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Microeconometric Analyses of the Formation and Valuation of Human Capital

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Chapter 1

Introduction

1.1 Overview

During the 1950s, economists accepted that education, ability and skills are a form of capital – namely *human capital* – and began to investigate it both as an input factor in production processes and as a production output of individual investments in knowledge and skills (Mincer, 1958; Schultz, 1961; Becker, 1964). Today, the term human capital is often used to paraphrase the stock of various cognitive and physical attributes: formal education, innate ability or talent, physical and psychological health, work experience, knowledge and practical and social skills (Becker, 2008). These forms of human capital are assumed to be and largely verified to be productive in an economic sense. They stimulate, at the aggregate level, economic growth and generate, at the individual level, positive labour market outcomes. Hence, investments in human capital formation are worthwhile from both a public and a private perspective (Romer, 1986; Barro, 2001; Mincer, 1974, 1991).

Public investments in human capital include spending on the educational sector and introducing legislations which aim at reducing inequalities or increasing the overall level of education, as well as developing certain skills in the population. Increasing the overall level of education and specialisation serves to meet rapidly changing labour market demands and enhances the competitiveness of an economy (e.g., Romer, 1987). Furthermore, offering similar educational opportunities for all members of a society reduces horizontal inequalities and thereby social tension (e.g., Stewart, 2000).

Individual investment in human capital formation can comprise the effort, time and money spent to attain, for example, additional degrees, acquire specific skills or even improve one's health. The advantages of a high stock of human capital are

manifold; it allows an individual to signal his or her ability to potential employers and thereby reduces the probability of unemployment and subsequently the risk of living in poverty, leads to relatively higher income and earnings, and increases occupational choice and the probability of promotion (e.g., Spence, 1973; Ashenfelter and Ham, 1979; Harmon and Oosterbeek, 2000).

According to economic theory, both public and private investments in human capital formation are made as long as the expected profits exceed the opportunity costs involved. A government has to decide between spending on education and spending on other sectors to enhance economic growth (Ben-Porath, 1967), while the individual invests in education as long as the expected return is greater than forgone earnings (Becker, 1964). Practically, the optimal level of investment is difficult to determine, as many factors influence the success of human capital formation on the one hand and the valuation of human capital on the other hand. Understanding the way in which the formation and valuation of human capital are affected by external factors and knowing the magnitude of the impacts is crucial to make optimal decisions about both public and private investments in human capital accumulation.

For some factors, the impacts have remained ambiguous and further research is therefore required. Three such factors – technological change, migration and violent conflict – are analysed in this dissertation. The chapters of this dissertation investigate empirically the impacts of these determinants on specific aspects of human capital formation and valuation that have not been analysed sufficiently in the economic literature so far. The impacts of these factors require in-depth empirical analyses in order to understand the origin of human capital heterogeneity. This understanding can then provide solutions to continued labour market inequalities.

The analyses are based on household level data sets from the United Kingdom (UK) and Mexico, and a primary school level data set from Northern Ireland. The variety of data sets analysed serves the objective of investigating particular factors in countries where they play a significant role and are not completely understood so far. For example, violent conflicts play a major role in the development of Mexico's economy but their specific impact on human capital accumulation and labour market outcomes has not been studied so far. Violent conflicts may also have long-run consequences on human capital formation, e.g. through the intergenerational transmission of adverse health effects or regional social deprivation. Mexico does

not serve as a suitable case, however, to comprehend how violent conflicts affect human capital accumulation in the long-run. Rather, the case of Northern Ireland, where violent conflicts ceased almost twenty years ago, allows the analysis of long-run consequences. Furthermore, analysing data sets from countries which stand at different stages of economic development provides a better comprehension of the interrelation of investments in human capital, economic outcomes and their advantageous and disadvantageous determinants. Over and above generating specific knowledge on these aspects of human capital formation and valuation, the analyses serve to derive policy recommendations which aim at mitigating adverse effects and reducing inequalities in educational opportunities and labour market outcomes.

The first part of the dissertation contributes to an emerging field in economic research, namely the economics of violent conflict. The abundance of violent conflicts today and in the previous century induces the requirement of the investigation of conflict determinants and outcomes, to both decrease the number and duration of conflicts and mitigate adverse impacts. The next chapter (**Chapter 2**), therefore, identifies the long-run consequences of "The Troubles" on primary school performance in Northern Ireland. This is followed by the analysis of the causal effect of mental health on individual labour supply during the drug-related violent conflicts in Mexico (**Chapter 3**).

The second part of the dissertation contributes to the literature on labour market inequality by analysing the determination of wage differentials between groups of workers who are endowed with different levels of human capital. For Mexico, the wage differential between rural and urban workers is analysed with a specific focus on the valuation of work experience, ability and education in formal and informal labour markets (**Chapter 4**). The next chapter (**Chapter 5**) examines the wage differential between high- and low-educated workers and the role of technological change in the determination of increasing wage inequality in the UK. The final analysis focuses exclusively on high-educated individuals by investigating the effect of a Higher Education reform in the UK on labour market outcomes of different types of Higher Education graduates (**Chapter 6**). This chapter combines the findings regarding the investment in human capital formation and the dynamics of the valuation of different stocks of human capital. In the following, each chapter's aim, approach and contribution are explained in more detail.

1.2 Content

Chapter 2: The legacy of conflict. Since World War II, more than half of all nations have been afflicted by violent conflict. An emerging literature investigates the consequences of violent conflicts on education and finds structural differences between individuals who were affected by a conflict and those who were not affected (see Blattman and Miguel, 2010, for an overview). Usually, individuals who were exposed to a violent conflict possess lower levels of cognitive and formal skills (Chamarbagwala and Morán, 2011; Justino, 2011; Shemyakina, 2011) and worse states of physical and psychological health (Akresh and Verwimp, 2006; Murthy and Lakshminarayana, 2006; de Walque and Verwimp, 2009). These findings are, in the majority of cases, derived from individual or household level data sets which are combined with data on conflict intensity by region of residence. Using such composite data sets, it is possible to identify a correlation between conflict intensity and adverse human capital outcomes. Whilst short-run effects have been studied extensively, the link between conflict intensity and long-run human capital outcomes and the mechanisms behind this phenomenon are not well understood.

The conflict in Northern Ireland, known as "The Troubles", which lasted from 1969 to 1994, is characterised by a low level of conflict intensity that offers the possibility to study the demand-side effects of violent conflict on human capital accumulation, whilst nearly 20 years of peace provides an opportunity to look at the long-run impacts. To do so, this chapter (co-authored with **Neil T.N. Ferguson**) investigates whether regional differences in social deprivation, which are correlated with historical conflict intensity, causally affect school outcomes. As violent conflict affects the social development of a region via a reduction in house prices and the accumulation of predominantly low-educated and relatively more unemployed adults, it is hypothesised that regional multiple deprivation imposes a relative disadvantage on the next generation which can be measured by average exam pass rates at primary school level.

To identify the causal effect of regional deprivation on average pass rates, an error-component two-stage least squares model, which accounts for endogeneity and selection, is employed. Historical levels of violence intensity serve as instruments for regional multiple deprivation. As the children in the sample were educated after the conflict, a direct link between historical conflict and contemporary school performance cannot be inferred. The database is a combination of detailed information

on terrorist violence, the Northern Ireland Multiple Deprivation Measure and primary school level data from the national, standardised Key Stage II exams for the years 1999/2000 to 2010/2011. It is found that schools located in deprived regions perform significantly poorer than those in other regions. By disentangling the different types of deprivation, such as employment deprivation, education deprivation, health deprivation, living environment and proximity to services deprivation and crime and disorder deprivation, the domains which have relatively strong impacts on primary school performance are analysed.

The results suggest a strong correlation between "The Troubles" and various forms of social deprivation and large impacts of deprivation on primary school performance. We find that health and crime deprivation affect next-generation human capital formation most strongly. Accordingly, government policies that simply aim at minimising financial deprivation are unlikely to be successful in improving education performance. Instead, a wider approach to combating deprivation, which focuses on the quality of local schools and involves policies that aim at improving parental health and minimising crime, is most suitable for improving local education performance.

Chapter 3: Mental health and labour supply. In the previous chapter, the long-run effects of the conflict in Northern Ireland on inequality in school performance are identified. It is shown that the adverse effects are transmitted via neighbourhood deprivation. A related strand of literature indicates that neighbourhood characteristics are correlated with many individual outcomes, among them mental health (e.g., Oreopolous, 2003; Latkin and Curry, 2003). For example, a neighbourhood which is affected by violent crime is more likely to have inhabitants who suffer relatively more often from anxiety and depression, as suggested mainly by the psychiatric literature (e.g., Cornaglia and Leigh, 2012; Giacaman et al., 2007).

Little scientific attention has been paid to the correlation between spatial differences in conflict intensity and differences in the perception of threat of violence and mental health. To shed light on this relationship, this chapter analyses the consequences of violent conflict on one particular aspect of human capital, namely the suffering from anxiety and depression. The analysis is based on a large household level data set from Mexico, the Mexican Family Life Survey (MxFLS), which is representative of the Mexican population. The survey was conducted in 2002

and 2005/6 and includes a questionnaire on the mental constitution of the interviewees which allows the quantification of a certain aspect of their mental health. In Mexico, violent conflicts between drug-trafficking organisations have resulted in a high number of casualties for many years (and increasingly in the last five years, i.e. after the survey was conducted). In this chapter, the immediate effect of violent conflict on human capital is analysed. The analysis shows that individuals who live in regions which are characterised by a high level of conflict intensity are more anxious and more likely to be depressed than individuals in regions with low conflict intensity.

The study has a second aim which is the identification of a causal effect of mental health on individual labour supply. In many developing countries, where welfare systems are not always well-established, the supply of labour, in one way or another, is necessary to survive. Despite large poverty reduction programs, this is also the case in Mexico. The question is: What happens to individuals' labour supply when they are too depressed to go to work or too anxious to work the preferred or required hours?

Similar to other studies on the causal effect of mental health and labour supply, an instrumental variable approach is employed. A unique feature of this study is that measures of conflict intensity, both at the macro level and at the micro level, are used to instrument mental health. Due to the low intensity of violence in 2002 and 2005/6, labour demand effects due to conflict are likely to be ruled out conditionally on the included covariates, endorsing validity of the instruments. The results based on IV-Tobit models show that a worse mental health state decreases both the intensive and extensive margin of individual labour supply strongly and significantly for men. For women, this effect cannot be identified since the instruments are weak in their case.

Taking into consideration that men are usually the main contributors to household income in Mexico, the findings demonstrate that Mexico's population does not only suffer from the violent conflicts between drug-trafficking organisations through anxiety or even depression, but also indirectly through labour market effects. These results are discussed in light of their relevance for Mexico's social development and economic growth.

Chapter 4: Migration magnet. The conflicts in Mexico affect the population's human capital and subsequently its supply of labour. The conflicts are likely to

have many other consequences, for instance on migration. Mexico has been an emigration country for many years and, as in many developing countries, external migration to the outside of its borders is accompanied by internal migration, such as flows from rural to urban areas. Mexico City as one of the largest cities in the world has attracted large numbers of rural-to-urban migrants. In many of Mexico's large cities, a continuing influx of rural-to-urban migrants can be observed, although unemployment and crime is high (Fields, 1975; Boucher et al., 2005; Cabral et al., 2010). What drives individuals to migrate despite these adverse perspectives?

The fourth chapter (co-authored with **John P. Haisken-DeNew**) intends to answer this question by examining the difference in the valuation of human capital between rural and urban areas. It focuses on three indicators of human capital, namely formal education, work experience and ability, and investigates how the differences in their valuation explain the wage differential between rural and urban workers.

In this chapter, separate wage equations for formal and informal workers in rural and urban Mexico are estimated using data from the MxFLS. The MxFLS offers the unique opportunity to include a measure of ability which is rare in household surveys and causes most studies to suffer from biased coefficients when estimating the wage return to human capital. The use of Probit and Multinominal logit models in the first stage in which personality traits and family characteristics serve as exclusion restrictions for working per se and working in the formal sector controls for different potential selection patterns. Whilst we do not find evidence for selection, Oaxaca-Blinder decompositions show that rural-urban wage inequality in the formal and informal sectors is determined by differences in observable human capital. In the informal sector, the wage differential is mainly explained by differences in returns to potential work experience.

In a subsequent part of the chapter, rural-to-urban migrants' labour market performance is analysed to identify the incentives to migrate from rural to urban areas. All in all, it is shown that all forms of human capital are rewarded in both the rural and urban labour markets but that the return to experience is unequally rewarded in urban and rural regions, with a significant advantage in cities. The discussion provided concludes that rural-to-urban migration is likely to continue and that the informal sector is likely to further increase.

Chapter 5: The hidden increase in wage inequality. The previous chapter shows that wage differentials exist between rural and urban workers in Mexico, and identifies the urbanity of a worker's environment to affect relative wage levels. Increasing urbanisation is one aspect of development which goes hand in hand with the process of globalisation. Economists have long claimed that the process of globalisation is an important driver of labour market inequalities (e.g., Wood, 1998; Taylor, 2002; Levy and Murnane, 2006). The process of globalisation is defined not only by human migration but combines the increasing openness of countries towards trade and technological change. These phenomena lead to shifts in both the supply and demand side of labour markets. Technological advancements and computerisation lead to an increase in the demand for high-skilled workers and a decrease in the demand for medium-skilled workers, as simple production processes substitute manual work (Autor et al., 1998).

The process of technological advancement has been shown to increase wage differentials between high- and low-skilled individuals in most developed countries (Berman et al., 1998; Bartel and Sicherman, 1999; Card and DiNardo, 2002). The rationale behind this finding is that technological change increases the demand for high-skilled workers, known as skill-biased technological change, which leads to relatively higher average wages for high-skilled workers.

In recent decades, the UK has, next to technological development, undergone many changes that are relevant for the labour market, most significantly a change in the educational sector. Educational reforms were passed with the intention of educating more than half of the population in Higher Education institutions (Walker and Zhu, 2008). This had the aim of meeting shifting labour market demands. The resulted increase in Higher Education graduates is likely to have caused an increase in heterogeneity among those graduates with respect to ability, or talent. If this is the case, the larger amount of highly educated individuals requires different screening processes by employers. A so far small strand of literature suggests that wage differentials do not only differ by degree of education, but also within the degree types, e.g., by ability. A hypothesis exists which makes technological change responsible for a relatively higher demand for high-ability individuals, known as the ability-biased technological change hypothesis (Galor and Moav, 2000; Stern, 2004), which would result in wage inequality among high-educated individuals.

To test this hypothesis empirically, this chapter analyses, firstly, the effect of tech-

nological change on the demand for high-educated individuals by estimating wage differentials between Higher Education graduates and non-graduates in the manufacturing sector in the UK. Using individual level data from the British Household Panel Survey (BHPS) and industry level data from the OECD, wage regressions are estimated which identify the effect of innovative activity on wages – the individual innovation wage premium – for university and lower educated workers. Innovative activity of an industry is proxied by expenditure on research and development (R&D) and patent applications to measure innovation input and innovation output, respectively.

Secondly, using different estimation methods for panel data, such as Fixed Effects, Random Effects, Mundlak and Hausman-Taylor models, in addition to pooled OLS allows controlling for both industry-specific ability and individual ability. The different methods offer the possibility to test the ability-biased technological change hypothesis. This study provides strong evidence for an increase in wage inequality induced by skill-biased technological change in the UK manufacturing sector between 1991 and 2006. The study contributes to the existing literature by empirically investigating, for the first time, the hypothesis that the change in demand for high ability due to innovation has increased. This implies that wage differentials exist within the group of high-educated workers due to differences in innate ability and industry-specific ability. However, the empirical results are ambiguous, as only R&D expenditure as a measure of innovative activity but not patent application suggests the existence of ability-biased technological change.

Chapter 6: Reaching high. The previous chapter distinguishes high- and low-educated individuals, i.e. individuals with a Higher Education degree and those without a Higher Education degree. Heterogeneity in educational levels has increased significantly in recent decades, especially the size and composition of the graduate population (Blanden and Machin, 2004; Chevalier and Lindley, 2009).

By focusing explicitly on Higher Education graduates, this chapter (co-authored with **Jan Kleibrink**) deals with heterogeneity within this group of individuals. In particular, the chapter analyses the effect of a Higher Education reform which changed the composition of Higher Education graduates. The Further and Higher Education Act of 1992 was mainly conducted through three channels: Firstly, the difference in funding schemes between universities and polytechnics was abrogated in 1992. Secondly, former polytechnics obtained the right to award accredited

Higher Education degrees. Thirdly, and most prominently, a renaming process started. In the course of the reform, almost all former polytechnics changed their names to universities.

This chapter analyses, for the first time, whether the reform has changed labour market outcomes of the two types of graduates. Wage differentials between polytechnic and university graduates in the UK are estimated using the BHPS, which provides a representative sample of the UK graduate population between 1991 and 2008. By employing a Heckman (1979) model for panel data (Wooldridge 1995), we control for various sources of potential selection bias. Similar to previous studies, it is found that polytechnic graduates earned on average lower wages than university graduates prior to the UK Further and Higher Education Act of 1992. New evidence is that wage differentials can be explained by a glass ceiling which prevented polytechnic graduates from reaching managerial and professional occupations. It is found that after the reform, they overtook graduates of traditional universities in terms of average wages. The results show that a fast change of employer perception of productivity of graduates from the two types of institutions happened after the reform. A sheepskin effect is a likely explanation, as an educational difference can hardly be implemented that quickly after the reform.

Whilst the last chapter indicates the relevance of the type of educational degree to being successful in the labour market, the other analyses conducted in this dissertation show that over and above an educational degree, other indicators of human capital predict labour market outcomes. Work experience is relatively more productive in urban informal labour markets than in rural informal labour markets in Mexico, and anxiety and depression, a form of mental health, affect individual labour supply. Especially the latter finding calls for policy intervention to protect vulnerable individuals from adverse income effects due to reduced labour supply. Job creation to allow individuals working close to their home to avoid commuting, providing psychological counselling services to deal with anxiety and depression and the fight against drug-trafficking are likely to be effective tools. However, their implementation is exacerbated by resource constraints and the unknown probability of success.

As the findings on the long-run consequences of the Northern Ireland conflict show, even the introduction of intensive policies to create social cohesion cannot eliminate social inequalities that result from the conflict which ceased almost twenty

years ago. The poor school performance in neighbourhoods which are relatively more deprived calls for policies which, firstly, enhance social development and, secondly, disentangle children's educational outcomes from their neighbourhood characteristics. This could be done by improving school quality, for example by employing more pedagogues and tutors who help children with their homework and beyond. Building on the existing literature on human capital formation and valuation, this dissertation shows that human capital is important in countries at all stages of economic development. In general, public investments in education should focus on the provision of equal access to education to solve labour market inequalities in the long-run.

Chapter 2

The Legacy of Conflict: Regional Deprivation and School Performance in Northern Ireland

Co-authored with Neil T.N. Ferguson

Abstract The relationship between deprivation and educational outcomes has been the subject of a long-running and deep debate in the economic literature. Predominantly, the literature proxies deprivation with measures of wealth. This paper explores a much wider measure and identifies a causal relationship between regional deprivation and school performance in Northern Ireland. Combining panel data on Key Stage II results from each of Northern Ireland's primary schools with the 2005 Northern Ireland Multiple Deprivation Measure, we show the net negative impact of this wider measure, whilst an extension explores the impacts of each single domain. Using an error-component two-stage least squares model, we account for school and neighbourhood selection and the potential endogeneity of our deprivation measure, showing spatial variation in historical violence, which occurred during "The Troubles", to be a valid instrument for deprivation. Our results confirm the negative impact of deprivation frequently found in the literature but also that, when the impacts of other deprivation domains are accounted for, education and crime deprivation, and not financial deprivation, play a significant role in determining outcomes. This confirms the limitations of using wealth as a proxy for neighbourhood deprivation, whilst suggesting that policies focusing only on income redistribution will be unsuccessful in improving education outcomes of those exposed to deprivation.[1]

[1]This chapter is published as Ruhr Economic Paper No. 419 (2013). The authors are grateful for comments by John P. Haisken-DeNew, Ingo Isphording, Michael Kind, Mathias Sinning, Anna Klabunde, Gerhard Kussel, participants at the 2012 HiCN Workshop and the RES Annual

2.1 Introduction

In Northern Ireland, a low-intensity conflict, colloquially known as "The Troubles" occurred between the death of Francis McCloskey in 1969 (Sutton, 1994) and the joint paramilitary ceasefires of 1994. We aim to exploit the uneven spatial distribution of this historical violence (Figure 1) and its relationship with adverse neighbourhood observables, in order to explore the relationship between deprivation and primary school performance. It is known that primary-level educational achievement plays an important role in child / adolescent development and future labour market outcomes, yet the topic has received little attention to date (Gibbons, 2002).

We employ the Northern Ireland Multiple Deprivation Measurement (NIMDM), which captures differences in neighbourhood quality via seven different domains; income, employment, education, health, living environment, proximity to services and crime. We match this regional deprivation measure to performance data for each primary school in Northern Ireland between the 2000/01 and 2010/11 academic years. Performance is measured by the proportion of children at each primary school achieving the minimum pass (Level 4) in the standardised national Key Stage II exams. Primary schools in the UK serve local communities and are typically distributed over small geographic areas. We propose this means that primary schools are closely linked to the location-level unobservables that form the background of the neighbourhood effects literature (Weinhardt, 2010, for example).

Noting the potential endogeneity of the NIMDM measure, we exploit a dataset of deaths directly linked to "The Troubles" (Sutton, 1994), which has been geographically mapped to Northern Ireland's 582 electoral wards by Ferguson (2012). Using the total number of deaths by ward and calculating the inverse distance weighting matrix to capture violence intensity in bordering wards, we have two instruments for the NIMDM. This instrumentation allows us to account for both the endogeneity of our deprivation measure and any unobserved school-level heterogeneity. Given the potential for selection into, or out of, neighbourhoods (wards) and school districts, we implement an error component two-stage least squares regression (Baltagi, 1981).

Conference 2013 and Mark Schaffer for provision of additional software.

Results in the first stage show a strong relationship between historical violence and contemporary deprivation. Beginning the analysis in the 2000/01 school year ensures that all children in our sample began their education after the conflict had ended in 1994, precluding any direct effects of continued violence. Consequently, in the second stage we show the impact of deprivation on primary school performance. We extend our analysis by disaggregating the NIMDM measure into its constituent domains, showing that the effects of exposure to education deprivation and crime deprivation are the most important determinants of poorer primary education outcomes. In contrast to the frequent use of individual, household or regional wealth as a proxy for deprivation, however, we find no unique effect from either the financial deprivation or employment deprivation domains, suggesting any policies focused only on income redistribution will fail to mitigate the negative impacts of prolonged deprivation or improve social mobility. Instead, a wider approach to combating uneven school performance is required. Given the relationship between deprivation and violence in Northern Ireland (Honaker, 2010), these results also imply that these persisting regional inequalities may prove to be an obstacle for the continued peace process.

The remainder of this paper is set out as follows: in the next section (2.2), we discuss and review the literature relevant to this study. In Section 2.3, we describe the data we use; in Sections 2.4 and 2.5, we introduce our methodology and results, respectively and, finally, we conclude in Section 2.6.

2.2 Literature Review

The positive role played by good primary education on the formation of human capital and of individuals' future labour market outcomes is uncontroversial (Sparkes, 1999). This notion, however, raises two important questions. Firstly, if there is a link between deprivation and primary school outcomes, then issues relating to a cycle of poverty must arise, suggesting that those children born to the most deprived parents would be those most likely to spend their adult lives in poverty. Secondly, a potential issue of endogeneity is raised, which appears in the literature as early as Tolley and Olsen (1971). Their logic argues that the richest regions have the greatest ability to invest in education infrastructure, suggesting richer parents gain access to better schools. Financial deprivation, therefore, plays only an indirect role in determining education outcomes, with the mechanism of this

effect being school quality, rather than income. Whilst this paper does not, necessarily, subscribe to this notion, we question the over-reliance on wealth to proxy deprivation throughout the literature.

Although these relationships are evident, the link between deprivation and primary school outcomes is understudied, as Gibbons (2002) notes. Until recently, this could be explained by the lack of detailed breakdown of primary school performance data. Whilst census data and detailed household panel surveys have provided information on post-primary achievement, such differentiations have not been available at primary school level. Unsurprisingly, therefore, much of the literature to date has looked at post-primary performance.

This literature has also, most frequently, looked at financial deprivation. The measurement of financial deprivation is difficult however, due to both controversial definitions and lack of data availability. A series of proxies, therefore, have been used; such as parental education (Cremer et al., 2003), income (Blau, 1999) and occupation (Oreopoulos and Stevens, 2008). Each of these proxies may still suffer identification issues, however. Education, income and occupation could equally be related to unobservable characteristics, such as latent ability, for example. Furthermore, the transfer mechanisms of financial deprivation to education outcomes are not immediately clear.

Fuller reviews of the financial deprivation literature can be found in the surveys of Haveman and Wolfe (1995) and Mayer (1997). Noting the potential for unobservable neighbourhood characteristics, however, more recent literature has turned to a quasi-experimental approach. Milligan and Stabile (2008) and Duncan (2011) use government income transfers. Both find positive relationships between income and educational attainment. Løken (2010) and Løken et al. (2012) use the uneven geographic dispersion of the Norwegian oil boom as exogenous variation and show pronounced positive impacts of increased income on school attainment amongst low income families. Weinhardt (2010) shows the negative impact of moving into a "low-quality" neighbourhood, where "quality" is measured by the proportion of social housing.

Bayer and Topa (2008), Davis-Kean (2005) and Cutler and Glaeser (1997) support the neighbourhood findings of Weinhardt (2010), whilst Oreopoulos and Stevens (2008) and Jacob (2004) show no significantly worse outcomes, based on proxies of quality. Goux and Maurin (2007) and Gibbons and Silva (2008) note the potential

impact of selection into neighbourhoods, however. Poorer families have less choice over where to live and, therefore, have less access to the best schools. This effect is also noted in Bayer and Ross (2006).

Despite the focus of this literature we argue, along the lines of Dahl and Lochner (2008), that income deprivation may be endogenous to the process. The increased attainment due to an increase in income noted in these papers may transmit itself through other unobservables that have also improved as a result of neighbourhoods becoming wealthier. Following Tolley and Olsen (1971), more resources may be available for local schools, improving their quality. In the cases of Løken (2010) and Løken et al. (2012), for example, this notion seems particularly pertinent – it seems unlikely that only families, and not an array of local infrastructure, benefitted from the oil boom. Thus, both children's opportunities and family income remain influenced by the same underlying factors.

Financial deprivation, therefore, at best seems to be only one of a number of potential sources of deprivation that could impact on children's outcomes. McLoyd (1990), for example notes the impact of health on individual outcomes, with the causal mechanisms also well established. Exposure to health deprivation, therefore, may not be intrinsically linked to financial deprivation but, intuitively, seems likely to impact on the outcomes of those exposed. Perhaps surprisingly, however, little work has looked at the intergenerational transfer of this relationship. Sun and Yao (2010) show a negative impact on the probability of entering and finishing middle school as a result of parental health shocks, while Choi (2011) shows that poor parental health is a significant indicator of their children's educational achievements. The thinness of this literature is discussed in Bratti and Mendola (2011), who find a negative impact on education enrolment in Bosnia as a result of self-reported poor maternal health, especially poor mental health.

Similar to the civil war in Bosnia in the early 1990s, the conflict in Northern Ireland has resulted in a considerably larger prevalence of mental health issues within its population compared to other countries. Post-traumatic stress disorder, depression and similar symptoms can be found until today among individuals who were exposed to the conflict (Curran, 1988; Loughrey and Curran, 1988; Muldoon and Downes, 2007). These outcomes are likely to be reflected in the deprivation measure on health, and may, as in the study by Bratti and Mendola, impact on children's school performance via, e.g., impaired interaction between depressed

parents and their children, yet may not be, explicitly, accounted for in a financial deprivation measure.

The continuing debate in the literature over both outcomes and methodologies suggests that the role of deprivation as a driver of educational outcomes is considerably more complex than simply an absence of financial resources at an individual or household level. Few previous studies tried to overcome the issues of unobservable neighbourhood effects and the complex series of interactions that define deprivation wider than simply as financial inequality. Examples are Lupton (2001), who uses a multiple deprivation index to study post-primary outcomes in the UK, and Gibbons (2002), who uses primary school level data and several measures of neighbourhood wealth in England.

Similar to Gibbons (2002), we use primary school level data. We believe that, given the absence of individual-level explanatory variables, such as time spent doing homework, or number of missed school days per year, little is lost by looking at average school level achievement. In the context of Key Stage II examinations, which each individual only sits once, a panel facilitating the measurement of individual effects could not be developed. This contrasts to our school level data, which allows modelling of school level unobservables and potential neighbourhood effects. Using variation in the proportion of individuals achieving the minimum pass rate (Level 4) at Key Stage II, we employ a nationally comparable measure of achievement at this level. Following Lupton (2001), we suggest that deprivation extends significantly further than comparison of incomes. Accordingly, we use the NIMDM, which builds an index of deprivation from seven different domains.

In the specific case of Northern Ireland, the authors are aware only of the studies of Shuttleworth (1995); Shuttleworth and Daly (1997) and Cummings et al. (2011). Cummings et al. (2011) look at the relationship between violence and children's "adjustment problems", which can easily be extrapolated to our question, whilst the others look at the direct impact of violence on those who were exposed to it. To our best knowledge, this is the first paper to explore the role of multiple deprivation on primary school level outcomes, and certainly the first to do so in post-conflict Northern Ireland. Furthermore, given our instrumentation of the multiple deprivation measures and our error-component modelling strategy, we believe that this work overcomes many of the identification issues that have been prevalent in the literature to date.

2.3 Data

We combine three major data sources for our empirical analysis. School performance data is taken from the Department of Education of Northern Ireland (DENI). Deprivation data is sourced from the Northern Ireland Multiple Deprivation Measure (NIMDM) from 2005, which was provided by the Northern Ireland Statistical Research Agency (NISRA) and obtained by the Social Disadvantage Research Centre at the University of Oxford. Finally, violence data is based on the authors' own construction of Sutton (1994).

We employ a panel of primary school data that runs from 2000/01 until 2010/11, with the exception of the 2003/04 academic year, which is unavailable due to a teachers' strike. We begin our analysis in 2000/01 as this is the first year in which all children in the cohort began their education after the 1994 ceasefires[2], precluding any direct effects of violence on their outcomes. We exclude private preparatory schools[3] and schools that did not provide data for Key Stage II achievements or Free School Meal Entitlement (FSME). This results in an unbalanced panel of $n \times T = 5,937$ school-years. We include information on the language used in each school (English or Gaelic), the number of pupils per school, the size of the examined cohort and the teacher-pupil ratio in each school. The average proportion of children achieving at least Level 4 in English and Mathematics in the Key Stage II exams is used to proxy school performance and serves as the outcome variable for our analysis. Key Stage II is an annual, formal and standardised national exam taken by children towards the end of primary school, at approximately age 10.

