \tag{1.4}$$

where y_{ijt} is the outcome for mother i, in region j, in time period t, α_j are region fixed effects and λ_t are time-period fixed effects. The areas' time-varying risk-adjusted cesarean rates are obtained by following the procedure in the previous section where model 1.1 is estimated separately on the two time periods, 1998-2002 and 2003-2005. Table 1.8 shows that increases in areas' risk-adjusted cesarean rates correspond to increases in the probability of complications following childbirth delivery for mothers with previous cesarean sections. A 10 percentage points increase in areas' risk-adjusted cesarean rate is associated to a 4.4 percentage points increase in the probability of healing problems, but the estimate is imprecise. One caveat to the analysis described in this section is that, although the probability of a second cesarean is very high, unobservable compositional differences across areas can derive from selection into the first cesarean. However, the analysis including fixed effects helps overcoming this caveat and confirms the result that higher cesareans rates are not related to higher ability in performing cesarean sections.

1.6 Maternal and Neonatal Mortality and Cesarean Rates

The results in the previous sections show that, as cesarean rates increase, physicians perform cesarean sections on less and less appropriate patients. Furthermore, I do not find evidence that an increase in cesarean rates is associated with improved quality of cesarean sections. This section studies the relationship between maternal and neonatal mortality and areas' risk-adjusted cesarean rates.

1.6.1 The Data

The data on neonatal and maternal mortality is part of the Health for All - Italy database, an information system that collects health data from several sources in order to provide an overview about health conditions and supply and demand of health care services. It contains about 4000 indicators of demographics, causes of deaths, hospital discharges by diagnosis, life styles, health care resources and life expectancy. Neonatal mortality is defined as the number of deaths within the first 29 days of life per 10,000 live births. Maternal mortality is defined as the number of deaths for which "complications of pregnancy, childbirth, and the puerperium" is listed as the primary cause of death per 10,000 births. Both variables are available at the province level ($N = 109$) from 2007 to 2011.

The National Program for the Evaluation of Healthcare Services provides data on unadjusted cesarean rates and risk-adjusted cesarean rates at hospital level from 2007 to 2012[1]. I compute the average cesarean rates by province and merge this data with the mortality data. The mean and standard deviations of maternal mortality are, respectively, 0.29 and 1.25. Neonatal mortality has mean 15.24 and standard deviation 9.54.

1.6.2 Empirical Strategies and Results

In order to study the relationship between maternal and neonatal mortality and areas' cesarean rates I use two different empirical strategies. First, I estimate the following model using OLS:

$$y_{pgt} = \alpha_p + \lambda_{gt} + \beta \cdot RACR_{pt} + \epsilon_{pgt} \tag{1.5}$$

where y_{pgt} is either maternal or neonatal mortality in province p in area $g \in \{North, Center, South\}$ and year t, $RACR_{pgt}$ is the risk-adjusted cesarean rate, α_p are province fixed effects and λ_{gt} are area-specific year fixed effects. Table 1.9 reports the estimate for β in equation 1.5. The specifications in column (1) and (2) do not include province fixed effects. Maternal mortality is not associated with risk-adjusted cesarean rates whereas neonatal mortality appears to be correlated with cesarean rates: a 10 percentage points increase in the risk-adjusted cesarean rate is associated with about 1 less death per 10,000 live births. With the inclusion of province fixed effects and area-specific year effects in column (4), however, the point estimate drops by half and becomes insignificant.

If changes in the risk-adjusted cesarean rates are correlated to shocks to neonatal and maternal mortality, the coefficients in table 1.9 do not have a causal interpretation. In order to use the cross-sectional variation, without relying on the assumption that differences in cesarean rates are uncorrelated with other characteristics that also affect mortality, I use the fraction of female gynecologists in province p to instrument for the average risk-adjusted cesarean rate in province p over the sample period 2007-2011. The structural equation of interest is

[1] The risk-adjustment procedure used by the National Program for the Evaluation of Healthcare Services for cesarean rates is based on logistic regressions including a variety of patient-level risk-factors. Detailed information about the methods are available online at http://95.110.213.190/PNEed13/.

$$\bar{y}_p = \alpha + \beta \cdot \overline{RACR_p} + \epsilon_p \tag{1.6}$$

where $\overline{y}_p$ and $\overline{RACR_p}$ are, respectively, the mortality outcomes and the risk-adjusted cesarean rate averaged across the sample period 2007-2011. I instrument $\overline{RACR_p}$ using the fraction of female gynecologists in province p in the year 2011. If female gynecologists attribute more importance to the choice of the delivery type, they might also be less incline to perform cesarean sections on less suitable patients. I assume that the probability of being followed during pregnancy by a female gynecologist is exogenously higher in areas with a higher fraction of female gynecologists. If female doctors are more involved at an emotional level in the choice of the delivery type we would expect the cesarean rate to decrease with the fraction of female gynecologists. Panel C in table 1.10 shows the first stage coefficient: a 10 percentage points increase in the fraction of women reduces the risk-adjusted cesarean rate by 1.9 percentage points. Column (1) in table 1.10 shows that there is no significant relationship between maternal mortality and risk-adjusted cesarean rates within area (panel A) whereas a 10 percentage points increase in the risk-adjusted cesarean rate corresponds to about 0.9 more neonatal deaths per 10,000 births (panel B), although such relationship is imprecisely estimated. The OLS relationship between mortality and risk-adjusted cesarean rates are likely to suffer from omitted variable bias due to unobservable patients' or provinces' characteristics. Indeed, column (3) in panel B in table 1.10 shows that the 2SLS coefficient for neonatal mortality is about zero, thus suggesting that a decrease in cesarean rates would not affect neonatal mortality. Notice, however, that the 2SLS estimates are imprecise, so some caution is needed in drawing conclusions. Column (3) in panel A shows that there is no significant effect of cesarean rates on maternal mortality. However, the point estimate is larger than the OLS estimate, but imprecisely estimated. It is not possible to conclude with certainty that maternal mortality is not benefited by higher cesarean rates.

One concern with the IV strategy described above is that the fraction of female gynecologists might affect neonatal and maternal health via channels other than the choice of whether to perform a cesarean section or not, thus violating the exclusion restriction. For instance, a higher fraction of female gynecologists might improve overall gynecological health thus biasing the effect on mortality toward zero. As a check for the presence of this channel I look at the relation between mortality rates due to breast cancer and the fraction of female gynecologists. Table 1.11 shows that there is no significant relationship between mortality for breast cancer and the fraction of female gynecologists. Although there can still be concerns about the exclusion restriction, this result is reassuring.

1.7 Conclusions

This paper documents the existence of sizable variation in the use of cesarean sections in Italy across geographical areas and over time. It then shows that patients' suitability to cesarean sections decreases as risk-adjusted cesarean rates increase. High-use areas do not seem to have higher ability in performing cesarean sections relative to other areas, nor do they seem to develop higher ability in performing cesareans with the increase in the use of this procedure over time. Finally, it assesses the relation between risk-adjusted cesarean rates and maternal and neonatal mortality using both panel data analysis and instrumental variables and finds no evidence that cesarean rates affect these outcomes.

These results suggest that high cesarean rates do not emerge from an increase in the use of cesarean sections all across the board but rather doctors target cesarean sections towards more appropriate patients in general, so as the cesarean rates rise for non-medical reasons, the suitability of patients for cesareans at the margin declines.

Even though cesareans are performed on less and less appropriate patients, areas characterized by higher risk-adjusted cesarean section rates might develop higher productivity in performing cesarean sections. I test this hypothesis by relating the probability of having complications following a cesarean section with the area's risk-adjusted cesarean rate for the sub-sample of women that received a previous cesarean section. I find that a 10 percentage points increase in the risk-adjusted cesarean section rate corresponds to an about 3 percentage points increase in the probability of complications. Using a fixed effects panel data regression I further show that the risk-adjusted cesarean rate is also positively related to the probability of complications following a cesarean section for women that had a previous c-section.

The last step in the analysis is to examine the relation between maternal and neonatal mortality and the area's risk-adjusted cesarean rate. No significant relation is found using within-province variation nor in a cross-sectional regression where the risk-adjusted cesarean rate is instrumented with the fraction of female gynecologists.

The combined evidence presented in this paper supports the view that lowering cesarean sections would not have negative consequences on patients' outcomes, but rather could benefit patients and surely reduce the costs for healthcare provision.

Table 1.1: FRACTION OF CESAREAN BIRTHS

	All births	No previous cesarean
Any Cesarean	0.35	0.26
Scheduled Cesarean	0.22	0.13
N	5812	5000

Column (1) reports the fraction of cesarean births among all births. Column (2) reports the fraction of cesarean births among mothers that did not have a previous cesarean section. Any Cesarean is a dummy that equals 1 for any cesarean birth. Scheduled cesarean is a dummy that equals 1 for scheduled cesarean births and 0 else.

Table 1.2: FRACTION OF CESAREAN BIRTHS BY GEOGRAPHICAL AREA

Area	North-East	North-West	Center	South and Islands
	Panel A: All births			
Any Cesarean	0.28	0.27	0.34	0.43
Scheduled Cesarean	0.14	0.14	0.20	0.29
N	1136	1228	990	2026
	Panel B: No previous cesarean section			
Any Cesarean	0.21	0.19	0.24	0.32
Scheduled Cesarean	0.09	0.08	0.10	0.19
N	1017	1075	844	2458

Panel A reports the fraction of cesarean births and scheduled cesarean births among all births by geographical area. Panel B reports the fraction of cesarean births and scheduled cesarean births among mothers that do not have previous cesarean sections.

Table 1.3: SUMMARY STATISTICS FOR THE CONTROL VARIABLES

	mean	sd
Amniocen=1 if the woman underwent prenatal diagnostic checks	0.30	0.46
Diabetes=1 if the woman reports having suffered from diabetes during pregnancy	0.02	0.15
Gestosis=1 if the woman reports having suffered from gestosis	0.03	0.18
Hypertension=1 if the woman reports having suffered from hypertension during pregnancy	0.04	0.20
Body Mass Index	229.67	36.11
Birthweight in kg	3.25	0.51
Hospitalization=1 if the woman was hospitalized during pregnancy	0.66	0.47
Smoking=1 if the woman was an abitual smoker	0.22	0.42
Age below 24	0.05	0.22
Age above 35	0.25	0.43
Primipar	0.43	0.49
Previous Cesarean	0.14	0.35
Gestation month at delivery:		
6th month=1 if delivery happens at 6th month of pregnancy	0.00	0.04
7th month=1 if delivery happens at 7th month of pregnancy	0.02	0.12
8th month=1 if delivery happens at 8th month of pregnancy	0.07	0.25
Low Education=1 if the woman holds a low-education degree	0.45	0.50
High Education=1 if the woman holds a high-education degree	0.12	0.33
Employed=1 if the woman is employed	0.54	0.50
Never Married=1 if the woman was never married	0.07	0.26
Divorced=1 if the woman is divorced	0.02	0.13
Widowed=1 if the woman is widowed	0.01	0.07
Separated=1 if the woman is separated	0.02	0.15
Dummy for Quarter of Birth 1	0.24	0.43
Dummy for Quarter of Birth 3	0.26	0.44
Dummy for Quarter of Birth 4	0.26	0.44
Dummy for Year of Birth 98-99	0.10	0.30
Dummy for Year of Birth 2000	0.15	0.36
Dummy for Year of Birth 2001	0.15	0.35
Dummy for Year of Birth 2003	0.18	0.39
Dummy for Year of Birth 2004	0.19	0.39
Dummy for Year of Birth 2005	0.06	0.23
N	5790	

The table reports the definition and mean and standard deviation for all the variables used in the logistic model to build the appropriateness measure and the risk-adjusted cesarean rates.

Table 1.4: Appropriateness and Risk-Adjusted Cesarean Rates

	Predicted Probability of:	
	Any Cesarean	Scheduled Cesarean
	(1)	(2)
	Panel A: All birthweights	
log(RACR)	-0.067**	-0.052*
	(0.021)	(0.020)
cons	0.474***	0.316***
	(0.026)	(0.030)
N	2027	1270
	Panel B: Low birthweights	
log(RACR)	-0.196***	-0.143**
	(0.045)	(0.036)
cons	0.330***	0.142**
	(0.024)	(0.038)
N	231	124
	Panel C: Normal birthweights	
log(RACR)	-0.062**	-0.057*
	(0.019)	(0.021)
cons	0.475***	0.315***
	(0.025)	(0.032)
N	1796	1146
N clusters	21	21

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

The dependent variable in column (1) is the predicted probability of any cesarean section. The dependent variable in column (2) is the predicted probability of a scheduled cesarean section. Panel A reports the estimates for all birthweights, panel B reports the estimated coefficients for the sub-sample of low-birthweight births (at or below 2.5kg) and panel C reports the estimates for the sub-sample of normal-birthweight births (above 2.5kg). RACR is the risk-adjusted cesarean rate for column (1) and the risk-adjusted rate of scheduled cesareans in column (2).

Table 1.5: APPROPRIATENESS AND RISK-ADJUSTED CESAREAN RATES WITHIN REGION

	Appropriateness
log(RACR)	-0.194**
	(0.056)
I(2003-2005)	0.077***
	(0.014)
cons	0.312***
	(0.059)
Region Fixed Effects	Yes
N	2027
N clusters	21

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

The data is divided in two time periods: 1998-2002 and 2003-2005. Each time period is used to get separate estimates for both appropriateness and areas' risk-adjusted cesarean rates. Standard errors clustered at region level in parentheses. The omitted time period is 1998-2002. RACR is the risk-adjusted cesarean rate.

Table 1.6: COMPLICATIONS AND RISK-ADJUSTED CESAREAN RATES: SUB-SAMPLE OF CESAREAN BIRTHS

	Any Problem	Healing Problems	Gynecological Problems
	(1)	(2)	(3)
RACR	-0.235*	0.115	0.065
	(0.109)	(0.076)	(0.062)
N	2038	2038	2038
N clusters	21	21	21

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

All regressions include the full set of patients' controls described in the previous section. The outcomes in columns (1) to (3) are dummy variables that equal one if a woman experienced any complication, healing problems or gynecological problems following childbirth delivery. RACR is the risk-adjusted cesarean rate. Standard errors (in parentheses) are clustered at the region level.

Table 1.7: COMPLICATIONS AND RISK-ADJUSTED CESAREAN RATES: SUB-SAMPLE OF WOMEN WITH PREVIOUS CESAREAN SECTIONS

	Any Problem	Healing Problems	Gynecological Problems
	(1)	(2)	(3)
RACR	-0.153	0.278**	-0.049
	(0.138)	(0.094)	(0.075)
N	753	753	753
N clusters	21	21	21

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

All regressions include the full set of patients' controls described in the previous section. The outcomes in columns (1) to (3) are dummy variables that equal one if a woman experienced any complication, healing problems or gynecological problems following childbirth delivery. RACR is the risk-adjusted cesarean rate. Standard errors (in parentheses) are clustered at the region level.

Table 1.8: COMPLICATIONS AND RISK-ADJUSTED CESAREAN RATES WITHIN REGION
SUB-SAMPLE OF WOMEN WITH PREVIOUS CESAREAN SECTIONS

	Any Problem	Healing Problems	Gynecological Problems
	(1)	(2)	(3)
RACR	-0.100	0.437*	0.295
	(0.218)	(0.175)	(0.183)
I(2003-2005)	-0.018	-0.014	-0.003
	(0.049)	(0.032)	(0.016)
cons	0.523***	0.004	-0.023
	(0.071)	(0.062)	(0.065)
Region fixed effecs	Yes	Yes	Yes
N	812	812	812
N clusters	21	21	21

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

The outcomes in columns (1) to (3) are dummy variables that equal one if a woman experienced any problem, healing problems or gynecological problems following childbirth delivery. All models include region fixed effects. The data is divided in two time periods: 1998-2002 and 2003-2005. Each time period is used to get separate estimates for areas' risk-adjusted cesarean rates.

Table 1.9: MORTALITY AND CESAREAN RATES: PANEL DATA ANALYSIS

	Maternal Mortality		Neonatal Mortality	
	(1)	(2)	(3)	(4)
RACR	-0.002	0.003	0.114***	0.016
	(0.002)	(0.004)	(0.032)	(0.013)
Province Fixed Effects	No	Yes	No	Yes
Area Fixed Effects	Yes	No	Yes	No
Year Fixed Effects	Yes	Yes	Yes	Yes
Area by Year Fixed Effects	No	Yes	No	Yes
N	523	523	523	523
Nclusters	108	108	108	108

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

RACR is the risk-adjusted cesarean rate (in percentage points) at province level as computed by the National Program for the Evaluation of Healthcare Services. The specifications in columns (1) and (3) include dummies for North, Center and South and years fixed effects. The specifications in columns (2) and (4) include province fixed effects and area-specific year effects. Maternal mortality is the number of deaths due to complications during pregnancy and childbirth delivery per 10,000 births. Neonatal mortality is the number of deaths within 29 days from birth per 10,000 live births. Standard errors are clustered at the province level.

Table 1.10: MORTALITY AND CESAREAN RATES: IV ESTIMATES

	OLS (1)	Reduced Form (2)	2SLS (3)
		Panel A: Maternal Mortality	
RACR	-0.004 (0.006)		-0.024 (0.034)
Fraction of Female Gynecologists		0.474 (0.679)	
		Panel B: Neonatal Mortality	
RACR	0.086 (0.048)		0.008 (0.265)
Fraction of Female Gynecologists		-0.146 (5.266)	
		Panel C: First Stage	
		RACR	
Fraction of Female Gynecologists		-19.394* (9.546)	
Area Fixed Effects	Yes	Yes	Yes
N	109	109	109

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

Column (1) reports OLS estimates of the relationship between mortality and risk-adjusted cesarean rates. Column (2) reports the estimated relationship between the outcomes and the fraction of female gynecologists. Column (3) reports the 2SLS estimates of the relationship between mortality and risk-adjusted cesarean rates. All specifications include dummies for the North and the South. The outcome in panel A is defined as the number of deaths due to complications during pregnancy and childbirth delivery per 10,000 births, whereas panel B reports the estimates for neonatal mortality and panel C reports the first stage coefficient from a regression of Risk-Adjusted Cesarean Rates on the fraction of female gynecologists and dummies for the North and the South. RACR is the risk-adjusted cesarean rate expressed in percentage points. Robust standard errors in parentheses.