Our regional deprivation measure is the NIMDM from 2005. The NIMDM is a five-yearly measure that aims to identify small-area concentrations of deprivation in Northern Ireland and provides information on seven domains, each of which is designed to measure a distinct type of deprivation. We use the 2005 wave as it is temporally closer to more of our data than the 2010 wave. A previous version of the NIMDM from 2001 is not geographically comparable to 2005, whilst changes

[2]We accept that some violence, fatal and otherwise, has been ever-present in Northern Ireland since 1994. This violence, however, is not on the same scale of the pre-1994 violence and is controlled for in our analysis.

[3]Whilst most primary schools in Northern Ireland service local communities, it is unlikely that most pupils attending preparatory schools live in the region(s) surrounding the school. On this basis, we exclude these institutions.

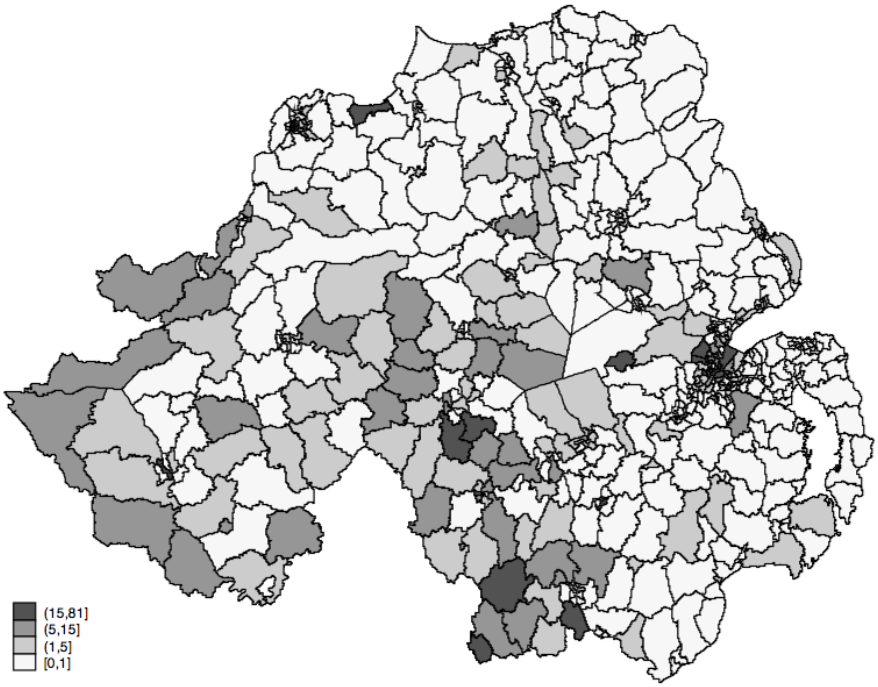
in the sub-indicators between 2005 and 2010 preclude like-for-like comparison of these years. The domains and their weights, suggested by NISRA, in the multiple measure are as follows: Income Deprivation (25%), Employment Deprivation (25%), Health Deprivation and Disability (15%), Education, Skills and Training Deprivation (15%), Proximity to Services (10%), Living Environment (5%) and Crime and Disorder (5%).

Each domain is built from a series of sub-indicators. Income deprivation, for example, is based on indicators such as the proportion of households on Income Support, the proportion of households with State Pensions only and other indicators such as proportion of the population receiving Jobseekers Allowance, Housing Benefit, Working Tax Credits, Child Tax Credits, etc. A full list of each domain's indicators can be found in Table 2.A.4 in the Appendix. We construct an overall multiple deprivation measure which consists of the weighted average of all domains. Following (Haisken-DeNew and Sinning, 2010, e.g.,), who show how weighting of social deprivation can effect the estimated impact on outcomes variables, we apply the weights suggested by NISRA and use equal weights as a robustness check. We extend the analysis to test the impact of each single domain, whilst controlling for the impact of the remaining domains, which offers deeper insight into the transfer mechanisms and further overcomes the weighting issue discussed above.

We choose Northern Ireland's 582 electoral wards as our level of geographic disaggregation, due to the presentation of both deprivation and violence data at this level[4]. We extract data from Sutton's (1994) database, which provides detailed information on fatal incidents that are directly related to the conflict. We construct a variable, *deaths*, which is the total number of fatalities which occurred in a ward between the death of Francis McCloskey in June 1969 and the PIRA ceasefire of August 1994. Figure 2.3.1 displays the spatial variation of deaths by electoral wards. In total, the conflict counts almost 3,600 deaths. Over 200 wards experienced no fatal violence during the conflict. Others experienced in excess of 75 fatalities. Whilst some notable incidents have occurred since 1994, fatal violence has been extremely rare since the paramilitary ceasefires.

[4]A larger disaggregation, Super Output Areas (890), also exists but is not feasible due to a lack of other control data at this level. We do not believe the lower disaggregation of electoral wards is problematic to our analysis, however, as on average each ward contains only 1.9 primary schools.

Figure 2.3.1: Number of Conflict-related Deaths by Wards between 1969 and 1994 in Northern Ireland



Source: Authors' construction using data by Sutton (1994).

Table 2.3.1: Descriptive Statistics of Violence Data

	Mean	Std.Dev.	Min	Max
No. of Deaths by Ward	4.76	9.11	0	81
Deaths per 1,000 inhabitants	1.57	2.95	0	25
No. of Deaths ≥ 1	0.61	0.49	0	1
No. of Deaths ≥ 5	0.25	0.44	0	1
No. of Deaths ≥ 10	0.15	0.36	0	1
Bombing incidents	3.58	10.04	0	152
Shooting incidents	5.77	11.14	0	111
N		6,631		

Note: Authors' calculations based on Sutton (1994).

Table 2.3.1 provides summary statistics on conflict intensity. It can be seen that the number of deaths per ward ranges from 0 to 81 and has a mean of 4.77. In 61% of all wards, at least one death occurred, with more than five occurring in 25% of wards and more than ten deaths in 15% of wards. We divide the total number of

deaths by the resident population in 2001.[5]

We construct a spatial lag of violence[6], in order to increase our instrumentation options. This variable measures the impact on deprivation of living close to a high-violence area. To this historical violence data, we add data on the annual number of contemporaneous bombing and shooting incidents to control for any continuing violence[7].

Table 2.3.2: Descriptive Statistics of School Data

	Low Violence Area		High Violence Area		Difference	
	Mean	Std.Dev.	Mean	Std.Dev.	Diff	SE
Average Pass Rate	79.18	(12.92)	77.11	(14.52)	0.72**	(0.34)
Number of Pupils	31.1	(23.95)	29.9	(21.72)	1.0*	(0.6)
Pupil-Teacher Ratio	19.74	(2.96)	19.50	(2.95)	0.07	(0.07)
Exams in Gaelic	0.01	(0.11)	0.02	(0.15)	-0.01***	(0.00)
Catholic School	0.44	(0.50)	0.60	(0.49)	-0.14***	(0.01)
Free School Meal 10-25%	0.4	(0.50)	0.4	(0.49)	0.0	(0.0)
Free School Meal 25-50%	0.20	(0.40)	0.29	(0.45)	-0.06***	(0.01)
Free School Meal 50+%	0.05	(0.21)	0.14	(0.35)	-0.04***	(0.01)
Percentage of Catholics	40.55	(29.13)	60.20	(28.15)	-13.37***	(0.74)
All Persons 0-15	680	(324)	760	(320)	-43.62***	(8.17)
All Persons 16-39	934	(485)	1081	(757)	-84.36***	(14.33)
All Persons 40-59/64	814	(305)	852	(303)	-12.79*	(7.68)
All Persons 60/65+	465	(177)	509	(225)	-25.91***	(4.83)
MDM score	5.10	(3.01)	6.76	(4.05)	-0.89***	(0.08)
Income Domain	0.20	(0.10)	0.30	(0.15)	-0.06***	(0.00)
Employment Domain	0.15	(0.05)	0.19	(0.07)	-0.03***	(0.00)
Education Domain	20.76	(14.05)	27.21	(18.45)	-2.96***	(0.39)
Health Domain	-0.17	(0.62)	0.17	(0.81)	-0.23***	(0.02)
Proximity to Serv. Domain	-0.34	(0.77)	-0.22	(0.99)	-0.04**	(0.02)
Living Environment Domain	21.84	(11.12)	27.95	(13.37)	-5.40***	(0.30)
Crime and Disorder Domain	17.34	(16.54)	23.16	(22.32)	-2.42***	(0.46)
N	4,946		1,685		6,631	

Note: Authors' calculations based on Key Stage II data, MDM scores from NISRA (2005) and Sutton (1994). In a high violence area, at least 5 deaths occurred. SE: Standard Error. *,** and *** denote significance level of 10%, 5% and 1%, respectively.

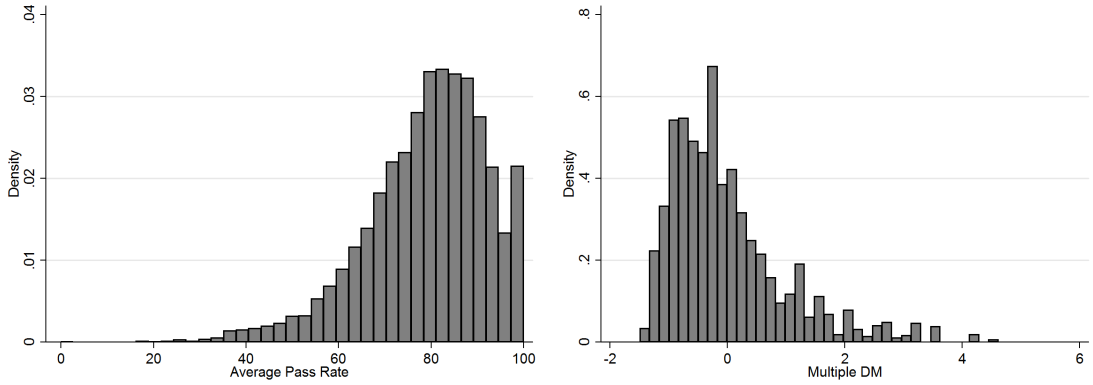
Table 2.3.2 provides summary statistics on the overall NIMDM score and the single domains, school level variables and population size by ward and age. We provide these descriptive statistics for two samples: schools located in areas of high violence ($\geq$ 5 deaths) and schools located in areas of low violence ($<$ 5 deaths).

[5]The geographic boundaries of the wards used in this paper did not come into common use until the census in 2001. Accordingly, we use population data from this year as a proxy of deaths per capita. Although contemporaneous population data would be more desirable, earlier data do not exist at this unit of analysis.

[6]We construct a row-normalised, inverse-distance spatial weighting matrix. Due to Northern Ireland's small geographic size, we do not truncate the impacts of "distant" violence.

[7]These data were provided on request from the Police Service of Northern Ireland (PSNI) and are disaggregated to District Crime Units (DCU), which are significantly larger than electoral

Figure 2.3.2: Average Pass Rates and MDM Score Density



Source: Authors' construction.

In low-violence areas, the proportion of children meeting or exceeding the minimum standard pass rate stands at 79.62%, whereas in high-violence areas, 77.67% of students reach this standard, with the difference being statistically significant. High violence areas are typically larger in terms of population and are significantly more deprived than low-violence regions, with an average NIMDM score of 6.8 in high-violence areas and 5.1 in low-violence areas. Figure 2.3.2 shows the distribution of the proportion of children meeting or exceeding the minimum standard pass rate and the NIMDM score.

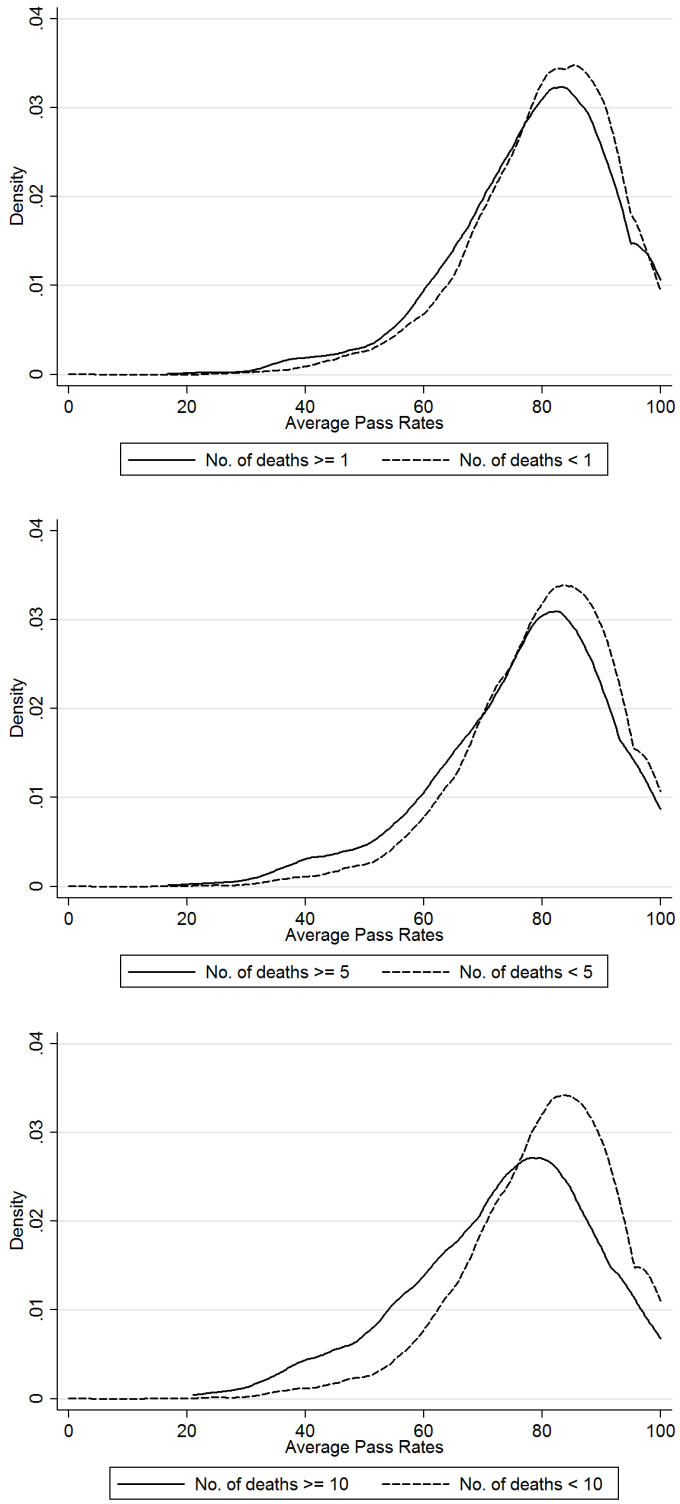
For the regression analysis, the NIMDM scores are standardised with mean zero and a standard deviation of one. In Figure 2.3.3, we provide Kernel density plots of average pass rates for high ($\geq$ 10 deaths), medium ($\geq$ 5 deaths) and low ($\geq$ 1 death) conflict regions. It can be seen that, as violence increases, the density plots diverge; with a higher density of high pass rates in low-violence regions.

2.4 Estimation Methods

As shown in the descriptive statistics, the unconditional relationship between regional multiple deprivation and school performance is negative. This relationship is unsurprising but questions remain about the causal relationship. Is there a direct (causal) impact of deprivation on children's outcomes, or do only parents with lower ability live in deprived areas, suggesting only a correlation transmitted via,

wards, explaining the high number of incidents recorded.

Figure 2.3.3: Average Pass Rates Density by Violence Intensity



Source: Authors' construction.

e.g., ability? Indeed, should we implicitly assume a causal relationship, these notions remain important for interpretation of our outcomes, particularly in terms of the scale of the coefficients.

As is known from the literature on the intergenerational transmission of human capital, children's educational achievement depends strongly on the education and health states of their parents (e.g., Black et al., 2005; Choi, 2011; Haveman and Wolfe, 1995; Holmlund et al., 2011; Gertler et al., 2004). The roots of this intergenerational dependence may be different styles of upbringing between high- and low-educated parents, or ability, which is usually higher among high-educated individuals than among low-educated individuals (Becker, 1964; Griliches and Mason, 1972; Mincer, 1958).

Unobserved school-level heterogeneity, such as teacher quality or ethos, could similarly be correlated with both deprivation and school performance. As these differences are unobservable and consequently omitted from the regression, an identification of the effect of deprivation is likely to be biased in simple Ordinary Least Square (OLS) regressions. The usual way to deal with omitted variable bias is to instrument the endogenous variable with one or more variables that are correlated with the endogenous variable and uncorrelated with the error term (Angrist and Pischke, 2009). We can write the basic relationship we are interested in as a hierarchical model

$$APR_{ijt} = \beta_0 + \beta_1 MDM_j + \beta_2 X_{it} + \beta_3 Z_{jt} + u_i + v_j + \epsilon_{ijt}, \tag{2.1}$$

where i is the subscript for individual schools, j is the subscript for electoral wards, t is a subscript for years, APR is average pass rates, MDM is the multiple deprivation measure, which is endogenous, X and Z are vectors of exogenous regressors at the school and electoral ward level, respectively, u is school unobserved heterogeneity, v is electoral ward unobserved heterogeneity, β's are regression coefficients and ϵ is the error term. If u and v were observable, the error term would be uncorrelated with the regressors. Since we cannot observe u, the OLS coefficient of MDM is inconsistent and biased, because $COV(u_i, \epsilon_i) \neq 0$.

Following an instrumental variable approach, we regress the endogenous variable MDM on all exogenous regressors X, Z and instruments IV:

$$MDM_j = \alpha_0 + \alpha_1 X_{it} + \alpha_2 Z_{jt} + \alpha_3 IV_j + \eta_j \tag{2.2}$$

where α are regression coefficients and η is the error term. For IV to be valid instruments they must be partially correlated with MDM, i.e. $\alpha_3 \neq 0$, and they must be uncorrelated with the error term ϵ , i.e. $COV(IV, \epsilon) = 0$ (Wooldridge, 2002).

In an extended analysis, the causal effect of each single domains on school APR is identified by estimating separate models for each. In these models we include a multiple deprivation measure consisting of the remaining domains, raising the concern of two potentially endogenous variables. By generating two instruments (deaths and the spatial lag of deaths), we are able to present a just-identified analysis of this relationship. We believe historical violence to be a valid instrument as the NIMDM comprises a range of domains that could be related to historical violence. These domains, however, also capture any other effects of historical violence on contemporaneous school performance. Due to potential collinearity between the two instruments, which would not allow us to identify a causal effect in the just-identified case, we use the third polynomial of the *deaths* variable. Model statistics show that this is a valid transformation of the instruments.

We are concerned with another potential bias which is rooted in selection of families into or out of deprived neighbourhoods. It has been shown that with increasing conflict intensity, house prices increased in less violent neighbourhoods as people moved away from high-violence areas (Besley and Mueller, 2012). Selection is likely to be determined by financial means, causing increased deprivation in conflict areas, as relatively rich people move away. If we presume that selection varies by school catchment area, denoted by u_i in Equation 2.1, our instruments would account for this type of selection bias.

However, if families do not select into school catchment areas but select into wards (which are greater in size than school catchment areas), the instrumentation could not account for this potential bias. In fact, school catchment areas are not enforced and parents can enrol their children in any primary school, unless a school is over-subscribed (BBC Learning – Parents: Support your child's education, 2013). This reduces the incentive for parents to move into a certain school catchment area. Rather, parents may choose their place to live on a lower level of regional disaggregation, such as ward level.

Selection into wards can be seen as a 'random effect', which is represented by v_j in Equation 2.1. To avoid this potential bias in our estimated coefficients, we

estimate a random effects two-stage least squares model (RE2SLS). This model is explained in Balestra and Varadharajan-Krishnakumar (1987). It allows for a more general error structure than is required for consistency in the 2SLS estimation. Clarke et al. (2010) discuss the usefulness of estimating random effects models in education research. Although their smallest unit of observation are pupils and the second level of analysis are schools, the modelling strategy can easily be 'up-scaled' in the sense that our unit of observation are schools and the second level are electoral wards. Clarke et al. state that, apart from the strong and often unrealistic assumption of independence between the 'random (second level of analysis) effects' and the other regressors, the random effects approach is preferable over the fixed effects approach.

We also estimate an error-component two-stage least squares model (EC2SLS) proposed by Baltagi (1981). The EC2SLS model is essentially an extension of the Balestra and Varadharajan-Krishnakumar (1987) model but uses a larger set of instruments. While RE2SLS uses the the GLS transformed instruments X, Z, in EC2SLS both the within-transformed instruments, $\widetilde{Z}$, and the between-transformed instruments $\overline{Z}$ are used. Accordingly, EC2SLS uses up to double the number of instruments and is shown to be more efficient in small samples (Baltagi and Liu, 2009). Baltagi (2008) provides more technical details of the methods[8].

2.5 Results

2.5.1 Multiple Deprivation

Our results link contemporaneous spatial differences in multiple deprivation to the intensity of historical violence, although we are agnostic on attributing causality to this relationship. Indeed, it seems highly probable that both are interlinked. In Column 1 of Table 2.5.3, the results from the 'first stage' regressions[9], it is shown that the number of historical deaths in a region is a positive and accurate predictor of current deprivation. Although these effects are not large in magnitude, they are shown to be strong enough to identify a causal relationship in the second stage of

[8]The RE2SLS and EC2SLS models are calculated using xtivreg3 (Schaffer, 2013) in Stata

[9]These 'first stage' outputs are simple OLS regressions of the MDM score on the total number of deaths (the third polynomial divided by 1,000 and the other control variables.

our regression[10].

The OLS estimates identified in Column 2 of Table 2.5.3 are immediately suggestive of the negative impact of deprivation on the probability of attaining the minimum Key Stage II pass. In this model, a one standard deviation increase in the NIMDM score is associated with a 1.5 percentage points drop in children attaining the minimum criteria. This effect increases to almost 2.5 percentage points (Column 3) when we follow a random effects approach, which accounts for specific ward unobservables. We see further increases in magnitude when we adopt two-stage approaches, with effects suggesting a drop of almost 4.8 percentage points, due to a marginal increase in the level of regional deprivation, as shown in Columns 4, 5 and 6 of Table 2.5.3. In different terms, this means an increase by one unit of the MDM score reduces APR by approximately 1.4 percentage points, as one standard deviation of MDM before standardising is 3.4. Due to the treatment of instruments and the increased efficiency of the outputs, we favour EC2SLS and base our discussion on these outcomes, although the coefficients from 2SLS and RE2SLS are of comparable scale and support such findings.

Comparison of the coefficients between our one-stage and two-stage analyses suggests that the direction of bias is towards zero, which appears to contradict the traditional theory of "ability". In these suggestions, two potentially reinforcing effects may occur; firstly, that there is a direct causal impact of deprivation on education outcomes and, secondly, deprivation may also be correlated with unobservables such as the average ability of those who live in a neighbourhood. Those with the greatest ability are those most likely to move away from deprived areas, resulting in a non-causal relationship between ability and outcomes, leading to a larger coefficient, biased away from zero, than in the true relationship. Despite this history, however, we do not find a bias towards zero surprising or unexplainable.

Firstly, we focus on a significantly wider definition of deprivation than features in the literature. The typical explanations for bias, therefore, are not entirely relevant to our measure. The potential link between ability, income and deprivation, for example, would play less of a role in our analysis than in most. By contrast, the link between ability and the road distance to a GP, dentist, optician or accident and emergency room, as accounted for in our Proximity to Services domain seems

[10]The Cragg-Donald Wald F Statistic identifies that the instrument is strong, passing the Stock-Yogo thresholds at 5%.

Table 2.5.3: Base Results

	First Stage MDM Score[1]	Second Stage Average Pass Rate[1]				
	1 OLS	2 OLS	3 RE	4 2SLS	5 RE2SLS	6 EC2SLS
Deaths[3]	0.004***	–	–	–	–	–
	(0.001)					
Multiple DM	–	-1.525***	-2.432***	-3.388	-4.461**	-4.794***
		(0.434)	(0.346)	(2.149)	(1.927)	(0.579)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	5937	5937	5937	5937	5937	5937
R^2	0.559	0.252		0.243	0.938	0.938
R^2 centered				0.243	0.331	0.330
R^2 overall			0.245			
χ^2			966			
F	24	30		30	3208	3203
p	0.000	0.000	0.000	.	0.000	0.000
CD Wald F				133	205	68
Sargan statistic				0	0	56
Sargan χ^2-p						0.000

Note: [1] Dependent variable. OLS = Ordinary Least Squares, RE = Random Effects, 2SLS = Two-Stage Least Squares, RE2SLS = Random Effects Two-Stage Least Squares, EC2SLS = Error Component Two-Stage Least Squares. CD = Cragg-Donald Wald F statistic for weak instrument identification test. Standard errors in parentheses. Standard errors are clustered at Ward level in OLS, RE and 2SLS models and based on the the GLS variance estimator in the RE2SLS and EC2SLS models. *,** and *** denote significance level of 10%, 5% and 1%, respectively.

significantly less clear-cut. Our Health domain measure, similarly, focuses on issues such as mental health and cancer rates, which, again does not seem intrinsically linked to ability.

For this reason, we have remained agnostic on the direction of bias throughout our discussion. In our MDM measure it is implied that a financially deprived ward with good access to services and a comparatively wealthy ward in the countryside, and therefore distant from services, could be equally deprived, but that they are deprived in different ways. Whilst we observe a statistically significant difference in the parent teacher ratio, with schools in more deprived areas exhibiting more teachers per pupil, other such direct interventions may be unobservable. In the UK, such policies include active funding streams based on deprivation, for example[11], such as the Early Years Entitlement, which we do not observe. The nature of our bias would suggest that such initiatives are effective in mitigating the impacts of regional deprivation on school-level achievement but cannot eliminate the problem.

[11] http://www.education.gov.uk/schools/adminandfinance/financialmanagement/schoolsrevenuefunding/archive/a0014385/school-funding-deprivation-indicator

We conduct a series of robustness checks by altering the form of our first instrument. In this baseline analysis, we use the third order polynomial of deaths but results are shown to be robust to other levels of polynomial, to deaths per 1,000 inhabitants (using the 2001 census) and a series of dummy variables that take the value of one if a threshold of violence is reached (1 death, 5 deaths and 10 deaths) and zero if not[12]. In the appendix we provide the results from the base regressions including both the third order polynomial and the spatial lag of deaths as instruments. This table 2.A.2 also shows the other coefficients which do not differ to the coefficients in Table 2.5.3.

2.5.2 Single Deprivation Domains

That there is a link between deprivation and children's schooling outcomes is uncontroversial and should come as no surprise. Despite such uncontroversial findings, however, significant debate has taken place in the literature, particularly regarding the role of financial deprivation on human capital accumulation. In this section, we attempt to shed further light on these outcomes by analysing each of the domains separately. Practically, we treat both the single domain and an unweighted sum of the remaining domains as endogenous by introducing the spatial lag of deaths as our second instrument. These results are displayed in Table 2.5.4. In these specifications, we repeat our earlier analysis on the multiple deprivation measure. As robustness checks, we also include a weighted measure of the remaining MDM measures and use different polynomials of our instruments. As before, our findings are robust across a majority of our models, although in the just-identified 2SLS and RE2SLS models, there is some effect from multicollinearity. The results from these models are provided in Table 2.A.3. Appendix table 2.A.1 further shows the conditional correlation between the instruments and all deprivation domains.

The most noticeable result presented in this section shows that neither the income domain, nor the employment domain, are shown to have any impact on educational achievement when other sources of deprivation are accounted for. Despite this finding, however, the sum of the other domains is shown to be significant, suggesting that deprivation has associated negative impacts on educational outcomes, although financial deprivation, alone, does not. Not only does this stand in direct

[12]These results can be obtained from the corresponding author on request

Table 2.5.4: Single Deprivation Measure: EC2SLS Results

	Deprivation Measure						
	Income	Empl.	Education	Health	Liv.Env.	Prox.Serv.	Crime
Single indicator	-0.882	-0.353	-2.380**	0.409	-0.010	0.323	-3.308***
	(1.718)	(1.840)	(1.010)	(2.271)	(1.434)	(1.334)	(1.230)
MDM w/o indicator	-4.565***	-5.024***	-3.477***	-5.666***	-5.456***	-5.516***	-3.300***
	(1.618)	(1.725)	(1.239)	(1.931)	(1.129)	(0.997)	(0.913)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5937	5937	5937	5937	5937	5937	5937
R^2 centered	0.322	0.322	0.322	0.321	0.322	0.324	0.310
F	2719	2723	2676	2699	2728	2883	2248
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CD Wald F	16	11	16	5	8	14	14
Sargan statistic	51	51	51	51	50	53	44
Sargan χ^2-p	0.001	0.001	0.001	0.001	0.001	0.001	0.007

Note: *Dependent variable. OLS = Ordinary Least Squares, RE = Random Effects, 2SLS = Two-Stage Least Squares, RE2SLS = Random Effects Two-Stage Least Squares, EC2SLS = Error Component Two-Stage Least Squares. CD = Cragg-Donald Wald F statistic for weak instrument identification test. Standard errors in parentheses. Standard errors are clustered at Ward level in OLS, RE and 2SLS models and based on the the GLS variance estimator in the RE2SLS and EC2SLS models. *,** and *** denote significance level of 10%, 5% and 1%, respectively.

contrast to the suggestions of much of the literature, it is also provides a rationale for the mixed results in the financial deprivation literature.

We propose, therefore, that any research that aims to study the impact of deprivation using, solely, financial deprivation runs one of two risks of increasing severity. The first of these risks is an identification problem, where financial deprivation is inferred to cause worse outcomes, rather than acting as a proxy for wider deprivation. In such situations, policy recommendations seem likely to be misdirected towards improving regional economic performance, rather than the other underlying drivers of deprivation, which actually cause the adverse outcomes. The second occurs in situations where financial deprivation may not even be an accurate proxy of deprivation; in such cases, conclusions suggesting that deprivation does not cause adverse outcomes at all may lead to policy inaction and a sustention of the negative impacts of deprivation.

In all seven of these analyses, the 'remainder' of the multi-deprivation measure is shown to be a negative and significant driver of adverse educational outcomes, with the negative impacts shown, once more to be, approximately, five percentage points for a one standard deviation increase in multiple deprivation. Over and above this 'remainder', however, only the education and crime domains are shown to have impacts. An increase in the education deprivation domain by one stan-

dard deviation is shown to lead to a lower APR of 2.4 percentage points, holding the multiple deprivation domain and all other regressors constant. The multiple deprivation domain, in this case, reduces APR by 3.5 percentage points, when increased by one standard deviation and holding all other regressors constant. A linear combination of these two coefficients approximates to the coefficient shown in Chapter 2.5.1, when only multiple deprivation is included. This also holds for the crime domain where the linear combination of the coefficients is slightly larger but not statistically different from the education case.

The immediate suggestion that educational deprivation causes poorer educational outcomes might seem self-evident but the research presented in this paper deals with an assessment of the ages between 9 to 11, whilst the 2005 education deprivation domain pertains only to education of students older than 14. The literature shows, however, strong intergenerational transfer of parents' educational outcomes. Accordingly, parents affected by poor post-primary education in a region are likely to transfer these poor outcomes to their children and to the performance of local primary schools, in the longer term. From this we infer that our education domain depicts the aggregate level of parents' education and is therefore, logically, a significant driver of primary school outcomes. This domain includes a measure of the prevalence of attainment of the adult population in each location, including the percentage of individuals without any qualifications or skills, supporting the above notion.

The crime domain measure is broad, including acts from arson to property damage. We propose, therefore, that the impact of crime is likely to be a combination of supply- and demand-side issues. On the demand side, we think of a potentially damaging impact of engagement on low-level criminal activity. This may include access to harmful substances, for example; or incentives for truancy or engagement in anti-social behaviour and so forth. On the supply side we propose higher local crime rates result in property damage to schools and increased numbers of lost school, which have an obvious direct impact on the potential of that school to do well.

2.5.3 Discussion

Whilst our results provide strong evidence on the role of deprivation in the determination of primary school outcomes, the specific historical context of conflict

in Northern Ireland adds further concern to these findings. That the regions that were most affected by "The Troubles" remain the most deprived is suggestive of significant regional horizontal inequalities, which are commonly cited as a cause of the violence (see Fitzduff and O'Hagan, 2009; Honaker, 2010). This suggests that, in Northern Ireland, there is a two-fold role for counter-deprivation policies; firstly, they help increase social mobility and reduce the disadvantage of outcomes associated with growing up in deprived regions and secondly, they become an important instrument for the continuing peace process in the state[13].

The link between primary school performance and later life outcomes suggest that those who grow up in the most deprived regions are those who can expect the poorest life outcomes. Given the predominance of young people involved in on-going inter-community street violence in Northern Ireland and that such disturbances occur, predominantly in comparative deprived regions, continued deprivation must be seen as a contributory factor to an undesirable but common feature of life in Northern Ireland. Until suitable policies are implemented to reduce the enduring post-conflict deprivation, it seems likely that such disturbances will remain common.

We propose, both in Northern Ireland and elsewhere, that a narrow policy focus, however, will be unsuccessful in delivering aims of improving life-time outcomes for those affected by deprivation. Financial policies, such as direct welfare transfers, seem unlikely to improve education or social mobility, yet are commonly relied upon by governments. Instead, a wider approach to combating deprivation, which focuses on the quality of local schools, improved access to services and social networks, that aim to improve parental health and that aim to minimise crime are all required to improve primary school performance and in breaking the cycle of long-term regional deprivation.

[13]We looked at descriptive statistics (Table 2.A.6), which compares two samples; a Catholic primary school sample and a non-Catholic primary school sample. Catholic primary schools, typically, are located in areas that experienced higher conflict intensity than non-Catholic schools, whilst there are also higher levels of FSME and deprivation in the areas in which Catholic schools are situated. Despite these differences, however, contemporary crime, average pass rates and other school indicators do not differ due a school's religious designation.

2.6 Conclusion

The important link between human capital accumulation and future labour market outcomes has been well-established in the literature. By extension, human capital accumulation itself can become an important anti-poverty device. Over and above a reflection of innate abilities, however, a growing body of literature has sought to find the role of exposure to deprivation, both individually and in neighbourhoods, on human capital accumulation. The impacts of living in deprived neighbourhoods has been shown to impact on individual outcomes (e.g. Weinhardt, 2010; Oreopolous, 2003; Jacob, 2004; Durlauf, 1996; Gibbons, 2002; Bauer et al., 2011).

Despite this work, finding a suitable measurement of deprivation is difficult and the role of neighbourhood effects are not well understood, suggesting potential issues with identification of causal relationships. In this paper, we aim to overcome these outstanding issues. Following the suggestion of Gibbons (2002), we employ a measure which focuses on several domains of deprivation. Our measure, Northern Ireland's multiple deprivation measure includes; income deprivation, employment deprivation, health deprivation and disability, education, skills and training deprivation, proximity to services deprivation, living environment deprivation and crime and disorder. Using a weighted average of these domains, we estimate the effect of multiple deprivation on the proportion of primary school children meeting or exceeding the minimum acceptable standard in the Key Stage II exams in Northern Ireland. We overcome any potential endogeneity by introducing historical violence in Northern Ireland as an instrument for our deprivation measure.

Our results shed new light on the causal impact of deprivation on school-level outcomes by showing only indirect effects of financial and employment deprivation. In both situations, these measures are shown to be insignificant determinants of outcomes when other sources of deprivation are accounted for. This contrasts significantly with a literature that has, broadly, sought to measure deprivation through a series of financial proxies. Furthermore, it suggests that any attempt to tackle the adverse outcomes associated with deprivation will fail if they focus, only, on individual or local economic factors. These findings also suggest the potential pitfall inherent in the literature's, hitherto, over-reliance on financially-based proxies for regional deprivation. In many cases, as in this paper, financial deprivation is strongly correlated with net regional deprivation but this is not inherently the case. Indeed, even in situations such as ours, causal identification is lacking if there

is a focus, only, on financial deprivation. We further show that the role of deprivation occurs through the channels of education deprivation and crime deprivation, both showing a significant adverse impact on primary school performance over and above an index of the remaining domains. Accordingly, policies must focus on improving general neighbourhood characteristics, rather than simply neighbourhood income or employment opportunities.

Northern Ireland is an interesting test case as regional and horizontal inequalities have been prevalent since the creation of the country in 1921. The history of the country, also, serves as an important feature in facilitating this study. Northern Ireland suffered a long-run, low-intensity conflict, in which nearly 3,600 individuals lost their lives in a series of terrorist attacks. Whilst cultural identity and nationalism played important roles in this conflict, the real and perceived horizontal inequalities between the Protestant and Catholic communities are frequently cited as causes of the conflict (Fitzduff and O'Hagan, 2009) and as drivers of the intensity of violence (Honaker, 2010).

The results not only show that violent conflict is associated with long-term deprivation but that it also has long-term implications for children who were born following the conflict. Persisting regional inequalities, therefore, are not only a barrier to social mobility but also an obstacle for a continued peace process. The endurance of these effects suggests that governments have, hitherto, failed to address these issues which, in the specific context of Northern Ireland appears to have two potentially reinforcing negative effects. Firstly, that it reduces the expected life outcomes of those living in deprived neighbourhoods and, secondly, that it facilitates the ongoing, low-level street disturbances that frequently occur between Northern Ireland's rival communities. That these street disturbances could further sustain regional deprivation suggests the urgent requirement for suitable policy interventions that tackle the full array of deprivation domains.

2.A Appendix

Table 2.A.1

	Deprivation Measures								
	Multiple	Multiple	Income	Empl.	Education	Health	Liv.Env.	Prox.Serv.	Crime
Deaths[3]	0.004***	0.003***	0.005***	0.004***	0.004***	0.003***	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Spatial Lag Deaths	–	0.063***	0.036***	0.038**	0.056***	0.046***	0.056***	0.062***	0.041**
		(0.016)	(0.013)	(0.015)	(0.019)	(0.012)	(0.015)	(0.011)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5937	5937	5937	5937	5937	5937	5937	5937	5937
R^2	0.559	0.593	0.679	0.600	0.529	0.501	0.397	0.637	0.477
F	24	26	39	28	18	24	15	39	17
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: Ordinary Least Squares regressons with clustered standard errors (Ward level). Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 2.A.2: Base Results - Two instruments

	First Stage MDM Score[1]	Second Stage Average Pass Rate[1]				
	1 OLS	2 OLS	3 RE	4 2SLS	5 RE2SLS	6 EC2SLS
Deaths[3]	0.003***	–	–	–	–	–
	(0.001)					
Spatial Lag Deaths	0.063***	–	–	–	–	–
	(0.016)					
Multiple DM	–	-1.525***	-2.432***	-5.194***	-5.528***	-4.970***
		(0.434)	(0.346)	(1.110)	(0.949)	(0.573)
Total enrolment	0.001**	0.017***	0.013***	0.020***	0.015***	0.015***
	(0.000)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Number of Pupils	-0.004	-0.229***	-0.213***	-0.235***	-0.209***	-0.210***
	(0.003)	(0.038)	(0.033)	(0.041)	(0.033)	(0.033)
Number of Pupils sqrd.	0.000	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pupil-teacher ratio	-0.007	-1.441**	-0.609	-1.464**	-0.580	-0.313
	(0.067)	(0.635)	(0.438)	(0.662)	(0.441)	(0.465)
Pupil-teacher ratio sqrd.	0.000	0.041***	0.018	0.041**	0.016	0.010
	(0.002)	(0.016)	(0.011)	(0.016)	(0.011)	(0.012)
Gaelic exams	-0.015	5.596***	2.934*	5.889***	3.282**	3.332**
	(0.181)	(1.967)	(1.498)	(2.206)	(1.543)	(1.540)
Catholic School	-0.046	1.342**	1.300**	1.174*	1.233*	1.227*
	(0.064)	(0.550)	(0.619)	(0.604)	(0.661)	(0.666)
Free School Meal 10-20%	0.289***	-2.791***	-2.055***	-1.745***	-1.383***	-1.450***
	(0.041)	(0.526)	(0.444)	(0.618)	(0.482)	(0.459)
Free School Meal 20-40%	0.742***	-6.346***	-4.855***	-3.514***	-3.152***	-3.341***
	(0.065)	(0.714)	(0.578)	(1.088)	(0.743)	(0.635)
Free School Meal > 40%	1.475***	- 14.455***	- 10.312***	-8.162***	-6.236***	-6.681***
	(0.142)	(1.319)	(0.912)	(2.225)	(1.415)	(1.082)
Catholic inhabitants (%)	-0.002	0.013	0.014	0.007	0.017	0.015
	(0.002)	(0.012)	(0.011)	(0.014)	(0.012)	(0.012)
All Persons 0-15	0.001***	-0.000	-0.001	0.004	0.001	0.000
	(0.000)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
All Persons 16-39	0.000	-0.001	-0.000	0.000	0.000	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
All Persons 40-59/64	-0.003***	0.001	0.002	-0.009**	-0.004	-0.003
	(0.000)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
All Persons 60/65+	0.001**	-0.004	-0.004*	0.004	0.001	-0.000
	(0.001)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)
Bombing incidents	-0.003*	0.041*	0.028	0.017	0.022	0.023
	(0.002)	(0.023)	(0.020)	(0.024)	(0.020)	(0.020)
Shooting incidents	0.007**	-0.030	-0.012	0.026	0.005	0.004
	(0.003)	(0.026)	(0.023)	(0.027)	(0.023)	(0.023)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	5937	5937	5937	5937	5937	5937
R^2	0.593	0.252		0.217	0.933	0.933
R^2 overall			0.245			
χ^2			966			
F	26	30		28	2948	2960
p	0.000	0.000	0.000	.	0.000	0.000
CD Wald F				317	513	77
Sargan statistic				1	0	55
Sargan χ^2-p				0.323	0.556	0.001

Note: [1] Dependent variable. OLS = Ordinary Least Squares, RE = Random Effects, 2SLS = Two-Stage Least Squares, RE2SLS = Random Effects Two-Stage Least Squares, EC2SLS = Error Component Two-Stage Least Squares. CD = Cragg-Donald Wald F statistic for weak instrument identification test. Standard errors in parentheses. Standard errors are clustered at Ward level in OLS, RE and 2SLS models and based on the the GLS variance estimator in the RE2SLS and EC2SLS models. *,** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 2.A.3: Single Deprivation Measures

	Dependent Variable: Average Pass Rate			
	1 OLS	2 RE	3 2SLS	4 RE2SLS
Income DM	1.114*	0.328	0.412	-0.166
	(0.649)	(0.594)	(2.269)	(2.718)
MDM w/o income	-2.153***	-2.601***	-5.869**	-5.614**
	(0.589)	(0.534)	(2.410)	(2.335)
Controls	Yes	Yes	Yes	Yes
R-squared	0.253	0.245	0.208	0.320
CD Wald-F			175	172
Employment DM	0.639	-0.010	0.564	-0.207
	(0.573)	(0.529)	(2.989)	(3.669)
MDM w/o empl.	-1.880***	-2.375***	-5.974**	-5.582*
	(0.594)	(0.514)	(2.847)	(3.029)
Controls	Yes	Yes	Yes	Yes
R-squared	0.252	0.245	0.208	0.320
CD Wald-F			82	74
Education DM	-1.041**	-1.626***	-1.885	-2.542
	(0.438)	(0.387)	(2.225)	(2.628)
MDM w/o educ.	-0.632	-1.054***	-4.320	-3.786
	(0.443)	(0.409)	(3.050)	(2.902)
Controls	Yes	Yes	Yes	Yes
R-squared	0.252	0.245	0.204	0.320
CD Wald-F			50	60
Health DM	-0.327	-0.576	0.780	-0.483
	(0.447)	(0.449)	(4.675)	(6.879)
MDM w/o health	-1.237**	-1.977***	-6.202	-5.339
	(0.499)	(0.467)	(4.363)	(5.965)
Controls	Yes	Yes	Yes	Yes
R-squared	0.252	0.245	0.203	0.320
CD Wald-F			23	15
Liv.Env. DM	-0.347	-0.381	-2.422	-2.422
	(0.392)	(0.347)	(3.396)	(4.084)
MDM w/o liv.env.	-1.265**	-2.219***	-3.901	-4.710
	(0.495)	(0.393)	(2.658)	(3.036)
Controls	Yes	Yes	Yes	Yes
R-squared	0.252	0.245	0.206	0.321
CD Wald-F			27	24
Prox.Serv. DM	-0.485	-0.668	-1.720	0.243
	(0.438)	(0.437)	(7.524)	(7.658)
MDM w/o prox.serv.	-1.265***	-2.088***	-4.017	-5.991
	(0.469)	(0.394)	(6.692)	(6.899)
Controls	Yes	Yes	Yes	Yes
R-squared	0.252	0.245	0.222	0.321
CD Wald-F			5	8
Crime DM	-0.522	-1.005***	-4.572	-2.248
	(0.369)	(0.357)	(10.449)	(9.034)
MDM w/o crime	-1.184***	-1.797***	-2.782	-4.469
	(0.384)	(0.348)	(5.819)	(6.642)
Controls	Yes	Yes	Yes	Yes
R-squared	0.252	0.245	0.186	0.309
CD Wald-F			3	5

Note: OLS = Ordinary Least Squares, RE = Random Effects, 2SLS = Two-Stage Least Squares, RE2SLS = Random Effects Two-Stage Least Squares. CD = Cragg-Donald Wald F statistic for weak instrument identification test. Standard errors in parentheses. Standard errors are clustered at Ward level in OLS, RE and 2SLS models and based on the the GLS variance estimator in the RE2SLS. *,** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 2.A.4: Northern Ireland Multiple Deprivation Measure 2005

Sub-Domain	Indicators
Income deprivation	Income Support households; Job Seeker's Allowance households; Working Families' Tax Credit households; Disabled Person's Tax Credit households
Employment deprivation	Unemployment claimant count of women aged 18-59 and men aged 18-64 averaged over 4 quarters; Incapacity Benefit claimants women aged 18-59 and men aged 18-64; Severe Disablement Allowance claimants women aged 18-59 and men aged 18-64; Participants in New Deal for Young People (18-24 years) who are not included in the claimant count; Participants in New Deal for 25+ who are not included in the claimant count; Invalid Care Allowance claimants women aged 18-59 and men aged 18-64
Education deprivation	GCSE/GNVQ points score; Key Stage 3 data; Proportions of those leaving school aged 16 and not entering Further Education; Absenteeism at secondary level (all absences); Proportions of 17-20 year olds who have not successfully applied for Higher Education; Proportions of Years 11 and 12 pupils not in a grammar school; Proportions of post primary pupils with Special Educational Needs in mainstream schools
Health deprivation	Years of Potential Life Lost; Comparative Illness and Disability Ratio; A combined measure of two indicators (i) individuals suffering from mood or anxiety disorders, based on prescribing and (ii) suicides; People registered as having cancer (excluding non-melanoma skin cancers)
Living environment deprivation	SOA level housing stress; Houses without central heating; Household overcrowding; LGD level rate of acceptances under the homelessness provisions of the Housing (Northern Ireland) Order 1988 and the Housing (Northern Ireland) Order 2003, assigned to the constituent SOAs; SOA level local area problem score
Proximity to services deprivation	Road distance to a GP premises; Road distance to an Accident and Emergency hospital; Road distance to a dentist; Road distance to an optician; Road distance to a pharmacist; Road distance to a Job Centre or Jobs and Benefit office; Road distance to a Post Office; Road distance to a food shop; Road distance to the centre of a settlement of 10,000 or more people
Crime and disorder deprivation	Violence, robbery and public order; Burglary; Vehicle theft; Criminal damage; Malicious and deliberate primary fires; Disturbances

Note: A more detailed description can be found at NISRA (2005).

Table 2.A.5: Robustness Checks: Varying Instrument

	EC2SLS			
	D/pop	D $\geq$ 1	D $\geq$ 5	D $\geq$ 10
Multiple DM	-4.600***	-5.188***	-4.657***	-4.594***
	(0.590)	(1.110)	(0.598)	(0.563)
Controls	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
N	5937	5937	5937	5937
F	2909	430	2740	3414
p	0.000	0.000	0.000	0.000
CD Wald F	73	144	75	69
Sargan statistic	60	12	57	61
Sargan χ^2-p	0.000	0.981	0.000	0.000

Note: RE2SLS = Random Effects Two-Stage Least Squares. EC2SLS = Error Component Two-Stage Least Squares. First stage of RE2SLS model reported; EC2SLS includes group means and time-demaned regressors in the first stage. Sargan test for overidenitification. In RE2SLS the model is just identified. CD = Cragg-Donald Wald F statistic for weak instrument identification test. Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 2.A.6: Descriptive Statistics School Data by Religious Determination

	Catholic Schools		Protestant Schools		Difference	
	Mean	Std.Dev.	Mean	Std.Dev.	Diff	Std.Dev.
No. of Deaths by Ward	4.62	(8.97)	2.82	(6.65)	-1.80***	(0.20)
Average Pass Rate	79.3	(12.92)	79.0	(13.37)	-0.3	(0.3)
Total enrolment	214.06	(158.71)	218.76	(148.50)	4.70	(3.99)
Number of Pupils	30.25	(23.05)	31.21	(23.38)	0.96	(0.60)
Pupil-teacher ratio	19.94	(2.76)	20.03	(3.12)	0.09	(0.08)
Free School Meal 10-20%	0.3	(0.47)	0.3	(0.47)	0.0**	(0.0)
Free School Meal 20-40%	0.35	(0.48)	0.20	(0.40)	-0.15***	(0.01)
Free School Meal > 40%	0.14	(0.35)	0.10	(0.30)	-0.04***	(0.01)
Catholic inhabitants (%)	62.82	(25.54)	30.35	(25.26)	-32.48***	(0.66)
All Persons 0-15	747.98	(352.69)	659.34	(292.51)	-88.64***	(8.38)
All Persons 16-39	1087.72	(531.22)	1015.69	(543.74)	-72.03***	(13.98)
All Persons 40-59/64	815.39	(303.26)	847.93	(311.41)	32.54***	(8.00)
All Persons 60/65+	451.53	(181.05)	507.01	(195.19)	55.49***	(4.90)
Bombing incidents	3.84	(11.56)	3.45	(9.42)	-0.39	(0.27)
Shooting incidents	5.64	(11.96)	5.56	(10.63)	-0.08	(0.29)
Multiple DM	5.85	(3.27)	5.24	(3.47)	-0.61***	(0.09)
Income DM	0.26	(0.13)	0.19	(0.11)	-0.07***	(0.00)
Employment DM	0.18	(0.06)	0.15	(0.06)	-0.03***	(0.00)
Education DM	23.81	(14.69)	21.19	(16.23)	-2.61***	(0.40)
Health DM	0.01	(0.71)	-0.16	(0.67)	-0.17***	(0.02)
Services DM	-0.41	(0.88)	-0.22	(0.77)	0.19***	(0.02)
Living Env. DM	25.90	(11.55)	21.16	(12.10)	-4.74***	(0.31)
Crime DM	18.34	(19.22)	19.30	(17.69)	0.96**	(0.48)
N	2799		3138		5937	

Note: Authors' calculations based on Key Stage II data, MDM scores from NISRA (2005) and Sutton (1994).

Chapter 3

Mental Health and Labour Supply: Evidence from Mexico's Ongoing Violent Conflicts

Abstract In Mexico, conflicts between drug-trafficking organisations result in a high number of deaths and immense suffering in the population every year. Little scientific research exists which identifies and quantifies the monetary and non-monetary consequences of ongoing violent conflicts on individuals. Using the Mexican Family Life Survey for 2002 and 2005, the causal effect of mental health (symptoms of depression/anxiety) on the extensive and intensive margin of labour supply for working-aged men and women is estimated. Measures of the ongoing drug-related violent conflicts both at the macro level using intentional homicide rates by region and at the micro level indicated by the presence of armed groups in the neighbourhood serve as instruments for mental health. The results show a significant adverse impact of the conflicts on anxiety for men and women. Based on IV-Tobit model results, a worse mental health state decreases individual labour supply strongly and significantly for men. The findings demonstrate that Mexico's population not only suffers from the violent conflicts between drug-trafficking organisations by anxiety or even depression but also indirectly from less household income through less work which in turn has consequences for Mexico's social development and economic growth.[1]

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3.1 Introduction

In the last two decades, the drug-related conflicts in Mexico where drug trafficking organisations (DTOs) fight over trafficking routes into the United States has increased dramatically. A high number of crimes, such as corruption, assaults, kidnappings, torture, rapes and homicides, are being committed regularly. The extent to which the lack of national security harms Mexico's social and economic development, and consequences of wars and conflicts on individuals in general, have received little attention in scientific research (Blattman and Miguel, 2010). Only a few studies explicitly focus on the effects of violent conflict on labour market outcomes, such as Abadie and Gardeazabal (2003); Calderón and Ibáñez (2009); Menon and van der Meulen Rodgers (2011); Miaari and Sauer (2011) and Bozzoli et al. (2010). For a better understanding of the monetary and non-monetary consequences of violent conflict on civil society, in this study the impact of Mexico's drug-related conflicts on mental health measured by symptoms of depression/anxiety (SDA) – a main determinant of mental health – is estimated. Further, as an attempt to quantify this impact in economic terms, it is investigated as to which extent deteriorated mental health affects the extensive and intensive margin of individual labour supply. While a reduction in individual labour supply has negative consequences on income, aggravation of mental health can also induce substantial non-monetary costs, e.g., for the dependent children of the anxious/depressed adult (e.g., Heckman, 2006; Petterson and Albers, 2001; Bratti and Mendola, 2011).

Within the Mexican population, anxiety/depression is a serious health issue. Belló et al. (2005) estimate that 4.5% of the population aged 18 to 65 are affected by depression and an even higher rate have experienced a period of depression of more than 12 months in life. The effect of mental illnesses such as depression, anxiety or psychological distress on labour market participation and labour supply has been investigated in many studies for different countries. The main body of this literature uses instrumental variable (IV) approaches to control for the reverse causality between mental health and labour supply. Recent innovative approaches are, e.g., Chatterji et al. (2007) who use early onset psychological disorders and religious activities as instruments in a sample of Latin American and Asian immigrants in the U.S., Ojeda et al. (2010) who use measures of social support and Frijters et al. (2010) who use the incidence of the death of a close friend in the

Household, Income and Labour Dynamics in Australia survey. All studies find a large negative effect of aggravated mental health on labour market participation or labour supply. For developing countries and countries afflicted by armed conflicts, the literature is almost non-existent with one exception: Das et al. (2009) use mental health surveys from five developing and transition countries (Bosnia and Herzegovina, Indonesia, Mexico, India and Tonga) and study correlations between mental health, socio-economic status and labour market participation.

This study is based on data from the Mexican Family Life Survey (MxFLS, or ENNVIH in Spanish), a representative household survey, for the years 2002 and 2005 – years in which drug-related violence was intense but not as severe as it became in 2008, when drug-related homicides have dramatically increased by approximately 600% from one year to another (Shirk, 2010). Overall, drug-related homicide rates have accumulated to 20,000 in the last decade (Shirk, 2010).

The MxFLS includes a battery of questions to determine a person's emotional well-being and a large number of other health, socio-economic and labour market variables. An individual's emotional well-being is measured via a 20-item questionnaire with four different answering possibilities. The latent variable from these 20 items is derived in this study using the partial-credit Rasch model, deduced from item response theory (IRT) (Masters, 1982). Similar to the studies cited above, an IV approach is employed. Exploiting regional variation in violence data to instrument mental health allows identifying the causal effect of violent conflicts on anxiety/depression among the Mexican population and to which extent economic outcomes in terms of labour supply are indirectly affected by violent conflicts. It has been documented in a large number of studies by practitioners, health researchers and social scientists that exposure to armed conflicts and violence has severe impacts on mental health (e.g., Kessler, 1997; Kendler et al., 1999; Latkin and Curry, 2003; Giacaman et al., 2007). The SDA questionnaire in the survey measures various levels of severity of mental health aggravation, ranging from sleeping problems to serious depression. The empirical methodology used in this study requires that exposure to violent conflicts as they happened in Mexico during the first half of the 2000s does not directly affect individual labour supply but only via deterioration of mental health. This implies that no demand shocks exist which are correlated with conflict intensity. One argument supporting the validity of the assumption is the fact that no shocks in conflict intensity occurred during the investigated period, and hence, any labour demand shocks should be unrelated

to conflict intensity. Furthermore, at the aggregate level, no correlation between the unemployment rate and conflict intensity can be detected for any of the 15 Mexican states included in this study (see below). Several other arguments on the validity and anecdotal evidence by CAMEXA (2010), Osorio (2011) and Ríos (2008) to support this assumption are provided. Due to potential corner solution problems in the dependent variables, Tobit and IV-Tobit models are estimated.

The empirical findings reveal that exposure to violent conflicts has significant effects on anxiety and suggest that Mexico's society suffered severely from the violent conflicts in the early 2000s. Furthermore, men who suffer from SDA possess a lower probability to be working and worked both fewer weeks in the last year and fewer hours in the previous week. For women, no effects on labour supply are found. The causal effects found for men show that the conflicts indirectly affect labour income through reduced work which in turn may have long-term impacts on Mexico's social development and economic growth. The analysis helps to understand the monetary and non-monetary consequences of low to medium level intensity of violent conflicts in general and in Mexico in particular. To the author's best knowledge, no study exists which identifies the causal effect of anxiety on labour supply in violent conflict settings. Furthermore, the analysis contributes to the literature on violence in Mexico which is small so far and only looks at the determinants of violence and violence intensity rather than the consequences.[2]

The outline of the study is as follows. The next section gives some background information on the drug-related conflicts in Mexico and summarises the literature on (1) the relationship between armed conflicts and mental health and (2) the impact of mental health on labour market participation and labour supply. Section 3.3 explains the methodological approach in detail and Section 3.4 describes the data. Subsequently, the results are being presented and discussed in Section 3.5, which also provides checks of robustness. Section 3.6 concludes.

3.2 Background

Mexico's location has served as the transit for drug trafficking between Central America and the United States for decades. Drug trafficking has increased since the

[2]One notable exception is Dell (2011) who looks at the effect of drug-related violence on formal and informal wages after 2008.

1980s when Colombia's largest trafficking organisation co-operated with Mexican cartels to transport cocaine into the U.S. (Felbab-Brown, 2009). While Mexico's DTOs focused mainly on the demand for drugs in the U.S. during the 1980s and 1990s, domestic demand has also gained importance in recent years (Pacheco, 2009). As a result, the DTOs do not only fight over trafficking routes but have also started to fight over local domestic end-user markets in Mexico. Through the death or arrest of cartel leaders, fluctuations in size, number and power of DTOs occur. Violent conflicts exist between DTOs, within DTOs where hierarchical levels can be imposed through violence, and between DTOs and security forces. In a number of cases, former police and military employees established and/or rule DTOs. For example, the Guadalajara cartel, one that was most influential during the 1980s, was founded by a police officer (Mahadevan, 2011). This provides an indication for the influential role of corruption and bribery in Mexican institutions which also occur among its political leaders (Shirk, 2010).

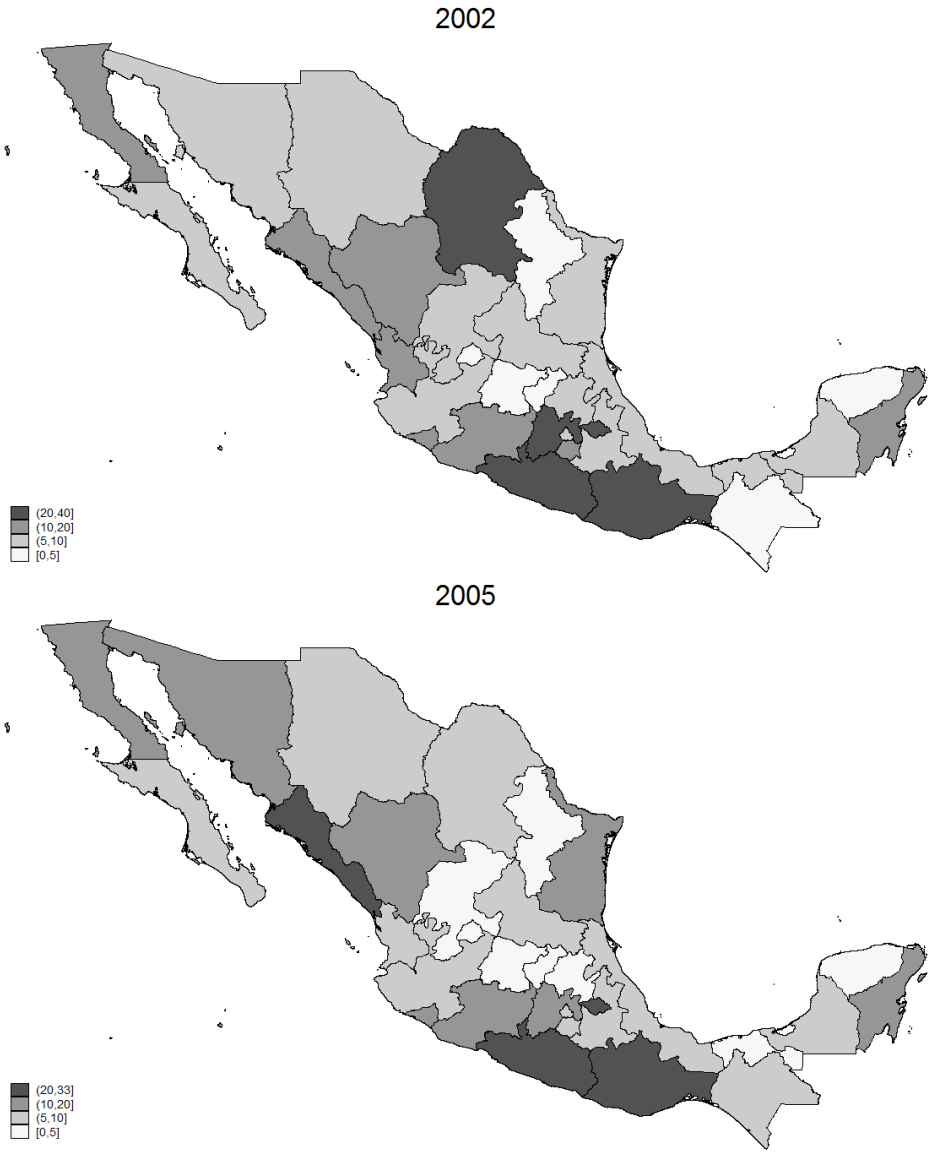
The competition between the DTOs over trafficking routes and markets has led to an increased number of fights and stronger violence. Apart from intentional homicide, other common crimes, such as kidnapping, assault, torture and battery, are committed. In 2002 and 2005, the years of investigation of this study, homicide rates on the state level ranked between 1 and 40 per 100,000 inhabitants.[3] Figure 3.2.1 shows the incidence of drug-related homicides for the years 2002 and 2005 based on data from ICESI. The rates suggest that drug-related violence is not only a problem at the border to the U.S. but also in other parts of the country, where trafficking routes exist.