Table 1.11: SUPPORTING EVIDENCE FOR THE EXCLUSION RESTRICTION: MORTALITY FOR BREAST CANCER AND FRACTION OF FEMALE GYNECOLOGISTS

	Breast Cancer Mortality Rate
	(1)
Fraction of Female Gynecologists	0.458
	(0.636)
SOUTH	-0.328*
	(0.157)
NORTH	0.865***
	(0.141)
_cons	3.466***
	(0.341)
N	109

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

Mortality for breast cancer is the number of deaths due to breast cancer per 10,000 women. Robust standard errors in parentheses.

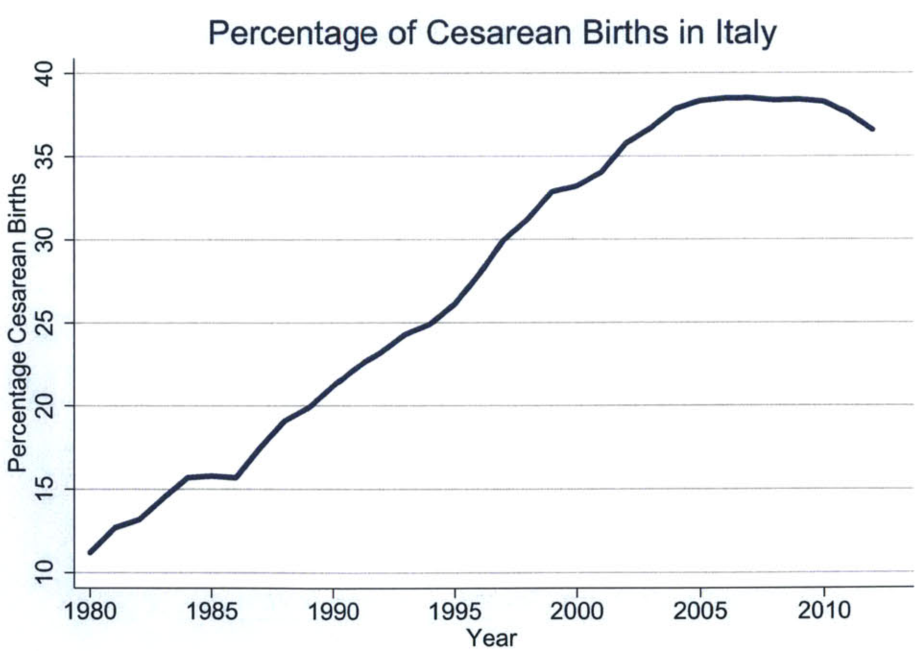

Figure 1-1: Evolution of Cesarean Rates in Italy. 1980-2012. Data Source: Health For All Database, 2013.

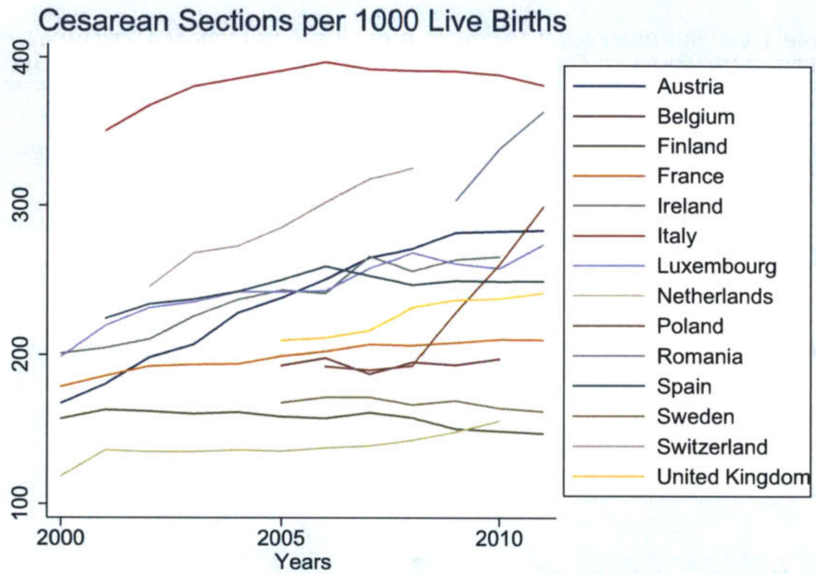

Figure 1-2: Cesarean Section Rates across Countries. Data Source: European Health for All Database, 2013.

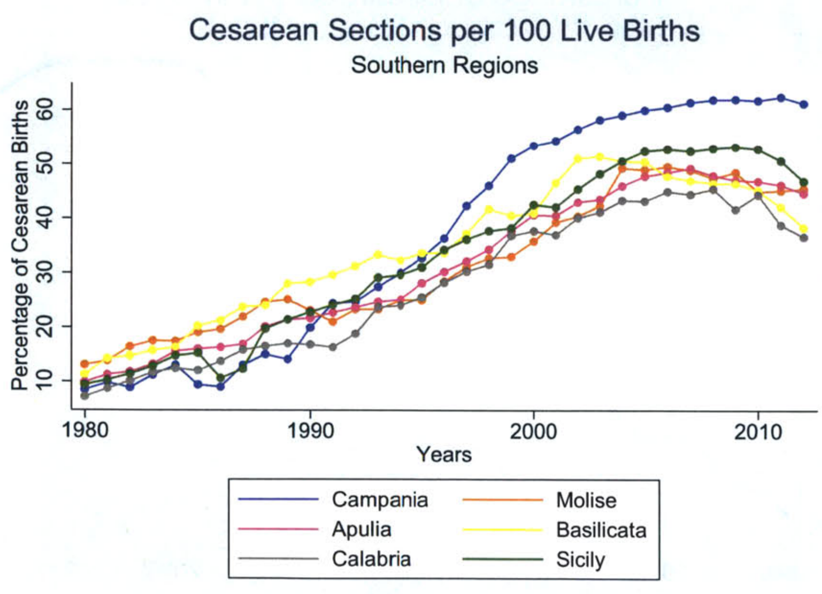

Figure 1-3: Cesarean Births per 100 Live Births in the South. Data Source: Health for All - Italy database.

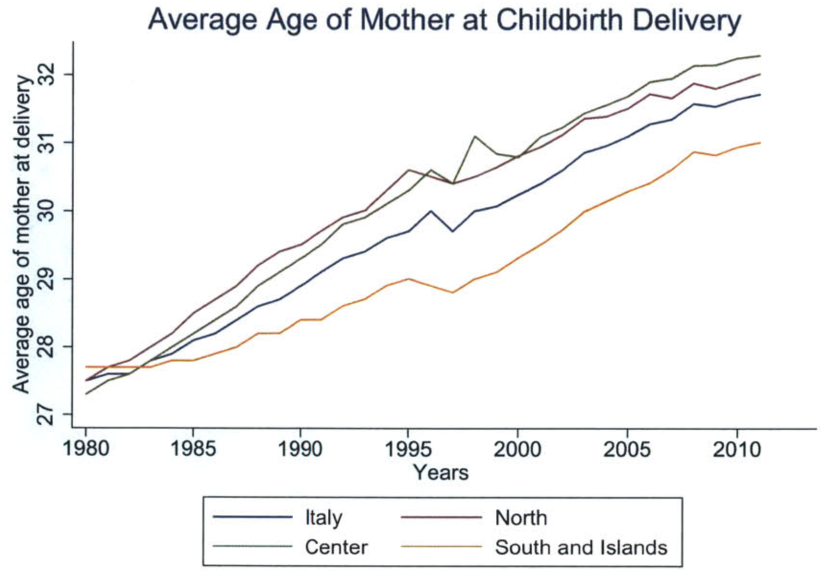

Figure 1-4: Average Mother's Age at Childbirth Delivery by Broad Geographical Area. The blue line shows the trend in average mother's age at childbirth delivery in Italy. The red line refers to the North, the green line refers to the Center and the yellow line refers to the South and the Islands. Data Source: Health for All - Italy database.

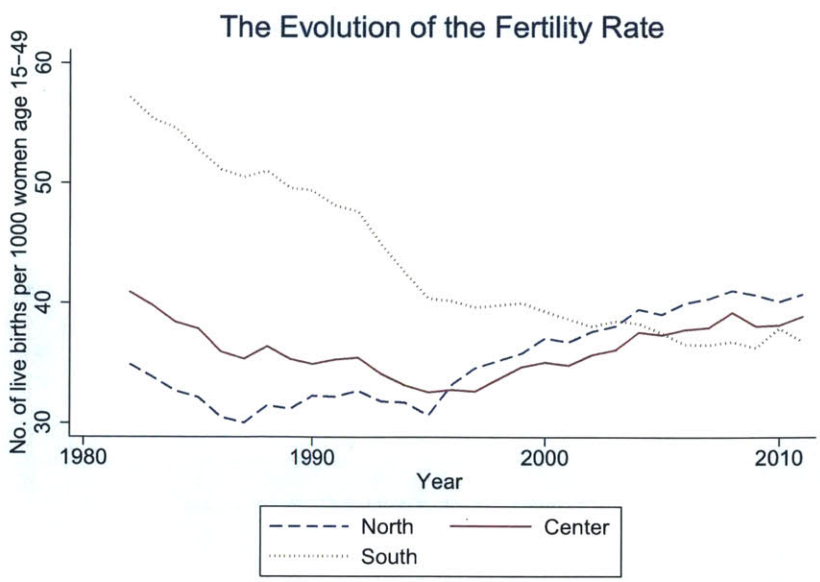

Figure 1-5: The Evolution of the Fertility Rate over Time across Broad Geographical Areas. The figure plots the number of live births per 1000 women age 15-49 from 1980 to 2011 for the three broad geographical areas: the North (dashed line), the Center (solid line) and the South (dotted line). Data Source: Health for All - Italy database.

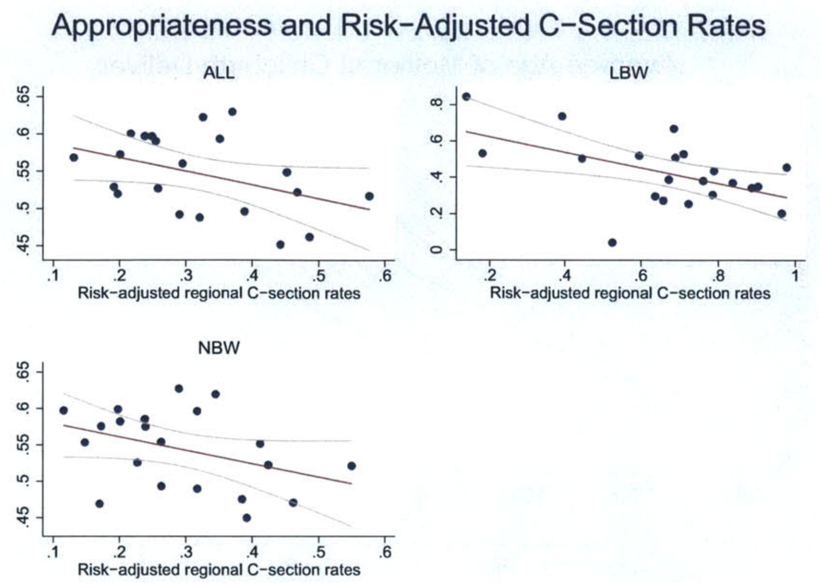

Figure 1-6: Relation between Average Appropriateness and Risk-Adjusted Regional Cesarean Section Rates for Cesarean Births. Each plot shows the relation between average appropriateness and regional risk-adjusted cesarean rates for all birth-weights (ALL), low-birthweight births (LBW) and normal-birthweight births (NBW).

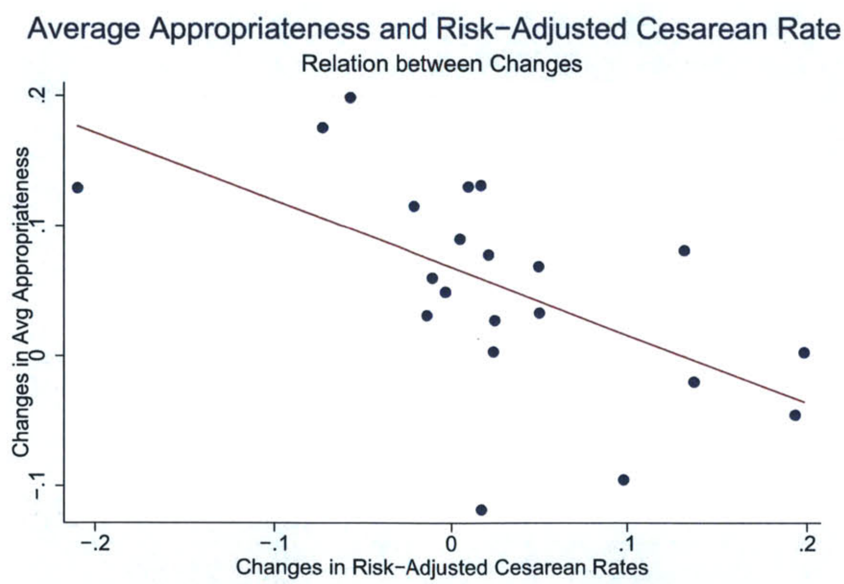

Figure 1-7: Relation between Changes in Average Appropriateness and Changes in Risk-Adjusted Cesarean Rates across Regions for Cesarean Births. The figure plots the relation between changes in average appropriateness and risk-adjusted cesarean rates across regions. The time-varying measure of appropriateness and the time-varying measure of risk-adjusted cesarean rates are obtained from a logistic model where all coefficients are allowed to vary between the two time periods 1998-2002 and 2003-2005 (see text for more details).

Chapter 2

Paid Sick Leave and Employee Absenteeism

2.1 Introduction

Absenteeism is systematically higher among public employees relative to their private sector counterparts (D'Amuri (2011)). The high levels of absenteeism have long been considered a plague of the public sector and one of the determinants of low productivity and high labor costs, in Italy as well as in other European countries (Bonato and Lusinyan (2007)) and in developing countries (Banerjee and Duflo (2006)). Nonetheless the literature on absenteeism mostly focuses on the private sector.

This paper studies the effects of a change in sick leave policy that took place in 2008 in the Italian public administration. The reform modified both the monitoring system and the monetary penalty of sick leave absences and involved all public sector employees, estimated in 3.2 millions in 2012. The focus of this study is on the National Health Service, which accounts for about 21% of the total number of workers employed in the public administration. Using administrative data I show that absenteeism largely decreased following the reform and that changes in absenteeism are related to the increase in the monetary penalty for an absence. Using a differences in differences strategy and exploiting variation in changes to the replacement rate for sick leave I estimate that a 1 percentage point decrease in the replacement rate reduces absenteeism by 1%.

The change in sick leave policy became effective in July 2008 and increased both monitoring and the monetary penalty for sickness absences. Monitoring for sickness absences in Italy takes the form of random medical visits aiming to certify an employee's temporary inability to work. An employee on sick leave is required to be available at home for a given time window to receive the visit. The policy change increased this time window from 4 to 11 hours. However, for each sick leave episode there can only be one medical visit and the worker is discharged from the legal obligation of being at home upon receiving it. Thus an increase in the time window can have the effect of discouraging healthy workers from taking short-term sick leaves. As for the replacement rate, before the reform an employee on sick leave received full compensation. The new law introduces cuts to ancillary payments and accessory components of the pay. Thus the changes in the replacement rate are not homogeneous across workers but rather they vary due to differences in the compensation structure.

I measure exposure to the change of the replacement rate introduced with the reform using the average realized ratio between ancillary payments and total compensation using data from 2001 to 2007. I limit to the pre-reform period because in the post period the realized ratio is mechanically related to the absences. I then relate such measure to changes in absenteeism by using a differences in differences setting. Under the assumption that monitoring has the same proportional effect on absences within hospitals I estimate that a 1 percentage point increase in the absenteeism penalty measure reduces absenteeism by 1%.

D'Amuri (2011) uses data from the Italian Labor Force Survey to study the effect of monitoring changes introduced by the same reform on the probability of an absence. He compares public sector employees to private sector employees, following the subsequent monitoring changes that took place in Italy between 2008 and 2010 and concludes that monitoring is responsible alone for reducing absences. This paper differs from D'Amuri (2011) along several dimensions. First, I use administrative data and exploit variation within the public sector to estimate the causal impact of a change in the replacement rate and focus my analysis on the National Health Service, which is excluded from the analysis conducted in D'Amuri (2011)[1]. The monitoring system for sick leave absences takes the form of random medical inspections to be performed in a given time window by physicians that are employed by the National Health Service. Doctors employed in the public sector are monitored by their own colleagues, thus monitoring might not be as effective as in other sectors. Furthermore absenteeism in the health care sector has potentially serious consequences, given the fundamental importance of promptness in providing health care. Second, I use a different strategy, which allows me to identify the impact of small changes to the replacement rate.

De Paola *et al.* (2014) use micro data on 889 workers from a public university in Italy and identify the effect of the policy change using a regression discontinuity design. They show that the probability of an absence decreases more the bigger the reduction in the replacement rate for a given worker. However, they use contemporaneous measure of earning losses, which is mechanically negatively related to absences in the period after the reform. Furthermore, they use data on clerical workers in a specific institution, thus raising the question about the external validity of their analysis.