The effect that conflict settings, civil wars and other stressful life events have on mental disorders and illnesses has well been documented by psychologists, health researchers and social scientists. There is no doubt that mental health is impaired by such events.[4] For instance, Cornaglia and Leigh (2012) investigate the impact of crime on mental health of non-victims, arguing that the cost of crime on non-victims' mental well-being may be even higher than the cost induced for direct victims. Variation in local crime rates is used to estimate the impact of crime on mental well-being of the population in the respective localities. They find that

[3]Instituto Ciudadano de Estudios sobre la Inseguridad (ICESI), 2011, "Estadísticas oficiales", retrieved: May 3rd, 2011, from http://www.icesi.org.mx/estadisticas/estadisticas_oficiales.asp.

[4]See Kessler (1997) for an overview of the literature.

Figure 3.2.1: Intentional Homicide Rates in 2002 and 2005



Note: Intentional homicide rates per 100,000 inhabitants. Author's construction using data from ICESI.

violent crime and newspaper coverage of criminal incidents have a strong impact on emotional well-being. For a civilian in Mexico, the fights between DTOs are likely to harm everyday life by causing anxiety and fear or even depression symptoms, not only because of reports in the newspapers but also because of increased presence of police and security forces in the streets.

de Jong et al. (2003) use epidemiological surveys to look at post-war mental disorders. They find that post-traumatic stress disorders and anxiety disorders are

the most common health issues in their samples and state that post-conflict health programmes should focus on a variety of mental health problems. Murthy and Lakshminarayana (2006) give an overview of the effects of war on the mental health state of the societies in Southeast Asian countries and the Middle East. They summarise that women and children are affected most severely and that social and psychological support is associated with better mental health.

Using data from the German Socioeconomic Panel, Brück and Müller (2010) show that both crime and terror lead to worries among both victims and non-victims. Based on a survey of Palestinian adolescents, Giacaman et al. (2007) investigate mental health states after collective and individual exposure to violence through the military. They find that collective exposure to conflict has a strong and similar effect as individual exposure on mental health.

The latter two studies show that not only direct victims of violence are affected by mental distress, but also that indirect or common exposure affects individual mental health. This justifies the use of drug-related homicides and the presence of armed groups in the neighbourhood as measures of exposure to violent conflicts in Mexico, rather than, for example, focusing on individuals who have directly been involved in a violent act or have lost a family member due to conflict. Apart from the fact that access to such data is rare, the latter statistics cannot be used as instruments because they may directly affect individual labour supply through physical damage and lack in household income.

Instrumental variable approaches are commonly used in the context of mental health and labour supply due to the reverse causal relationship between the two phenomena, i.e. mental illness leads to lower labour supply; simultaneously, unemployment or working few hours or weeks affects mental well-being. One example is a study based on the Household, Income and Labour Dynamics in Australia survey in which the incidence of death of a close friend is used as an instrument for mental health to estimate the causal effect of mental health on labour market participation (Frijters et al., 2010). Other instruments that have been used are early onset psychological disorders and religious activities (Chatterji et al., 2007), measures of social support (Ojeda et al., 2010), and information on mental health history and mental health of the respondent's partner (Ettner et al., 1997). The studies commonly find negative effects of mental illness on labour market outcomes, with differences by socio-economic groups. So far, no study on this relationship exists

which focuses on countries which have been or are currently affected by violent conflicts.

An important fact that has been highlighted in some studies is that diagnostic data is only seldom available (Ettner et al., 1997; Chatterji et al., 2007). In many surveys, mental health is self-assessed which may lead to a substantial attenuation bias in the estimated effect of mental health on labour market outcomes. The MxFLS also allows the use of diagnostic data, exhibiting a strong advantage to other household surveys.

The findings of this study reveal the impact of the violent conflicts in 2002 and 2005. It appears likely that the consequences of violent conflicts have become even more severe with the escalation in 2008, just a little more than one year after the start of Felipe Calderón's presidency. In 2006, he declared 'war' against the drug cartels, and military troops entered the streets of civil society (Shirk, 2010). The 'drug war' accelerated in 2008, counting more than 6000 drug-related homicides in that year committed by cartel members, policemen, the military and other security personnel.[5] The latest wave of the MxFLS (2008) is not included in this study, as the escalation of violence is likely to induce direct labour demand effects. This would violate the assumption of no direct correlation between violence and labour demand which is necessary for the estimation strategy to be valid.

3.3 Estimation Methods

3.3.1 Reverse Causality

The estimation of a causal effect of SDA on labour supply is hampered by the reverse causal relationship between these two variables. On the one hand, a depressed person may work less, i.e. have lower labour supply, because there are hours or days in which the person feels unable to leave the house and work. Even at lower levels of SDA, a person may work less because he or she changes routes to go to work to avoid walking or driving alone through insecure areas, or may not work in the evening hours because he or she is too anxious to walk in the

[5] Shirk (2010) uses the number of killings reported in Mexican newspapers, which differ among each other and from government statistics. As it is difficult to judge if governmental statistics or newspaper counts are more reliable, this statistic is used here to give some intuition of how intensive the conflict has become.

dark. Labour migrants may not want to travel long distances any more leading to lower labour supply and so on. On the other hand, having no job or not being able to work as much as preferred may lead to SDA (Clark and Oswald, 1994; Theodossiou, 1998). Hence, in a simple ordinary least squares (OLS) regression, a causal effect of mental health on labour supply cannot be identified and the OLS estimator is inconsistent. Instead, a partial correlation between the two variables is identified by the coefficient of the mental health variable. To identify a causal effect of symptoms of anxiety/depression, an Instrumental Variable (IV) approach is employed.

The main, structural equation of interest, the effect of SDA (mental health m) on the intensive margin of labour supply ($y, y > 0$), i.e. the number of weeks or hours worked, can be written as:

$$y_{it} = \alpha_1 + \beta m_{it} + \gamma_1 X_{it} + \epsilon_{1it}, \tag{3.1}$$

where i is an index for the individual and t is a time index, X is a vector of controls and ϵ is the error term. In this model, m_{it} is an endogenous variable which is regressed on all variables X_{it} and the instrument(s) c in the first stage. The reduced-form model can be written as:

$$m_{it} = \alpha_2 + \gamma_2 X_{it} + \delta c_{it} + \epsilon_{2it}. \tag{3.2}$$

Given that the variable c is a valid instrument, i.e. $E(\epsilon_1|c) = 0$ and m and c are partially correlated, the IV estimator is consistent and can be interpreted as a causal effect. In a following subchapter it is discussed in detail why the instruments used are assumed to be valid conditionally on the exogenous regressors. The identified causal effect in the case of a binary instrument (*armed groups in the neighbourhood*) is a local average treatment effect (LATE), or average treatment effect for a subpopulation of compliers, i.e. those individuals whose mental health outcome deteriorates due to a change in the instrument (Angrist and Imbens, 1995). In the case of the continuous instrumental variable (*intentional homicide rates*), the identified effect is the causal marginal treatment effect (MTE) (Heckman and Vytlacil, 2007). Given that the endogenous regressor SDA is continuous, the effects are weighted by the compliers, where the weights are determined by how the compliers are distributed over the range of the endogenous variable m. Hence, the estimated

effects have to be interpreted within the scope of the particular subpopulation of compliers and cannot be interpreted as the average effect of the whole sample population. It has to be kept in mind that in the binary instrument *armed groups in the neighbourhood*, only 10% of the population are affected. To increase the number of compliers, the models are estimated including both instruments jointly. When using two instruments, the estimated effect is the weighted average of the causal effects for the two instrument specific compliant subpopulations (Imbens, 2010).

Instrumental Variable Probit (IV-Probit) models are estimated to identify the effect of SDA on the probability to be working, i.e. the extensive margin of labour supply. In the results tables, marginal effects are displayed. Since the data are an unbalanced panel, observations for each individual are not independent and thus standard errors are clustered at the individual level. In the linear models, standard errors are two-way clustered at both the individual and household level.[6] Standard errors are then also robust to arbitrary within-panel autocorrelation. As, for example, Moulton (1990) shows, standard errors are likely to be downward biased in models where aggregate variables are matched to individual level analyses, it would be preferable to cluster standard errors at the state level (homicide data is at the state level). However, too few clusters would be constructed using this approach such that the estimated covariance matrix of moment conditions is not of full rank. Hence, it has to be kept in mind that in the IV models, standard errors may be downward biased. In the IV-Tobit models (explained below), standard errors are bootstrapped, bypassing the problem of clusters.

It will be tested for overidentification based on Hansen's J statistic in the models where two instruments are used. Hansen's J statistic is reported rather than the Sargan-Hansen test because of clustered standard errors (Baum et al., 2007). Furthermore, tests for weak instruments are conducted. First, the Stock and Yogo (2005) test statistic is reported. Following this test, the instrument is weak if the minimum Eigenvalue statistic of the first stage exceeds the critical values.[7] It will

[6] To estimate the models in Stata the command *ivreg2* by Baum et al. (2002) is used. The multi-way clustered standard error procedure for non-nested samples is explained in Cameron et al. (2011).

[7] The minimum Eigenvalue statistic is identical to the Angrist-Pischke first-stage F (Angrist and Pischke, 2009) in the case of two instruments, and the Kleinbergen-Paap rk Wald-F in the case of one instrument.

be indicated in the result tables whether the Eigenvalue statistics is less than the Stock-Yogo 25% critical value test or not.

Finally, it has to be noted that estimating Fixed Effects-IV models may also be an adequate alternative approach. However, with the data at hand, a Fixed Effects model is not feasible for the following reasons: (1) Only two waves are available for the study in which only 50% of the interviewed individuals are part of both waves; (2) for the 50% of individuals little time-variation exists in the measure of SDA.

3.3.2 Corner Solution

When estimating the causal effect of SDA on the intensive margin of labour supply, it has to be taken into account that only 92% of men and 36% of women in the sample have positive values for weeks and hours worked. In fact, for some individuals the optimal outcome of the dependent variable may be the corner solution $y = 0$. Not controlling for this corner solution may lead to potential bias in the estimated coefficients. This is likely to be the case in the coefficient on mental health because a depressed person may have lost his or her job due to SDA. Then, labour supply is not just lower than that of mentally healthy individuals but equals zero, while the independent variables are fully observed. To account for the corner solution in the dependent variable, a Type-I-Tobit model is applied. Furthermore, to account for reverse causality, an IV-Tobit model is estimated. Since interest is in the causal effect of mental health on labour supply for those individuals who have positive hours of work (the latent variable), marginal effects for the positive values, i.e. $E(y|x, y > 0)$, are presented in the regression tables. All models are estimated for men and women separately.

3.3.3 Validity of the Instruments

Two variables are included to instrument mental health. They are used to proxy the regional differences in exposure to conflict or perception of threat of violence within Mexico's civil society. The intuition is that individuals are likely to exhibit a higher level of anxiety and/or depression symptoms in regions where conflicts are more intense. The two variables measure the intensity of violent conflicts at the macro and micro level, respectively. The micro level indicator of violent conflict is the presence of armed groups in the neighbourhood. This information is taken

from the household crime and victimisation questionnaire of the Mexican Family Life Survey which provides the individual level data for this study. This variable is a dummy variable taking the value 1 if an individual reports that armed groups are present in his or her neighbourhood and 0 if they are not present. The macro level indicator is the number of intentional homicides per 100,000 inhabitants per state in 2002 and 2005 provided by ICESI.

To be valid instruments the presence of armed groups and intentional homicide rates must not directly affect labour supply but only via deterioration in mental health – conditionally on the included covariates. It has been shown for other countries that regional violent conflicts are associated with the development of the regional economy and hence, job opportunities (see Deininger, 2003, for an overview). Rare examples of studies on direct links between conflicts and labour supply are Miaari and Sauer (2011) and Mansour (2010). While a direct relationship is also likely to be the case after the escalation of conflict intensity in Mexico in 2008 (although no study exists so far), this is unlikely for the years 1998 to 2007 during which little time variation in intentional homicide rates existed and conflict intensity was relatively low.

As a proxy for labour demand, unemployment rates are displayed together with intentional homicide rates in Figure 3.A.2 for the years 1998 to 2010 for all fifteen states which are part of the Mexican Family Life Survey. It can be seen that before 2008, unemployment rates and intentional homicide rates do not follow the same pattern. Also, it can be seen that no shocks in conflict intensity occurred during this period. Rather, a steady intensity can be observed. At the same time, large fluctuations in unemployment rates can be observed. Anecdotal evidence for the independence between conflict intensity and labour demand is provided by CAMEXA (2010) who show that German direct investment in Mexico is not responsive to crime rates. Since no shocks in conflict intensity can be observed, it can be ruled out that labour demand shocks are directly linked to the relatively low conflict intensity during the investigated time span.

To further rule out direct correlation between intentional homicide rates and the presence of armed groups in the neighbourhood and local labour demand shocks, economic and social development indicators are included in the regressions. At the municipality level, human development indices (HDI) on health standards,

educational levels and income levels are obtained from UNDP[8] for the years 2000 and 2005. Unfortunately, HDI data on municipality level are not available for 2002, hence the UNDP data for 2000 is matched to the 2002 wave of the MxFLS data[9] and the 2005 data is matched to the 2005 wave. Additionally, state level emigration rates[10], GDP (at 2005 prices)[11] and registered and unregistered unemployment rates[12] are included. Table 3.3.1 shows that intentional homicide rates and the presence of armed groups are only marginally correlated with emigration rates, unemployment, GDP, or health, education and income indices. Moreover, studies by Osorio (2011) and Ríos (2008) on Mexican conflicts show, on the verge, that poverty/GDP is not linked to conflict intensity.

Including these aggregate measures in the regression is the best way to ensure that intentional homicide rates are a measure of exposure to the conflicts and not the regional labour market, influencing labour supply only via mental health by triggering anxiety or even depression symptoms. Finally, one drawback of this measure is that it is prone to measurement error. Homicide rates in Mexico are unlikely to be exact, especially in those areas where the conflicts are very intense. Shirk (2010) provides a discussion of this problem. It is reasonable to assume that this measurement error is uncorrelated with the other regressors and does not cause any problems in the regressions.

Instead of using intentional homicide rates at the state level it would be desirable to include measures at a more disaggregated level to benefit from more variation and precision. However, counts of intentional homicides at a more disaggregated

[8]United Nations Development Programme (UNDP), "Índice de Desarrollo Humano Municipal en México 2000-2005", retrieved July 15th, 2011, from http://www.undp.org.mx/spip.php?article893.

[9]Although the data is from different years, matching the 2000 HDI data with MxFLS data from 2002 seems to be a better approach than not controlling for municipality characteristics at all.

[10]Emigration rates are gender-age-state-specific differences in population size between 1990 and 2000 corrected for mortality. The calculation is based on Census data for 1990 and 2000 retrieved from IPUMS (https://international.ipums.org/international/) and mortality data available from INEGI (http://sc.inegi.org.mx/sistemas/cobdem/creararbolfiltroservlet). Further details on the calculation can be found in Haisken-DeNew and Michaelsen (2011).

[11]Data retrieved from Sistema Estatal y Municipal de Bases de Datos (SIMBAD) from Instituto Nacional de Estadística, Geografía e Informática (INEGI) at http://sc.inegi.org.mx/sistemas/cobdem/creararbolfiltroservlet.

[12]INEGI "Encuesta Nacional de Ocupación y Empleo (ENOE)", retrieved May 5th, 2011 at http://www.inegi.org.mx/est/contenidos/espanol/sistemas/enoe/infoenoe/default.aspx?s=est&c=14042.

(municipality) level for the years 2002 and 2005 were only available for urban areas.[13] When merging this data with the MxFLS, more than two thirds of the observations would be lost, since only half of the Mexican states are covered by each data set and they only coincide partly. Hence, instead of municipality level statistics, the state level homicide rates are used. Using the number of direct victims, such as the number of household members lost due to conflicts, would not be a valid instrument as a direct relationship between being a member of such a household and the supply of labour is likely (added worker effect). Furthermore, being exposed to violent conflict instead of being a direct victim is likely to be measured better by a higher aggregation of intentional homicide rates (while controlling for direct victimisation). As mentioned earlier, solely the reading of newspaper articles about criminal incidents reduces people's mental health (Cornaglia and Leigh, 2012).

[13] Centro de Investigación y Docencia Económicas (CIDE) "Geocrimen – Análisis Espacial y Series de Tiempo", http://geocrimen.cide.edu/.

Table 3.3.1: Correlation between Economic Development and Armed Conflict

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Homicides/100,000 inhabitants	1.000								
(2) Armed groups neighbourhood	0.035	1.000							
	(0.000)								
(3) Unemployment rate, registered	-0.326	0.009	1.000						
	(0.000)	(0.142)							
(4) Unemployment rate, unregistered	0.247	0.032	-0.078	1.000					
	(0.000)	(0.000)	(0.000)						
(5) Emigration rate	0.084	-0.001	-0.191	0.223	1.000				
	(0.000)	(0.906)	(0.000)	(0.000)					
(6) HDI health	-0.072	0.042	0.152	0.042	-0.045	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
(7) HDI education	-0.134	0.050	0.380	-0.061	-0.099	0.745	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(8) HDI income	-0.164	0.051	0.282	-0.022	-0.129	0.831	0.825	1.000	
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)		
(9) Deprived neighbourhood	0.015	0.062	0.035	0.109	0.067	0.102	0.133	0.122	1.000
	(0.016)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

3.4 Data

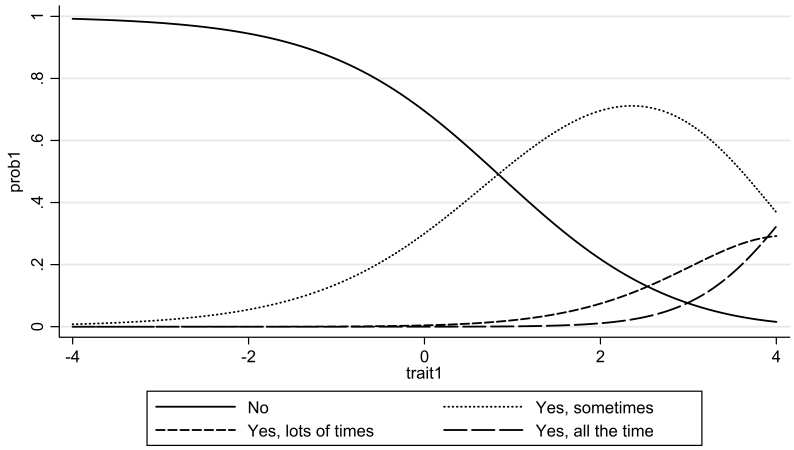
The data used is the Mexican Family Life Survey, a large household panel collected in 2002, 2005 and 2008. The first two waves, which are publicly available at present, are exploited in this study. The MxFLS contains data on about 8,400 households, is representative at the national level for rural and urban households (Rubalcava and Teruel, 2006). A variety of topics is covered by the questionnaires, ranging from education, employment and crime victimisation to health status, and many more. After deleting observations with missing or implausible information, almost 25,000 person-year-observations remain for male and female individuals aged 20 to 65. Excluded from the sample are individuals who retired, students, and those unable to work due to disabilities and prolonged sickness. Figure 3.A.1 indicates in which municipalities interviews have been conducted. Comparing Figures 3.2.1 and 3.A.1 reveals that interviews have taken place in regions of all levels of conflict intensity.

The individuals' mental health status can be interpreted from the responses to a mental health questionnaire which was adapted by researchers of the Mexican Institute of Psychiatry (Calderon, 1997) on the basis of the depression scale of the Center for Epidemiologic Studies (CES) (see Radloff, 1977).[14] Its purpose is the quantitative diagnosis of depression/anxiety symptoms using a battery of 20 questions, such as "In the last four weeks, have you had a hard time sleeping at night?" and "In the last 4 weeks, have you wished you would die?". Each question can be answered with four response categories indicating the intensity. Each answer is given points from 1 (no) to 4 (yes, always). The scale consists of the sum of the responses with equal weights, consequently ranging from 20 to 80 (Calderon, 1997). Figure 3.4.2 displays its highly right-skewed distribution. According to Calderon (1997), individuals can be classified into four categories: normal persons (89.6%), persons with a certain level of anxiety (8.5%), persons with an average depression (1.7%) and persons with severe depression (0.2%). The numbers do not necessarily coincide with estimates by, e.g., Belló et al. (2005) due to different diagnostic methods used. Based on these questions, an increase in the scale does not necessarily imply the diagnosis of anxiety or even depression. Rather, an increase can

[14] The scale of the Center for Epidemiologic Studies has been used widely and its properties are highlighted in, e.g., Radloff (1977), Roberts (1980) and Weissman et al. (1977).

be due to, for instance, light sleeping problems or it can indicate whether someone felt sad or angry during the last four weeks. The fact that somebody is tired, angry or anxious is likely to influence his or her taste for work or ability to work.

Figure 3.4.1: Category Probability Curves



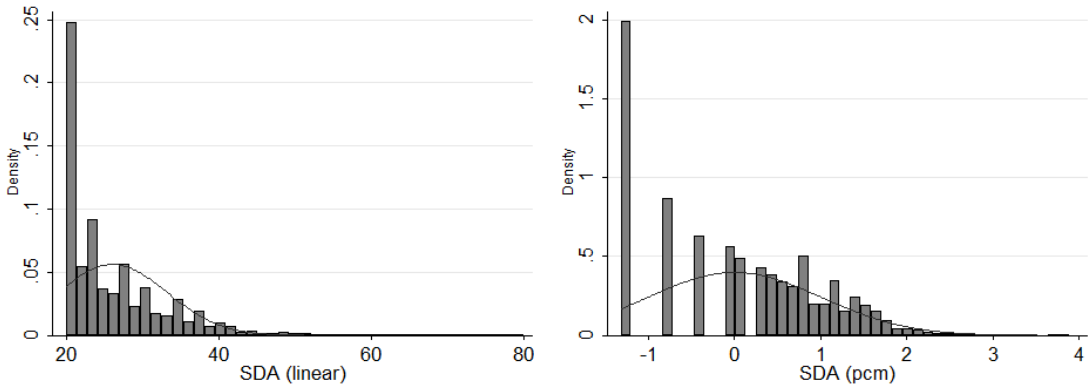
Source: Authors' calculations based on MxFLS.

A person's mental health state is actually not observable and is being recorded via the 20 items of the CES questionnaire. Item response theory offers statistical models to measure the latent variable. A partial-credit Rasch model is the appropriate model for measuring SDA based on the 20 items with 4 response categories. The mathematical background and rationale is explained in Masters (1982), it has previously been used in, e.g., Cole et al. (2004), Covic et al. (2007) and Ryan and Sinning (2009) and is implemented in Stata as explained in Zheng and Rabe-Hesketh (2007). Figure 3.4.1 displays the category probability curves. The resulting variable SDA (pcm) is standardised with mean zero and standard deviation 1. Its distribution is displayed in Figure 3.4.2 and exhibits a highly, but less than in the linear case, right-skewed shape.

The dependent variables are (a) *working* which is a dummy variable equal to 1 if individual labour supply possesses positive values and 0 otherwise, measuring the extensive margin of labour supply, (b) number of *weeks worked* during the last twelve months and (c) number of *hours worked* in the previous week to the interview, both measuring the intensive margin of labour supply. The variable *working* is not identical to "labour market participation" as usually analysed in the literature because here, registered unemployed individuals are not considered

as being working. Registered unemployment is very low in Mexico (approx. 3.3%, Table 3.A.1 in the appendix). About 92% of the male sample and 36% of the female sample have been working during the 12 months before the interview. The number of weeks worked in the last 12 months is on average 46 weeks for men and women. Men work on average 45 hours per week and women 36 hours per week (Table 3.A.1).

Figure 3.4.2: Distributions of SDA Scales



Source: Authors' calculations based on MxFLS.

A large number of controls at the individual, household, municipality and state levels are included in the regressions. Individual and household level controls are age, living in a rural area (less than 2,500 inhabitants) as compared to an urban area, belonging to an indigenous group, the educational level (primary education, secondary education, or more than secondary education), household size, household wealth proxied by house ownership and whether or not the family has savings, whether or not the individual has ever changed residence (migrant), and whether or not the respondent was a victim of a criminal incident in the past, the region in which the respondent lives (Central, North-East, North-West, South or West) and whether or not the neighbourhood can be considered deprived, meaning that abandoned buildings are present. One concern could be that in regions with high conflict rates, informal employment shares are also high and that informal employment is associated with lower labour supply. Descriptive analysis with respect to this relationship does not provide evidence for this, though, and is therefore not further treated as relevant. Moreover, to account for the fact that the death of a household member potentially increases the probability of the onset of depression symptoms and simultaneously causes changes in household time allocation with

respect to labour, a variable is included which is equal to 1 if the respondent has lost a household member due to death in the last five years and 0 otherwise.

Interviews were conducted from mid to end 2002 and late 2005 to mid 2006. Although these years do not cover a calendar year, homicide rates from the respective calendar years are used. This is not unreasonable because mental health is measured via questions which refer to the last four weeks before the interview. In studies on determinants of mental well-being it has been shown that the time interval to which the questions on mental well-being refer does not significantly matter (e.g., Oswald and Powdthavee, 2007; Oswald and Wu, 2011). Hence, although the questions on mental health in the MxFLS refer to the last four weeks before the interview, they can reasonably be matched to data on homicides that cover a longer time span.

3.5 Results

3.5.1 Violent Conflicts and Symptoms of Depression and Anxiety

A simple unconditional correlation between SDA and the presence of armed groups in the neighbourhood reveals that those respondents who gave a positive answer (about 10% of the sample) have a higher mean score in the depression variable; it is 26.9 compared to 25.9 for those who live in a neighbourhood where armed groups are not present, and statistically significant.

Table 3.5.1 shows the regression results of the effect of intentional homicide rates and the presence of armed groups in the neighbourhood on symptoms of depression/anxiety, controlling for state, municipal, household and individual characteristics. All coefficients of interest have the expected sign and are statistically significant at the 1% level. For men, the results indicate that an increase in intentional homicides by 1 per 100,000 inhabitants is associated with an increase in 0.005 standard deviations in SDA, i.e. approximately ($5.78 \times 0.005 =$) 0.03 points on the linear SDA scale. Stating that armed groups are present in the neighbourhood is associated with 0.117 standard deviations higher level of SDA, i.e. approximately 0.7 points on the linear SDA scale. Including both measures of violent conflicts in the regressions simultaneously does not change the coefficients significantly. For women, the effects are similar to those for men: An increase in

Table 3.5.1: Effect of Violent Conflicts on SDA

	Dependent variable: SDA (pcm)		
	(1)	(2)	(3)
MEN			
Homicides/100,000 inhabitants	0.005***	–	0.005***
	(0.002)		(0.002)
Armed groups neighbourhood	–	0.117***	0.116***
		(0.039)	(0.039)
N	10227	10227	10227
R^2	0.055	0.055	0.056
F	20	20	20
p	0.000	0.000	0.000
Test of joint significance			
χ^2 (2)	–	–	16.88
p	–	–	0.000
WOMEN			
Homicides/100,000 inhabitants	0.005***	–	0.005***
	(0.001)		(0.001)
Armed groups neighbourhood	–	0.094***	0.091***
		(0.032)	(0.032)
N	14733	14733	14733
R^2	0.062	0.061	0.063
F	33	33	32
p	0.000	0.000	0.000
Test of joint significance			
χ^2 (2)	–	–	23.63
p	–	–	0.000

Note: OLS regressions. Standard errors are two-way clustered on individuals and households. Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. The other coefficients can be found in Appendix Tables 3.A.2 and 3.A.3.

intentional homicide rates by 1 per 100,000 inhabitants leads to an increase in symptoms of anxiety/depression by 0.005 and the presence of armed groups is associated with 0.094 standard deviations higher SDA. The result tables, including also the coefficients of the control variables, can be found in the appendix (Tables 3.A.2 and 3.A.3).

The magnitude of the effect does not seem to be particularly high. However, when comparing the size of the effect of the presence of armed groups in the neighbourhood to the coefficient of having been a victim of violence or robbery within the last five years the magnitude of the effect does not appear marginal. In fact, for men, these effects are similarly strong. Furthermore, having lost a household member within the last five years increases SDA by a ninth of a standard deviation. This effect is even smaller than the presence of armed groups in the neighbourhood, although this difference is not statistically different. The results further show that being indigenous is associated with higher values on the SDA scale, while having

obtained a high school or college degree leads to lower levels of SDA. Household size and financial wealth, as indicated by owning a house or having savings, are not associated with SDA on average, however, the effects are likely to be reflected in higher levels of education which is correlated with financial wealth and household size. For women, the effects of having been a victim and having lost a household member within the last five years are also comparable to the presence of armed groups in the neighbourhood. Some other regressors are considerably different though. While indigenous women compared to non-indigenous women do not have different average values on the SDA scale, next to a high school or college degree, owning a house and having savings strongly reduces the average value on the SDA scale.

All in all, these results suggest that both men and women in adult age suffered from the conflicts in 2002 and 2005. Taking into account that only few severely insecure regions are part of the MxFLS, the overall effects are probably even larger than the effects found here for individuals living in areas with low to medium levels of conflict. However, it implies that simply the news about another casualty or even the detection of a mass grave is likely to spread anxiety among the Mexican population even when they are not directly affected. As mentioned earlier, Cornaglia and Leigh (2012) also found that solely newspaper covering of criminal events affects adult mental health.

As homicide statistics are probably underreported the here estimated effects are lower bounds. Considering that homicide rates have increased dramatically since the beginning of 2008, the impact of homicide rates on SDA does not seem to be so negligible any more. It takes on average 30 killings per 100,000 inhabitants to increase the SDA scale by one point. As an extreme example, in Chihuahua, the state which is home to Ciudad Juárez, one of the world's most dangerous cities directly at the border to the U.S. counted 49.1 intentional homicides per 100,000 inhabitants in 2008 (Shirk, 2010). Assuming all other controls did not change between 2002/2005 and 2008, inhabitants of Ciudad Juárez have on average approximately 1.4 points more on the SDA scale (or approximately 0.25 standard deviations) than individuals in a place with zero killings.

Finally, while these results only demonstrate psychological costs of conflict, looking at the subsequent negative effects of SDA on labour supply will provide insights into the economic consequences of these violent conflicts.

3.5.2 Mental Health and Labour Supply

Participation

In Table 3.5.2, the effect of SDA on labour market status (*working*) for men is presented. The complete regression tables can be found in the appendix (Table 3.A.4). All the coefficients are marginal effects and are obtained from different regressions. Column 1 shows the estimates from simple Probit models. A negative correlation between SDA and the probability to be working is found. The effect is very small, but statistically significant. It indicates that an increase on the SDA scale by 1 standard deviation is associated with a reduction of the probability to work by 1 percentage point. In columns IV (1) and IV (2) mental health is instrumented with intentional homicide rates and the indicator for armed groups in the neighbourhood, respectively, and with both variables in the last column.

The coefficients are only significant when using homicide rates as an instrument and when using two instruments. An overidentification test based on the Amemiya-Lee-Newey minimum 2-statistic (obtained from the two-step rather than the MLE method)[15] indicates that the instruments are valid. For men, the causal effects are much larger than the conditional correlation estimated in the Probit model. Based on the findings with two instruments, an increase in SDA by 1 standard deviation lowers the probability to be working by 26 percentage points. In other words, an increase in the linear scale (which takes the values 20 to 80) by 5.78 points, or 30 percentage points, leads to a lower probability to be working by 26 percentage points. This effect seems very large but it is not when considering that an increase by 1 homicide per 100,000 inhabitants increases SDA by 0.03 points. Hence, an increase by 1 homicide per 100,000 inhabitants leads via an increase in SDA by 0.03 points to a decrease in the probability to be working by (26/5.78 =) 4.5 percentage points. Furthermore, it has to be kept in mind that this effect is the weighted average treatment effect for the subpopulation of compliers. The impression is that few individuals are very responsive in their mental health to conflict intensity and become completely unable to work.

[15]Unfortunately, there is currently no test implemented in Stata for the MLE model. In the next section it will also be shown that the instruments are strong for men, while they are not for women, at least not in the linear case. A weak instrument test for non-linear models could not be found.

For women, neither a correlation nor a causal effect of mental health on participation is found (see Table 3.A.5). The latter finding is not surprising as women often do not actively participate in the labour market for other reasons than health issues, such as the number and age of their children. Since the effect for men is large and men are usually the main contributors to household income in Mexico, the findings are also economically relevant and indicate the severe effect that the conflict indirectly has on labour market participation.

Table 3.5.2: Effect of SDA on Participation – Men

	Probit	IV-Probit		
	–	IV (1)	IV (2)	IV (1+2)
SDA (pcm)	-0.010***	-0.311***	-0.173	-0.260***^{A}
	(0.003)	(0.066)	(0.108)	(0.068)
N	10227			

Note: SDA: Symptoms of depression/anxiety. Each coefficient is obtained from a different regression. The numbers are marginal effects. Standard errors are clustered on the individual level. Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. IV (1) = intentional homicide rates on state level, IV (2) = armed groups in neighbourhood. When two instruments are included, a test for overidentification is pursued. The test statistic is the Amemiya-Lee-Newey minimum χ^2-statistic (obtained from the two-step rather than the MLE method) and ^{A} indicates that $p > 0.1$, i.e. instruments are valid.

Labour Supply

As shown in the previous section, mental illness restrains some men from working and hence from actively contributing to household income. The measure of mental health does not only measure whether a person is severely depressed but also whether a person is anxious or 'just' unhappy. An increase in the level of SDA may not lead to the complete drop out of the labour market, but can lead to periods in which the affected person is not able to work. These periods could have the length of several weeks or only a day, or just one or two hours in the morning, when the person feels, for instance, unable to get out of bed. When a person feels too anxious to walk home from work when it is dark, this could also reduce the number of hours worked per day. Furthermore, seasonal labour migrants may decide that it is too dangerous to travel to a remote workplace, reducing the number of job opportunities, and hence the number of weeks worked. Several other circumstances can be imagined.

The regression results for men are shown in Table 3.5.3 for the dependent variable *weeks worked*. The results in the first row can also be found in the Appendix table 3.A.6, which additionally displays the coefficients of the control variables and more regression statistics. The OLS coefficients provide evidence of a negative correlation

Table 3.5.3: Effect of SDA on Weeks Worked – Men

Linear Regression	OLS	IV		
	–	IV (1)	IV (2)	IV (1+2)
SDA (pcm)	-0.820***	-16.240**	-9.579*	-12.676***^{A}
	(0.136)	(7.364)	(5.282)	(4.341)
A-P First stage χ^2	–	7.300^{+}	7.827^{+}	7.225^{+}
N	9444			
Tobit Regression	Tobit	IV-Tobit		
	–	IV (1)	IV (2)	IV (1+2)
SDA (pcm)	-1.306***	-28.397***	-16.616***	-22.130***
	(0.198)	(5.468)	(5.473)	(3.954)
N	10227			

Note: Each coefficient is obtained from a different regression. In Tobit and IV-Tobit results marginal effects are presented. Standard errors are clustered on individuals in the OLS and Tobit models and bootstrapped with 400 replications in the IV and IV-Tobit models. Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. The coefficients from the Tobit and IV-Tobit models are marginal effects for E(y|x, y>0). IV (1) = homicide rates on state level, IV (2) = armed groups in neighbourhood. When two instruments are included, the Hansen's J test for overidentification is pursued. ^{A} indicates that the critical value $p > 0.1$, i.e. instruments are valid. $^{+}$ denotes strong instruments (not tested in Tobit models): $\chi^2 >$ Stock/Yogo's (2005) critical value (25% maximal IV size).

between SDA and the number of weeks worked. Specifically, a 1 standard deviation increase on the scale is associated with 0.820 fewer weeks per year worked.

Columns 2 to 4 display the results from the IV models which allow a causal interpretation of the SDA coefficient. Using intentional homicide rates (IV 1) to instrument SDA, the coefficient is much larger than in the OLS regression. An increase in the SDA scale by 1 standard deviation leads to 16.24 fewer weeks worked. As explained in the methodology section, this effect is the marginal treatment effect for the compliers, i.e. it is the average effect for individuals who respond to conflict with higher SDA. Hence, the effect cannot be interpreted as the impact of deterioration in mental health on the average labour supply in the (sample) population but only for a subpopulation of compliers. The existence of a subpopulation for which the conflict indirectly reduces labour supply via deterioration in mental health is an important finding, even though it is not externally valid for the entire population.

Using the presence of armed groups in the neighbourhood as an instrument, the coefficient measures the LATE: An increase by 1 standard deviation in SDA leads to 9.6 fewer weeks worked for the compliers. Although in both models with just one instrument the instrument is strong and the coefficient is statistically significant, it is worth estimating the effect of SDA on labour supply using both instruments

jointly. This increases the number of compliers and leads to more reliable estimates, given the overidentifying restrictions are valid which is indicated by ^{A} in Table 3.5.3. The model with two instruments provides the best model statistics, i.e. the overidentifying restrictions are valid and the instruments are strong and, as shown above, jointly statistically significant in the first stage. Based on this model, an increase by 1 standard deviation of the SDA scale leads to 12.7 fewer weeks worked. In other words, this means that an increase in the linear SDA scale by one point (for which it takes on average 30 per 100,000 additional intentional homicides) reduces the number of weeks worked by approximately (12.676/5.78 =) 2.19.

The coefficients from the Tobit and IV-Tobit models have the same sign and are all statistically significant at the 1% level. They are more than 50% larger in size than the linear IV estimates. The causal effect of an increase of 1 standard deviation in SDA leads to a decrease in the number of weeks worked by 22.13 when using both instruments. These coefficients measure the effect of a deterioration in mental health induced by the presence of armed groups in the neighbourhood or an increase in homicide rates for those persons who react to either or both of these instruments with higher SDA. In comparable numbers, according to the IV-Tobit model an increase in the linear SDA scale by 1 point reduces the number of weeks worked by 3.83.

For women, the conditional correlation obtained from OLS regression is negative but a causal effect cannot be identified. The coefficients are insignificant in the IV and Tobit models and have surprisingly a positive sign in the IV-Tobit models (see Table 3.A.7 in the Appendix). However, the model statistics show that the instruments are weak in all models and the overidentifying restrictions are not valid. Hence, no conclusion can be made about the impact of mental illness on women's labour supply using the instruments chosen. The instruments may not be relevant for women because (1) the number of observations is too small and/or (2) women's mental health is more reactive to other external and internal influences than men's (Rosenfield, 1989; Piccinelli and Wilkinson, 2000; Sandanger et al., 2004) and the measures of conflict do not lead to more variation in the measurement of SDA in women. As men are more likely to be victims of drug-related conflict the effects may also be more likely to be present among men.

While large labour supply reduction effects can be found with respect to the weeks worked, an increase in SDA is also likely to reduce the number of hours worked. For

men, qualitatively similar effects are found when using *hours worked* as the dependent variable. Each instrument is strong and when both instruments are used, the overidentifying restrictions are valid. While the instrument *intentional homicide rates* leads to a high and statistically significant coefficient of -23.5 as a response to an increase in SDA by 1 standard deviation, including the other instrument leads to a smaller, still negative but statistically insignificant coefficient. Again, the results from the model with two instruments provide the best model statistics and are used for interpretation. The IV regression results reveal that an increase in SDA by 1 standard deviation leads to an average of 14.6 fewer hours worked in the previous week for compliers. The results from IV-Tobit models are – as with *weeks worked* – about 50% larger than with linear IV regressions. When controlling for the fact that some individuals do not supply labour due to symptoms of depression/anxiety or other reasons, i.e. the extensive margin, for those individuals who supplied at least one hour of labour in the previous week, an increase in SDA leads to 22.4 fewer hours in the previous week for the subpopulation of compliers. Hence, an increase by 30 homicides per 100,000 inhabitants leads to a reduction in hours worked by 3.88 via an increase in the linear SDA scale by one point. This is approximately 10% of the average number of hours worked in Mexico in 2002 and 2005.[16]For women, causal effects cannot be identified using *hours worked* for reasons similar to those associated with *weeks worked*.

The effects found for men are large and imply a considerable impact of SDA on the intensive margin of labour supply and thus labour income. Since men are usually the household head and the main household income contributors, an increase in the level of anxiety consequently has negative impacts on household expenditure. Given that poverty is still very high in Mexico, reduced household income induced by mental illness can have considerable consequences for poor families.

[16]According to OECD statistics (http://stats.oecd.org/Index.aspx?DataSetCode=ANHRS), average annual hours worked per person were 1,888 in 2002 and 1,909 in 2005, which breaks down to about 36-37 hours per week.

Table 3.5.4: Effect of SDA on Hours Worked – Men

Linear Regression	OLS	IV		
	–	IV (1)	IV (2)	IV (1+2)
SDA (pcm)	-0.645***	-23.539**	-5.278	-14.625**^{A}
	(0.188)	(11.672)	(7.509)	(6.616)
A-P First stage χ^2	–	6.265^{+}	5.822^{+}	5.753^{+}
N	9288			
Tobit Regression	Tobit	IV-Tobit		
	–	IV (1)	IV (2)	IV (1+2)
SDA (pcm)	-1.204***	-35.833***	-10.309*	-22.243***
	(0.221)	(6.715)	(6.079)	(4.469)
N	10279			

Note: Each coefficient is obtained from a different regression. In Tobit and IV-Tobit results marginal effects are presented. Standard errors are clustered on individuals in the OLS and Tobit models and bootstrapped with 400 replications in the IV and IV-Tobit models. Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. IV (1) = homicide rates on state level, IV (2) = armed groups in neighbourhood. When two instruments are included, the Hansen's J test for overidentification is pursued. ^{A} indicates that the critical value $p > 0.1$, i.e. instruments are valid. $^{+}$ denotes strong instruments (not tested in Tobit models): χ^2> Stock/Yogo's (2005) critical value (25% maximal IV size).

3.5.3 Robustness Checks

Several robustness checks have been conducted. First, in the model where the presence of armed groups in the neighbourhood serves as an instrument, state dummies are included in the model to account for state fixed effects which could potentially affect labour supply through labour demand patterns possibly related to violent conflicts but not captured by the macro variables already included. The results do not significantly change by including state dummies.

All models are estimated using homicide statistics on the municipality level (from INEGI). As explained earlier, these data cover only urban areas and only overlap partly with the MxFLS. While this imposes more variation in the conflicts measure, a loss of more than half of the observations hinders the detection of statistically significant results. In fact, in some cases the effect of SDA on labour supply is rendered insignificant. However, the overall picture still suggests a strong impact of deterioration in mental health on labour supply induced by an increase in homicide rates.

For robustness and different interpretation purposes, different versions of the SDA scale are calculated and used to estimate the effect of violent conflicts on SDA and the subsequent effect of SDA on individual labour supply. The three ver-

sions of the SDA scale are: (1) the linear additive (linear), ranging from 20 to 80 with equal weights, (2) the linear version divided into percentiles (perc) and (3) a principal-component factor (pcf) obtained from factor analysis. All results are almost identical to those obtained from the partial-credit Rasch model version of the SDA scale (pcm) and can be obtained from the author on request.

3.6 Conclusion

Active participation in the labour market and labour supply are usually the main determinants of household income. Whether an individual can participate and how much an individual can work is influenced by his or her mental health status. In this study, the effect of symptoms of depression/anxiety (SDA) – a main determinant of mental health – on participation and labour supply, i.e. the extensive and intensive margin of labour supply, is estimated using the Mexican Family Life Survey for the years 2002 and 2005.

The estimation of a causal effect of mental health on labour supply is hampered by reverse causality: Better mental health does not only increase the probability to work or the number of weeks per year or hours per week; higher levels of mental health are also affected by actively participating in the labour market, since a job is usually associated with social interaction, structured time schedules and labour income. To overcome the problem of reverse causality, mental health is instrumented by two new instruments which refer to the ongoing violent conflicts in Mexico. Drug-trafficking organisations are fighting over trafficking routes into the U.S. and increasingly over domestic markets. With the local and federal police, and recently also the military, being involved in the 'fight against drugs', various crimes are being committed in Mexico which directly and indirectly affect the population.

The instruments which proxy exposure to violent conflicts are (1) *intentional homicide rates* which are measured at the state level (macro indicator, continuous variable) and (2) *the presence of armed groups in the neighbourhood* (micro indicator, binary variable). Most of the interviewed individuals are unlikely to have lost a household member or to have experienced injury due to the violent conflicts directly (which would directly affect labour supply). Rather, cases of homicides are read and heard about in the news, and the presence of armed groups in the neighbourhood spreads anxiety and may even lead to depression symptoms. To control

for the fact that these measures could directly affect labour supply, various regional economic indicators are included in the regressions, additionally to personal and household characteristics. Several arguments for the validity of the instruments are provided.

The findings are based on IV-Probit and IV-Tobit models which are estimated for the dependent variables active labour market participation, the number of weeks worked in the previous year and the number of hours worked in the previous weeks. The results provide strong evidence for a negative effect of violent conflicts on mental health for both men and women. For men, an increase in SDA by 1 standard deviation is associated with a significantly lower probability of 23 percentage points to be active in the labour market. In other words, an increase by 1 homicide per 100,000 inhabitants in a state increases symptoms of anxiety/depression by 0.03 points (on a scale from 20 to 80) which in turn reduces the probability to be working by 4.5 percentage points. Furthermore, an increase on the linear SDA scale by 1 point leads to 3.83 fewer weeks worked in the previous year and 3.88 fewer hours worked in the last week. The effects are large and statistically significant. The causal effects identified are valid for a subpopulation of compliers, i.e. those men who respond to changes in the conflict measures with higher SDA. Hence, the identified average treatment effects are not the average effects for the whole (sample) population, but they demonstrate that for a part of the population, the conflict directly affects mental health and consequently has detrimental impacts on labour market participation and labour supply. For women, a causal effect of SDA on labour supply cannot be identified, which may be due to weak instruments and the fact that women's mental health responds to other influences than conflict intensity more strongly than men's. It is also not surprising that men are more responsive to the ongoing violent conflict because they are more likely to be victims.

Mexico's violent conflicts cause collective harm to the country's population. With many families in Mexico still being poor, a reduction in labour supply may have considerable consequences for household income. Since men are usually the main contributors to household income, a decrease in labour supply reduces household expenditure which subsequently affects Mexico's economic growth. An increase in SDA and a reduction in labour supply also affect social development in the long run since children of mentally ill parents are likely to suffer not only from reduced income but also from hampered personal interaction. Hence, deterioration in mental health does not only incur monetary costs in terms of reduced labour

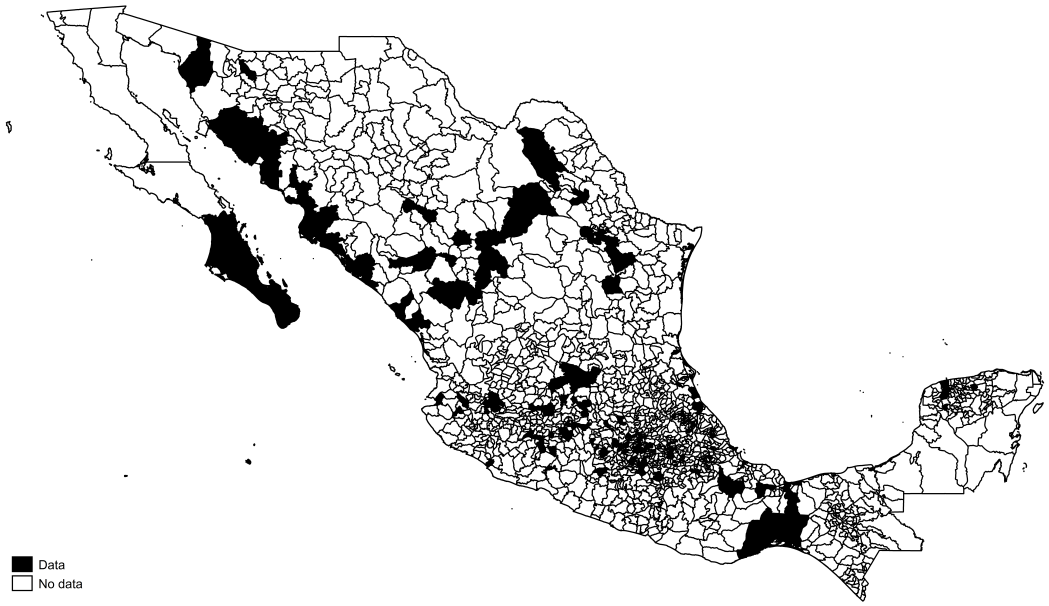
income through a reduction in individual labour supply but also non-monetary costs on dependent children and other family members in the environment of the mentally ill person. From a policy perspective, apart from addressing drug-related crime more effectively, the provision of psychological counselling services for those suffering from anxiety or even depression seems to be an essential tool to counteract symptoms of anxiety and depression. Whether that is also a tool against reduced labour supply or whether reduced street insecurity is the only way to counteract the adverse productivity effects, unfortunately, exceeds the scope of this study. However, financial support should be provided for those families whose income is sufficiently low due to the problems associated with mental ill-health.

The data only represent the years 2002 and 2005 – years in which organised crime and death rates have been considerably high. However, with the start of Felipe Calderon's presidency in 2006, the military entered the streets to "fight the war on drugs". Since the beginning of 2008, homicides have increased dramatically. Furthermore, violence has reached other dimensions – children were involved in an event to spread terror by parties involved in the "drug war" (The New York Times, 2011). The increasing number and severity of the events is likely to increase the onset of symptoms of depression/anxiety even more – with consequences for labour supply – among others.

Finally, it has to be noted that the author does not claim that the instruments are universally applicable in the analysis of relationships between conflict and labour markets and that the results are externally valid. At times of higher conflict intensity labour supply could be directly linked to the conflict. Furthermore, as the situation in some parts of Mexico has escalated since 2008, imposing higher levels of national insecurity, worse effects on mental health and labour supply than shown in this study may be found.

3.A Appendix

Figure 3.A.1: Municipalities in which Interviews Have Been Conducted



Note: Author's construction based on MxFLS.

Table 3.A.1: Descriptive Statistics

	Men				Women			
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
Dependent variables								
Working	0.92	0.27	0	1	0.36	0.48	0	1
Weeks worked previous year	46.86	11.84	0	52	45.82	13.64	0	52
Hours worked previous week	44.79	17.29	0	84	36.43	19.40	0	84
SDA Scales								
SDA (pcm)	0	1	-1.11	4.54	0	1	-1.52	3.68
SDA (linear)	24.14	5.78	20	80	27.39	7.61	20	80
SDA (perc)	36.31	30.35	1	100	52.42	32.04	1	100
SDA (pcf)	0.00	1.00	-0.69	9.83	0.00	1.00	-0.94	7.01
Instruments								
Homicides/100,000 inhabitants	10.97	8.13	1.20	40.28	11.12	8.54	1.20	40.28
Armed groups neighbourhood	0.09	0.29	0	1	0.10	0.30	0	1
Individual Characteristics								
Age	38.76	12.21	20	65	38.38	12.09	20	65
Indigenous	0.12	0.33	0	1	0.12	0.32	0	1
High school	0.08	0.28	0	1	0.08	0.27	0	1
College	0.10	0.30	0	1	0.06	0.24	0	1
House owner	0.81	0.40	0	1	0.80	0.40	0	1
Savings	0.24	0.42	0	1	0.23	0.42	0	1
HH size	9.69	4.56	1	37	9.73	4.50	1	37
Children < 2 in HH	0.28	0.45	0	1	0.28	0.45	0	1
Migrant	0.28	0.45	0	1	0.32	0.47	0	1
Death of HH member	0.08	0.28	0	1	0.08	0.28	0	1
Victim	0.13	0.34	0	1	0.07	0.26	0	1
Rural	0.40	0.49	0	1	0.40	0.49	0	1
North-West	0.22	0.42	0	1	0.21	0.40	0	1
North-East	0.20	0.40	0	1	0.20	0.40	0	1
South	0.20	0.40	0	1	0.20	0.40	0	1
West	0.20	0.40	0	1	0.20	0.40	0	1
Central	0.16	0.37	0	1	0.17	0.37	0	1
Federal District	0.02	0.14	0	1	0.02	0.14	0	1
Regional characteristics								
Deprived neighbourhood	0.41	0.49	0	1	0.41	0.49	0	1
Emigration rate	0.12	0.11	-0.13	0.40	0.11	0.08	-0.09	0.33
UR, registered	3.31	1.24	0.63	6.15	3.28	1.26	0.63	6.15
UR, unregistered	14.50	5.77	6.25	27.13	14.50	5.67	6.25	27.13
HDI health	0.85	0.06	0.59	0.99	0.85	0.06	0.59	0.97
HDI education	0.82	0.06	0.50	0.90	0.82	0.06	0.50	0.90
HDI income	0.69	0.10	0.23	0.88	0.69	0.10	0.23	0.88
N	10227				14733			

Note: UR = unemployment rate.

Table 3.A.2: Effect of Violent Conflicts on SDA - Men (long)

	Dependent variable: SDA (pcm)		
	(1)	(2)	(3)
Homicides/100,000 inhabitants	0.005***	–	0.005***
	(0.002)		(0.002)
Armed groups neighbourhood	–	0.117***	0.116***
		(0.039)	(0.039)
Age	-0.012**	-0.013**	-0.013**
	(0.006)	(0.006)	(0.006)
Age sqrd	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Indigenous	0.079**	0.068*	0.079**
	(0.037)	(0.036)	(0.037)
High school	-0.106***	-0.111***	-0.109***
	(0.036)	(0.036)	(0.036)
College	-0.175***	-0.178***	-0.175***
	(0.034)	(0.034)	(0.034)
House owner	-0.004	0.002	-0.004
	(0.028)	(0.028)	(0.028)
Savings	-0.032	-0.039	-0.035
	(0.026)	(0.026)	(0.026)
HH size	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)
Rural	-0.082***	-0.082***	-0.079***
	(0.028)	(0.028)	(0.028)
Death of HH member	0.091**	0.093**	0.090**
	(0.037)	(0.037)	(0.037)
Year 2005	-0.049*	-0.055**	-0.047*
	(0.027)	(0.027)	(0.027)
Victim	0.186***	0.192***	0.186***
	(0.031)	(0.031)	(0.031)
Children < 2 in HH	-0.050**	-0.049*	-0.049**
	(0.025)	(0.025)	(0.025)
Migrant	0.006	0.004	0.005
	(0.024)	(0.024)	(0.024)
Regional dummies	Yes	Yes	Yes
Regional characteristics	Yes	Yes	Yes
Constant	Yes	Yes	Yes
N	10227	10227	10227
R^2	0.055	0.055	0.056
F	20	20	20
p	0.000	0.000	0.000
Test of joint significance			
χ^2 (2)	–	–	16.88
p	–	–	0.000

Note: Standard errors are two-way clustered on individuals and households. Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 3.A.3: Effect of Violent Conflicts on SDA - Women (long)

	Dependent variable: SDA (pcm)		
	(1)	(2)	(3)
Homicides/100,000 inhabitants	0.005***	–	0.005***
	(0.001)		(0.001)
Armed groups neighbourhood	–	0.094***	0.091***
		(0.032)	(0.032)
Age	0.004	0.003	0.004
	(0.005)	(0.005)	(0.005)
Age sqrd	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)
Indigenous	0.041	0.036	0.043
	(0.031)	(0.032)	(0.031)
High school	-0.177***	-0.175***	-0.175***
	(0.031)	(0.031)	(0.031)
College	-0.338***	-0.337***	-0.339***
	(0.034)	(0.034)	(0.034)
House owner	-0.087***	-0.081***	-0.086***
	(0.024)	(0.024)	(0.024)
Savings	-0.047**	-0.054**	-0.050**
	(0.023)	(0.023)	(0.023)
HH size	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
Rural	-0.079***	-0.079***	-0.077***
	(0.024)	(0.024)	(0.024)
Death of HH member	0.114***	0.114***	0.111***
	(0.031)	(0.031)	(0.031)
Year 2005	-0.039*	-0.047**	-0.039*
	(0.023)	(0.023)	(0.023)
Victim	0.181***	0.188***	0.180***
	(0.033)	(0.033)	(0.033)
Children < 2 in HH	-0.035	-0.033	-0.034
	(0.022)	(0.022)	(0.022)
Migrant	0.062***	0.061***	0.062***
	(0.019)	(0.019)	(0.019)
Regional dummies	Yes	Yes	Yes
Regional characteristics	Yes	Yes	Yes
Constant	Yes	Yes	Yes
N	14733	14733	14733
R^2	0.062	0.061	0.063
F	33	33	32
p	0.000	0.000	0.000
Test of joint significance			
χ^2 (2)	–	–	23.63
p	–	–	0.000

Note: Standard errors are two-way clustered on individuals and households. Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 3.A.4: Effect of SDA on Participation – Men (long)

	Probit	IV-Probit		
	–	IV (1)	IV (2)	IV (1+2)
SDA (pcm)	-0.010***	-0.311***	-0.173	-0.260***
	(0.003)	(0.066)	(0.108)	(0.068)
Age	0.012***	0.009**	0.012***	0.011***
	(0.001)	(0.004)	(0.002)	(0.003)
Age sqrd	-0.000***	-0.000	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Indigenous	0.009	0.030**	0.021	0.028**
	(0.008)	(0.013)	(0.013)	(0.013)
High school	-0.008	-0.042***	-0.028	-0.038**
	(0.010)	(0.016)	(0.019)	(0.016)
College	-0.003	-0.059***	-0.034	-0.051**
	(0.010)	(0.019)	(0.025)	(0.020)
House owner	-0.015**	-0.016	-0.019**	-0.018*
	(0.007)	(0.011)	(0.009)	(0.011)
Savings	0.009	-0.001	0.006	0.002
	(0.006)	(0.011)	(0.009)	(0.010)
HH size	-0.000	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Children < 2 in HH	0.018***	0.006	0.015*	0.011
	(0.006)	(0.012)	(0.009)	(0.011)
Migrant	0.007	0.010	0.010	0.010
	(0.006)	(0.010)	(0.008)	(0.009)
Death of HH member	-0.020**	0.009	-0.007	0.002
	(0.010)	(0.017)	(0.015)	(0.016)
Victim	0.005	0.059***	0.034	0.050***
	(0.008)	(0.017)	(0.022)	(0.016)
Rural	-0.003	-0.029**	-0.018	-0.024**
	(0.007)	(0.012)	(0.013)	(0.012)
Deprived neighbourhood	0.001	0.040***	0.022	0.033***
	(0.005)	(0.012)	(0.016)	(0.012)
Central	0.037**	0.024	0.038	0.033
	(0.015)	(0.036)	(0.026)	(0.032)
Emigration rate	0.048*	0.096**	0.083*	0.094**
	(0.028)	(0.044)	(0.042)	(0.043)
Unemployment rate, registered	0.002	-0.004	-0.001	-0.003
	(0.003)	(0.005)	(0.004)	(0.005)
Unemployment rate, unregistered	0.000	-0.001*	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)
HDI health	0.047	0.107	0.093	0.102
	(0.090)	(0.143)	(0.126)	(0.137)
HDI education	-0.071	-0.224	-0.171	-0.204
	(0.090)	(0.144)	(0.138)	(0.141)
HDI income	0.157**	0.015	0.110	0.060
	(0.062)	(0.115)	(0.096)	(0.105)
Year 2005	-0.021***	-0.038***	-0.034***	-0.038***
	(0.006)	(0.010)	(0.011)	(0.010)
Regional dummies	Yes	Yes	Yes	Yes
N	10227	10227	10227	10227
χ^2	194	2664	578	1411
p	0.000	0.000	0.000	0.000

Note: The coefficients are marginal effects. Standard errors are clustered on individuals. Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1% respectively. IV (1) = murder rates at state level, IV (2) = armed groups in neighborhood.

Table 3.A.5: Effect of SDA on Participation – Women

	Probit	IV-Probit		
	–	IV (1)	IV (2)	IV (1+2)
SDA (pcm)	0.004	0.193**	0.160	0.181**^{A}
	(0.004)	(0.095)	(0.139)	(0.081)
N	14733			

Note: Each coefficient is obtained from a different regression. The numbers are marginal effects. Standard errors are clustered on the individual. Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. IV (1) = homicide rates on state level, IV (2) = armed groups in neighbourhood. When two instruments are included, a test for overidentification is pursued. The test statistic is the Amemiya-Lee-Newey minimum χ^2-statistic (obtained from the two-step rather than the MLE method) and ^{A} indicates that $p > 0.1$, i.e. instruments are valid.