The results found in this paper suggest that reducing the replacement rate for sick leave absences has a sizable effect on absenteeism: a 1 percentage point decrease in the replacement rate reduces absenteeism by 1%. The net effect on labor costs from the policy is ambiguous given the observed reduction in absenteeism, and it depends, among other things, on the productivity gains induced by the reform. Ziebarth and Karlsson (2010) study the effect of statutory pay for sick leave absences in Germany both on absenteeism and labor costs. They show that the direct impact of reducing the replacement rate is higher than the indirect impact

[1] D'Amuri (2011) excludes the health care sector and the education sector because the data he uses do not allow him to identify whether workers are employed in the public or the private sector.

on labor costs through a reduction in absences, with a 6.7% estimated reduction in labor costs. Thus reducing the replacement rate can be a source of funding to increase monitoring. If the increase in monitoring has a first order impact on absenteeism, while small decreases in the replacement rate correspond to small distortions from the first best full insurance level and a first order decrease in labor costs, then the policy mix implemented in 2008 in the Italian public sector can be a way to approach optimal sick leave policy. For the monitoring system to work it is necessary that workers assign a high enough probability to the event of receiving an inspection. If the fear of inspections is enough to deter absenteeism, inspections are ex post inefficient. In 2012 there were about 1.2 millions visits for a total cost of about 50 millions of euros, and only 8.2% of such visits resulted in a reduction of the sick leave. In 2013 the National Institute of Social Security, responsible for the inspections, announced a reduction in the number of visits to limit the cost. It will be interesting to evaluate whether such announcement had an impact on sick leave absences. This would allow one to shed light on the extent to which costly inspections can be reduced while keeping unaffected the deterrence effect.

The economic literature on absenteeism has developed relatively recently. Brown and Sessions (1996) provide a survey of early theoretical and empirical contributions on absenteeism. Part of the literature has focused on the determinants of absenteeism (Barmby *et al.* (1991), Johansson and Palme (1996), Ichino and Moretti (2009)), its relation to the business cycle (Arai and Thoursie Skogman (2001); Askildensen *et al.* (2005); Leigh (1985)), work conditions (Ose (2005)), employment protection laws (Ichino and Riphahn (2003) and Lindbeck *et al.* (2006) show that job security increases absences) and across countries differences (Barmby *et al.* (2003), Bonato and Lusinyan (2007)). This paper is more related to the branch of the literature that has studied the effects of policy changes on workers' absences: using long time series data from Sweden Henrekson and Persson (2004) find that less generous sick leave compensation policies lead to lower absenteeism, Johansson and Palme (2005) use variation in the changes in sickness insurance across duration spells to estimate the elasticity of absence incidence to the cost of an absence and Ziebarth and Karlsson (2010) show a negative impact of cuts in statutory replacement rate for sickness absences for private sector employees in Germany.

In designing the optimal sick leave policy governments have to take into account the trade-off between full insurance and moral hazard concerns (Johansson and Palme (2005)).

The paper proceeds as follows: section 2 describes the reform, section 3 gives a brief description of the context in which this paper studies the reform, section 4 describes the data and the sample selection procedures, section 5 and 6 discuss the results and the last section concludes.

2.2 The Change in Sick Leave Policy: Compensation and Monitoring

With law n. 133/2008 the newly installed right-wing government modified the regulation on sick leave for workers employed in the Public Administration sector. The reform was highly publicized, as it was part of a broader campaign against inefficiencies in the public sector that received a lot of media attention and it affected about 3 million workers.

The change involved both sick leave compensation and monitoring. Before the reform public employees were entitled to receive full compensation during sick leave[2].

Monitoring takes the form of random medical visits. Before 2008 workers on sick leave were required to be available during a 4 hours time window, from 10 am to 12 pm and from 5 pm to 7 pm. Such obligation ceases when a designated physician certifies the worker's temporary incapability to work. The 2008 reform increased the time window for random inspections to 11 hours, from 8am to 1pm and from 2pm to 8pm. In July 2009 a new law change restored the historical 4 hours time window. Starting February 2010 the time window for inspections covers 7 hours, from 9am to 1pm and from 3pm to 6pm. The law does not allow for more than one visit per sick leave episode, the rationale being that inspections only serve the purpose of certifying temporary inability to work, and cannot be used to force the worker to stay at home during sick leave. Unjustified absence of a worker during the inspection leads to loss of the replacement rate and one day of salary, and eventually to layoff[3].

As for sick leave compensation, the 2008 reform reduced the replacement rate by applying cuts to ancillary payments and productivity bonuses. The general provision of the law applies to all public employees, but the monetary cuts to be applied to sick leave compensation vary across workers depending on their compensation structure, as determined by national collective bargaining contracts stipulated between unions and the Agency for Bargaining Representation of the Public Administrations (ARAN). On average the reform cut the replacement rate for sick leave by 20% (RGS, 2008), but there is variation across occupational categories, job positions, tenure etc.

2.3 The context: The Italian National Health Service

The reform described above involved all Public Administrations. This paper focuses on the National Health Service, which accounts for about 21% of the public sector workers. This section provides background information about the Italian National Health System.

The Italian health market is characterized by the presence of universal compulsory public insurance - with a small fraction[4] of the population complementing public insurance with private insurance - and a

[2]The replacement rate during sick leave of different lengths was regulated by National Collective Bargaining Contract and varied slightly across contractual categories.

[3]If more than 3 unjustified absences are recorder in 2 subsequent years or more than 7 in the last 10 years.

[4]5% of the total number of households based on a Bank of Italy estimate.

system of public and private providers. The law guarantees consumers of health care services freedom of choice between public and private providers - public insurance covers services supplied by "licensed" private health care providers.

The National Health Service, established in 1978, is a complex system of institutions and services aiming to "the promotion, maintenance and recovery of physical and psychological health of the entire population..."[5] In 1999 it became a system of Regional Health Systems organized on two levels of political governance - national and regional. At the local level there are two different types of institutions: Local Health Authorities (LHAs) and Independent Hospitals (IHs). Local Health Authorities are in charge of distributing health care services in a given area, both directly and by negotiating agreements with other public providers and licensed private providers. Direct production is carried out by hospitals and specialistic clinics directly managed by the Local Health Authorities. Other public providers include Independent Hospitals, big public hospitals, independent of the Local Health Authorities, which produce health care services, based on contractual agreements with Local Health Authorities.

The number of Local Health Authorities has been varying over time with a general tendency to make each LHA coincide with a province. However major cities have several LHAs. Currently there are 145 Local Health Authorities and 90 Independent Hospitals.

2.4 Data and Sample Selection

I use data from the Italian Annual Count, a yearly census survey, managed by the Inspectorate General for Personnel Regulations and the Analysis of Public Sector Labor Costs (IGOP), collecting information on public sector employment and labor costs. The survey is conducted by the State General Accounting Department according to the provisions set forth by Title V of Legislative Decree n. 165/2001 and covers all the institutions that are part of the Public Administration aggregate and fall under the provisions of the above-mentioned decree.

The information collected through the survey is the official information base for Parliament and Government decisions concerning public sector employment. The data are also used for the drafting of the annual report to the Parliament on the management of the financial resources assigned to public sector personnel.

The scope and the coverage of the survey is very broad, in fact it targets nearly 10 thousand public administrations, accounting for about 3.4 million employees and over 134 billion Euros of annual expenditures for personnel.

The data are collected by institution and position in the occupation and include the number of employees, number of absences, wages, salaries and supplementary components of pay. I use data from 2001 to 2012 for all the local institutions of the National Health System. Over the years some institutions merged into a bigger institution and the definition of some job positions changed over time. I aggregate the data across the

[5] art. 1 Law 833/1978.

different institutions/positions up to the level of aggregation for which I have data in every year. I restrict the sample to those observations for which none of the relevant variables are missing and drop the top 5% of the distribution of per capita sick leaves for each occupation. I include five occupations that account for 98-99% of the total Italian National Health System employees. The included occupational categories are medical doctors, healthcare executives, healthcare services providers (nurses from now on), admins and technicians. Finally I balance the panel by dropping all the position-by-institution cells that I do not observe in every year. The resulting data-set consists of 34,800 observations, 2,900 cells per 12 years. The final sample includes 206 institutions and 5 occupational categories, further divided in 27 job positions. If data for a given job position at a given institution is missing in any given year, that cell is dropped from the sample. This means that an institution is in the sample if data about at least one job position is available for every year from 2001 to 2012. In order to ensure that the sample selection does not drive the results I repeat the analysis using different sample selection rules for both the balanced and the unbalanced panel.

Table 2.1 reports summary statistics. The average job position by institution cell has about 138 employees but the median cell has 57 employees. Given that the cells have different sizes, it is not surprising that there is huge variation in the number of days off for sick leave. Average per capita sickness absences are about 11 days in a year and the average ratio between non-base compensation and total compensation is 0.049.

2.4.1 The Evolution of Sick Leave Absenteeism over time

This section shows the evolution of sick leave absences over time in the Italian National Health System. Figure 2-1 shows the number of days off per employee in each year due to sick leave absences. Per employee sickness absences increase between 2001 and 2003 and oscillate between 2003 and 2007 around an average level of about 13 days per year. There is a sharp decrease in 2008, which continues in 2009. They are slightly higher in 2010, but they go down again in 2011 and 2012. Figure 2-2 shows the evolution of per employee sickness absences by occupation. Doctors have the lowest level of absences, with an average number of per capita sick leave absences of 7.3 between 2001 and 2007. The same statistic takes value 10.6 for non-medical healthcare executives. Nurses take an average of 13.7 days off per year before 2008, admins 14.4 and technicians show the highest absenteeism level, with an average number of days off for sick leave of 16.7. Starting in 2008 there is a decrease in per capita sick leaves for all the occupations. The average number of sickness absences goes down by about 3 days for all occupations, except for doctors, whose per capita absences go down by less than two days.

Subsequent monitoring changes took place in July 2009 and February 2010. In July 2009 the time window for medical inspection goes from 11 to 4 hours and in February 2010 it goes up again from 4 hours to 7 hours. There is no evidence of an increase in absences in 2009, however the less restrictive monitoring was in force only for 6 months, so the yearly structure of the data does not allow to draw clear conclusions. Figure 2-2 shows a small increase in the level of absenteeism for non-managerial positions in 2010 relative to 2009. This increase coincides with the strengthening in monitoring that takes place in February 2010. However it is also consistent with a delay in the effect of monitoring. Thus the increase registered in 2010 could be a residual effect of the weakening of monitoring introduced in 2009. The fact that the increase is only registered for non-managerial positions is consistent with the idea that non-managerial positions respond more to monitoring changes. D'Amuri (2011) suggests that this phenomenon can be explained by wage compression in the public sector and the existence of rents for low job positions. The dynamics shown in figure 2-2 are also consistent with the opposite result: doctors and health care executives respond to the 3 hours increase in monitoring more than other occupational categories. The monitoring changes applied to all public workers, so it is not possible to identify an untreated group.

2.5 Increasing the Monetary Penalty for an Absence: Empirical Strategies and Results

As explained above the policy changed both the monitoring and the monetary penalty of a sickness absence. Before the reform workers compensation included all bonuses and accessory payments for the first six months of sickness absence. The reform reduced the replacement rate by applying cuts to ancillary payments and productivity bonuses. There is thus variation in the reduction of the replacement rate across workers. The compensation structure of Italian public sector employees is mostly determined by national collective bargaining agreements. Labor relations in the National Health System are governed by three National Collective Bargaining Agreements. Each of them applies to a broad category of workers: doctors and vets, non-doctors health executives and non-executives. The last category includes nurses, admins and technicians. The wage structure varies to a great extent across occupations and within occupations across job positions and tenure.

In order to separately identify the effect of the changes in the monetary costs from the changes in the monitoring introduced with the 2008 reform, I use a differences in differences strategy exploiting variation in the monetary cost of an absence across job position-by-institution cells.

The reform at study cuts the replacement rate for the first 10 days of sick leave absences. More specifically wage cuts are to be applied to ancillary payments and productivity bonuses. Thus the change in the monetary penalty for an absence varies across workers depending on the structure of their compensation. Using administrative data on workers compensation from 2001 to 2007, I build the average percentage incidence of ancillary payments on total compensation for each job position and institution. Figure 2-3 shows the overall variation in this absenteeism penalty measure, while figure 2-2 shows the variation across job-position by hospital cells by occupation.

The main estimating equation is

$$log(p.c.sickdays)_{jht} = \alpha_{jh} + \alpha_t + \beta \cdot Z_{jh} \cdot Post_t + \epsilon_{jht} \tag{2.1}$$

in which $log(p.c.sickdays)_{jht}$ is the natural logarithm of per capita sickness absences in job position j, institution h and year t,$\alpha_{jh}$is a full set of job position by institution fixed effects, α_t indicate years fixed effects, $Z_{jh}$is the absenteeism penalty measure described above and $Post_t$ is a dummy variable that takes value one from 2008 onward.

The specification in equation 2.1 allows for different absenteeism levels for each job position by institution cell. The same job position is allowed to have different absenteeism levels across institutions, and the same institution is allowed to have different absenteeism levels across job positions. Thus identification of the causal effect relies on the assumption that any difference in trends across job position by institution cells is independent on Z_{jh}. Under the assumption that the change in monitoring has the same percentage effect on absenteeism across cells, we can interpret the coefficient β in equation 2.1 as the effect of decreasing the replacement rate for sick leave absences. Figure 2-5 shows that there is a negative correlation between absenteeism levels in the pre-period and the cost measure Z_{jh}. In order to mitigate the potential concern of heterogeneous monitoring effects across absenteeism levels, one may consider to include the average absenteeism level in the pre-period interacted with $Post_t$ in equation 2.1, but OLS gives inconsistent estimates in presence of serial correlation. I thus choose to parameterize the dependence of the monitoring effects on the levels of absenteeism using a log specification and assume that monitoring has a homogeneous proportional effect across cells.

Table 2.2 reports the estimates for the coefficient of interest for different models. Standard errors are clustered at the institution level in every specification. Each column includes a different set of fixed effects. Column (1) in table 2.2 reports the estimates for the interaction between the absenteeism penalty measure Z and the *Post* dummy in a specification that includes institutions fixed effects, job positions fixed effects and year fixed effects. A 1 percentage point increase in the absenteeism penalty measure corresponds to a 1.24% decrease in per capita sickness absences. Column (2) in table 2.2 reports the estimates from equation 2.1. A one percentage point increase in Z reduces absenteeism by about 0.65%. Column (3) in table 2.2 includes institution-by-year fixed effects to account for potential differential impacts of monitoring across institutions. The point estimate from this model suggests that a one percentage point increase in Z reduces absences by about 1%. The decrease in the estimated coefficient from column (1) to column (2) reflects the fact that lower absenteeism levels are correlated with higher Z within hospitals across job positions. Thus, the additive structure for job position and hospital fixed effects is rejected. The decrease in the estimated coefficient from column (2) to column (3) in table 2.2 is consistent with the idea that institutions with higher levels of absenteeism are more affected by the change in monitoring. Given that higher levels of Z correspond to lower absenteeism levels in the pre-reform period, it can be that institutions with higher Z experience smaller reductions in absenteeism for the part that concerns monitoring. Thus the estimated effect of the absenteeism penalty measure is biased toward zero when not controlling for institution-specific time effects. The estimates in column (4) and (5) in table 2.2 are obtained respectively including occupation by year fixed effects alone and with institution by year fixed effects. These two specifications respectively allow for the monitoring change to have different impacts across occupations and both across occupations and across institutions. One can argue that random medical inspections have different impacts on doctors than technicians, for example because of within-profession favors. The point estimates are close to zero and not significant. This result might be a combination of the institutional setting that determines public workers compensation structure in Italy and measurement error. The compensation structure of workers in the same occupation is determined by the same collective bargaining agreements. Within occupation the compensation structure can vary based on productivity, workers composition and availability of funds. The standard errors in column (4), however, do not increase considerably, suggesting that there is enough variation within occupations. One possibility is that the measurement error in the absenteeism penalty measure due to misreporting, is more severe within occupations. Thus the inclusion of occupation by year fixed effects might worsen the downward bias and even revert the sign of the estimates. In other words, the variation across institutions and job positions within the same occupation might be misleading. If measurement error has a systematic component at the institution level then the measurement error issue becomes less serious when I include institution by year fixed effects. This observation might explain why the point estimate of interest is slightly more negative for the specification in which both institution by year and occupation by year fixed effects are included.

Column (2) and (3) in table 2.2 suggest that the change in the absenteeism penalty measure has a sizable negative impact on absenteeism. This result is not in contrast with D'Amuri (2011), which concludes that most of the reduction in absenteeism is due to changes in monitoring, because the actual changes in the absenteeism penalty measure were fairly small (Z has mean 0.05). Column (2) and (3) also rely on across occupations comparisons. Figure 2-5 shows the trends across occupations before and after the introduction of the policy and provides support to the assumption of parallel trends across occupations. Under the assumption of homogeneous proportional monitoring effects across occupations, the estimates in column (3) provide the causal effect of a change in the absenteeism penalty measure on absenteeism. Figure 2-7 shows that absenteeism levels are not on parallel trends across occupations, thus providing additional support for the log specification.

Table 2.3 shows that the results are not driven by the exclusion of cells that do not appear in all years. A comparison between panel A and panel B in table 2.3 confirms that the results are very similar in the balanced and the unbalanced panel. Table 2.4 shows the estimates using different sample selection rules for the unbalanced panel. Panel A uses the full sample, panel B excludes the top 5% of the per capita absences, panel C excludes the top 3% and panel D the top 1%. The results are very similar across all sample selection rules.

2.6 Event Study Analysis

Identification in the differences in differences setting relies on the assumption that differences in trends across institution by job positions cells are uncorrelated with treatment status. This section presents the event study analysis for the changes in the absenteeism penalty measure.

Figure 2-8 shows the estimates from the following model:

$$log(p.c.sickdays)_{jht} = \alpha_{jh} + \alpha_t + \sum_{\tau=2001}^{2006} \beta_\tau \cdot Z_{jh} \cdot \mathbf{1}\left(year = \tau\right)_t + \sum_{\tau=2008}^{2012} \beta_\tau \cdot Z_{jh} \cdot \mathbf{1}\left(year = \tau\right)_t + \epsilon_{jht} \quad (2.2)$$

in which $log(p.c.sickdays)_{jht}$ is the natural logarithm of per capita sickness absences in job position j, institution h and year t,$\alpha_{jh}$is a full set of job position by institution fixed effects, α_t is a full set of year fixed effects, $Z_{jh}$is the cost measure described above standardized to have mean zero and standard deviation one and β_τ are time varying coefficients on the cost measure. Equation 2.2 includes interactions between the cost measure and year dummies for every year excluded 2007. Under the assumption of parallel trends $\beta_\tau = 0$ for $\tau < 2007$. Figure 2-8 reports the point estimates for β_τ in equation 2.2 and 95% confidence intervals. There is no evidence of pre-trends, as the point estimates in the pre-period are close to zero and not statistically different from zero. The point estimates of β_τ for $\tau > 2007$ show the dynamics of the effect of the policy. There is no significant effect in 2008 and in 2009, while the effect becomes negative and significant in 2010 and fades away gradually in 2011 and 2012. The dynamics are somewhat surprising as the policy change took place between June and August 2008 and again suggest that the change in the monetary cost had only a marginal impact on absenteeism. On the other hand the estimated effect might be small because of omitted variable bias: the cost measure Z is negatively correlated with absenteeism levels. If the effect of monitoring is higher the higher the absenteeism level, then the estimate reported in figure 2-8 are downward biased. In line with this hypothesis, allowing for heterogeneous monitoring effects across institutions increases the point estimate for the change in cost as reported in column (3) of table 2.2 and shown in figure 2-10. Such observation motivates my choice of specifying the outcome variable as the logarithm of per capita absenteeism rather than using the levels. As additional evidence supporting the log specification I estimate model 2.2 in levels. Figure 2-9 reports the estimated coefficients and 95% confidence intervals for the following model:

$$p.c.sickdays_{jht} = \alpha_{jh} + \alpha_t + \sum_{\tau=2001}^{2006} \beta_\tau \cdot Z_{jh} \cdot \mathbf{1}\left(year = \tau\right)_t + \sum_{\tau=2008}^{2012} \beta_\tau \cdot Z_{jh} \cdot \mathbf{1}\left(year = \tau\right)_t + \epsilon_{jht} \quad (2.3)$$

in which all variables are as defined above, while the outcome variable is the number of days off due to sick leave divided by the number of workers in job position j, institution h and year t. The presence of pre-trends in levels is clear. Before 2007 absenteeism was going down in cells characterized by higher average non-base to total compensation ratios, while the trend turns after the policy change. The observed pattern in the pre-period is consistent with the averages shown in figure 2-2: occupations with higher levels of absenteeism are on steeper trends. The pattern in the period after the reform is consistent with heterogeneity of monitoring effects across absenteeism levels: the decrease in absenteeism levels is bigger the higher the initial level of absenteeism.

2.7 Conclusions

This paper studies a reform that took place in Italy in 2008 affecting all public sector employees characterized by both an improvement in monitoring and a decrease in the replacement rate. Using a differences in differences strategy I relate the changes in absenteeism with the changes in the replacement rate for sick leave absences. Under some identifying assumptions spelled above I estimate that a 1 percentage point increase in the absenteeism penalty measure reduces absenteeism by 1%.

This result is not in contrast with D'Amuri (2011) which analyzes the effects of the 2008 reform and subsequent monitoring changes on the public sector workers as a whole (excluding the National Health Service) and finds evidence that most reduction in sick leave absences is due to monitoring changes rather than changes in the replacement rate. In fact the changes in the replacement rate were fairly small (5 percentage points on average). Thus the estimate in this paper together with D'Amuri (2011) imply that both a strengthening of monitoring and a decrease in the replacement rate are effective in reducing absenteeism. Increasing monitoring, however, can lead to high costs, which the government would need to finance potentially distorting other sectors of the economy. Reducing the replacement rate reduces costs for the government for equal levels of absenteeism. The net effect on labor costs from the policy is ambiguous given the observed reduction in absenteeism, and the net effect depends, among other things, on the productivity gains induced by the reform. Ziebarth and Karlsson (2010) study the effect of statutory pay for sick leave absences in Germany both on absenteeism and labor costs. They show that the direct impact of reducing the replacement rate is higher than the indirect impact on labor costs through a reduction in absences, with a 6.7% estimated reduction in labor costs. Thus reducing the replacement rate can be a source of funding to increase monitoring. If the increase in monitoring has a first order impact on absenteeism, while small decreases in the replacement rate correspond to small distortions from the first best full insurance level and a first order decrease in labor costs, then the policy mix implemented in 2008 in the Italian public sector can be a way to approach optimal sick leave policy. For the monitoring system to work it is necessary that workers assign a high enough probability to the event of receiving an inspection. If the fear of inspections is enough to deter absenteeism, inspections are ex post inefficient. In 2012 there were about 1.2 millions visits for a total cost of about 50 millions of euros, and only 8.2% of such visits resulted in a reduction of the sick leave. In 2013 the National Institute of Social Security, responsible for the inspections, announced a reduction in the number of visits to limit the cost. It will be interesting to evaluate whether such announcement had an impact on sick leave absences. This would allow to shed light on the extent to which costly inspections can be reduced while keeping unaffected the deterrence effect.

Table 2.1: SUMMARY STATISTICS

	Mean	sd	p25	p50	p75
Number of employees	137.83	274.84	27	57	123
Days off for sick leave	1640.58	3672.96	184	579	1467.5
Per capita sickness absences	10.94	6.66	5.87	9.90	14.78
Non-base to total compensation	0.05	0.04	0.02	0.04	0.07
N	34800				

The table reports mean, standard deviation, 25th, 50th and 75th percentiles for the distribution of number of employees, number of days off in a year for sick leave and per capita sickness absences across job positions by institutions cells for the years 2001-2012. The last row reports summary statistics for the ratio between non-base compensation and total compensation averaged across years 2001-2007.

Table 2.2: ABSENTEEISM RESPONSE TO CHANGES IN THE ABSENTEEISM PENALTY MEASURE

	Log(Per Capita Sickness Absences)				
	(1)	(2)	(3)	(4)	(5)
Z_Post	-1.24****	-0.65***	-1.02****	0.06	-0.19
	(0.24)	(0.25)	(0.21)	(0.23)	(0.26)
Institution FEs	Yes	Yes	Yes	Yes	Yes
Job Position FEs	Yes	Yes	Yes	Yes	Yes
Institution-by-Job Position FEs	No	Yes	Yes	Yes	Yes
Institution-by-Year FEs	No	No	Yes	No	Yes
Occupation-by-Year FEs	No	No	No	Yes	Yes
N	34800	34800	34800	34800	34800

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Column (1) includes institutions fixed effects and job position fixed effects, column (2) includes a full set of institution-by-job position fixed effects. Column (3) adds institution-by-year fixed effects to account for heterogeneous monitoring effects across institutions. Column (4) includes a full set of institution-by-job position fixed effects and occupation-by-year fixed effects. Column (5) includes institution-by-job position fixed effects, institution-by-year and occupation-by-year fixed effects. Standard errors in parenthesis are clustered at the institution level to allow for arbitrary serial correlation within institution. The sample includes 206 institutions, 27 job positions and 5 occupational categories: doctors, health care executives, admins, nurses and technicians. The table only reports the coefficient of interest, namely the interaction between the absenteeism penalty measure Z and a dummy for the post reform.

Table 2.3: ABSENTEEISM RESPONSE TO CHANGES IN THE ABSENTEEISM PENALTY MEASURE: COMPARISON BETWEEN BALANCED AND UNBALANCED SAMPLE

	Log(Per Capita Sickness Absences)				
	(1)	(2)	(3)	(4)	(5)
			Panel A: Balanced Panel		
Z_Post	-1.24****	-0.65***	-1.02****	0.06	-0.19
	(0.24)	(0.25)	(0.21)	(0.23)	(0.26)
N	34800	34800	34800	34800	34800
			Panel B: Unbalanced Panel		
Z_Post	-1.29****	-0.56**	-0.86****	0.15	-0.0739
	(0.24)	(0.25)	(0.21)	(0.24)	(0.23)
N	59918	59918	59918	59918	59918
Institution FEs	Yes	Yes	Yes	Yes	Yes
Job Position FEs	Yes	Yes	Yes	Yes	Yes
Institution-by-Job Position FEs	No	Yes	Yes	Yes	Yes
Institution-by-Year FEs	No	No	Yes	No	Yes
Occupation-by-Year FEs	No	No	No	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Column (1) includes institutions fixed effects and job position fixed effects, column (2) includes a full set of institution-by-job position fixed effects. Column (3) adds institution-by-year fixed effects to account for heterogeneous monitoring effects across institutions. Column (4) includes a full set of institution-by-job position fixed effects and occupation-by-year fixed effects. Column (5) includes institution-by-job position fixed effects, institution-by-year and occupation-by-year fixed effects. Standard errors in parenthesis are clustered at the institution level to allow for arbitrary serial correlation within institution. The sample includes 206 institutions, 27 job positions and 5 occupational categories: doctors, health care executives, admins, nurses and technicians. The table only reports the coefficient of interest, namely the interaction between the absenteeism penalty measure Z and a dummy for the post reform. Panel A restricts the sample to the job position by institutions cells that appear in every year, while panel B uses all the data.

Table 2.4: UNBALANCED PANEL: COMPARISON BETWEEN DIFFERENT SAMPLE SELECTION RULES

	Log(Per Capita Sickness Absences)			
	(1)	(2)	(3)	(4)
		Panel A: Full Sample		
Z_Post	-1.429***	-0.725**	-1.094****	0.268
	(0.21)	(0.24)	(0.23)	(0.32)
N	62997	62997	62997	62997
		Panel B: Cut top 5%		
Z_Post	-1.314****	-0.603***	-0.907****	0.156
	(0.193)	(0.228)	(0.213)	(0.238)
N	59848	59848	59848	59848
		Panel C: Cut top 3%		
Z_Post	-1.353****	-0.616***	-0.927****	0.162
	(0.193)	(0.227)	(0.214)	(0.236)
N	61111	61111	61111	61111
		Panel D: Cut top 1%		
Z_Post	-1.394****	-0.637***	-0.959****	0.193
	(0.203)	(0.236)	(0.222)	(0.245)
N	62368	62368	62368	62368
Institution FEs	Yes	Yes	Yes	Yes
Job Position FEs	Yes	Yes	Yes	Yes
Institution-by-Job Position FEs	No	Yes	Yes	Yes
Institution-by-Year FEs	No	No	Yes	No
Occupation-by-Year FEs	No	No	No	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Column (1) includes institutions fixed effects and job position fixed effects, column (2) includes a full set of institution-by-job position fixed effects. Column (3) adds institution-by-year fixed effects to account for heterogeneous monitoring effects across institutions. Column (4) includes occupation-by-year fixed effects. Standard errors in parenthesis are clustered at the institution level. The sample includes 206 institutions, 27 job positions and 5 occupational categories. Panel A uses the full sample, panel B excludes the top 5% of the per capita sickness absences, panel C excludes the top 3% and panel D excludes the top 1%.

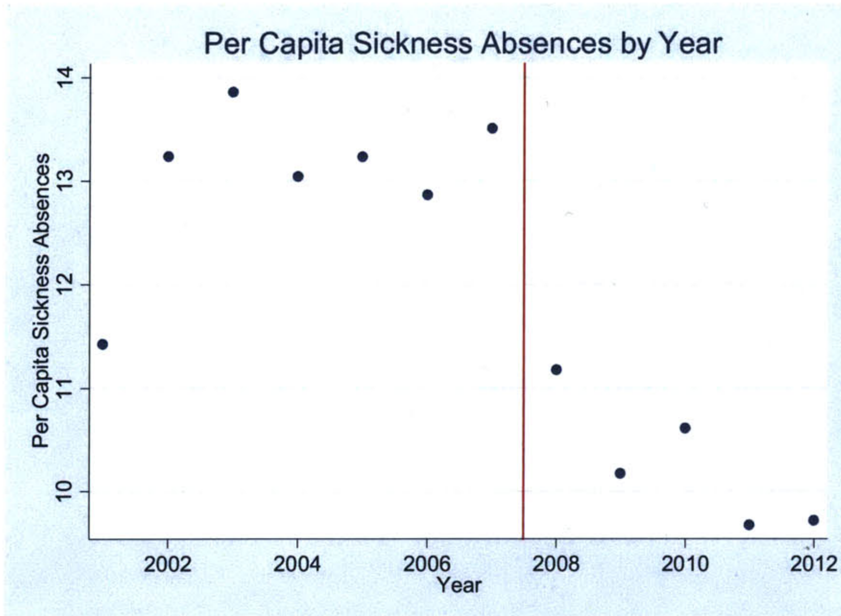

Figure 2-1: Per capita number of days off due to sick leave by year. The vertical line indicates 2007. The change in sick leave policy happens in June 2008.

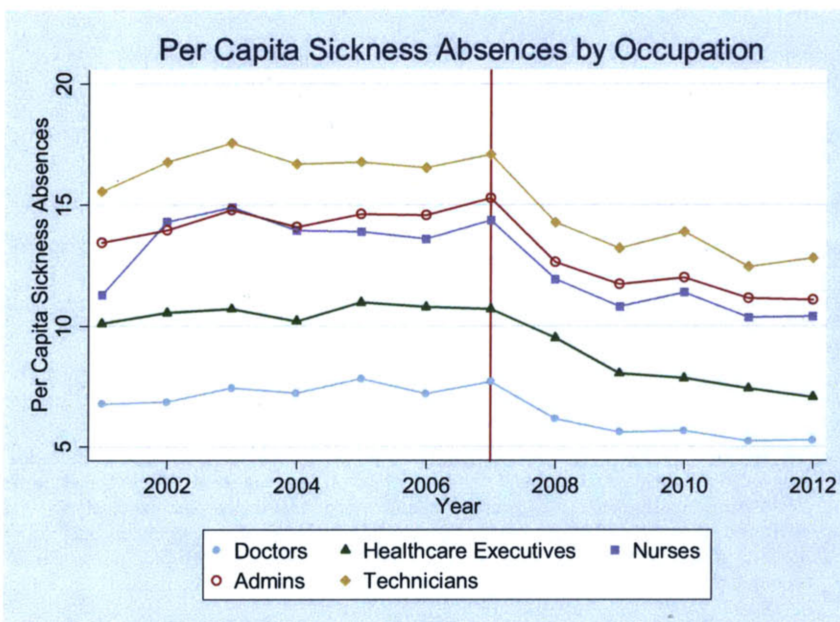

Figure 2-2: Per capita number of days off due to sick leave by occupation and year. The vertical line indicates 2007. The change in sick leave policy happens in June 2008.

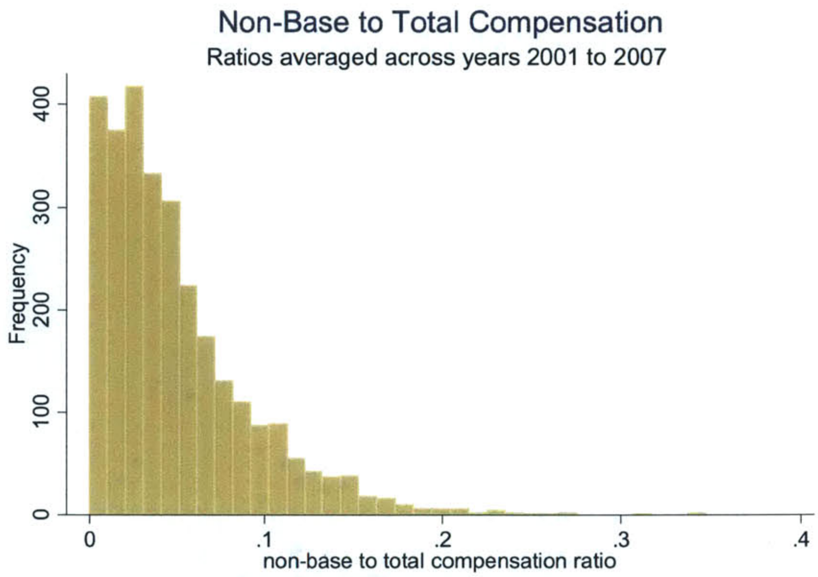

Figure 2-3: Overall variation in the non-base compensation relative to total compensation. This measure is obtained by computing the average ratio across years 2001 to 2007 between non-base compensation and total compensation at the job position by institution level.

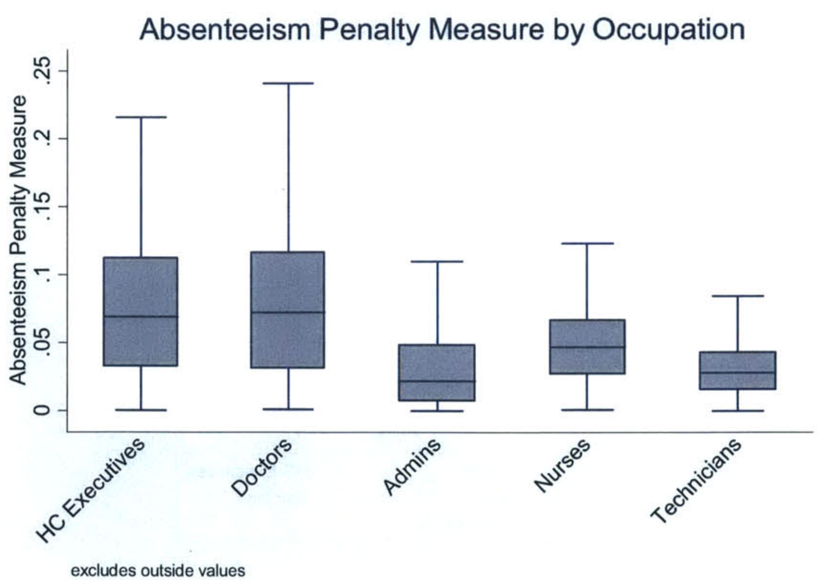

Figure 2-4: Box plots of non-base to total compensation ratios, averaged across years 2001 to 2007, by occupation. The within-occupation variation is a combination of variation across job positions and across institutions.