Table 3.A.6: Effect of SDA on Weeks Worked – Men (long)

	OLS	IV		
	–	IV (1)	IV (2)	IV (1+2)
SDA (pcm)	-0.820***	-16.240**	-9.579*	-12.676***
	(0.136)	(7.364)	(5.282)	(4.341)
Age	0.555***	0.398***	0.466***	0.432***
	(0.077)	(0.133)	(0.105)	(0.108)
Age sqrd	-0.006***	-0.002	-0.004**	-0.003*
	(0.001)	(0.002)	(0.002)	(0.002)
Indigenous	0.014	0.869	0.500	0.645
	(0.428)	(0.792)	(0.577)	(0.624)
High school	0.624	-0.972	-0.282	-0.605
	(0.419)	(1.022)	(0.757)	(0.742)
College	0.915**	-1.395	-0.397	-0.877
	(0.355)	(1.239)	(0.912)	(0.821)
House owner	-0.659**	-0.601	-0.626	-0.613
	(0.309)	(0.511)	(0.386)	(0.440)
Savings	0.506*	-0.039	0.196	0.076
	(0.285)	(0.531)	(0.405)	(0.431)
HH size	-0.000	-0.009	-0.005	-0.006
	(0.034)	(0.053)	(0.041)	(0.046)
Children < 2 in HH	0.002	-0.791	-0.449	-0.612
	(0.306)	(0.597)	(0.454)	(0.461)
Migrant	-0.194	-0.115	-0.149	-0.135
	(0.278)	(0.442)	(0.338)	(0.382)
Death of HH member	-1.544***	-0.302	-0.839	-0.612
	(0.514)	(0.965)	(0.717)	(0.745)
Victim	-1.273***	1.387	0.238	0.774
	(0.390)	(1.404)	(1.027)	(0.915)
Rural	-1.733***	-2.908***	-2.400***	-2.646***
	(0.335)	(0.745)	(0.569)	(0.551)
Deprived neighbourhood	-0.057	1.715*	0.949	1.306**
	(0.263)	(0.949)	(0.688)	(0.622)
Central	-1.084	-2.155	-1.692	-1.922
	(0.757)	(1.504)	(1.066)	(1.221)
Emigration rate	-0.149	2.772	1.510	2.108
	(1.479)	(2.602)	(2.005)	(2.101)
Unempl. rate, registered	0.389***	0.117	0.234	0.188
	(0.146)	(0.265)	(0.195)	(0.211)
Unempl. rate, unregistered	-0.082***	-0.149***	-0.120***	-0.134***
	(0.025)	(0.050)	(0.038)	(0.039)
HDI health	-5.843	-2.503	-3.946	-2.892
	(5.115)	(7.603)	(6.127)	(6.676)
HDI education	-9.999**	-18.372**	-14.755**	-16.893**
	(4.840)	(7.967)	(6.559)	(6.718)
HDI income	16.610***	10.129*	12.928***	11.524***
	(3.185)	(5.434)	(4.272)	(4.403)
Year 2005	-0.201	-1.010	-0.661	-0.835
	(0.359)	(0.649)	(0.509)	(0.521)
Constant	38.986***	47.509***	43.827***	45.713***
	(3.623)	(6.777)	(5.309)	(5.411)
Regional dummies	Yes	Yes	Yes	Yes
N	9444	9444	9444	9444
R^2 centered	0.042	-1.298	-0.390	-0.750
R^2 uncentered	0.943	0.862	0.917	0.895
F	13	5	8	7
p	0.000	0.000	0.000	0.000
A-P First stage χ^2	–	7.300	7.827	7.225
Shea's r^2		0.001	0.001	0.002
Hansen's J	0.000	0.000	0.000	0.570
H's J-p	–	–	–	0.450

Note: Standard errors are two-way clustered at individual and household level in the OLS, and IV models. Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. IV (1) = homicide rates at state level, IV (2) = armed groups in neighbourhood.

Table 3.A.7: Effect of SDA on Weeks Worked – Women

Linear Regression	OLS	IV		
	–	IV (1)	IV (2)	IV (1+2)
SDA (pcm)	-0.564***	11.503	-1.770	3.802
	(0.199)	(13.733)	(8.566)	(7.108)
A-P First stage χ^2	–	1.744	2.316	1.942
N		5262		
Tobit Regression	Tobit	IV-Tobit		
	–	IV (1)	IV (2)	IV (1+2)
SDA (pcm)	0.060	9.210**	5.632	7.847**
	(0.163)	(4.149)	(5.128)	(3.235)
N		14780		

Note: Each coefficient is obtained from a different regression. In Tobit and IV-Tobit results marginal effects are presented. Standard errors are clustered on individuals in the OLS and Tobit models and bootstrapped with 400 replications in the IV and IV-Tobit models. Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. IV (1) = homicide rates on state level, IV (2) = armed groups in neighbourhood. When two instruments are included, the Hansen's J test for overidentification is pursued. ^{A} indicates that the critical value $p > 0.1$, i.e. instruments are valid. $^{+}$ denotes strong instruments (not tested in Tobit models): χ^2> Stock/Yogo's (2005) critical value (25% maximal IV size).

Table 3.A.8: Effect of SDA on Hours Worked – Men (long)

	OLS	IV		
	–	IV (1)	IV (2)	IV (1+2)
SDA (pcm)	-0.645***	-23.539**	-5.278	-14.625**
	(0.188)	(11.672)	(7.509)	(6.616)
Age	0.454***	0.221	0.407***	0.303**
	(0.099)	(0.195)	(0.129)	(0.141)
Age sqrd	-0.006***	-0.001	-0.005**	-0.003
	(0.001)	(0.003)	(0.002)	(0.002)
Indigenous	-0.977*	0.235	-0.732	-0.246
	(0.587)	(1.141)	(0.720)	(0.820)
High school	-0.945	-3.113**	-1.384	-2.290**
	(0.610)	(1.490)	(0.949)	(1.000)
College	-3.394***	-6.735***	-4.070***	-5.460***
	(0.620)	(1.949)	(1.278)	(1.233)
House owner	-1.260***	-1.301*	-1.268***	-1.284**
	(0.450)	(0.752)	(0.465)	(0.581)
Savings	0.958**	0.004	0.765	0.390
	(0.431)	(0.870)	(0.545)	(0.622)
HH size	-0.079*	-0.105	-0.084*	-0.095
	(0.044)	(0.077)	(0.047)	(0.059)
Children < 2 in HH	0.029	-1.163	-0.212	-0.681
	(0.406)	(0.924)	(0.569)	(0.630)
Migrant	-0.211	-0.236	-0.216	-0.235
	(0.403)	(0.657)	(0.418)	(0.514)
Deprived neighbourhood	-0.258	2.442	0.289	1.385
	(0.365)	(1.510)	(0.951)	(0.908)
Death of HH member	0.132	1.988	0.508	1.248
	(0.632)	(1.405)	(0.882)	(0.959)
Victim	0.671	4.657**	1.478	3.118**
	(0.524)	(2.201)	(1.429)	(1.333)
Rural	-1.999***	-3.542***	-2.311***	-2.889***
	(0.457)	(1.106)	(0.676)	(0.740)
Central	-0.576	-2.049	-0.874	-1.579
	(1.544)	(2.644)	(1.705)	(2.051)
Emigration rate	0.168	3.894	0.922	2.295
	(1.908)	(3.735)	(2.281)	(2.691)
HDI health	-7.173	-0.137	-5.749	-2.090
	(6.364)	(10.737)	(6.988)	(8.207)
HDI education	23.321***	9.904	20.606***	14.691*
	(6.324)	(12.051)	(7.919)	(8.892)
HDI income	1.874	-8.136	-0.151	-4.372
	(4.075)	(8.269)	(5.367)	(5.907)
Unempl. rate, registered	0.245	-0.207	0.154	-0.034
	(0.193)	(0.402)	(0.252)	(0.286)
Unempl. rate, unregistered	-0.005	-0.115	-0.027	-0.071
	(0.033)	(0.078)	(0.049)	(0.053)
Year 2005	-0.405	-1.694*	-0.666	-1.228*
	(0.440)	(0.950)	(0.621)	(0.661)
Constant	28.386***	40.882***	30.914***	36.057***
	(5.005)	(10.217)	(6.563)	(7.291)
Regional dummies	Yes	Yes	Yes	Yes
N	9288	9288	9288	9288
R^2 centered	0.033	-1.624	-0.034	-0.584
R^2 uncentered	0.899	0.725	0.891	0.834
F	10	4	9	6
p	0.000	0.000	0.000	0.000
A-P First stage χ^2	–	6.265	5.822	5.753
Shea's r^2		0.001	0.001	0.002
Hansen's J	0.000	0.000	0.000	2.006
H's J-p	–	–	–	0.157

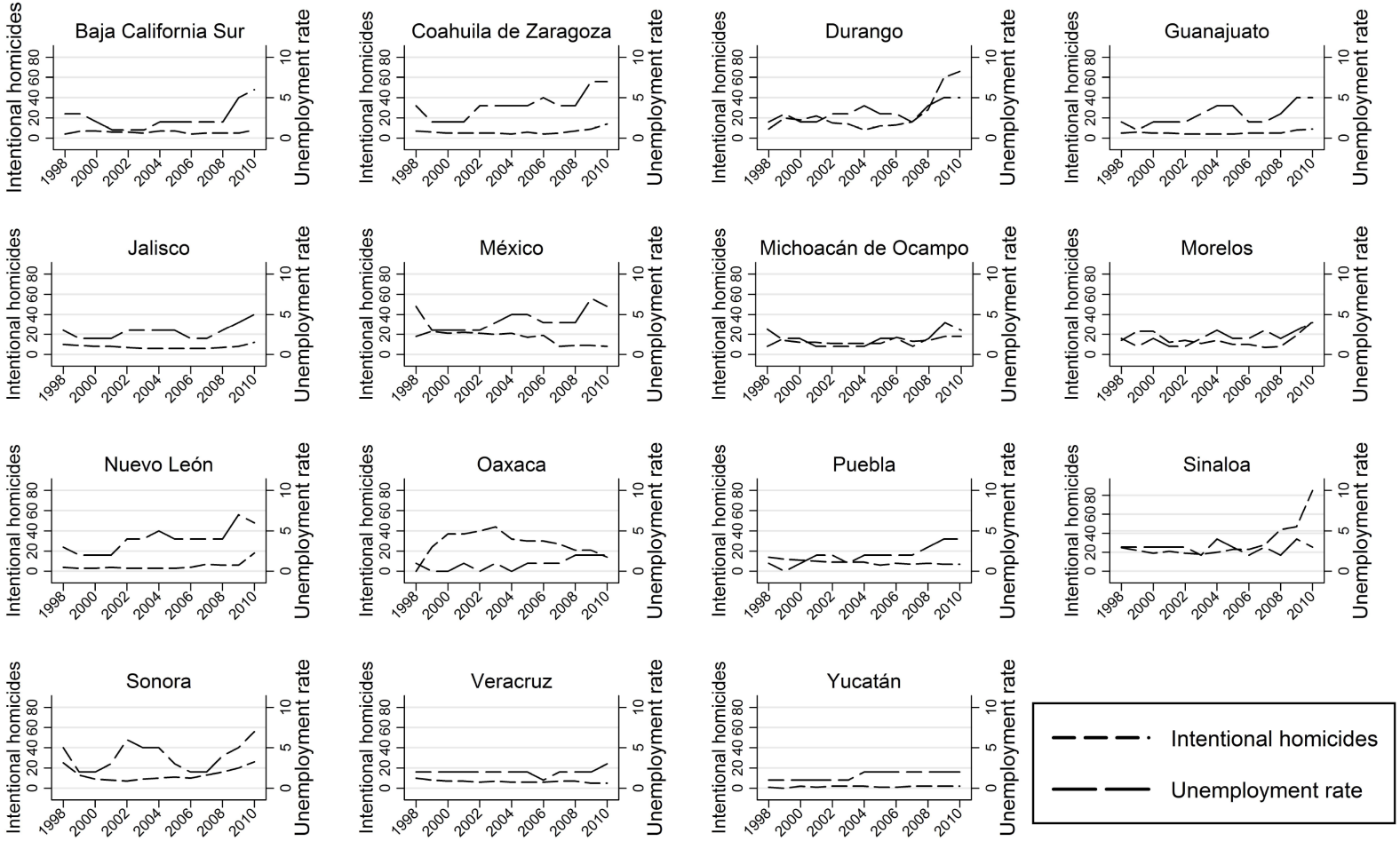
Note: Standard errors are two-way clustered at individual and household level in the OLS, and IV models. Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. IV (1) = homicide rates at state level, IV (2) = armed groups in neighbourhood.

Table 3.A.9: Effect of SDA on Hours Worked – Women

Linear Regression	OLS	IV		
	–	IV (1)	IV (2)	IV (1+2)
SDA (pcm)	-0.845***	-24.387	-10.517	-16.516
	(0.276)	(22.627)	(13.766)	(12.407)
A-P First stage χ^2	–	1.771	2.157	1.898
N		5169		
Tobit Regression	Tobit	IV-Tobit		
	–	IV (1)	IV (2)	IV (1+2)
SDA (pcm)	-0.022	4.170	4.018	4.098
	(0.143)	(3.576)	(4.382)	(2.789)
N		14733		

Note: Each coefficient is obtained from a different regression. In Tobit and IV-Tobit results marginal effects are presented. Standard errors are clustered on individuals in the OLS and Tobit models and bootstrapped with 400 replications in the IV and IV-Tobit models. Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. IV (1) = homicide rates on state level, IV (2) = armed groups in neighbourhood. When two instruments are included, the Hansen's J test for overidentification is pursued. ^{A} indicates that the critical value $p > 0.1$, i.e. instruments are valid. $^{+}$ denotes strong instruments (not tested in Tobit models): χ^2> Stock/Yogo's (2005) critical value (25% maximal IV size).

Figure 3.A.2: Unemployment Rates and Homicide Rates over Time by State



Source: Author's construction using data from INEGI, 2011 and ICESI, 2011.

Chapter 4

Migration Magnet: The Role of Work Experience in Rural-Urban Wage Differentials

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Abstract In this study separate wage equations for formal and informal workers in rural and urban Mexico are estimated using data from the Mexican Family Life Survey (MxFLS). We control for different potential selection patterns using Probit and Multinominal logit models in the first stage in which personality traits and family characteristics serve as exclusion restrictions for working per se and working in the formal sector. Whilst not finding evidence for selection, Oaxaca-Blinder decompositions show that rural-urban wage inequality in the formal and informal sectors is determined by differences in observable human capital. In the informal sector, the wage differential is mainly explained by differences in returns to experience. Furthermore, we analyse rural-to-urban migrants' labour market performance. The findings suggest that rural-to-urban migration will continue and the informal sector will further increase.[1]

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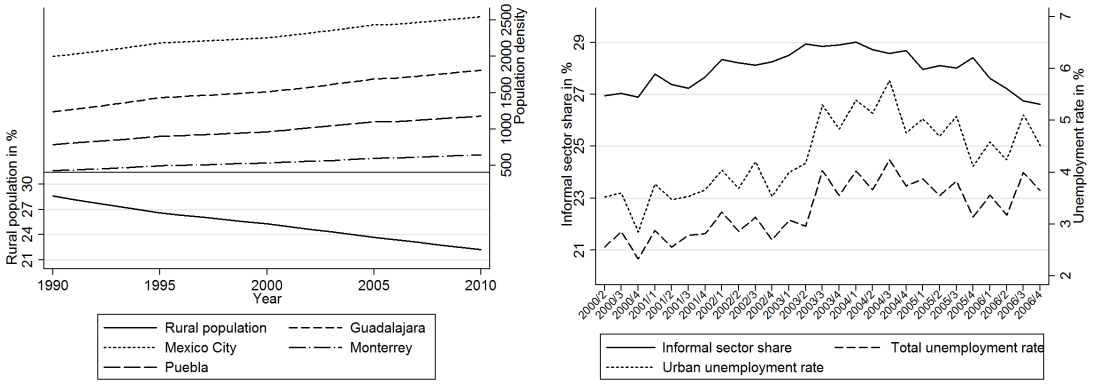
4.1 Introduction

Theories of economic development postulate that rural-to-urban migration is the driving force of a country's economic development. Following Todaro (1969) and Harris and Todaro (1970) individuals migrate from rural to urban areas to find well paid employment unavailable in rural areas. If migrants do not find a job with rewards exceeding their reservation wage they will stay unemployed or return. In this model the unemployment rate acts as the driving force in determining the migration equilibrium. The theory is extended by Lucas (2004) who argues that high urban wages are attributed to high skills and not accessible for low skilled immigrants. In his model, individuals migrate to the cities to accumulate work experience as a form of human capital formation. According to human capital theory (Becker, 1964), the accumulation of experience will raise future earnings prospective. This will in turn reduce poverty and welfare dependency. Following this augmentation, the two main incentives to migrate are (1) earning high wages and (2) the accumulation of human capital.

This requires that wages are higher in the cities than in the countryside, which has been clearly demonstrated by economists for decades (e.g. Mazumdar, 1976; Meng and Zhang, 2001; Glaeser and Maré, 2001). Besides the wage differences between rural and urban regions, wage differences exist between the types of jobs a worker can obtain, such as a formal job or an informal job. Early theories by Lewis (1954) and Fields (1975) suggest that the informal sector is the disadvantaged segment of a dual labour market in which workers are not protected by social security regulations and are in weak bargaining positions with their employers. In the last decades, some developing countries have shown an unexpected development: the informal sector has been increasing. This has aroused the interest of economists to test the segmented market hypothesis empirically. For Mexico, e.g. Maloney (1999), Maloney (2004), Marcouiller et al. (1997) and Bargain and Kwenda (2009) show that informal work is indeed voluntary for reasons such as opportunity costs and flexibility. Hence, instead of simply queuing for a formal job, individuals earn wages and accumulate human capital in the informal sector.

In Mexico, as in many other countries, wage differentials have many dimensions, e.g. between rural and urban employment and between formal and informal sectors. An urban wage premium enhances rural-to-urban migration which in turn can lead to social and economic problems, such as un- and underemployment,

Figure 4.1.1: Urbanisation, Unemployment and Informal Sector Shares



Source: The World Bank (http://data.worldbank.org/country/mexico), OECD Metropolitan database (http://stats.oecd.org/index.aspx) and INEGI (http://www.inegi.org.mx/).

poverty, crime and an increasing informal sector rather than to economic development. Figure 4.1.1 (left) shows the decrease of the rural population and the increase of population density in four of Mexico's largest cities, namely Mexico City, Guadalajara, Puebla and Monterrey. It shows that between 1990 and 2010 the rural population decreased from 29% to 22% while population density in the cities rose. All four example cities show a similar development, i.e. an increase in population density of about 25% within 20 years. Furthermore, Figure 4.1.1 (right) displays the development of the urban and total open unemployment rate in Mexico over the period 2000 to 2006 and the rise in informal employment over the same period. It can be seen that the urban unemployment rate is much higher than the total open unemployment rate, but exhibits the same pattern. Moreover, the higher the unemployment rate is, the larger is the informal sector share. These macroeconomic indicators suggest that the increase in rural-to-urban migration, rising urban population density, high unemployment and a large informal sector share go hand-in-hand.

Still, individuals migrate to the cities. Mexico's urban population grew from 66% to 76% between 1980 and 2005 (World Bank, 2010). We contribute to the explanations of the driving forces of rural-to-urban migration in Mexico by investigating the differences in wages between rural and urban areas. Focusing on the argument that rural-to-urban migration is induced by the incentive to accumulate human capital in form of work experience, this paper analyses the returns to work experience and other human capital related factors for rural and urban salaried workers. It is further analysed to what extent these components of human capital endowment

can explain the wage differential and which role the informal sector plays.

Using the novel and representative Mexican Family Life Survey (MxFLS, or ENNVIH in Spanish), this is the first study which investigates wage differentials between rural *and* urban areas in Mexico. Former studies on wage gaps between groups in Mexico were restricted to urban areas as representative data on the whole population was not available before the publication of the MxFLS.[2] This study uses the second wave (MxFLS-2) which consists of data collected in the second half of 2005 and early 2006.

To overcome the potential econometric problem of self-selection into work as opposed to not working and selection into different sectors of the labour market, a Heckman (1979) selection-bias correction model is applied, using family characteristics and personality traits as exclusion restrictions. We find no selection bias, but, as expected, large and significant urban wage premia in both the formal and informal sectors. Subsequently, Oaxaca-Blinder decomposition techniques are used to show to which extent the rural-urban wage differential can be explained by (a) individuals' components of human capital endowment differences and (b) differences in unobservable characteristics. The results suggest structural differences between the formal and informal sector. In both the formal and informal sector, the rural-urban wage differential is explained by differences in levels of human capital endowment (education, experience and cognitive ability). In the informal sector, the unexplained part of the wage differential is solely driven by differences in returns to experience. In the formal sector, no differences in returns to components of human capital endowment are found. Moreover, we analyse rural-to-urban migrants' labour market performance to identify the role of experience in migrants' labour rewards and offer explanations of low returns to experience in both rural and urban Mexico. The results suggest that rural-to-urban migration will continue and the informal sector will further increase. Policies need to address this by increasing employment probabilities and the incentive for formal employment.

The paper is organised as follows. In the next section, the existing literature on rural-urban wage differentials and migration incentives is reviewed. Section 4.3 describes the empirical strategy to identify wage differentials and account for selectivity bias. In Section 4.4, the data is explained and descriptive statistics are

[2]The commonly used Mexican data is the National Urban Employment Survey (ENEU), which has only recently been expanded to rural areas.

provided. Section 4.5 discusses the main findings, Section 4.6 provides a discussion and the last section concludes.

4.2 Literature Review

The literature on rural-to-urban migration is based on the theoretical models by Todaro (1969) and Harris and Todaro (1970). According to their models, people migrate from rural to urban areas to find high wage jobs which are not available in rural areas. If people do not find a job with higher rewards than their reservation wage they will stay unemployed or return; the unemployment rate acts as the driving force on determining the migration equilibrium. This theory is extended by, e.g., Lucas (2004) who argues that high urban wages are attributed to high skills and not accessible by low skilled immigrants. In his model, people migrate to the cities to accumulate work experience as a form of human capital.

Newer models of migration also include social factors such as previous migration experience, networks and inequalities in the migration decision. One factor that has received much attention in recent years is relative deprivation, i.e. the perception of an individual or household to be worse off or disadvantaged compared to a particular reference group, for example, other families in the same village (Quinn, 2006; Stark and Taylor, 1989, 1991). Quinn (2006) uses the data from the Mexican Migration Project for the year 2004 and finds that relative deprivation explains part of the migration decision for internal migrants but not for those who migrate to the United States. Klabunde (ming), in a sophisticated agent-based model using data from the Mexican Migration Project, finds that network ties are an important factor explaining both migration from Mexico to the U.S. and return migration. Gould (2007) argues that working in a city increases workers' productivity (see also Glaeser and Maré, 2001). Based on data of the U.S., he finds that white-collar workers receive a wage premium in rural areas if they gathered work experience in a city, whereas blue collar workers' urban work experience is not rewarded more than rural experience. Hence, the incentive to accumulate human capital in the city is part of the migration decision and return migration is dependent on the sector of occupation.

In Mexico, increasing urbanisation has led to economic and social problems such as increasing under-employment and high crime rates. Furthermore, wage inequality increased as more productive and human capital intensive firms settled in the cities

and pay higher wages than rural, often less productive, firms (Gong and van Soest, 2002; Bosch and Maloney, 2007; Levy, 2008). That these higher wages exist even after controlling for components of human capital endowment, costs of living and other characteristics is shown by, e.g., Glaeser and Maré (2001) for the U.S.

When investigating rural-urban wage differentials in Mexico, it has to be taken into account that the labour market is further divided into formal and informal employment. In fact, many authors do not focus on rural-urban wage differentials but on differences between formal and informal wages. Exemplary studies that find wage penalties for workers in the informal sector are provided by Bargain and Kwenda (2009, 2010) who compare informal-formal sector wage gaps in Brazil, South Africa and Mexico. For Mexico, they use the ENEU and restrict their survey to male dependent workers in urban areas. Using Fixed Effects quantile estimation they are not able to control for self-selection into sectors but for other unobserved time-invariant characteristics. The median penalty for working informally is stable during 2004-2007 at about 9%. Hanson (2010) and Arias et al. (2010) state that the informal sector in Mexico's cities has increased which is partly due to perverse registration incentives induced by social insurance regulations (Levy, 2008). Furthermore, informality hinders economic development as productivity tends to be low in informal firms (Hsieh and Klenow, 2009).

Another study on wage differentials between informal and formal sectors in Mexico was conducted by Gong and van Soest (2002) using the 1992/1993 waves of the ENEU, restricting their sample to workers in Mexico's five major cities. In line with, e.g., Maloney (1999) they find wage differentials for high-educated workers but not for low-educated workers. This implies that formal sector jobs are inaccessible for low-educated workers in Mexico's urban areas.

Several articles have been published investigating not only wage differentials but also labour mobility between sectors (Maloney, 1999, 2004; Bosch and Maloney, 2007, 2008). They note that informal employment is a desirable choice (see Marcouiller et al., 1997; Maloney, 1999) and see the informal sector as a result of competitive markets where individuals choose the informal sector voluntarily because of more flexibility and avoidance of tax payments. The segmented market hypothesis is commonly rejected for Mexico.

Meng (2001) provides one of the few studies which distinguish formal and informal labour and investigate rural-urban migration in the same context. For China, she

finds that urban work experience raises the probability of becoming a formal worker and that wage differences are mainly explained by observable components of human capital endowment.

A complicacy in the literature on informal labour markets is the different definitions of informality, which impede the comparison of the results. Generally, the most commonly used definitions can be classified into two groups. First, the *legal* definition is based on the contribution to the social security system (e.g. Tannuri-Pianto and Pianto, 2002; Bosch and Maloney, 2007, 2008). Informal workers are those who do not contribute to the social security system and, simultaneously, do not benefit from social security regulations such as health care and pension schemes. Another *legal* definition is based on the formality of the workers' contracts. Here, informal workers are those who do not have a written contract and, consequently, cannot assert their labour rights. However, they may enjoy more flexibility. The other group of definitions is based on *productivity* grounds. According to them, the informal sector comprises workers in firms with fewer than or equal to five employees (e.g. Maloney, 1999; Gong and van Soest, 2002), based on the argument that small firms tend to neither register their business nor their employees. The problem with firm size as a measure is that larger firms tend to pay higher wages and are at risk of being caught defaulting on registering as their number of employees increases. Hence, they are more likely to register (El Badaoui et al., 2008). In this study, the most unambiguous *legal* definition is used which corresponds to registration with the social security system.

To our best knowledge, all existing studies for Mexico are based on either rural or urban household surveys or solely on migrants. Using the novel Mexican Family Life Survey (MxFLS) allows the investigation of wage differentials between rural and urban workers in different sectors.

4.3 Estimation Methods

The empirical strategy to identify the determinants of the rural-urban wage differential and to find out which wage related factors are mainly driving rural-to-urban migration is to estimate wage regressions and to apply Blinder-Oaxaca decomposition techniques.

One issue that has to be taken into account when estimating wage equations

for different groups of workers is selection bias of different sources. The most obvious source is the selection bias from self-selection into work vs. not working, i.e. sample selection. The other source is, given that an individual is working, self-selection into one sector of the labour market, distinguishing between formal salaried employment, informal salaried employment and self-employment.[3] As the wages of the self-employed are determined very differently to salaried workers, they are excluded from the sample.[4] Hence, the remaining sectors are formal salaried employment and informal salaried employment.

To account for potential selection bias in Ordinary Least Square (OLS) wage regressions, Heckman (1979) selection models are estimated. By applying the two-step model we account for potential bias from selection into work per se and for selection into formal as opposed to informal employment.

In the first step, a Probit model is estimated to determine the probability of individual i actively working ($a_i = 1$) as opposed to not working ($a_i = 0$) which can be written as

$$Pr(a_i = 1|Z_i) \equiv \gamma Z_i + u_i, \tag{4.1}$$

where Z_i are observed characteristics of the individual, such as human capital, personality and family indicators, γ is the vector of coefficients of these variables and u_i is the error term which is normally distributed with zero mean and unity variance. We include a variable which counts the number of elderly and the number of infants in the household as exclusion restrictions in the model which accounts for potential bias from selection into work.

In the models that account for potential bias from selection into formal as opposed to informal work, additionally indicators of whether a person is honest (a person does not agree to the statement "laws are there to be broken") and his or her risk attitude serve as exclusion restrictions.

Subsequently, the non-selection hazard (also known as inverse Mill's ratio) $\lambda_{w/nw}$ is calculated from the estimated parameters of the selection equation. This is included

[3] See e.g. Magnac (1991) for evidence of self-selection into the informal sector.

[4] See e.g. Hamilton (2000) for a discussion on the difficulty of measuring self-employed earnings.

in the second step wage regression which has the following form

$$\ln y_i = \alpha_i + \beta X_i + \delta \lambda_{w/nw} + \epsilon_i, \tag{4.2}$$

where y_i is the hourly wage of individual i, β is a vector of coefficients of observable personal and household characteristics X_i and ϵ_i the error term which is assumed to be normally distributed with zero mean and variance σ^2. y_i is observed if and only if $\gamma Z_i + u_i > 0$, i.e. $a_i > 0$. Since we do not find evidence for selection bias, we base the following estimations on OLS and will report the results from OLS regressions only.

Subsequently, the two-fold Blinder-Oaxaca decomposition technique (Blinder, 1973; Oaxaca, 1973) is used to find out in how far differences in wages between rural and urban workers are explained by differences in observable characteristics and to which extent differences remain unexplained. The decomposition technique can be written as

$$\overline{\ln y^R} - \overline{\ln y^U} = \hat{\beta}^R(\overline{X^R} - \overline{X^U}) + (\hat{\beta}^R - \hat{\beta}^*)\overline{X^R} + (\hat{\beta}^* - \hat{\beta}^U)\overline{X^U} \tag{4.3}$$

where $\hat{\beta}^U$ and $\hat{\beta}^R$ are recovered from the separate wage equations of the rural and urban samples. β^* is a vector of coefficients from a pooled model over both samples which includes a dummy variable which identifies the populations. The left hand side of equation (4.3) is the raw wage gap, the right hand side consists of the explained part (difference in characteristics) and the unexplained part (differences in coefficients). To determine differences in returns to human capital endowment, the vector is weighted by the coefficients vector of the rural population. To identify the contribution of the human capital variables separately, we decompose the rural-urban wage differential in detail.

4.4 Data

The data used is the novel Mexican Family Life Survey (MxFLS, or ENNVIH in Spanish) which is a panel survey of approximately 8,440 Mexican households and 35,000 individuals. It is representative at the regional, urban-rural and state levels and contains information on individuals, households and communities in 2002 and 2005/06. The questions cover a variety of topics such as labour market status,

family characteristics, education, household income, health and self-evaluations.[5]

This study uses exclusively the second wave (MxFLS-2) because earnings variables seem less reliable in 2002.[6] The data is restricted to men and women between the age of 16 and 65 years. Self-employed workers, full-time students and the seriously ill (incapable) are excluded from the sample. The final sample consists of almost 10,000 individuals of whom 40% live in rural areas, i.e. in an area with less than 2,500 inhabitants. The detailed distribution of the workforce is displayed in Table 4.4.1. Those 'not employed' include also workers without remuneration. In rural areas 36% are salaried workers. In urban areas 49% are employed.