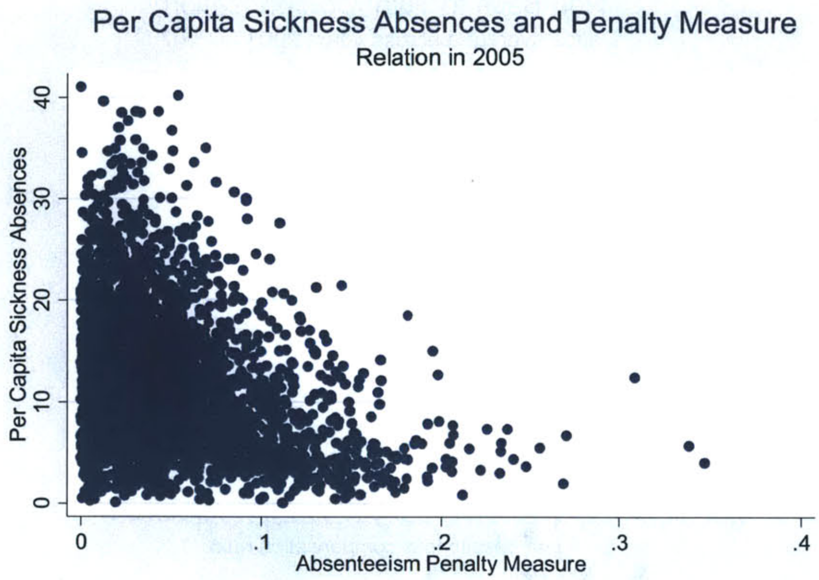

Figure 2-5: Cross-sectional relation between per capita sickness absences in 2005 and the absenteeism penalty measure Z.

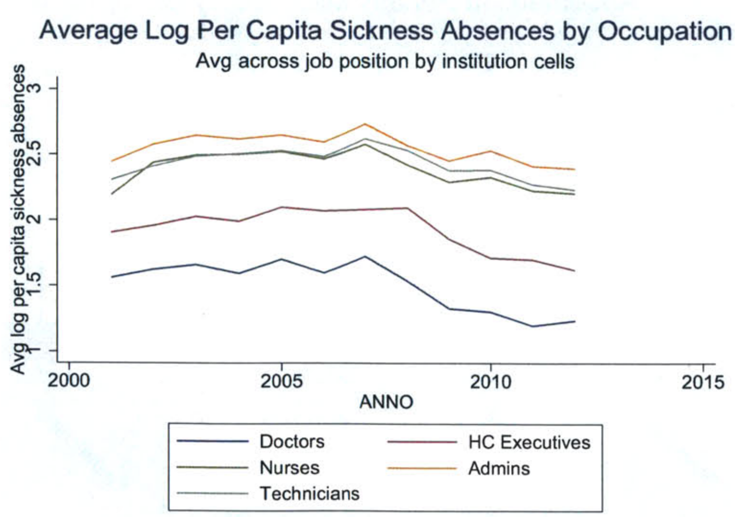

Figure 2-6: Across cells average log per capita sickness absences by occupation. The figure plots the average computed across job position by institution cells within each occupation over time. The different occupations appear to be on parallel trends before the introduction of the sick leave policy change.

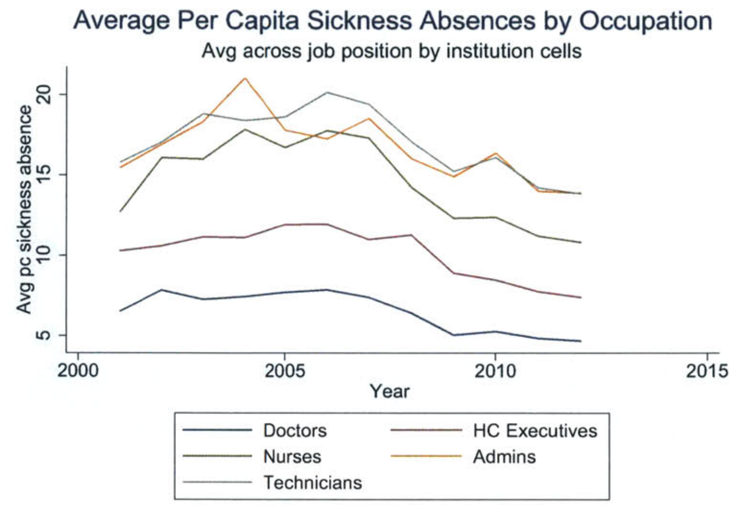

Figure 2-7: Across cells average per capita sickness absences by occupation. The figure plots the average computed across job position by institution cells within each occupation over time. Absenteeism levels do not appear to be on parallel trends across occupations before the introduction of the sick leave policy change, thus suggesting that a level specification is not supported by the data.

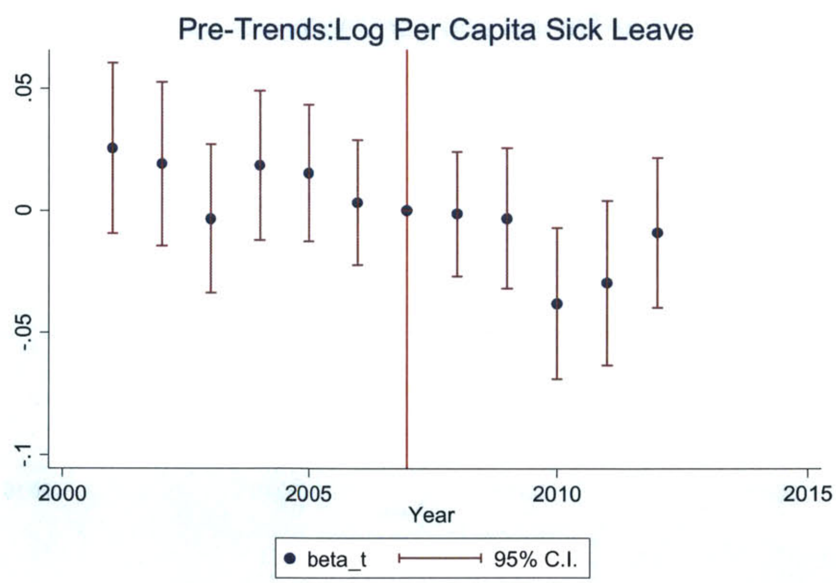

Figure 2-8: Point estimates and 95% confidence intervals for β_τ from equation 2.2. The specification includes a full set of institution by job position fixed effects and the cost measure interacted with year dummies, excluding 2007.The outcome variable is defined as the logarithm of the number of days off due to sick leave divided by the number of workers in job position j, institution h and year t.

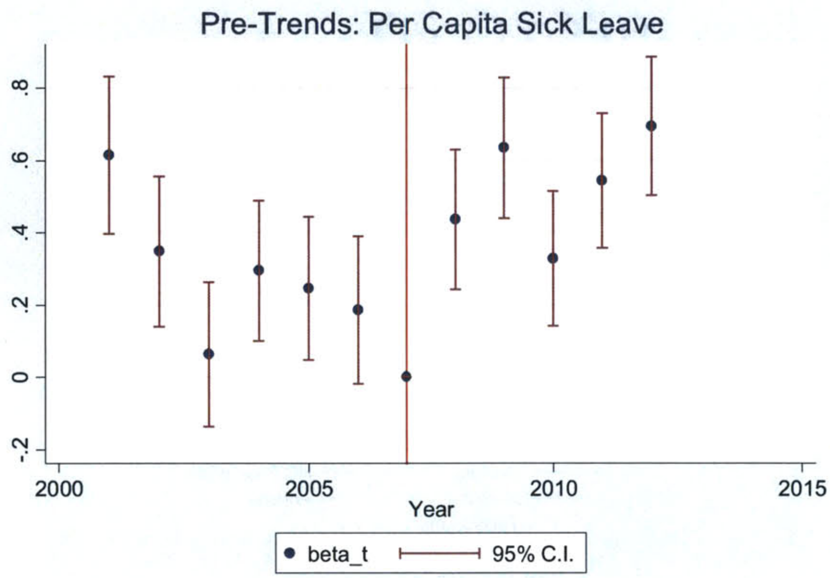

Figure 2-9: Point estimates and 95% confidence intervals for β_τ from equation 2.3. The specification includes a full set of institution by job position fixed effects and the cost measure standardized to have mean zero and standard deviation one interacted with year dummies, excluding 2007. The outcome variable is defined as the number of days off due to sick leave divided by the number of workers in job position j, institution h and year t.

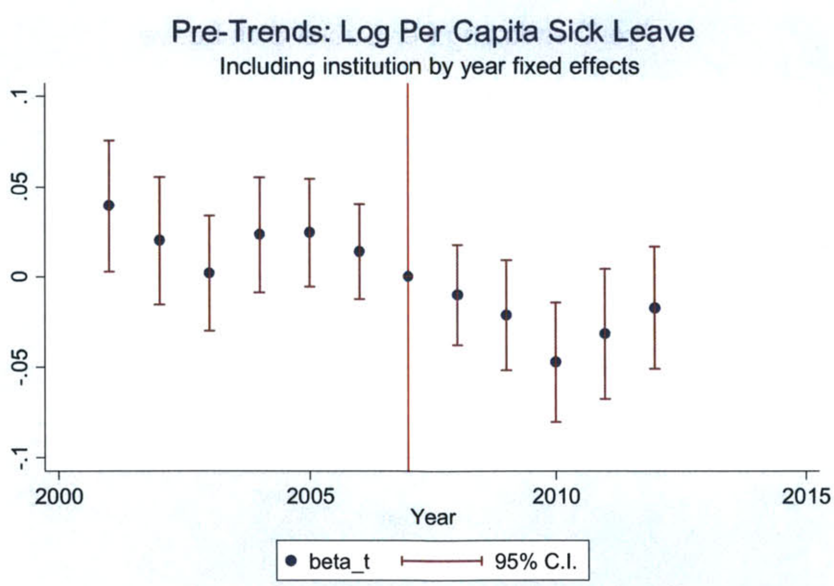

Figure 2-10: Point estimates and 95% confidence intervals for β_τ from equation 2.2 adding institution by year fixed effects. The specification includes a full set of institution by job position fixed effects, institution by year fixed effects and the cost measure interacted with year dummies, excluding 2007.The outcome variable is defined as the logarithm of the number of days off due to sick leave divided by the number of workers in job position j, institution h and year t.

Chapter 3

When the Mafia Comes to Town

3.1 Introduction

Organized crime in Italy developed first and foremost in some of the Southern regions. However, this phenomenon has spread and now affects also Northern and Central Italy and the other Southern Italian regions (IPAC (1994),Bandiera (2003)Ciconte (1998), Ciconte (2010), Sciarrone (1998), Varese (2011)). This paper focuses on "non-traditional" areas, i.e. those areas where organized crime was not originally present. There are several studies on the causes and the effects of organized crime on economic outcomes. However, to the best of my knowledge, the literature lacks a convincing identification, and merely focuses on traditional mafia regions. A focus on "non-traditional" areas is especially interesting because these areas typically have stronger institutions and better economic conditions. This allows one to isolate the causal effect of organized crime and to mitigate reverse causality issues related to the endogenous formation of organized crime in Southern Italy. Furthermore, the role of organized crime may be very different given the differing instutional features of the two regions, for instance, the mafia may prioritize instutitional control in the traditional areas, whereas prioritize monetary gain in the non-traditional areas.

This paper aims to determine the causal effect of the arrival of organized crime to "non-traditional" areas on social and economic outcomes and discuss the possible implications for the inefficiencies generated and how they affect the market system. The presence of mafias in "non-traditional" areas has long been denied or ignored. There is now a growing concern in Italy about the impact of the diffusion of mafias in these areas and their infiltration in the legal economy. "SOS businesses", an organization sponsored by Confesercenti, a major business association in Italy, has estimated the activities of Italian mafia to amount to 7% of Italian GDP in 2007. Another sign of the relevance of organized crime in the economy is that 1516 firms have been seized by Public Authorities until 2010 because they were discovered to be mafia-related. I use a natural experiment to estimate the effect of the arrival of members of organized crime on local economies by using a policy that operated in Italy between 1956 and 1988. The law allowed public authorities to forcibly relocate mafia members to another town in Italy for 3 to 5 years. Using variation in the number of resettled mafia members across provinces of destination I estimate the impact on the incidence of crime and homicides, and employment by industrial sector. I find no evidence of an effect on total crime rates nor homicides rates, while there is a very robust positive effect on employment in the construction sector: one more resettled mafioso per 100,000 inhabitants corresponds to an about 3% increase in employment. Anecdotal evidence suggests that the mafia preferred to limit the use of violence in non-traditional areas, so as not to attract the attention of legal enforcers, and instead invest there the proceeds of the illegal activities conducted elsewhere. The results in this paper are consistent with such evidence.

This paper is related to several strands of the literature. There is a recent literature in Italy on the effect of organized crime on local economies. Pinotti (2012) studies the effect of the formation of Sacra Corona Unita, SCU (an independent mafia organization) in Apulia on the GDP. Using a synthetic control method he estimates that the rise of organized crime is related to a 15% drop in GDP per capita over 30 years. The author discusses several caveats to a causal interpretation of this result. The main concern with this estimate is that the successful formation of a mafia organization in Apulia might be endogenous to changes in GDP per capita or that Apulia was hit by a negative shock that happened to be contemporaneous to the formation of SCU. Pinotti (2011) documents the existence of abnormal upswings in the homicide rate in mafia-affected regions during electoral periods. Coniglio *et al.* (2010) analyze the effect of organized crime on human capital accumulation and migration using a municipality-level panel data analysis that focuses on Calabria. They find that human capital accumulation is negatively affected by organized crime. Gennaioli *et al.* (2011) document a positive impact of public spending on organized crime using the case of the 1997 earthquake as a source of exogenous variation in public spending. Barone and Narciso (2012) instrument organized crime with rainfall in the 19th century and land productivity shifters and find that organized crime increases the amount of public funds to enterprises in Sicily. The contribution of this paper is twofold: I propose a new identification strategy and I estimate the causal impact of the diffusion of organized crime in "non-traditional" areas on crime and economic activity in the construction industry.

Also related to this study is the literature on the efficiency costs of corruption and the economics of extortion. Bertrand *et al.* (2007) present experimental evidence on corruption in India and show that corruption, intended as the ability to buy drivers' licenses without taking the test, "greases the wheel" but can also generate efficiency costs. Olken and Barron (2009) test industrial organization models of corruption and show that market structure affects the level of illegal payments. Similarly, the presence of different mafia organizations can affect the way organized crime operates, for instance the presence of different organizations can affect the level of payments for protection (Gambetta (1993)).

This paper is also related to the sociology literature on the origins of organized crime and its mechanisms of diffusion. Gambetta (1993) claims that the Sicilian Mafia is the business of private protection. It sells protection in areas where institutions are weak or enforces illegal contracts, since they cannot be enforced by legal institutions. For example mafia could play a big role in enforcing cartels in markets where cartels are not easily enforceable. Mafia would constitute a third party enforcer that can credibly inflict punishment in case of deviations. Bandiera (2003) provides an empirical test of Gambetta's theory. Along the same lines Varese (2011) offers an interesting perspective on the role of organized crime in the economy and some of the reasons why mafias succeeded in conquering new territories - the presence of significant sectors of the economy unprotected by the state can generate a demand for criminal protection, especially protection against competition, and a demand for services of dispute settlement.

The rest of the paper proceeds as follows. Section 2 presents the strategy used in the paper and the institutional details of the policy of forced resettlement. Section 3 describes the data. Section 4 describes the empirical strategy and the results for crime rates and homicides. Section 5 describes the empirical strategy and the results for employment by industrial sector and discusses caveats and possible channels driving the result. The last section concludes.

3.2 How to tackle this question: the policy of "Forced Resettlement"

Identifying the causal effects of organized crime on economic outcomes is particularly challenging. First, organized crime is hard to measure. The most often used measure for organized crime in the literature combines reported crimes and mafia-related homicides, but a problem with this approach is that under-reporting of crimes might be systematically more severe in areas where organized crime is more powerful. Furthermore crime reports are the equilibrium result of the interaction between enforcers and criminals. Under-reporting is less of a concern for homicides, but the time series pattern might be driven by mafia wars, which are exceptional events arguably related to periods of crisis in the organization. Second, there are endogeneity concerns: the diffusion of organized crime is potentially endogenous to local economic outcomes. Consider an attempt to analyzing the effect of organized crime on competition in a given local market. On one hand, organized crime can be attracted by high rents in markets with low competition. On the other hand, Gambetta (1993) suggests that organized crime is the business of private protection. Thus highly competitive markets might demand mafias' services in order to enforce cartels. In general both economically depressed and flourishing areas can attract organized crime. The former by providing a fertile breeding ground for criminal activities, the latter by providing attractive business opportunities to invest the proceeds of such criminal activities and/or money laundering.

This paper tackles this question by using as a natural experiment a legal institution that operated in Italy between 1956 and 1988: the "Soggiorno Obbligato" (Forced Resettlement from now on). The national law allowed public authorities to force relocation of a mafioso to a town chosen by the authorities themselves. The widespread use of this law has been considered one of the most important causes for the diffusion of organized crime in non-traditional areas. The law was inspired by the idea that mafiosos would quit their criminal activities once they were out of their criminal network. The institution attempted to isolate powerful ringleaders from other members in the Mafia by forcing them to relocate to another town, under the assumption that organized crime is a byproduct of Southern Italian society and culture and could not develop in other areas.

However, it is a common opinion now that forced relocation was not enough to prevent the concerned individuals from communicating with their original networks and instead helped them to expand their networks in new areas and to discover new business opportunities. The Italian Parliamentary Antimafia Commission wrote in 1994: *"Forced resettlement, largely used without careful choices and without appropriate guarantees of control, has practically dispersed in many areas in Italy several individuals belonging to the mafia and has* ***implanted them in areas that would have probably been otherwise immune.*** *[...] people gradually implanted themselves in the area, brought their families there, created a favorable environment for their activities. It was a process that* ***polluted the entire national territory****"* (IPAC (1994)). Also very interesting is the testimony of Gaspare Mutolo, a mafioso turned state witness, when asked about forced resettlement: *"The policy of forced resettlement has been a good thing, since it allowed us to contact other people, to discover new places, new cities"* (reported in Varese (2006)).