Table 4.4.1: Distribution of Individuals by Sectors

	Urban		Rural	
	Mean	Std.Dev.	Mean	Std.Dev.
Not working	0.51	(0.50)	0.64	(0.48)
Informal salaried	0.29	(0.45)	0.28	(0.45)
Formal salaried	0.20	(0.40)	0.08	(0.27)
N	5587		3807	

Note: Authors' calculations based on MxFLS-2.

Unfortunately, we are not able to control for differences in costs of living between rural and urban areas directly since consumer price indices (CPI) for Mexico are based on information collected in urban areas. Also, there was no question in the data set which could have been used as an alternative to the CPI for measuring costs of living. However, we include indices of health, education and income levels on the municipality level which are used to calculate the Human Development Index (HDI) (UNDP, 2008). This should account for structural economic differences by region.

The here used *legal* definition of the informal sector is based on the nature of the contract an employee has with his employer. Is the employee registered with the social security institute (IMSS) or a government worker (ISSSTE[7]), he or

[5]More details can be found at http://www.ennvih-mxfls.org/.

[6]In 2002 about 20% of salaried workers have non-positive wages while no salaried worker has non-positive wages in 2005. The reasons for this may not be due to idiosyncratic measurement error.

[7]The ISSSTE is the social security institution for public sector workers and the armed forces.

she is considered a formal worker, and an informal worker otherwise.[8] This *legal* definition is also used by, e.g., Bosch and Maloney (2007) and Bargain and Kwenda (2009). Registered workers are eligible to social security benefits which include health insurance, pension, child care, housing loans, life and work-risk insurance and sports and cultural facilities. Moreover, they are protected by firing regulations and severance pay.

The key dependent variable is log hourly real wage which is constructed by dividing reported average monthly earnings by 4.33 times reported average hours worked per week and deflated by the consumer price index. Individuals who failed to report positive wages (about 2%) and the top and the bottom two percentiles of the wage distribution were dropped from the sample. The main independent variables are experience, education and cognitive ability. Experience is modelled as Mincerian potential experience (age minus years of schooling minus 6) because job history is not available in the data. The individuals are divided into two education groups, i.e. education up to compulsory level (0-9 years of schooling) or more ($\geq$10 years), including high school and university graduates. A special feature of the MxFLS is that a Raven's test was conducted with almost every individual. The Raven's test scores measure an individual's cognitive ability.[9] In the economic literature that deals with returns to education it is argued that an individual's educational achievement is influenced by his or her intelligence or ability and the inclusion of a measure of intelligence would lead to endogeneity bias in wage regressions (Card, 1999; Psacharopoulos, 1994). The inclusion of the test score should lower the education estimates.

The included individual characteristics are age, being married, subjective health, dummies for being the household head and belonging to an indigenous group. Finally, family characteristics comprise household size, number of elderly and infants in the household and being a farm owner.

As not all public workers are registered with ISSSTE, e.g., public workers in educational institutions and workers of the public electricity companies, it is impossible to exclude all public workers and hence they form the group of formal workers together with all workers who are registered with IMSS.

[8] As Maloney (1998), Bosch and Maloney (2008) and Levy (2008) point out, workers, especially poor workers, are highly mobile between sectors and hence workers can actually not be labelled as formal workers or informal workers per se. For simplicity we use these terms here but actually, when referring to an informal (formal) worker, we mean an individual whose current job at the time of data collection is in the informal (formal) sector.

[9] See Raven et al. (2003) for more information about the test.

Table 4.4.2: Descriptive Statistics by Sector and Locality

	Informal				Formal			
	Urban		Rural		Urban		Rural	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Female	0.36	(0.48)	0.25	(0.43)	0.39	(0.49)	0.29	(0.45)
Married	0.51	(0.50)	0.52	(0.50)	0.59	(0.49)	0.56	(0.50)
Indigenous	0.07	(0.25)	0.17	(0.37)	0.06	(0.25)	0.11	(0.31)
Hh head	0.46	(0.50)	0.52	(0.50)	0.50	(0.50)	0.52	(0.50)
High educ.	0.28	(0.45)	0.10	(0.30)	0.43	(0.50)	0.32	(0.47)
Age 16-25	0.25	(0.44)	0.25	(0.44)	0.18	(0.38)	0.21	(0.41)
Age 26-35	0.28	(0.45)	0.27	(0.44)	0.33	(0.47)	0.30	(0.46)
Age 36-45	0.25	(0.43)	0.25	(0.43)	0.29	(0.45)	0.26	(0.44)
Age >46	0.22	(0.41)	0.23	(0.42)	0.21	(0.41)	0.23	(0.42)
Experience	21.1	(13.3)	23.8	(14.0)	20.3	(11.4)	21.9	(12.6)
Hrs/year	2101	(959)	1977	(990)	2281	(804)	2181	(919)
Raven test	0.55	(0.23)	0.49	(0.24)	0.59	(0.23)	0.54	(0.24)
Honest	0.81	(0.40)	0.80	(0.40)	0.83	(0.37)	0.82	(0.38)
Risky	0.37	(0.48)	0.39	(0.49)	0.38	(0.48)	0.41	(0.49)
Health	2.70	(0.64)	2.65	(0.63)	2.80	(0.63)	2.71	(0.71)
Hh size	9.95	(4.57)	10.64	(4.95)	9.39	(4.19)	9.90	(3.95)
No. of infants	0.38	(0.65)	0.41	(0.65)	0.30	(0.58)	0.38	(0.65)
No. of elderly	0.35	(0.89)	0.40	(0.91)	0.32	(0.86)	0.47	(1.05)
Farm	0.05	(0.22)	0.20	(0.40)	0.03	(0.17)	0.23	(0.42)
HDI health	0.91	(0.05)	0.84	(0.06)	0.92	(0.04)	0.85	(0.07)
HDI education	0.85	(0.04)	0.80	(0.06)	0.86	(0.03)	0.82	(0.06)
HDI income	0.75	(0.07)	0.66	(0.09)	0.77	(0.06)	0.69	(0.08)
N	1593		1074		1123		294	

Note: Authors' calculations based on MxFLS-2. Numbers are mean values and standard deviations in parentheses.

Table 4.4.2 provides descriptive statistics on these variables. It can be seen that the average years of work experience are higher in rural areas than in urban areas. This pattern is very similar in the formal and the informal sector with about 22-24 years in rural and about 20-21 years in urban areas. It appears that the differences in years of experience are driven by differences in years of education and are not due to age differences, as the age profiles do not differ largely between rural and urban residents. Years of work experience are highly correlated with age because we can only use potential experience. After discussing the main results, we will also discuss some robustness checks which show that the results for returns to experience differ from those for age.

Notably, the share of high-educated workers is very different between sectors. The

largest share of high-educated workers is in the urban formal sector with 43% of all workers. In the urban informal sector, 32% are university educated as well as 28% in the formal rural sector and only 10% of the informal workers in the rural areas have attended high school and/or university or college. Furthermore, the urban workforce performs better in the Raven's test score. These observations hint at the existence of self-selection into formal employment in rural and urban areas based on components of human capital endowment. Also, differences between rural and urban workers exist with regard to psychological indicators such as risk attitudes and honesty.

4.5 Results

4.5.1 All Workers

Table 4.5.1 shows the results of the wage regression for the whole sample. In column 1, it can be seen that a significant urban wage premium exists which amounts to 10 percentage points.[10] This finding is very similar to the results of Glaeser and Maré (2001) for the U.S. The wage regression for all workers in the sample is extended by interaction terms of the human capital variables with the urban residence dummy. Only the work experience interaction coefficients are significant and suggest that experience is more highly rewarded in urban areas than in rural areas by 1.2 percentage points. These findings are further supported by the separate wage equations for rural and urban workers (columns 3 and 4). While the return to one additional year of work experience is 2.3 percentage points in urban areas, it is not significantly different from zero in rural areas. Higher rewards for work experience in urban areas may play a role in the decision to stay in an urban area given one currently lives there or to migrate to a city given one currently lives in the countryside. However, the coefficients cannot be compared quantitatively as they were estimated in separate regressions. To see if experience is indeed such an important factor in explaining the wage differential, detailed decomposition analyses will be applied. Before we describe these results, we will discuss the findings of the formal/informal sector wage analyses.

[10]Since we do not find selection bias, we only discuss OLS regression results here. The probit and Heckman regression results are available from the corresponding author on request.

Table 4.5.1: Wage Regressions for All, Rural and Urban Workers

	All		Rural	Urban
	(1)	(2)	(3)	(4)
Urban	0.103***	-0.056	–	–
	(0.026)	(0.086)		
Exp*Urban	–	0.012**	–	–
		(0.006)		
Exp sq.*Urban	–	-0.000	–	–
		(0.000)		
High edu.*Urban	–	-0.004	–	–
		(0.053)		
Raven*Urban	–	0.023	–	–
		(0.086)		
Experience	0.018***	0.010**	0.007	0.022***
	(0.003)	(0.005)	(0.005)	(0.004)
Experience sqrd.	-0.000***	-0.000***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
High education	0.230***	0.237***	0.161**	0.240***
	(0.027)	(0.051)	(0.064)	(0.030)
Raven test	0.144***	0.126*	0.127*	0.158***
	(0.042)	(0.068)	(0.068)	(0.053)
Formal	0.125***	0.124***	0.137***	0.104***
	(0.021)	(0.021)	(0.044)	(0.024)
Other characteristics	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes
N	4086	4086	1370	2716
$\bar{R}^2$	0.395	0.396	0.357	0.372

Note: Robust standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. 15 state dummies, 23 industry dummies and 18 occupation dummies included. λ is the nonselection hazard variable generated from the probit model.

4.5.2 Formal vs. Informal Workers

As mentioned in the literature section, several authors have found wage differentials between formal and informal workers. We show that this differential also exists in 2005 in Mexico, even when distinguishing between rural and urban workers. That the differential exists in both the rural areas (14 percentage points) and in the cities (10 percentage points, Table 4.5.1, columns 3 and 4) is novel evidence because earlier studies on the formal wage gap in Mexico were mostly based on the National Urban Employment Survey which did not cover rural households until recently.

Figure 4.5.1: Returns to Experience in the Informal Sector

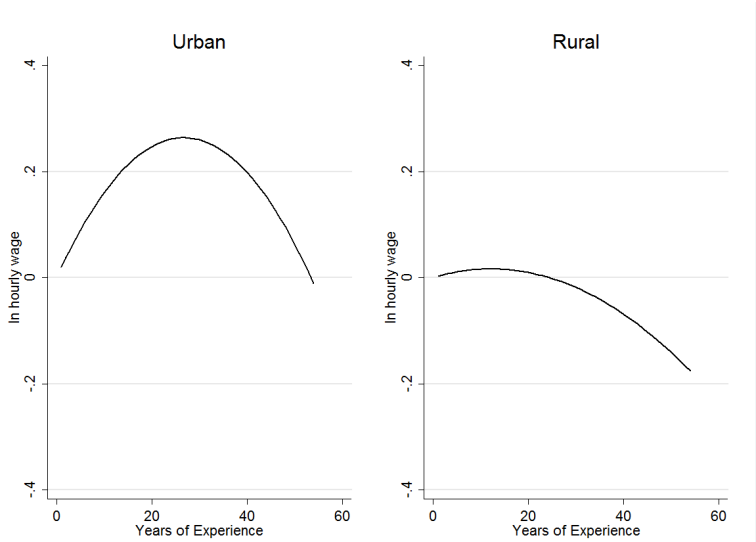
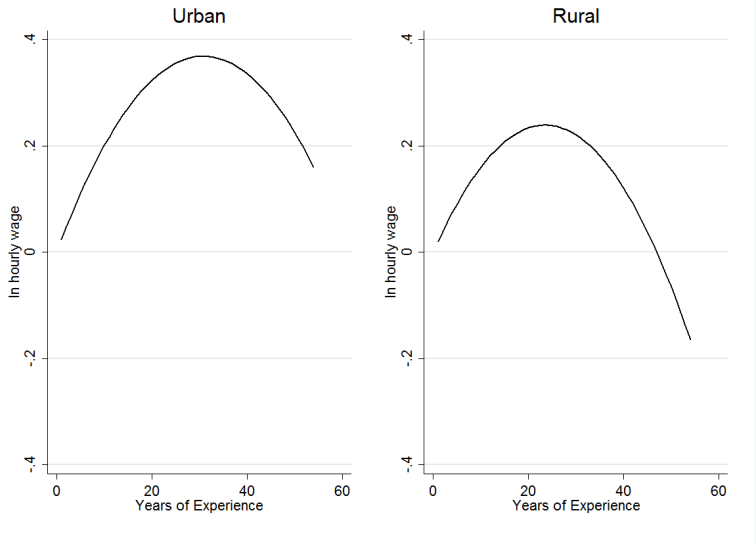


Figure 4.5.2: Returns to Experience in the Formal Sector



The results of the separate wage equations for formal and informal sector workers support what we have found in the wage equation for all workers but suggest quantitative differences between the sectors (the tables are in the appendix, 4.A.2 and 4.A.3). From the regression for informal workers we can see that a significant urban wage premium exists. Separating the sample into rural and urban workers further supports the hypothesis that human capital is differently rewarded in both regions. We find a high, significant return to high education of about 16 percentage points in the rural and 19 percentage points in the urban areas. For informal

workers there is no return to cognitive ability as the coefficient is not significantly different from zero. For informal workers in urban areas the return to experience is 1.4 percentage points higher than for informal rural workers (column 3). No other human capital related factors are significantly differently rewarded in urban than in rural areas. Figure 4.5.1 shows the return to experience graphically for informal workers and Figure 4.5.2 for formal workers. Note that the returns to experience are insignificant for rural workers in the informal sector while in the formal sector no significant difference in returns to experience can be found between rural and urban workers.

Furthermore, for formal workers, the results suggest that other human capital aspects, except education, are not productive in rural areas as the coefficients are not significantly different from zero. The results show that it is important to separate the workforce into different groups when the intention is to detect determinants of wage inequality. We will decompose the wage differential in the next section to uncover the role the different indicators of human capital play in the determination of rural-urban wage differentials.

In essence, the results suggest that experience is not rewarded in the rural areas but in urban areas. This will elevate the incentive to migrate to urban areas. As a consequence, the informal sector will increase in urban areas, assuming that the additional labour supply is not met by equally rising labour demand in the formal sector.

4.5.3 Blinder-Oaxaca Decomposition

The overall difference between urban and rural wages is 32% for informal workers and 22% for formal workers (Table 4.A.1 in the appendix). About one third of the differential in both the informal and the formal sector can be explained by observable characteristics. The detailed decomposition results are displayed in Table 4.5.2 for informal and formal workers, respectively. The results for informal workers show that differences in experience, education and cognitive ability largely explain the wage gap. By looking at the unexplained part, it can be seen that differences in coefficients of work experience account for the largest share of the unexplained part; the coefficient is 0.387 and statistically significant at the 5% level. Returns to education and cognitive ability do not play a role in the unexplained part of the rural-urban wage differential, nor do the returns to other characteristics. Hence,

there are significant differences in returns to experience, even after controlling for other observable characteristics and self-selection.

Table 4.5.2: Decomposition for Informal and Formal Workers

	OLS	
Informal	Explained	Unexplained
Experience	-0.040***	0.387**
	(0.013)	(0.168)
Experience sqrd.	0.041***	-0.184**
	(0.013)	(0.091)
High education	0.032***	0.005
	(0.007)	(0.013)
Raven test	0.006*	0.007
	(0.003)	(0.054)
Other	0.051**	-0.812
	(0.020)	(0.788)
N	2670	
Formal	Explained	Unexplained
Experience	-0.038*	0.016
	(0.021)	(0.239)
Experience sqrd.	0.041**	0.077
	(0.020)	(0.126)
High education	0.035***	0.032
	(0.010)	(0.034)
Raven test	0.012**	0.045
	(0.005)	(0.085)
Other	0.017	-0.013
	(0.030)	(0.186)
N	1420	

Note: Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. OLS: Ordinary Least Squares. The decomposition is formulated from the viewpoint of the rural population. For the underlying regressions see wage regression tables. *Other* includes 15 state dummies, work, individual and household characteristics.

In the formal sector, this difference in coefficients exists neither for experience nor for any other variable. Solely the differences in the average of the components of human capital endowment (education, experience and cognitive ability) explain the wage gap in the formal sector. This implies that it is not sufficient estimating separate wage equations for rural and urban workers in order to identify differences in returns to components of human capital endowment. This finding supports the hypothesis that urban firms are more human capital intensive and that they reward work experience more highly relative to rural firms.

4.5.4 Robustness Checks

We conduct a series of robustness checks to make sure that inconsistencies in the data set do not drive the results and that we did not oversee important differences between groups or selection processes. Therefore, we apply a Multinominal logit model in the first step in which the labour market choices are formal salaried employment, informal salaried employment and not working. The calculated inverse Mill's ratios from this model are included in the main wage equation. We neither find qualitative nor significant quantitative changes in the main results.[11]

Another potential pitfall concerns the definition of the education variable. Therefore, all regressions are run including a different education variable, which is equal to one if the individual has attained university and equal to zero if educational attainment was up to only high school level. In all regressions, the coefficient was larger and still significant, but not changing the results qualitatively.

One drawback of the data is that we cannot measure actual work experience as we do not have sufficient information on job history. As work experience is measured by age minus years of education minus 6, the correlation between our work experience variable and age is high (about 97%). To remedy the concern that we are not actually measuring the returns to potential work experience but the returns to age, we estimated all regressions including age instead of experience. The coefficients are larger for age than for experience and there are no significant differences between rural and urban workers. Hence, it can be concluded, that our experience variable is actually measuring the effect of work experience and not returns to age.

Moreover, all wage equations were estimated (a) including a cubic term of experience and (b) with experience without polynomials. For some groups of workers, the coefficients were also significant but the findings do not differ qualitatively from the discussed results.[12]

[11] We do not further discuss this methodology here as we are aware of the violation of the assumption of independent irrelevant alternatives in the Multinominal logit model.

[12] The result tables of the robustness checks are not displayed for the sake of brevity but can be obtained on request by the corresponding author.

4.5.5 Migrants' Labour Market Performance

In the subsequent analysis we investigate the labour market performance of rural-to-urban migrants to see whether it is in fact profitable for a rural worker to migrate to a city, given he could find employment in both rural and urban areas. Therefore we introduce a dummy variable which is equal to one if the individual has lived in a rural area at the age of 12 and in an urban area at the time of interview and zero otherwise with the aim of proxying the migration status of an individual. We add this variable to the regressors in the main wage regressions as well as in the first-step selection equation. In the following, we will only discuss the results for the informal and formal sector separately as we again find large differences between sectors concerning rural-to-urban migrants' labour market performance.

Table 4.5.3: Rural-to-urban Migrants' Labour Market Performance

	Informal		Formal	
	(1)	(2)	(3)	(4)
Migrant	-0.057	-0.083	0.023	-0.210
	(0.038)	(0.135)	(0.037)	(0.161)
Migrant× Exp.	–	0.001	–	0.012
		(0.009)		(0.011)
Migrant× Exp.^{2}	–	-0.000	–	-0.000
		(0.000)		(0.000)
Migrant× High Educ.	–	0.161**	–	0.108
		(0.081)		(0.074)
Migrant× Raven score	–	-0.013	–	0.078
		(0.145)		(0.154)
Experience	0.020***	0.019***	0.022***	0.018**
	(0.005)	(0.007)	(0.006)	(0.007)
Experience sqrd.	-0.000***	-0.000**	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
High education	0.182***	0.127**	0.300***	0.265***
	(0.044)	(0.053)	(0.041)	(0.047)
Raven test	0.105	0.107	0.258***	0.223**
	(0.072)	(0.105)	(0.078)	(0.101)
Other characteristics	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes
N	1593	1593	1123	1123
R^2	0.313	0.316	0.484	0.486
F	11	11	16	15
p	0.000	0.000	0.000	0.000

Note: Robust standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. The other characteristics are the same as in the previous models.

Our main interest lies in the analysis of rural-to-urban migrants' reward for human capital in the urban areas compared to all other individuals in urban areas, i.e. urban-urban migrants and non-migrants. Hence, including the migrant variable in the wage regression will show whether migrants experience an earnings penalty or earnings premium and whether this differs by components of human capital endowment. We neither find an average wage gap for migrants compared to non-migrants in the informal sector nor in the formal sector (see columns 2 and 4 in Table 4.5.3).[13] Interacting the rural-to-urban migrant dummy with the components of human capital endowment reveals some important information on how different rural-to-urban migrants profit from migration and whether migrating is reasonable in terms of wages. On the one hand, rural-to-urban migrants who have obtained a university degree enjoy an average wage premium of 16.1 percentage points compared to other high-educated workers. This coefficient is statistically significant at the 5% level. Interestingly, rural-to-urban migrants do not have different returns to experience than other urban workers. The coefficient is almost zero and insignificant. In the formal sector we cannot find wage gaps between rural-to-urban migrants and other urban workers.

This allows the conclusion that the high returns to experience found in the previous sections are indeed a pull factor into urban informal labour markets away from poor earnings possibilities in rural areas. Evidence on whether this has positive or negative effects on the rural population is mixed. While Boucher et al. (2005) find that internal migration increases the schooling level of the rural population through high-skill family migration networks, McKenzie and Rapoport (2011) find that (U.S.) migration leads to lower educational attendance and attainment in rural migrant households. On the other hand, it has been shown that remittances from international migrants serve as insurance against income shocks (Amuedo-Dorantes and Pozo, 2006). However, the latter two articles focus on international migration and are not necessarily valid for internal migration. Generally, the investigation of consequences of internal migration for the rural population has not received much attention in the literature so far.

[13] We also estimated several models controlling for potential selection bias in the migrant coefficient. Since no model provided evidence of such selection bias, we provide the OLS results here only.

4.6 Discussion

The findings provide evidence that rural-urban wage differentials are prevalent in Mexico and that differences exist in the decomposition of wages between formal and informal workers. Differences in all human capital related factors explain a large part of the rural-urban wage gap in the informal and formal sector. Additionally, in the informal sector, returns to experience are much lower for rural than for urban workers, even after controlling for a large number of observable characteristics. When considering that only a small part of the formal sector resides in rural areas and wages are significantly lower in rural areas, small returns to experience are definitely a push factor out of the rural and into the urban labour market, seemingly preferably and possibly easier into the informal sector when the individual is endowed with at least some years of experience. Furthermore, the results seem to explain, at least partly, the macroeconomic picture described in the introduction. If the observed wage pattern continues to exist, low returns to experience will not only act as a push factor away from rural areas and into cities but also serve as an impediment for return migration. The fact that rural-to-urban migrants do not have lower returns to experience than other workers supports this result. Furthermore, rural-to-urban migrants enjoy an average wage premium for high education. This will have further consequences for the existence of the informal sector. Assuming that formal jobs do not emerge as quickly as the rural population migrates and the social security protection system does not change, the size of the informal sector and unemployment will further increase in the cities.

Although we are able to control for a large number of personal characteristics, it is likely that unobserved person and firm characteristics explain parts of the wage differential. As has been shown by other authors, firms in the cities are more productive and, hence, pay higher wages (Glaeser and Maré, 2001; Gould, 2007). It seems plausible that work experience is only rewarded in urban firms rather than in rural firms, which is supported by our results. This will be an incentive for individuals to migrate to the cities to accumulate human capital in the form of work experience and be paid accordingly. This is also in line with the theoretical suggestion by Lucas (2004).

An explanation for low returns to experience in general could be high labour mobility which is prevalent in urban Mexico (e.g. Maloney, 1999; Gong and van Soest, 2002; Xiaodong et al., 2004). Many and fast job changes may impede a worker's

accumulation of valuable work experience and is a signal of low productivity for an employer. Although not testable with the data set at hand, it is likely that labour mobility is also high in rural Mexico. A combination of high labour mobility and low productivity in rural Mexico may be responsible for low returns to experience.

The findings give direction for policy in many respects. First, there is a need for the government to attract more firms in rural areas that value work experience or where worthy experience can be obtained to create incentives for potential migrants to stay. A few examples of foreign or international firms which settled in rural areas and enforced at least some economic and social development in the areas around the factory already exist. With the settling of a Volkswagen plant near Puebla in the 1960s, a previously poor rural area was turned into a flourishing city by improving the infrastructure and providing jobs for skilled and unskilled workers. Suppliers settled in a nearby business park, offering more and diverse employment possibilities. Waldkirch et al. (2009) provide evidence that an increase in FDI in Mexico is associated with more employment, especially in exporting and manufacturing industries. Furthermore, the presence of large inter- or multinational firms from developed countries helps to improve or at least maintain the health and safety standards, the adherence of human and labour rights and a relatively high wage level. Evidence for the latter in Mexico provide Cabral et al. (2010). Of course, there may also be examples in some countries, where the presence of foreign firms does not increase the standard of living and the freedoms of the employed workforce. However, there seems to be a tendency towards improvement of regional labour markets through the settlement of particular large firms with an international background (Spar, 1998).

Hand in hand with employment in a large firm goes an increased possibility to be registered with IMSS. The descriptive statistics show that the average number of employees in a firm that employs an informal worker is 50, while a formal worker has on average 119 co-workers. However, the attraction of large firms with an international background is not enough as a method to increase formal employment. As Levy (2008) explains, there are several incentives not to register and simply work informally. One is the high price for social security coverage which amounts to about 30% of a worker's wage in the lowest three deciles of the wage distribution. Furthermore, social security benefits have to be bought as a bundle even if the worker does not want or need all components. Other incentives are the various social protection benefits (health insurance, housing subsidies, pension schemes,

access to day care centres and life insurance) which can be bought independently and are almost free for poor workers when they are not registered with IMSS. Importantly, non-registration goes hand-in-hand with the avoidance of payroll taxes. These are reasons why the Social Security Law is violated massively, leading to a persisting large share of informal employment.[14] Hence, policies need to address the incentives to work formally, for example by changing the social insurance schemes.

Furthermore, reducing high labour turnover may enable workers to specialise and become more productive. Hence, the reasons for high labour turnover need to be addressed. Possible reasons are short legal periods of notice and severance for workers who terminate their job by choice. The labour market reforms currently discussed in Mexico should attend to these two points. Another possibility to add value to work experience would be certified on-the-job training. While on-the-job training enhances a worker's skills, it may also increase loyalty to the firm. In the literature review by Bartel (2000), a strong tendency towards high employer returns to investment in on-the-job training is shown. Loyalty towards the employing organisation is low in Mexico (Miller et al., 2001). Rather, loyalty to one's supervisor is strong (Martínez, 2003), leading to a spiral of job mobility given a worker is more likely to terminate his or her job when their supervisor leaves the firm.

4.7 Conclusion

This study investigates the differences in wages between rural and urban workers in the informal and formal sectors of Mexico's labour market. Using the novel, representative Mexican Family Life Survey (MxFLS) it has been shown that a large urban wage premium exists in Mexico and that returns to experience are small in rural areas compared to urban areas. Applying Blinder-Oaxaca Decomposition techniques and correcting for potential selection bias from sorting into formal, i.e. registered employment, it has been shown that in the informal sector the differences in returns to components of human capital endowment, such as work experience, education and cognitive ability, explain large parts of the rural-urban wage gap. Furthermore, the unexplained part is solely composed of the difference in returns to work experience between rural and urban workers. Hence, the more work expe-

[14] See Levy (2008) for a detailed description of Social Programs in Mexico and their outcomes.

rience a worker has accumulated, the higher is his monetary disadvantage when he or she works in a rural area as compared to an urban area. In the formal sector, only differences in education contribute to the explanation of the wage gap and no differences in coefficients can be identified. Furthermore, we find no difference in returns to experience for rural-to-urban migrants compared to non-migrants and even a positive wage premium for migrants with high education, supporting the results by Boucher et al. (2005).

The findings suggest that there is a large incentive for rural residents with at least some years of work experience to migrate from rural to urban areas in Mexico where they receive higher rewards for work experience. If the observed wage pattern continues to exist, the found low rural returns to experience will not only act as a push factor away from rural areas and into the big cities but also serve as an impediment for return migration. Moreover, assuming that the number of rural-to-urban migrants increases faster than formal jobs emerge, which seems realistic given the low incentives to register, unemployment, under-employment or informal employment will increase in the cities. This will lead to further economic and social problems and continuing low economic growth.

Our study shows that it is important to separate the population into different groups, especially distinguishing between rural and urban workers as their incentives and outcomes differ largely, even independently of personal endowment. To our knowledge, this is the first study for Mexico which is able to separate the Mexican workforce by formality and locality and highlights the importance of the investigation of different components of human capital endowment, especially work experience.

The results provide direction for policy. One way to counteract rural-to-urban migration would be the strategic attraction of particular large, international firms and FDI in rural areas. This improves infrastructure, creates jobs and supposedly facilitates to observe the (non-)adherence of labour rights. Furthermore, large (international) firms tend to pay relatively high wages and are more likely to register their workers with the IMSS, which in turn can reduce poverty and welfare dependency. In such firms, workers can accumulate work experience and become more productive for which they will then get paid accordingly. The settlement of such large firms and the related development could also serve as a pull factor for return migration to previously rural areas and also generate the incentive for the rural

population to stay. Finally, low returns to experience is likely to be the result of high labour turnover whose reasons – low provision of on-the-job-training, loyalty to the supervisor rather than the employing organisation, short periods of notice and severance pays – need to be addressed.

4.A Appendix

Table 4.A.1: Decomposition Overall Results

	All	Informal	Formal
Urban	2.979***	2.869***	3.134***
	(0.014)	(0.018)	(0.021)
Rural	2.626***	2.548***	2.910***
	(0.019)	(0.021)	(0.041)
Difference	0.353***	0.322***	0.224***
	(0.024)	(0.028)	(0.046)
Explained	0.248***	0.224***	0.069*
	(0.023)	(0.027)	(0.035)
Unexplained	0.105***	0.098***	0.155***
	(0.026)	(0.032)	(0.037)
N	4086	2668	1418

Note: Standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. The decomposition is formulated from the viewpoint of the rural population. For the underlying regressions see wage regression tables.