3.2.1 Institutional details of the policy

The law was passed in 1956 and it established that "... In case of serious danger, the person can be forced to relocate to a well-defined town" for three to five years. The law was very vague about how the destination place needed to be chosen and who was in charge of the choice. More details were contained in a subsequent legal provision, law 575/1965, that established a measure of forced resettlement specific to mafia members and added that "... Under exceptional public menace or danger for the concerned person, the Questore (Police Commissioner) or the National Director of Antimafia Prosecutions or the state prosecutor can ask the court to order forced relocation to a town, decided by the Questore, and with appropriate territorial and safety characteristics...". In 1982 the law was modified and some restrictions were established on the characteristics of the destination place: " ... forced relocation must be disposed in a town with no more than 5,000 inhabitants, far away from big metropolitan areas, so as to ensure an effective control ...". Forced resettlement was abrogated with the laws L. 327/1988 and L. 256/1993.

The documents of the Italian Parliamentary Antimafia Commission (IPAC from now on) contain some additional details about the implementation of forced resettlement. The IPAC examined the implementation of the law in 1976 and interrogated the President of the Palermo Court in order to collect information about how the destination town was chosen. The President of Palermo Court claimed that the Italian Department of the Interior compiled a list of towns where mafiosos could be relocated. The local Court then decided the destination from the list, preferring towns where the concerned person could be more easily controlled. He also said that the list changed over time. Unfortunately the document does not contain this list, nor any information about how the list was compiled. A useful piece of information is contained in the testimony of the Head of Italian Police in 1963. He said "we used to relocate people in Ustica, but then we had to stop because the population opposed to it. We did not manage to find an island where to send them, thus we sent them in several towns in Italy and we have a list of towns where we can send them" (IPAC (1976-1982)) .

3.3 The data

3.3.1 The data on forced resettlement, treatment definition and variation

This paper uses data on the total number of people resettled to each province in the period 1961-1972 (IPAC (1976-1982)).

I define the treatment as the number of people resettled to a province p per 100,000 inhabitants in the period 1961-1972. I normalize the treatment with respect to the population to have a measure of relative exposure to the arrival of mafiosos for provinces of different sizes. Measurement error can be a concern, for example because a good measure of treatment intensity should contain information on the importance of the resettled mafioso in his organization. There are several concerns with using this policy as a source of exogenous variation in the diffusion of organized crime. There might be corruption in the form of a mafioso being able to be resettled where he prefers. Other sources of selection might generate from the opposition of destination towns to the arrival of mafia members. Furthermore forced resettlement might be applied together with other security measures that limit the freedom of the resettled mafioso, thus reducing his ability to develop new networks in the place of destination.However I am relying on the assumption that the higher the number of people resettled to a province, the higher the probability that resettled mafiosos can establish connections in the province of destination. This assumption does not hold if leaders are sent to areas where no other members of the organization were ever sent, but still have a higher ability to build networks. However it is reasonable to assume that important members of the mafia would be applied additional control measures and thus would be less effective in building new connections in the destination towns. The choice of normalizing by the average population in the period 1961-1972 is not optimal if more populated areas offer more opportunities to the mafia to expand their networks. Population density might be key in this analysis and it is not taken into account in the definition of the treatment. An alternative choice can be to normalize the number of people resettled to province p by the area of the province. Given that there is no flawless choice for the normalization of the treatment I here use population as the most immediate one.

Figure 3-1 plots the distribution of the number of people resettled per 100,000 inhabitants (the treatment variable). The mean of the treatment variable is 7.22 and the standard deviation is 4.6. The total number of resettled people sent to province p in the period 1961-1972 has mean 30 and standard deviation 17. Italy has now 110 provinces, but the data is reorganized to reproduce the provincial boundaries in 1954, with 92 provinces. Excluding provinces belonging to Calabria, Campania, Sicily and Sardinia the number of provinces is 72. The total number of people resettled between 1961 and 1972 is 2360, excluding people resettled to provinces in Calabria, Campania, Sicily and Sardinia, the number of people resettled is 2154. The picture on the left in figure 3-2 shows a map of the intensity of the treatment across Italian provinces (at current borders), while the picture on the right shows the variation in the number of people resettled to each province without normalizing by the population. A comparison between the two figures shows that the normalization matters a lot for the identification of high intensity areas, since less populated provinces were assigned a higher per capita number of mafiosos.

3.3.2 The data-set on crime

The crime data-set contains the total number of crimes and the number of homicides by province and year for the period 1956-1975.

The series for total number of crimes covers all crimes reported by Police and Carabinieri from 1956 to 1975 (ISTAT (1956-1976)). The main source for this data-set is the Yearbooks of Judiciary Statistics, which has no distinction by type of crime. For the period 1958-1967 the available source (ISTAT (1958-1974)) reports crimes at the province level per broadly defined type of crime. Starting in 1968 the data set contains crimes reported by all Public Security Authorities and for which the penal action has started. This source distinguishes across types of crime in detail but the two sources are fairly different and not comparable. I thus use only data on the total number of crimes and only combine the data from the two available sources in order to form a panel for the number of homicides for the period 1956-1975, arguing that the difference in sources generates less of a concern for homicides relative to other types of crimes.

3.3.3 The data set on employment by sector

The data on employment by sector is extracted from the Census of Industry and Services. It covers the period 1951-2001 with decennial frequency, plus data for 1996 when there was a midway Census. The employment data distinguishes eight broad sectors: construction, manufacturing, mining, energy, transportation, commerce, credit and other services. The data collection method has improved over time. Until 1991 the gathering of data is based on the assumption of ignorance: the list of units to be included in the Census is compiled through the Census itself and the data collector executes a "door to door" analysis without knowing what he will find in the section he got assigned. After having collected the questionnaires, a match is performed with existing information to make sure no unit was ignored in the process.

Starting with the intermediate Census in 1996 and in 2001 the collection method changes dramatically. The National Institute of Statistics has now statistical archives about all the firms and the questionnaires are performed so as to update these archives. This change in the data collection process should allow a better coverage of individual firms and freelancers. However there are no reasons to believe that the variation in the effect of such changes is correlated with the treatment variable, while any general effect will be partialled out with the inclusion of year fixed effects.

3.4 Results

3.4.1 Econometric model and results for local crime rates

The empirical strategy is a differences in differences with the intensity of the treatment defined as the number of people resettled to province p per 100,000 inhabitants in the period 1961-1972.

The identifying assumption is that absent the treatment, any difference in trends between provinces would be independent of the treatment status.

There are several concerns with using this policy as a source of exogenous variation in the diffusion of organized crime. There might be corruption in the form of a mafioso being able to be resettled where he prefers or selection might arise from the opposition of destination towns to the arrival of mafia members. Furthermore, forced resettlement might be applied together with other security measures that limit the freedom of the resettled mafioso, thus reducing his ability to develop new networks in the place of destination. However, as long as selection is unrelated to the trends the identifying assumption is satisfied.

The estimating equation is

$$log(crimerate)_{prt} = \alpha_p + \lambda_{rt} + \delta logpop_{prt} + \beta N_{pr} Post_t + \epsilon_{prt} \tag{3.1}$$

where $log(crimerate)_{prt}$ is the natural logarithm of the total number of reported crimes per-capita in province p, region r in year t, α_p is province fixed effect, *logpop* is the log of the population, N_p is the total number of mafiosos resettled to province p in the period 1961-1972 per 100,000 inhabitants,λ_{rt} are region-specific year effects and *Post* is a dummy for $year \geq 1973$.

All the models are estimated using yearly data from 1956 to 1961 and 1973 to 1975.

Panel A of table 3.1 shows the results for all provinces, excluding provinces from Campania, Calabria, Sicily and Sardinia (the "traditional" areas). When controlling only for province and year fixed effects, the coefficients on the treatment are negative and non-significant. However, controlling for region-specific year effects, the coefficient on the interaction term becomes positive, but still non-significant. In model (3) I control for the log of the population. Once I control for population I am looking at the effect on the numerator only, and this is again very small and negative but not significant. Controlling for region-specific time effects flips the sign of the coefficients from negative to positive, but again they are not significant. Overall there is no evidence of an effect of the treatment on crime rates.

Panel B of table 3.1 shows results for the sub sample of provinces in Lombardy, Veneto, Emilia Romagna, Liguria, Tuscany, Piedmont and Friuli (Northern Italy excluding Valle d'Aosta and Trentino Alto Adige and including Tuscany). The estimates are positive and only marginally significant when I don't control for neither region-specific trends nor population. The coefficients are instead very small and not significant when allowing for differential trends across regions. I also estimated models with interactions between the intensity variable and each year in the post-treatment. The results for the entire sample are very similar but for Northern Italy provinces the treatment effect in 1973 and 1974 is marginally significant when I control for population but not if region-specific time effects are included.

Overall the null cannot be rejected, but this might be due to lack of power, rather than a zero effect. The available crime data does not report any distinction by type of crime, so the pattern of more mafia-related crimes, such as kidnappings for ransom, extortion, drug trafficking etc. might be hidden into the small positive point estimate on total crime rates, and the lack of precision of the estimates might be caused by the noise that is added when considering all types of crimes.

The results in table 3.1 do not change in a significant way when I include province specific linear trends. In order to look for pre-trends or changes in trends I estimate the following model:

$$log(crimerate)_{pt} = \alpha_p + \lambda_{rt} + \delta logpop_{pt} + \sum_{\tau=1958}^{1960} \beta_\tau N_p D\tau_t + \sum_{\tau=1962}^{1975} \beta_\tau N_p D\tau_t + \epsilon_{pt} \qquad (3.2)$$

where all the variables are defined as above and $D\tau_t$ is a dummy for $year = \tau$.

The graphs in figure 3-1 report the coefficients from equation 3.2. When controlling only for province and time fixed effects the coefficients show a slightly decreasing pattern, especially following 1968. This decreasing pattern might suggest that differences in trends are systematically related to the treatment status. This is consistent with high treatment provinces being on flatter trends than low treatment provinces. However, when I control for region specific trends this decreasing pattern disappears. There is no evidence of pre trends as the coefficients until 1965 are very close to zero. From 1966 the point estimates are bigger. However the estimates are imprecise so I do not have conclusive evidence on whether there is any effect. Figure 3-4 shows the pattern of coefficients for the sub-sample of provinces from Northern regions and Tuscany. When restricting the sample the point estimates are higher, however they are very noisy. Again I do not have enough power to conclude that there is no effect.

3.4.2 Results for homicides

The analysis for the incidence of homicides is conducted using Poisson regressions with the population as an exposure variable[1].

As described in the previous section the data on homicides has a break in 1968, where another source is available. Year fixed effects take care of this break to the extent that it affected all provinces in the same way. Figure 3-5, however, suggests that this might not be the case. The graph on the left plots the coefficients from a specification that controls only for province and year fixed effects. There is a significant drop in the coefficient from 1967 to 1968. The graph on the right plots coefficients from a specification that also includes region-specific time effects. As shown in the figure, the drop in the coefficient from 1967 to 1968 is now smaller, and there is more overlap in the confidence intervals. Given this issue, it is hard to interpret the estimates. The negative and significant effects shown in the graph can be a result of reducing the level of the coefficients from 1968 on. One thing that is worth noticing is that until 1967 the pattern of coefficients

[1] The Poisson specification is preferred to the log specification because there are province-year cells with zero homicides

does not show evidence of selection.

Figure 3-6 shows the estimated coefficients for the restricted sample: Lombardy, Piedmont, Liguria, Veneto, Friuli Venezia Giulia, Emilia Romagna and Tuscany. Again the coefficients are very hard to interpret because of the change in data source in 1968, but there is an increasing pattern after 1968. One possible interpretation is that the change in data source introduces a downward bias[2] that hides a positive effect of the policy on the incidence of homicides.

3.5 The effect on employment in different sectors

As discussed in the introduction, mafias' activities both in the legal and the illegal sector can have an important role in the economy. However the effect of mafias' activities can have different impacts across sectors. I measure the effect of resettled mafia members on the economy using employment in different sectors.

The empirical strategy closely follows the previous sections: differences in differences using variation across provinces of destination in the number of mafia members resettled per 100,000 inhabitants. The identifying assumption is that absent the treatment, differences in trends across provinces would be unrelated to the treatment status. The treatment assignment has to be independent on the trends or on any other unobserved characteristics that drives the trends. I will discuss caveats to the identification in the following subsection.

The main estimating equation is

$$log(emp)_{pjt} = \alpha_{pj} + \lambda_{tj} + \beta_{post,j} N_p \mathbf{1}(year \geq 1971)_t + \epsilon_{pjt} \tag{3.3}$$

The dependent variable is the natural logarithm of employment in province p and sector j. A level specification would constrain the outcomes to grow by the same absolute amount over each of the ten years interval, which would be inappropriate given the considerable variation in size across provinces. I estimate equation 3.3 for each sector using data from 1951 to 2001, at decennial frequency. As discussed above the data collection process changed dramatically in 1996, however if the impact of this change is homogeneous across provinces the results are unaffected. As a robustness check I show results also for the sub-sample of years up to 1991.

In order to analyze the possible existence of pre trends I estimate the following equation using only data for 1951 and 1961

$$log(emp)_{pjt} = \alpha_{pj} + \lambda_{tj} + \beta_{pre,j} N_p \mathbf{1}(year = 1961)_t + \epsilon_{pjt} \tag{3.4}$$

The coefficient β_{pre} shows whether the percentage growth in employment in different sectors is systematically

[2]High treatment areas are less affected by the change in data source.

different between treatment and control before the treatment is received. This is not a test of the identifying assumption, given that differences in trends related to the treatment status might arise at the same time as the treatment itself. However having no evidence of pre trends is reassuring.

Table 3.4 shows the estimates of equation 3.3 and equation 3.4 for Construction, Manufacturing, Mining and Energy. The first row in each column shows the coefficient β_{post} for different specifications, while the second row shows the coefficients β_{pre}. In the first column I control for province and year fixed effects. The second column controls also for region-specific time effects. The third column controls for province and year fixed effects and the log of the population and the last column controls for province and year fixed effects, region-specific time effects and log of the population. Each panel shows the estimates for different sectors. The estimates of β_{post} for construction, manufacturing and energy are positive and significant while the estimates of β_{pre} are small and not significant. Table 3.3 shows the estimates of equation 3.3 and equation 3.4 for transportation, commerce, credit and other services. The first row in each column shows the coefficient β_{post} for different specifications while the second row shows the coefficients β_{pre}. In the first column I control for province and year fixed effects. The second column controls also for region-specific time effects. The third column controls for province and year fixed effects and the log of the population. The last column controls for province and year fixed effects, region-specific time effects and log of the population. Each panel shows the estimates for different sectors. The estimates of β_{post} are very small in magnitude and not significant when I do not control for the log of the population while the estimates of β_{pre} are negative and significant for other services when I do not control for the log of the population and small and not significant otherwise and for all the other sectors. Overall there is not much evidence of an effect on transportation, commerce, credit and other services.

As an additional robustness check I estimate equation 3.3 including also province-specific linear trends. The results are shown in table 3.4. Overall the result for the construction industry is fairly robust while the results for other sectors change across specifications.

As discussed in the data section the data collection process changed dramatically in 1996. Thus I also estimate equation 3.3 with and without additional controls using only data up to 1991. The results are reported in tables A.1 and A.2 in the Appendix. The results without controlling for province-specific linear trends are very similar to the results in table 3.5 and table 3.3. When including province-specific linear trends the point estimates for construction are slightly smaller and not significant (the p-values vary across specifications from .055 to .09), but such specification is highly demanding, thus lack of precision is expected.

In order to look at the effect at different points in time I estimate the following equation for each sector

$$log(emp)_{pjt} = \alpha_{pj} + \lambda_{tj} + \beta_{1951,j}N_p\mathbf{1}(t = 1951) + \sum_{\tau=1971}^{2001} \beta_{\tau,j}N_p\mathbf{1}(t = \tau)_t + \epsilon_{pjt} \tag{3.5}$$

Equation 3.6 includes the interaction between the treatment N_p and time dummies for all the available years excluding 1961. Thus the coefficients β_τ are differences in differences coefficients using 1961 as the baseline year and the coefficient β_{1951} checks for the presence of pre-trends. Figure 3-7 shows the point estimates and 95% confidence intervals for the β coefficients in equation 3.6. The point estimate for the pre-trend is close to zero while the pattern of coefficients in the post period is hump-shaped. The estimate is positive and significant in all census years following 1961, and it is increasing until 1981 after which it starts decreasing. The magnitude in 1971 suggests an average positive impact on employment in 1971 of 2% for one more mafia member (per 100,000 inhabitants). However, the magnitude is difficult to interpret given that I cannot rescale the coefficients by the first stage.

The next subsections discuss caveats to identification and possible channels for the interpretation of the positive impact of resettled mafia members on employment in the construction industry.

3.5.1 Potential confounding factors

In the period between the end of the Second World War and the late 60s, in particular between 1958 and 1963, Italy experienced an unprecedented economic boom and went from being a poor, mainly rural nation to an industrial power. This growth came along with inter-regional migration of the population, from rural areas in Southern Italy to industrial areas in Northern Italy. There were also movements within regions, from rural areas to the cities. The needs of a changing society created a huge demand for transport and energy infrastructures. The real estate market also experienced a major boom under the pressure of increasing demand for housing around the largest cities. As a consequence there was massive property speculation.

Even though the economic boom and the construction boom affected the whole country, there might be a concern that high treatment is systematically related to higher growth in the construction industry. If highly rural areas were receiving a higher per-capita number of resettled mafia members. These areas might be experiencing a higher percentage growth in the construction industry because there is a higher movement from rural areas to central cities or simply because there is more room for expansion of the construction sector. However, given that there is no evidence of differential trends related to the treatment in the period 1951-1961, for this mechanism to generate spurious correlation it must be the case that it took place starting only after 1961. Given lack of more specific controls, I test this possibility by controlling for the log of employment in the construction sector in 1951. Notice that, while including the log employment in 1961 causes OLS estimates to be inconsistent[3], under the strong assumption of no serial correlation OLS gives consistent estimates for equation 3.6:

$$log(emp)_{pt} - log(emp)_{p1961} = \alpha_t + \beta_t N_p + \delta_t log(emp)_{pj,1951} + \epsilon_{pt} \quad for\ t \in \{1971, 1981\} \tag{3.6}$$

Table 3.5 shows the estimate for equation 3.6. For $t = 1971$ the point estimate is very small and not significantly different from zero, however for $t = 1981$ there is still a positive and significant (at the 5%) effect in the same order of magnitude as the estimates shown in the previous section. The coefficient δ_t is

[3] The logarithm of employment in 1961 is a function of the error term in 1961, and so is the error term in equation 3.6.

negative and significant, suggesting that there might be mean reversion. The drop in the point estimate for β_{1971} in equation 3.6 might be due to heterogeneous treatment effects and misspecification. Moreover, the fact that the point estimate for β_{1981} is still significant and that a graphical analysis reveals that the pattern of the coëfficients is qualitatively similar to the pattern shown in figure 3-7 mitigates the concern that the result might be driven by mean reversion.

3.5.2 Possible channels

Construction is considered one of the sectors mostly affected by mafias (Saviano (2007), Sciarrone (1998), Varese (2011)). Of the 1516 firms seized by Public Authorities until 2011, the share of construction firms is 27.11%. The broader sector of retail and wholesale, housing and vehicles repair accounts for 27.84% of the total. 10.03% is the share of hotels and restaurants, 8.97% for real estate firms. Public authorities seized 10,438 real estates, 2,639 of which were in "non-traditional" areas (ANBSC (2011)). The construction sector allows one to launder huge amounts of money relatively easily. Real estate firms and monopolistic position in the production of concrete and cement lend support to the investments in the construction sector by assuring control over a network that goes from input and production to sale.

A first step towards understanding the channels behind the positive estimate obtained above is to distinguish whether the increase in employment registered in the data corresponds to a real increase in economic activity in the sector or not. Part of the positive effect estimated might be driven by fake hires for the scope of money laundering. A possible way to tackle this question is to compare the occupations declared in the census of the population to the occupations declared in the census of the industry. However, my prior is that fake hires is not the driving mechanism behind the estimated positive impact.

If the increase in employment in the construction sector is instead driven by real expansion of the sector, there are several possible channels. First, mafia members might be simply trying to invest the proceeds of its illegal businesses in the construction industry. This per se does not necessarily generate inefficiencies. Suppose, for example, that there is a strictly increasing return to investment in the construction industry and that all that mafia does is to invest money in the industry without otherwise affecting the working of the market. Along these lines mafias might even be slacking liquidity constraints that would otherwise limit the expansion of the construction sector. Even though interest rates were low during the Italian economic boom, access to credit might still be limited by collateral constraints or other types of frictions. Then mafia might behave as a liquidity provider. Anecdotal evidence suggests that mafias do not limit themselves to simply invest the proceeds of their illegal activities and that they can potentially influence competition and/or generate corruption. However the question of whether this generates inefficiencies is still open. If corruption of officials in order to obtain building permits is just eliminating frictions, then there is no efficiency cost and the undesirability comes only from the disutility of corruption and the strengthening of the mafia. If instead the mafia bribes officials in order to obtain building permits in areas where the social cost of construction is higher than the benefit, corruption has an efficiency cost.

Anecdotal evidence from traditional areas gives some support for this channel. Salvatore Lima, mayor of Palermo between 1958 and 1963 (killed by the mafia in 1992) is considered responsible for what is known as the Sack of Palermo, a dramatic urbanization of the territory that changed the looks of the city. He was also accused of having favored mafia related firms. Tano Badalamenti, a mafia member resettled in the early 70s, was found guilty of bribing officials in order to have the airport built near his hometown so as to take part to the works with his construction firms.

Another way mafias might cause an expansion in the construction sector is by diverting public funds from other socially more beneficial investments into construction of infrastructures and buildings. This would amount to the mafia generating its own demand in the construction sector, not only directly via the diversion of public funds but also via a multiplier mechanism: building infrastructures in previously rural areas increases the value of the land and makes it valuable to build in those areas. Mafia might also invest more in the construction sector because of lower marginal costs due to the use of illegal practices. There is also growing concern about the fact that mafia related firms use poor cement and do not respect earthquake-proof regulations in construction (IPAC (1994)).

3.6 Conclusions

This paper studies the causal effect of the diffusion of organized crime in so-called "non-traditional" areas in Italy on both social and economic outcomes. There are several challenges that need to be faced when dealing with this question. First, measuring organized crime is a difficult task. Second, organized crime is endogenous to economic and social outcomes. Moreover the direction of the bias is unclear. If interested in analyzing the effect of organized crime on competition in a given local market, one needs to take into account that organized crime can be attracted by high rents in markets with low competition. On the other hand, highly competitive markets might demand mafias' services in order to enforce cartels. In general both economically depressed and flourishing areas can attract organized crime. The former by providing a fertile breeding ground for criminal activities, the latter by providing attractive business opportunities to invest the proceeds of such criminal activities and/or money laundering.

In order to overcome these issues I use a legal institution in force in Italy between 1956 and 1988. A law passed in 1956 allowed public authorities to order forced resettlement of mafia members to different towns. Using variation across destination provinces in the number of mafia members resettled to each province in the period 1961-1972 in a differences in differences setting, I estimate the impact of the exposure to mafia members on local crime rates, incidence of homicides and employment in different industrial sectors in the provinces of destination.

I do not find conclusive evidence for crime rates or homicides. The point estimates for crime rates are not significant, but I do not have enough power to draw clear conclusions. The lack of precision in the estimates might be due to the fact that there is no distinction across types of crime. Mafias are known to positively affect the incidence of some types of crime, like kidnappings for ransom, extortion, drug trafficking etc. However they might have a negative or zero impact on other types of crime, given that they might induce pet criminals to reduce their activity or to join the organization and focus on other more profitable activities. Unfortunately the data on homicides has a break in 1968 that might affect provinces in different ways depending on their treatment status. This makes the estimated coefficients very hard to interpret, so it not possible to determine the impact of the arrival of mafia members to these areas on homicides without using better data.

Motivated by the importance that is attributed to the activities of organized crime in the legal economy and especially in the construction industry, I estimate the effect of the exposure to mafia members in 1961-1972 on employment in different industrial and services sectors. I find evidence of a positive impact on several sectors. However, the positive impact on employment in the construction sector appears to be the most robust. This result is evidence of mafias' activities in the local economies and especially in the construction sector. Several channels that might be at play and the implications in terms of economic efficiency can be very different.

Future work will attempt to disentangle such channels and shed light on the consequences in terms of economic efficiency.

Table 3.1: THE IMPACT OF RESETTLED MAFIA MEMBERS ON CRIME RATES

	(1) logcrimerate	(2) logcrimerate	(3) logcrimerate	(4) logcrimerate
	Panel A EXCLUDING CAMPANIA, CALABRIA, SICILY AND SARDINIA			
Post*Treatment	-0.011	0.006	-0.008	0.006
	(0.008)	(0.009)	(0.009)	(0.009)
N	648	648	648	648
N_clust	72	72	72	72
	Panel B RESTRICTED SAMPLE: NORTHERN ITALY AND TUSCANY			
Post*Treatment	0.014	0.006	0.016*	0.004
	(0.009)	(0.011)	(0.009)	(0.010)
N	432	432	432	432
N_clust	48	48	48	48
Controls :				
Province and Year FEs	Yes	Yes	Yes	Yes
Region-specific year effects	No	Yes	No	Yes
Log(population)	No	No	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column 1 controls for province and year fixed effects, column 2 also controls for region specific time effects, column 3 controls for the log of the population and province and year effects and the last column includes all the previous controls. Standard errors are clustered at the province level. Panel A refers to the full sample exluding provinces from traditional areas. Panel B shows the estimates for the restricted sample of Northern provinces and Tuscany.

Table 3.2: THE IMPACT OF RESETTLED MAFIA MEMBERS ON EMPLOYMENT BY SECTOR (1) CONSTRUCTION, MANUFACTURING, MINING AND ENERGY

	(1) logemp	(2) logemp	(3) logemp	(4) logemp
		Panel A: Construction		
Post*Treatment	0.027**	0.028**	0.035***	0.038***
	(0.008)	(0.009)	(0.008)	(0.010)
Pre*Treatment	-0.003	0.012	-0.004	0.012
	(0.011)	(0.009)	(0.013)	(0.012)
		Panel B: Manufacturing		
Post*Treatment	0.031**	0.020*	0.043***	0.032**
	(0.009)	(0.009)	(0.010)	(0.010)
Pre*Treatment	-0.003	-0.005	-0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.006)
		Panel C: Mining		
Post*Treatment	0.020	-0.032	0.030	-0.027
	(0.019)	(0.018)	(0.019)	(0.020)
Pre*Treatment	0.008	-0.034*	0.010	-0.033
	(0.016)	(0.015)	(0.017)	(0.018)
		Panel D: Energy		
Post*Treatment	0.028***	0.024*	0.031**	0.025*
	(0.008)	(0.011)	(0.009)	(0.012)
Pre*Treatment	0.010	0.006	0.015	0.012
	(0.009)	(0.006)	(0.011)	(0.007)
Controls:				
Log(population)	No	No	Yes	Yes
Region-specific time effects	No	Yes	No	Yes
Province & time FEs	Yes	Yes	Yes	Yes
N_clust	72	72	72	72

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

Post*Treatment is β_{post} and Pre*Treatment is β_{pre}. Column 1 controls for province and year fixed effects, column 2 also controls for region-specific time effects, column 3 controls for the log of the population and province and year effects and the last column includes all the previous controls. The standard errors, reported in parentheses, are clustered at the province level.

Table 3.3: THE IMPACT OF RESETTLED MAFIA MEMBERS ON EMPLOYMENT BY SECTOR (2) TRANSPORTATIONS, COMMERCE, CREDIT AND OTHER SERVICES

	(1) logemp	(2) logemp	(3) logemp	(4) logemp
		Panel A: Transportations		
Post*Treatment	0.003	0.002	0.015*	0.019**
	(0.006)	(0.007)	(0.006)	(0.007)
Pre*Treatment	-0.001	-0.013	0.005	-0.003
	(0.005)	(0.006)	(0.004)	(0.005)
		Panel B: Commerce		
Post*Treatment	0.002	-0.004	0.015**	0.015***
	(0.006)	(0.005)	(0.005)	(0.004)
Pre*Treatment	0.001	-0.005*	0.004	0.002
	(0.003)	(0.002)	(0.003)	(0.002)
		Panel C: Credit		
Post*Treatment	0.011	0.004	0.021***	0.020*
	(0.006)	(0.008)	(0.006)	(0.008)
Pre*Treatment	0.001	0.001	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.004)
		Panel D: Other Services		
Post*Treatment	-0.011	-0.012	0.004	0.011
	(0.008)	(0.007)	(0.009)	(0.008)
Pre*Treatment	-0.014**	-0.018***	-0.006	-0.005
	(0.005)	(0.004)	(0.005)	(0.004)
Controls:				
Log(population)	No	No	Yes	Yes
Region-specific time effects	No	Yes	No	Yes
Province and time FEs	Yes	Yes	Yes	Yes
N_clust	72	72	72	72

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

Column 1 controls for province and year fixed effects, column 2 also controls for region-specific time effects, column 3 controls for the log of the population and province and year effects and the last column includes all the previous controls. Post*Treatment is $beta_{post}$ and Pre*Treatment is β_{pre}. The standard errors, reported in parentheses, are clustered at the province level.

Table 3.4: THE IMPACT OF RESETTLED MAFIA MEMBERS ON EMPLOYMENT BY SECTOR:CONTROLLING FOR PROVINCE-SPECIFIC LINEAR TRENDS

	(1) logemp	(2) logemp	(3) logemp	(4) logemp
		Panel A: Construction		
Post*Treatment	0.025**	0.027**	0.020*	0.019*
	(0.008)	(0.010)	(0.008)	(0.009)
		Panel B: Manufacturing		
Post*Treatment	-0.003	-0.003	0.005	0.007
	(0.006)	(0.008)	(0.005)	(0.008)
		Panel C: Mining		
Post*Treatment	0.011	-0.001	0.015	0.014
	(0.016)	(0.024)	(0.017)	(0.026)
		Panel D: Energy		
Post*Treatment	0.014	0.003	0.014	0.001
	(0.010)	(0.016)	(0.011)	(0.018)
		Panel E: Transportations		
Post*Treatment	0.001	0.007	0.005	0.013
	(0.006)	(0.010)	(0.004)	(0.007)
		Panel F: Commerce		
Post*Treatment	-0.001	-0.005	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
		Panel G: Credit		
Post*Treatment	0.005	-0.001	0.011**	0.006
	(0.004)	(0.006)	(0.004)	(0.005)
		Panel H: Other Services		
Post*Treatment	-0.011*	-0.011	0.002	0.006
	(0.004)	(0.006)	(0.004)	(0.005)
Controls:				
Province & time FEs	Yes	Yes	Yes	Yes
Province-specific linear trends	Yes	Yes	Yes	Yes
Log(population)	No	No	Yes	Yes
Region-specific time effects	No	Yes	No	Yes
N	504	504	504	504
N_clust	72	72	72	72

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

All columns include province-specific linear trends. The standard errors, reported in parentheses, are clustered at the province level.

Table 3.5: ROBUSTNESS CHECK

	(1)	(2)
	$log(emp)_{1971} - log(emp)_{1961}$	$log(emp)_{1981} - log(emp)_{1961}$
Treatment	0.004	0.023*
	(0.009)	(0.009)
logemp51	-0.187**	-0.150**
	(0.057)	(0.049)
_cons	1.743**	1.451**
	(0.537)	(0.447)
N	72	72

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

Robust standard errors in parentheses.

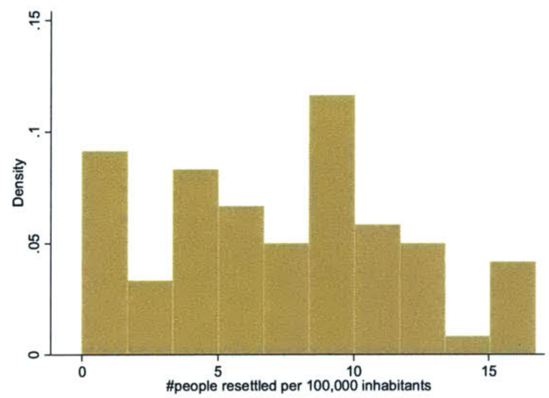

Figure 3-1: Histogram of the number of people resettled per 100,000 inhabitants.

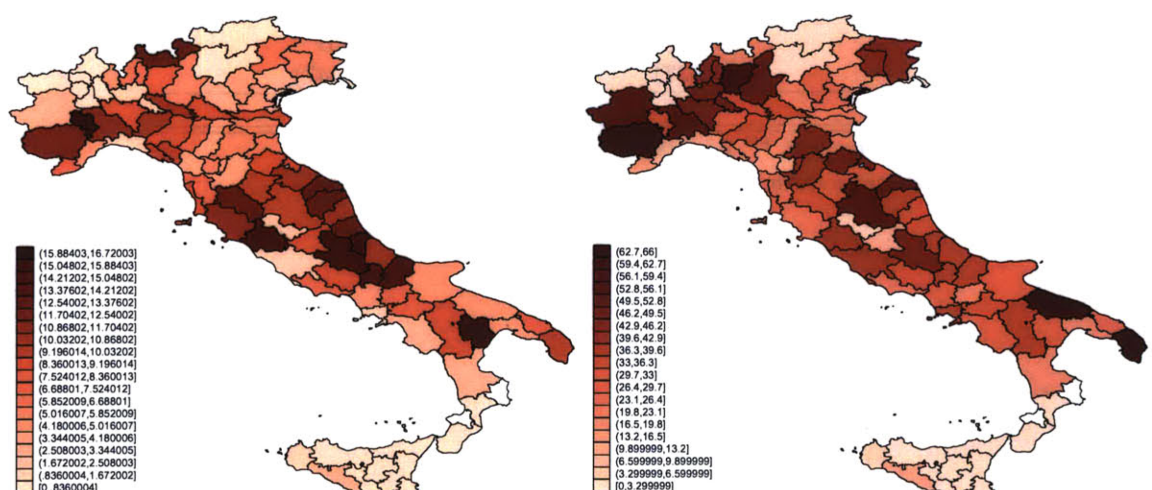

Figure 3-2: Map of the intensity of the treatment. On the left provinces with higher per capita number of resettled mafiosos are filled with darker colors. On the right provinces with higher total number of resettled mafiosos are filled with darker colors. \tiny Each graph is obtained by dividing the range of the variable in 20 equally sized bins.

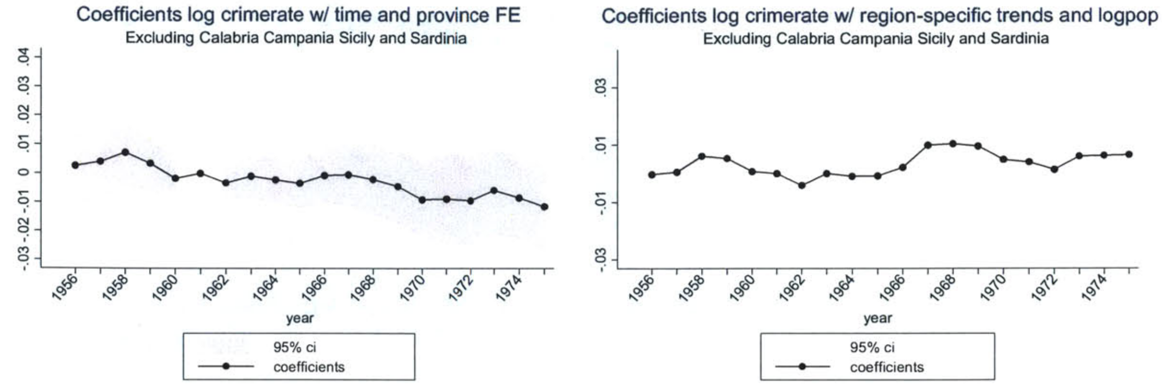

Figure 3-3: Estimates of β_τ from equation 3.2. The plots show estimates of the coefficients β_τ for different specifications. The specification in the plot on the left controls for province and year fixed effects. The estimates reported on the right plot on the right are based on models that include province and year fixed effects, region-specific time effects and the log of the population.

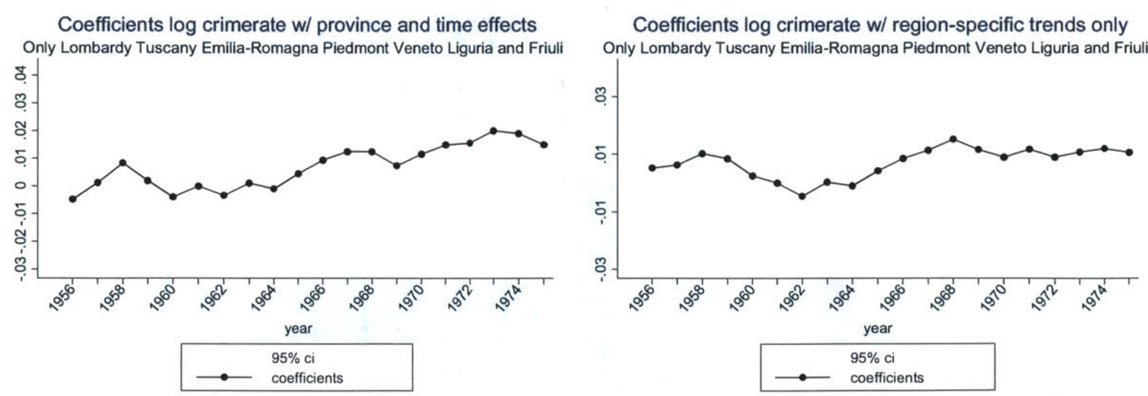

Figure 3-4: Estimates of β_τ from equation 3.2 for the restricted sample of Northern regions and Tuscany. The plots show estimates of the coefficients β_τ for different specifications. The specification in the plot on the left controls for province and year fixed effects. The plot on the right shows coefficients from a specification that includes province and year fixed effects together with region specific time effects.

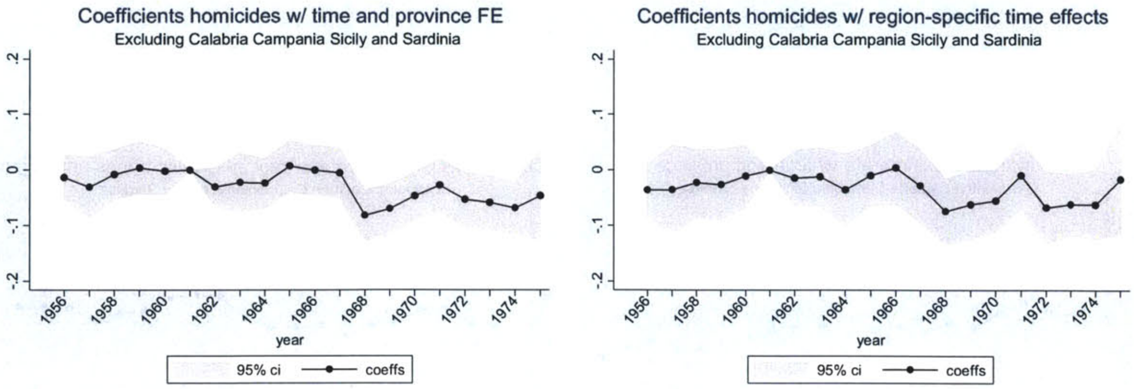

Figure 3-5: Coefficients for homicides. Full sample. The plot on the left shows the estimates from a specification that includes only time and province fixed effects. The plot on the right includes also region-specific time effects. The gray area in the plot corresponds to 95% confidence intervals.

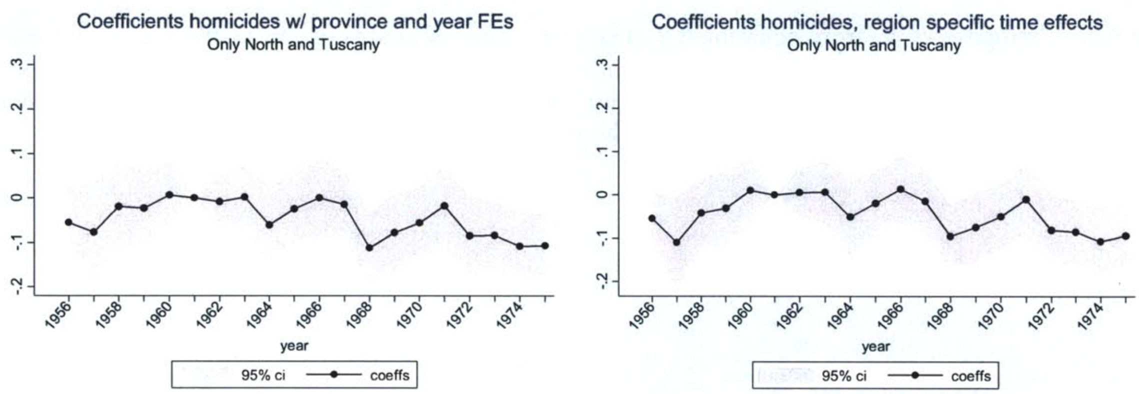

Figure 3-6: Results for homicides. Restricted sample: Lombardy, Piedmont, Liguria, Veneto, Emilia Romagna, Friuli Venezia Giulia and Tuscany. The plot on the left shows the estimates from a specification that includes only time and province fixed effects. The plot on the right includes also region-specific time effects. The gray area in the plot corresponds to 95% confidence intervals.

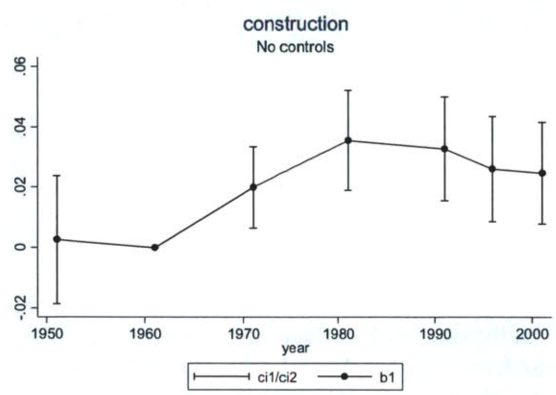

Figure 3-7: Estimates of equation 3.6. β_τ are differences in differences coefficients using 1961 as the baseline year and the coefficient β_{1951} checks for the presence of pre-trends. The vertical capped lines are 95% confidence intervals.

Appendix - Additional Robustness Checks

As discussed in the data section the data collection process changed dramatically in 1996. Thus I also estimate equation 3.3 with and without additional controls using only data up to 1991. The results without controlling for province-specific linear trends are very similar to the results in table 3.5 and table 3.3. However, when I include province specific linear trends the point estimates for construction are slightly smaller and not significant (the p-values vary across specifications from .055 to .09).

Table A.1: THE IMPACT OF RESETTLED MAFIA MEMBERS ON EMPLOYMENT BY SECTOR: SAMPLE RESTRICTED TO THE YEARS 1951-1991

	(1) logemp	(2) logemp	(3) logemp	(4) logemp
		Panel A: Construction		
Post*Treatment	0.028***	0.030**	0.032***	0.035***
	(0.007)	(0.009)	(0.009)	(0.010)
		Panel B: Manufacturing		
Post*Treatment	0.024**	0.015	0.033***	0.025**
	(0.008)	(0.009)	(0.009)	(0.009)
		Panel C: Mining		
Post*Treatment	0.018	-0.030	0.026	-0.024
	(0.018)	(0.019)	(0.019)	(0.021)
		Panel D: Energy		
Post*Treatment	0.026**	0.020	0.029**	0.021
	(0.008)	(0.011)	(0.009)	(0.014)
		Panel E: Transportations		
Post*Treatment	0.006	0.008	0.013*	0.021*
	(0.006)	(0.008)	(0.005)	(0.008)
		Panel F: Commerce		
Post*Treatment	0.002	-0.005	0.013**	0.012**
	(0.005)	(0.004)	(0.005)	(0.004)
		Panel G: Credit		
Post*Treatment	0.010	0.003	0.019***	0.016*
	(0.006)	(0.007)	(0.005)	(0.007)
		Panel H: Other Services		
Post*Treatment	-0.012	-0.013	0.001	0.009
	(0.007)	(0.006)	(0.008)	(0.007)
Controls:				
Province & time FEs	Yes	Yes	Yes	Yes
Log(population)	No	No	Yes	Yes
Region-specific time effects	No	Yes	No	Yes
N	360	360	360	360
N_clust	72	72	72	72

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

Differences in differences estimates on the restricted sample 1951-1991. The standard errors, reported in parentheses, are clustered at the province level.

Table A.2: THE IMPACT OF RESETTLED MAFIA MEMBERS ON EMPLOYMENT BY SECTOR: SAMPLE RESTRICTED TO THE YEARS 1951-1991 AND PROVINCE-SPECIFIC LINEAR TRENDS

	(1) logemp	(2) logemp	(3) logemp	(4) logemp
		Panel A: Construction		
Post*Treatment	0.014	0.017	0.013	0.014
	(0.009)	(0.010)	(0.009)	(0.010)
		Panel B: Manufacturing		
Post*Treatment	-0.002	-0.002	0.005	0.006
	(0.005)	(0.006)	(0.005)	(0.007)
		Panel C: Mining		
Post*Treatment	0.010	0.020	0.011	0.032
	(0.018)	(0.023)	(0.019)	(0.024)
		Panel D: Energy		
Post*Treatment	0.005	0.001	0.006	0.003
	(0.011)	(0.016)	(0.012)	(0.019)
		Panel E: Transportations		
Post*Treatment	-0.013	-0.014	-0.001	0.004
	(0.009)	(0.016)	(0.005)	(0.009)
		Panel F: Commerce		
Post*Treatment	-0.0001	-0.003	0.003	0.004
	(0.003)	(0.003)	(0.003)	(0.002)
		Panel G: Credit		
Post*Treatment	0.002	0.000	0.007	0.005
	(0.00354)	(0.005)	(0.004)	(0.005)
		Panel H: Other Services		
Post*Treatment	-0.006	-0.008	0.007	0.007
	(0.00505)	(0.007)	(0.004)	(0.005)
Controls:				
Province & time FEs	Yes	Yes	Yes	Yes
Province-specific linear trends	Yes	Yes	Yes	Yes
Log(population)	No	No	Yes	Yes
Region-specific time effects	No	Yes	No	Yes
N	350	350	350	350
N_clust	70	70	70	70

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

Differences in differences estimates on the restricted sample 1951-1991 including province-specific linear trends. The standard errors, reported in parentheses, are clustered at the province level.

Bibliography

ANBSC (2011). *Seconda relazione sulle attivita' svolte.* Agenzia nazionale per l'amministrazione e la gestione dei beni sequestrati e confiscati alla criminalita' organizzata.

ARAI, M. and THOURSIE SKOGMAN, P. (2001). Incentives and Selection in cyclical absenteeism. *Labor Economics*, **12** (2).

ASKILDENSEN, J. E., BRATBERG, E. and NILSEN, I. A. (2005). Unemployment, Labour Force Composition and Sickness Absence: A Panel Data Study. *Health Economics*, **14** (11).

BAICKER, K., BUCKLES, K. S. and CHANDRA, A. (2006). Geographic Variation In The Appropriate Use of Cesarean Delivery. *Health Affairs*, **25** (5).

— and CHANDRA, A. (2005). The Effect of Malpractice Liability on the Delivery of Healthcare. *Forum for Health Economics & Policy*, **8**.

BANDIERA, O. (2003). Land reform, the market for protection, and the origins of the sicilian mafia:theory and evidence. *Journal of Law, Economics and Organization*, **19**, 218–244.

BANERJEE, A. and DUFLO, E. (2006). Addressing Absences. *Journal of Economic Perspectives*, **20** (1).

BARMBY, T., ERCOLANI, M. and TREBLE, J. (2003). Sickness Absence: an International Comparison. *The Economic Journal*, **112** (980).

—, ORME, C. D. and TREBLE, J. (1991). Worker Absenteeism: An Analysis Using Microdata. *The Economic Journal*, **101** (405).

BARONE, G. and NARCISO, G. (2012). The effect of mafia on public transfers. *mimeo*.

BERTRAND, M., DJANKOV, S., HANNA, R. and SENDHIL, M. (2007). Obtaining a driver's license in india: An experimental approach to studying corruption. *Quarterly Journal of Economics*, **122**, 1639–1676.

BONATO, L. and LUSINYAN, L. (2007). Work Absence in Europe. *IMF Staff Papers*, **54** (3).

BROWN, S. and SESSIONS, J. G. (1996). The Economics of Absence: Theory and Evidence. *Journal of Economic Surveys*, **10** (1).

CAVALIERI, M., GUCCIO, C., LISI, D. and PIGNATARO, G. (2013). Effects of Tariffs Differentials on Cesarean Sections in Italy.

CHANDRA, A. and STAIGER, D. (2007). Productivity spillovers in health care: Evidence from the treatment of heart attacks. *Journal of Political Economy*, **115** (1).

— and — (2014). Expertise, Underuse and Overuse in Healthcare. *Unpublished manuscript.*

CICONTE, E. (1998). *Mafia, Camorra e 'Ndrangheta in Emilia Romagna.* Panozzo Editore.

— (2010). *'Ndrangheta padana.* Rubbettino.

CONIGLIO, N., CELI, G. and SCAGLIUSI, C. (2010). Organized crime, migration and human capital formation: Evidence from the south of italy. *S.E.R.I.E.S.*, **WP 0028**.

CURRIE, J. and MACLEOD, B. (2013). Diagnosis and Unnecessary Procedure Use: Evidence from C-Section, nBER Working Paper Series.

D'AMURI, F. (2011). Monitoring, monetary incentives and workers' rents in determining absenteeism. *Bank of Italy Working Paper.*

DE PAOLA, M., SCOPPA, V. and PUPO, V. (2014). Absenteeism in the Italian Public Sector: The Effects of Changes in Sick Leave Policy. *Journal of Labor Economics*, **32** (2).

DIMARZO, C. (2012). Medical Malpractice: The Italian Experience. *Chicago-Kent College of Law Review*, **53**.

DUBAY, L., KAESTNER, R. and WAIDMANN, T. (1999). The impact of malpractice fears on cesarean section rates. *Journal of Health Economics*, **18** (4).

ECKER, J. and FRIGOLETTO, F. (2007). Cesarean Delivery and The Risk-Benefit Calculus. *The New England Journal of Medicine.*

FRANCESE, M., PIACENZA, M., ROMANELLI, M. and TURATI, G. (2012). Understanding Inappropriateness in Health Care. The Role of Supply Structure, Pricing Policies and Political Institutions in Caesarean Deliveries. *University of Turin, Department of Economics and Statistics Working Paper Series,* (1).

GAMBETTA, D. (1993). *The Sicilian Mafia: the business of private protection.* Harvard University Press.

GENNAIOLI, C., ONORATO, M., PEROTTI, R. and TABELLINI, G. (2011). Public spending and organized crime: The case of the 1997 marche and umbria earthquake. *Mimeo.*

GRUBER, J., KIM, J. and MAYZLIN, D. (1999). Physician fees and procedure intensity: the case of cesarean delivery. *Journal of Health Economics*, **18** (4).

— and OWINGS, M. (1996). Physican financial incentives and cesarean section delivery. *The RAND Journal of Economics*, **27** (1).

HENREKSON, M. and PERSSON, M. (2004). The Effects on Sick Leave of Changes in the Sickness Insurance System. *Journal of Labor Economics*, **22** (1).

ICHINO, A. and MORETTI, E. (2009). Biological Gender Differences, Absenteeism and the Earnings Gap. *American Economic Journal: Applied Economics*, **1** (1).

— and RIPHAHN, R. T. (2003). The Effect of Employment Protection on Worker Effort: A Comparison of Absenteeism During and After Probation. *CEPR Discussion Papers*, (3847).

IPAC (1976-1982). *Relazione Conclusiva e documentazione allegata.* Department of the Interior.

— (1994). *Relazione sulle risultanze dell'attivita' del gruppo di lavoro incaricato di svolgere accertamenti su insediamenti e infilitrazioni di soggetti ed organizzazioni di tipo mafioso in aree nontradizionali*, vol. doc. n. 11.

ISTAT (1956-1976). *Yearbooks of Judiciary Statistics.* Istituto Nazionale di Statistica.

— (1958-1974). *Yearbooks of Provincial Statistics.* Istituto Nazionale di Statistica.

JOHANSSON, P. and PALME, M. (1996). Do economic incentives affect work absence? Empirical evidence using Swedish micro data. *Journal of Public Economics*, **59** (2).

— and — (2005). Moral Hazard and Sickness Insurance. *Journal of Public Economics*, **89** (9-10).

KIM, B. (2007). The Impact of Malpractice Risk on the Use of Obstetrics Procedures. *The Journal of Legal Studies*, **36** (S2).

LEIGH, J. P. (1985). The Effect of Unemployment and the Business Cycle on Absenteeism. *Journal of Economics and Business*, **37** (2).

LINDBECK, A., PALME, M. and PERSSON, M. (2006). Job Security and Work Absence: Evidence from a Natural Experiment. *IFN Working Paper*, (660).

OLKEN, B. A. and BARRON, P. (2009). The simple economics of extortion: Evidence from trucking in aceh. *Journal of Political Economy*, **117** (3), 417–452.

OSE, S. O. (2005). Working conditions, compensation and absenteeism. *Journal of Health Economics*, **24** (1).

PINOTTI, P. (2011). Organized crime, violence and the quality of politicians: Evidence from southern italy. *Bocconi University, mimeo.*

— (2012). The economic cost of organized crime: Evidence from southern italy. *Bocconi University, mimeo.*

RGS (2008). *Conto annuale per l'anno 2007.* Tech. rep., Ragioneria Generale dello Stato.

SAVIANO, R. (2007). *Gomorrah.* Farrar, Straus and Giroux.

SCIARRONE, R. (1998). *Mafie vecchie, mafie nuove. radicamento ed espansione.* Donzelli.

VARESE, F. (2006). How mafias migrate: The case of the 'ndrangheta in northern italy. *Law and Society Review*, **40** (2), 411–444.

— (2011). *Mafias on the Move: How Organized Crime conquers new Territories.*

ZIEBARTH, N. R. and KARLSSON, M. (2010). A natural experiment on sick pay cuts, sickness absence and labor costs. *Journal of Public Economics*, **94** (11-12).