Table 4.A.2: Wage Regressions for All, Rural and Urban Informal Workers

	All				Rural		Urban	
	OLS	HM	OLS	HM	OLS	HM	OLS	HM
Urban	0.098***	0.093***	-0.054	-0.050	–	–	–	–
	(0.032)	(0.034)	(0.103)	(0.103)				
Exp*Urban	–	–	0.014**	0.014**	–	–	–	–
			(0.007)	(0.007)				
Exp sq.*Urban	–	–	-0.000*	-0.000*	–	–	–	–
			(0.000)	(0.000)				
High edu.*Urban	–	–	-0.020	-0.020	–	–	–	–
			(0.074)	(0.074)				
Raven*Urban	–	–	0.001	0.001	–	–	–	–
			(0.105)	(0.105)				
Experience	0.014***	0.017***	0.006	0.008	0.003	0.005	0.020***	0.024***
	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
Experience sqrd.	-0.000***	-0.000***	-0.000	-0.000**	-0.000	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
High education	0.179***	0.170***	0.198***	0.190***	0.159**	0.131*	0.189***	0.193***
	(0.038)	(0.037)	(0.065)	(0.066)	(0.076)	(0.077)	(0.045)	(0.045)
Raven test	0.108**	0.114**	0.106	0.111	0.091	0.100	0.112	0.117
	(0.053)	(0.055)	(0.078)	(0.081)	(0.079)	(0.081)	(0.071)	(0.075)
Hh size	-0.001	0.002	-0.001	0.002	0.005	0.007	-0.004	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.005)
Indigenous	-0.063	-0.075*	-0.063	-0.074*	-0.103*	-0.112*	-0.049	-0.070
	(0.042)	(0.044)	(0.042)	(0.044)	(0.054)	(0.058)	(0.075)	(0.072)
Female	-0.197***	-0.427***	-0.199***	-0.402**	-0.282***	-0.517**	-0.157***	-0.420**
	(0.038)	(0.164)	(0.038)	(0.164)	(0.065)	(0.256)	(0.048)	(0.198)
Hh head	0.024	0.094	0.024	0.086	0.067	0.134	0.006	0.097
	(0.032)	(0.059)	(0.032)	(0.059)	(0.049)	(0.086)	(0.042)	(0.080)
Married	0.098***	0.017	0.098***	0.026	0.050	-0.007	0.108***	-0.016
	(0.027)	(0.063)	(0.027)	(0.063)	(0.045)	(0.074)	(0.035)	(0.098)
Constant	2.077***	1.885***	2.165***	1.989***	2.659***	2.464***	1.689**	1.756**
	(0.331)	(0.360)	(0.336)	(0.365)	(0.446)	(0.516)	(0.725)	(0.683)
Hrs/year	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HDI health	0.125	-0.147	0.138	-0.104	-0.302	-0.538	0.349	-0.114
	(0.460)	(0.535)	(0.460)	(0.532)	(0.642)	(0.795)	(0.843)	(0.863)
HDI education	-0.106	-0.158	-0.103	-0.151	-0.713	-0.727	1.238	0.738
	(0.479)	(0.496)	(0.478)	(0.492)	(0.555)	(0.576)	(1.525)	(1.408)
HDI income	1.483***	1.786***	1.486***	1.756***	2.298***	2.638***	0.210	0.689
	(0.355)	(0.427)	(0.354)	(0.426)	(0.499)	(0.646)	(0.697)	(0.793)
$\lambda_{f/inf}$	–	0.287	–	0.254	–	0.229	–	0.403
		(0.200)		(0.201)		(0.244)		(0.296)
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2668	9393	2668	9393	1075	3806	1593	5587
$\bar{R}^2$	0.323		0.323		0.309		0.284	
χ^2		1329		1344		569		689
p	0.000	0.000	0.000	0.000		0.000	0.000	0.000

Note: Robust standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. OLS: Ordinary Least Squares, HM: Heckman Selection 2nd step. λ is the nonselection hazard variable generated from the probit model. 15 state dummies, 23 industry dummies and 18 occupation dummies included. λ is the nonselection hazard variable generated from the first-step probit model.

Table 4.A.3: Wage Regressions for All, Rural and Urban Formal Workers

	All				Rural		Urban	
	OLS	HM	OLS	HM	OLS	HM	OLS	HM
Urban	0.133***	0.142***	0.059	0.068	–	–	–	–
	(0.044)	(0.053)	(0.175)	(0.171)				
Exp*Urban	–	–	-0.003	-0.003	–	–	–	–
			(0.012)	(0.010)				
Exp sq.*Urban	–	–	0.000	0.000	–	–	–	–
			(0.000)	(0.000)				
High edu.*Urban	–	–	-0.001	-0.004	–	–	–	–
			(0.081)	(0.080)				
Raven*Urban	–	–	0.053	0.054	–	–	–	–
			(0.159)	(0.160)				
Experience	0.025***	0.026***	0.026**	0.027***	0.024**	0.022*	0.022***	0.023***
	(0.005)	(0.006)	(0.011)	(0.010)	(0.011)	(0.013)	(0.006)	(0.007)
Experience sqrd.	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
High education	0.303***	0.321***	0.308***	0.323***	0.248**	0.221	0.297***	0.310***
	(0.039)	(0.068)	(0.080)	(0.098)	(0.101)	(0.228)	(0.041)	(0.062)
Raven test	0.236***	0.244***	0.202	0.206	0.177	0.166	0.257***	0.264***
	(0.069)	(0.073)	(0.137)	(0.147)	(0.149)	(0.151)	(0.078)	(0.081)
Hh size	-0.004	-0.004	-0.004	-0.004	0.022***	0.022***	-0.009**	-0.009**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)	(0.004)	(0.004)
Indigenous	-0.030	-0.031	-0.026	-0.026	-0.168	-0.169	0.016	0.016
	(0.057)	(0.058)	(0.056)	(0.058)	(0.141)	(0.109)	(0.071)	(0.069)
Female	-0.049	-0.071	-0.046	-0.061	0.056	0.079	-0.073*	-0.089
	(0.040)	(0.078)	(0.040)	(0.079)	(0.083)	(0.198)	(0.044)	(0.075)
Hh head	0.064	0.076	0.068*	0.076	0.175**	0.167*	0.055	0.066
	(0.040)	(0.056)	(0.040)	(0.056)	(0.085)	(0.096)	(0.047)	(0.062)
Married	0.024	0.016	0.025	0.020	-0.028	-0.024	0.025	0.019
	(0.032)	(0.040)	(0.032)	(0.040)	(0.070)	(0.080)	(0.036)	(0.043)
Hrs/year	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	3.613***	3.447***	3.651***	3.531***	2.879***	3.004***	2.547***	2.340**
	(0.484)	(0.700)	(0.509)	(0.739)	(0.754)	(1.134)	(0.818)	(1.129)
HDI health	-0.656	-0.622	-0.647	-0.621	0.126	0.147	-1.171	-1.094
	(0.640)	(0.596)	(0.645)	(0.596)	(1.019)	(0.909)	(0.886)	(0.911)
HDI education	-0.615	-0.590	-0.591	-0.570	-0.941	-0.929	1.658	1.795
	(0.696)	(0.743)	(0.688)	(0.746)	(0.950)	(0.951)	(1.537)	(1.585)
HDI income	1.318**	1.364**	1.313**	1.345**	0.995	0.900	1.059	1.013
	(0.564)	(0.546)	(0.558)	(0.546)	(1.292)	(1.225)	(0.825)	(0.821)
$\lambda_{f/inf}$	–	0.044	–	0.030	–	-0.038	–	0.036
		(0.138)		(0.140)		(0.283)		(0.138)
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1418	9393	1418	9393	295	3806	1123	5587
$\bar{R}^2$	0.459		0.460		0.505		0.454	
χ^2		1150		1159		419		945
p		0.000		0.000		0.000	0.000	0.000

Note: Robust standard errors in parentheses. *,** and *** denote significance level of 10%, 5% and 1%, respectively. OLS: Ordinary Least Squares, HM: Heckman Selection 2nd step. λ is the nonselection hazard variable generated from the probit model. 15 state dummies, 23 industry dummies and 18 occupation dummies included.

Chapter 5

The Hidden Increase in Wage Inequality: Skill-biased and Ability-biased Technological Change

Abstract This study provides strong evidence for an increase in wage inequality induced by skill-biased technological change in the UK manufacturing industry between 1991 and 2006. Using individual level data from the BHPS and industry level data from the OECD, wage regressions are estimated which identify the effect of innovative activity on wages – the individual innovation wage premium – for university and less educated workers. Innovative activity is defined by R&D expenditure and patent applications to measure innovation input and innovation output, respectively. Using different estimation methods for panel data, such as Fixed Effects, Random Effects, Mundlak and Hausman-Taylor models, in addition to pooled OLS allows controlling for both industry-specific and individual ability. Using R&D expenditure as a measure for innovative activity additionally provides evidence for ability-biased technological change.[1]

[1] An earlier version is published as Ruhr Economic Papers No. 262 (2011). The initial idea for this chapter originates from my Bachelor thesis entitled "Innovation, Returns to Education and Skill-biased Technological Change", which I presented at the Scottish Economic Society Annual Meeting in 2009. I would like to thank Thu-Van Nguyen for superb research assistance. Many thanks for helpful comments and suggestions to John P. Haisken-DeNew, participants at the 45th Annual Conference of the Canadian Economic Association in Ottawa, 2011, and the 26th Annual Congress of the European Economic Association in Oslo, 2011.

5.1 Introduction

The wage premium for higher education has been well studied for all developed countries and various determinants have been investigated to explain the development in the past decades. The United Kingdom (UK) exhibits a different development of wage patterns as compared to other European countries where wage inequality existed but was constant over time. Similar to the U.S. and Canada the wage premium and returns to education increased dramatically in the 1970s and the 1980s (Leuven et al., 2004; Harmon and Walker, 1999; Card and DiNardo, 2002) and for many authors the driving force of this development is skill-biased technological change (SBTC) (Haskel and Slaughter, 2002; Levy and Murnane, 2006).

SBTC is the shift in the market demand from low- to high-skilled workers induced by technological progress. The increasing efficiency of high-skilled labour and the decreasing demand for low-skilled workers tend to result in higher wages for the high-skilled and decreasing or at least stagnating wages for the low-skilled. According to Bartel and Sicherman (1999), a strong relationship existed between wages and technological change in the 1980s and early 1990s in the U.S. They suggest that the education wage premium in technology-intensive industries can be associated with an increase in the demand for higher educated workers with higher ability. They conclude that ability variation within the group of higher educated workers has increased. In compliance with these findings, Galor and Moav (2000) developed a growth model in which wage inequality is induced by ability-biased technological change (ABTC) rather than skill-biased technological change. In this model, technological change is responsible for an increase in the demand for high ability. They argue that heterogeneity in skills exists not only between skill groups but also within skill groups which leads to more wage inequality.

Recent findings for the UK show stagnating average education premia. Following Silles (2007), the returns to education did not increase since the 1990s. Purcell et al. (2005) find even decreasing skill premia in the 1990s that arose from higher supply of high skilled workers, among other factors. That implies that the demand for high skilled workers was saturated by the higher supply so that premia stagnate or even decrease.

In fact, since the beginning of the 1990s, the number of university students in-

creased sharply because of at least two reasons: First, the general policy-induced expansion of the educational system and intensive economic growth which motivated young individuals to obtain higher degrees with the aim to earn higher wages in the future and second, the Further and Higher Education Act from 1992. By this Act, the polytechnics and colleges that focused on applied education and offered credentials that were lower ranked than those from standard universities were changed to 'New Universities'. Thus, the Act created a higher supply of university-educated workers.

Against this background, this study hypothesises that the increase in the supply of university graduates led to more heterogeneity in qualifications and other human capital related factors, such as ability, and that graduates with high ability sort into innovative industries in which ability is relatively higher rewarded. In other words, it tests (1) whether there is a hidden increase in wage inequality due to changes in skill and ability distributions and (2) whether technological change increased not only the demand for skills, i.e. SBTC, but moreover the demand for high ability, i.e. ABTC.

To analyse the hypotheses, this study uses the British Household Panel Survey (BHPS) for the years 1991 to 2006 and industry level data from the OECD Statistical database. Whilst using aggregate industry-level data is no novel contribution to the literature, exploiting the richness of the individual level data set of the BHPS to analyse the hypotheses is done for the first time. Rather than estimating average wage inequality over the investigation time span, this study focuses specially on the development of wage inequality in this time span. The focus on the manufacturing sector is due to data restrictions; data related to innovative activity are mostly only available and relevant for the manufacturing sector. To proxy innovative activity, two measures are used; the amount of R&D expenditure, serving as a measure of innovation input, and the number of patent applications, serving as a measure of innovation output. By estimating the individual innovation wage premium for different types of workers, both the SBTC hypothesis and the ABTC hypothesis will be tested. The SBTC hypothesis will be tested directly using time period interactions in the regression models. As previous evidence on SBTC is mixed due to different estimation strategies, data sets and underlying assumptions, this new approach will add to the existing discussion on the existence of SBTC in the UK. Employing several panel data estimation techniques, such as Random Effects, Fixed Effects, Mundlak and Hausman-Taylor models, to account

for different sources of ability-bias allows an indirect test of the ABTC hypothesis.

This analysis follows up closely the studies by Bartel and Sicherman (1999) and Taylor (2002) who investigated the 'technological change premium' in the U.S. and in Great Britain, respectively. The approach of this study is an extension in at least two respects. First, it uses additional panel estimation models which allow controlling for both individual and industry-specific ability and reduces biases in the estimated wage premia. Second, by adding time variables it is possible to investigate variations over time and hence to identify the effects of technological change more explicitly.

The main new aspect of this study is that it empirically tests, though indirectly, the ABTC hypothesis modelled by Galor and Moav (2000) which has not been done so far. Hence, this is the first study for the UK, which combines data from the BHPS and industry level data on input and output related factors of innovative activity to investigate both the SBTC and the ABTC hypotheses. The intention of the study is to shed more light on the complicated relationship between technological change and the demand for high-educated workers at times when the share of university graduates has almost doubled within 20 years and reached more than 50% of school leavers in 2006.

The results show that the graduation wage premium was high but constant (approximately 30 percentage points) during the investigated period according to all estimation methods. This is in line with previous studies for the UK. In the last period (mid 2000s), the graduation wage premium decreased in non-innovative sectors, while the individual innovation wage premium increased significantly by up to 25 percentage points. This implies that the demand for graduates was higher in innovative industries than in non-innovative industries and supports the SBTC hypothesis. The effect is found using both indicators for innovative activity. The coefficients of innovative activity measured by R&D expenditure for higher educated workers are smaller when it is controlled for industry-specific and individual ability, indicating that the coefficients are upward biased in the pooled Ordinary Least Squares (OLS) regressions and that the demand for high ability in innovative industries is considerably high. The latter is suggestive evidence for the ABTC hypothesis. However, when using patent applications as a measure of innovative activity, the ABTC hypothesis is not supported.

The findings have important implications for the future development of wage in-

equality in the UK. First, wage inequality between high- and low-educated workers is likely to increase given that demand for graduates in innovative industries increases, i.e. if SBTC continues. Second, wage inequality within the group of high-educated workers is likely to further increase if the number of graduates further increases. A higher number of graduates increases heterogeneity among graduates and reduces the signal of high ability previously implied by a university degree.

The paper is organised as follows. The next section (5.2) presents the recent literature on SBTC and ABTC. Section 5.3 elaborates theoretically the role of innovative activity in the determination of wages and wage differentials. Section 5.4 explains the estimation methods and the data are described in Section 5.5. The main empirical results and implications are presented and discussed in Section 5.6. Finally, Section 5.7 concludes.

5.2 Literature Review

Whilst the literature on SBTC is large and characterised by an ambiguity about the existence and the measurement of SBTC, the strand of the literature that is concerned with ABTC is rather small, at least because of the complication of measuring the effect of ability on wages. In the following, the literature on SBTC will be summarised and the most influential findings will be discussed. Subsequently, studies concerned with ABTC will be reviewed to setup the framework for the study at hand[2].

In the late 1970s and 1980s, there was the so-called computer revolution in the UK that changed long-run patterns of income distribution. Wages for high-skilled workers increased and wages for low-skilled workers decreased. Many authors have found these wage premia primarily in innovative industries or firms which exhibit high levels of technological change (Katz and Murphy, 1992; Autor et al., 1998; Haskel and Slaughter, 2002; Levy and Murnane, 2006). Innovative industries are characterised by technological progress, the use of specific IT equipment, the implementation of R&D and a high number of patent applications. In consequence, highly qualified workers are needed to meet the high demand. Highly educated workers are known to have a comparative advantage with respect to the adoption and the implication of new technologies (Bartel and Lichtenberg, 1987).

[2]Note that the terms 'technological change' and 'innovation' will be used interchangeably.

Evidence for SBTC has been found in the 1970s and 1980s. Numerous micro- and macroeconomic studies document the statistical correlation of using new technology and the shift in the share of high-skilled employment (e.g., Bartel and Lichtenberg, 1987) on the one hand and the income distribution (e.g., Autor et al., 1998) on the other hand. Economic theory and evidence of SBTC is provided by Acemoglu (2002) who models endogenous SBTC, Aghion (2002) who proves Schumpeterian growth theory in relation to wage inequality and Katz and Murphy (1992) who examine the effect of SBTC on wage differentials in 1992 for the U.S., taking the fluctuating supply of college graduates between 1963 and 1987 into consideration.

Another study that analyses wage differentials and SBTC is Corsini (2008), who estimates a Fixed Effects model for European countries using (among others) the BHPS of the 1990s and the beginning of the 2000s but does not look at changes over time. In the first part of the paper, Corsini (2008) investigates the correlation between SBTC and wage differentials between high- and low-skilled workers. He measures the intensity of technological change by R&D expenditure relative to national GDP and states that SBTC is the driving force of the wage differentials. His interpretation of the result is that skilled workers are more able to adapt to changes in technology and have advantages in periods of intensive technological progress.

Taylor (2002) uses individual-level data from the General Household Survey in Britain for the years 1973 to 1994 and shows that technological change has an increasing effect on the returns to education and occupation at higher levels of the education and occupation distributions. The results from a pseudo panel approach are highly different to the OLS results. This is because it can be controlled for fixed cohort effects in this pseudo panel method, however it does not allow controlling for individual ability. Though, individual ability may be the driving force of an increasing wage differential between high- and low-educated workers. Additionally to the advantage of having actual individual panel data, the analysis provided here uses data of a more recent time period in which wage inequality has been apparently declining (Purcell et al., 2005; Silles, 2007).

Card and DiNardo (2002) provide evidence for the college versus high school wage gap in the U.S. in the 1980s and 1990s in reference to SBTC. They argue that the rise in wage inequality was an episodic event in the U.S. A recent study by

Marquis et al. (2011) tries to shed light on the causes of wage inequality in the U.S. in a vintage capital model. In this model, it can be shown how technological change affects labour demand. The authors report that technological transition accounts for only 5% of the observed increase in wage inequality in the U.S. They speculate that factors such as lack of job-related training at the low end of the skill distribution and increased human capital at the high end are more important in the determination of shifts in the skill distribution than technological change.

Whilst wage inequality was high in the 1980s in the UK (Machin, 1996, 1998), recent findings suggest a decline in the wage premium (Silles, 2007; Purcell et al., 2005; O'Leary and Sloane, 2011). Silles (2007) estimates the returns to education for men and women using data from the British General Household Survey for the years 1985 to 2003. She computes the returns to years of education using OLS regression and finds that the returns for men increased slightly over the investigated period and the returns for women even declined.[3] Purcell et al. (2005) find that the skill premium declined in England. They investigate the education-wage relationship for two graduate cohorts (1995 and 1999) and suggest that the increasing amount of high educated graduates since the 1990s is partly responsible for this development[4].

Taber (2001) argues that high college premia in the US in the 1980s are upward biased due to unobserved ability and that the demand for high-ability workers has been increasing. Bartel and Sicherman (1999) argue that high-ability high-educated workers sort into industries which are characterised by a high level of technological change. They investigate the education wage premium using individual level data for the U.S. and merge it with industry level data on technological change.

The literature on ABTC is rather scarce but builds on the insights given by studies

[3]Detailed studies of returns to education are provided for example by Harmon and Walker (1999), Harmon and Oosterbeek (2000), Card (1999) and Leuven et al. (2004).

[4]The main reasons for the increasing number of graduates in the UK are the following. The Labour Party's target of getting 50% of young people into Further and Higher Education is a long-lasting education policy and has led to a large-scale expansion of the educational system in the UK. Moreover, the Further and Higher Education Act from 1992 changed the polytechnics and colleges, which focused on applied education as a preparation for work and offered credentials that were lower ranked than those from standard universities, to 'New Universities'. A further reason is the intensive economic growth which motivated young individuals to obtain higher degrees with the aim to earn higher wages in the future. These factors created a larger supply of university educated workers which is likely to have led to more heterogeneity in qualifications and other human capital related factors, such as ability, among graduates.

on SBTC. It has to be taken into consideration that with an increasing number of graduates the share of highly able individuals is unlikely to proportionally increase as well, or in other words, more less able individuals obtain a university degree than in earlier years. This raises the question whether wage inequality within graduates exists. Galor and Moav (2000) proposed an economic growth model which suggests that wage inequality exists both between skill groups and within skill groups due to higher variation in ability within the groups of high-educated workers. They suggest that technological change increases the returns to ability and thereby accelerates wage inequality. Andersson et al. (2009) and Stern (2004) explicitly look at the wage premium for scientists. They argue that the relationship between wages and science is characterised by an ability bias and that innovative sectors pay relatively more for high ability. Unfortunately, the BHPS does not provide a measure of ability, which makes the direct test of within-group heterogeneity in wage premia impossible. Instead, the study provides an indirect test via the different econometric models which account for various sources of unobserved heterogeneity.

Finally, the measurement of SBTC and especially ABTC is hampered by the limited availability of appropriate data. Most studies are based on firm or industry data (Bratti and Matteucci, 2005; Haskel and Slaughter, 2002; Dunne et al., 2004; Corsini, 2008) which lack individual worker characteristics. Only few studies such as Bartel and Sicherman (1999), Stern (2004) and Andersson et al. (2009) are based on individual panel data. Similar to Bartel and Sicherman (1999) this study uses individual panel data and merges industry level data to control for individual, workplace and industry characteristics.

5.3 Theoretical Background

In presenting the theoretical background of the determination of wages, a formulation similar to that of Griliches (1979) and Taber (2001) is used. A simple version of the wage equation without subscripts can be written as

$$w = \beta Edu + \mu_1 \theta_1 + \epsilon \tag{5.1}$$

where w is the wage rate, Edu is the level of education which can either be high ($Edu = hedu$) or low ($Edu = ledu$). The term θ_1 represents an unobserved effect which determines the wage rate and the level of education simultaneously, i.e. edu-

cation is endogenous. θ_1 is a place holder for all kinds of unobserved characteristics, such as innate ability, managerial skills, ambition or assertiveness. The literature on returns to education is mainly concerned with unobserved ability which is correlated with both the wage rate and the obtained educational level. It is assumed that more able individuals are more likely to obtain higher degrees (Card, 1999). In the following, θ_1 is named individual ability, but it is left to the interpretation of the reader whether the effect is indeed ability or other related unobservable characteristics that are correlated with both education and the wage rate.

The commonly found wage differential between graduates and lower educated workers is defined by

$$\begin{aligned} & E\left[w|Edu = hedu\right] - E\left[w|Edu = ledu\right] \\ & = \beta hedu - \beta ledu + \mu_1 \left(E\left[\theta_1|Edu = hedu\right] - E\left[\theta_1|Edu = ledu\right]\right), \end{aligned} \tag{5.2}$$

i.e. the differential can be decomposed into the difference in returns to education ($\beta hedu - \beta ledu$) and the difference in the returns to ability with the induced ability bias $\mu_1 \left(E\left[\theta_1|Edu = hedu\right] - E\left[\theta_1|Edu = ledu\right]\right)$. Hence, an increase in the wage differential is the effect of (a) an increase in the return to education, (b) an increase in the return to unobserved individual ability or (c) an increase in the ability differential between graduates and lower educated workers.

A large strand of the literature has found particularly high wage differentials between workers of different educational or skill levels in firms or industries which exhibit certain features such as large firm size, multinationality or technological change [5]Bartel and Sicherman (1999) suggest that technological change induces greater wage differences between high and low skilled workers. Most of these attributes such as technological change are indicators for the extent of innovative activity of a firm or industry. To account for differences in innovative activity among the industries in which the individuals are employed, a continuous variable $Inn = inn_1, inn_2, ..., inn_\infty$ is added to the above model. Furthermore, it is assumed

[5]For example, Schmidt and Zimmermann (1991) provide evidence for a positive firm size-wage relationship. Girma et al. (2001) and Taylor and Driffield (2005) show that foreign direct investment increases wage inequality. Borjas and Ramey (1995) show that rising wage inequality can be explained by trade intensity.

that unobservable industry-specific ability[6], denoted θ_2, exists. By including these terms, Eq. (5.1) expands to:

$$w = \beta Edu + \gamma Inn + \mu_1\theta_1 + \mu_2\theta_2 + \epsilon. \tag{5.3}$$

This equation includes the wage differential between different educational levels, different levels of ability and the ability bias as in Eq. (5.2), and the wage differential between different rates of innovative activity (e.g. $\gamma inn_1 - \gamma inn_2$), the wage differential between differences in returns to industry-specific ability and the industry-specific ability bias:

$$\begin{aligned} &E\left[w|Inn = inn_1\right] - E\left[w|Inn = inn_2\right] \\ &= \gamma inn_1 - \gamma inn_2 + \mu_2 \left(E\left[\theta_2|Inn = inn_1\right] - E\left[\theta_2|Inn = inn_2\right]\right). \end{aligned} \tag{5.4}$$

The unobservable industry-specific effect is by assumption a typical Random Effect that is uncorrelated with the other explanatory variables (as in Bartel and Sicherman, 1999).[7] This industry-specific ability could for example be some kind of visual creativity required in the software industry. With this expansion, an increase in the wage differential can be due to the effects of (a), (b), or (c) explained above, or (d) an increase in the return to innovative activity, (e) an increase in the return to unobserved industry-specific ability or (f) an increase in the industry-specific ability differential between innovative and non-innovative industries.

Certain jobs require certain skills and abilities. Jobs which are related to innovative activity are likely to require certain skills, such as logical thinking and mathematical knowledge, which allow the possessor the adoption and invention of new technology. A few studies have suggested that positive wage effects of innovative activity are attributed to higher education and advanced skills because high-educated workers are more able to adapt to new technology more quickly than low-educated workers (Bartel and Sicherman, 1999; Andersson et al., 2009; Stern, 2004). To take account of this, a variable is introduced which measures the effect of innovative activity conditional on a high level of education. A third unobservable

[6]Industry-specific ability can here also be any kind of unobserved heterogeneity at the industry level which is correlated with wages and innovative activity.

[7]Note that this assumption is necessary for the application of a GLS model.

effect is then likely to determine the wage rate which is "innovation ability" θ_3, being correlated with wages, innovative activity and education. Eq. (5.3) becomes:

$$w = \beta Edu + \gamma Inn + \delta(Inn|Edu = hedu) + \mu_1\theta_1 + \mu_2\theta_2 + \mu_3\theta_3 + \epsilon. \qquad (5.5)$$

Innovation ability is assumed to be the ability to invent, develop or adopt a new product which is more likely to be innate in high-educated workers than in low-educated workers. This does not imply that low-education workers cannot have good ideas for a new product or the improvement of an existing product. Rather, the implementation is more likely to be pursued by a higher ranked, normally higher educated, co-worker who consequently receives the wage gain from the original idea. The equation implies that the group of university graduates is differentiable into those with higher ability and those with lower ability. An increase in the wage differential between high- and low-educated workers can now be due to the concepts (a) to (f), or (g) an increase in the return to high education attributed to innovative activity δ, (h) an increase in the return to innovation ability μ_3 or (i) an increase in the innovation ability bias. If the wage differential between graduates and lower educated workers is increasing over time and is correlated with innovative activity, this suggests that SBTC exists. Furthermore, if there is an (additional) increasing premium for workers with high ability associated with innovative activity, this implies that ABTC is present. The investigation of these hypotheses requires the investigation of wage patterns over time. This is done by adding time variables T_t to Eq. (5.3) and Eq. (5.5). The next section explains this procedure in more detail and describes the estimation methods used.

5.4 Estimation Methods

The static relationship between innovative activity of the employing industry and individual wages can be estimated as formulated in Eq. (5.3). Adding subscripts for individual i, working in industry j at time t, and additional individual control variables, such as socio-economic and workplace characteristics summarised in X, and an overall constant α, Eq. (5.3) becomes

$$w_{ijt} = \alpha_{ij} + \beta Edu_i + \gamma Inn_{jt} + \lambda X_{ijt} + \theta_{1i} + \theta_{2j} + \epsilon_{ijt}, \qquad (5.6)$$

with θ_1 and θ_2 being time-invariant and λ representing the coefficient vector of X. Accordingly, Eq. (5.5) becomes

$$w_{ijt} = \alpha_{ijt} + \beta Edu_i + \gamma Inn_{jt} + \lambda X_{ijt} + \delta(Edu \times Inn)_{ijt} + \theta_{1i} + \theta_{2j} + \theta_{3ij} + \epsilon_{ijt}, \quad (5.7)$$

where θ_3 is also time-invariant. Estimating the equations using pooled OLS will result in efficient but biased estimates. In particular, the coefficient on the education variable (β) will be upward biased because it is endogenous, as it is correlated with unobservable individual ability θ_1. Moreover, the coefficient on the interaction term between innovative activity and education will be upward biased due to endogeneity, as it is correlated with unobservable innovation ability θ_3. The solution to this kind of bias would be the estimation of a Fixed Effects (FE) model in which all variables are time-demeaned. By time-demeaning, the unobserved time-invariant effects, such as ability, drop out of the regression equation and the estimation gives unbiased results of the endogenous regressors. However, the variable on education also drops out because it is time-invariant by definition.[8] Since education is the main variable of interest, other methods than FE transformation are necessary when the static relationship is estimated.

A method that avoids the bias which results from industry-specific ability θ_2 is the Random Effects (RE) model. Under the estimation of a Random Effects model the individual specific effects are assumed to be i.i.d. Here, θ_2 is assumed to possess these properties. The coefficients in the Random Effects model are estimated via Generalised Least Squares (GLS) and are consistent and efficient given the correlation between the individual effects and the explanatory variables imply no correlation between the explanatory variables and the error term. As pointed out before, θ_1 and θ_3 are correlated with the explanatory variables *Edu* and the interaction term. This induces correlation between the error term and these regressors. Hence, the RE model can solve the problem of industry-specific ability bias but cannot account for the other ability-biases. Furthermore, a Hausman test suggests that a FE model is appropriate.

One solution is the method proposed by Mundlak (1978). He proposed to estimate a RE model which allows for correlation between the explanatory variables and

[8] All individuals who obtained a university degree after or while having worked in the manufacturing industry are deleted from the sample.

the individual unobserved heterogeneity where the individual effects are a linear combination of the time averages of all the explanatory variables such that

$$\theta_{1i} = \pi_1 \bar{X}_{ij} + u_{1i} \tag{5.8}$$

and

$$\theta_{3ij} = \pi_3 \bar{X}_{ij} + u_{3ij} \tag{5.9}$$

where $\bar{X}$ is a vector of all time-demeaned explanatory variables and u is the i.i.d. disturbance term. Practically, this means estimating Eq. (5.6) and Eq. (5.7) including $\pi_1 \bar{X}_{ij}$ and $\pi_3 \bar{X}_{ij}$. The Mundlak model, essentially being a Fixed Effects model, also accounts for unobserved industry-specific effects because it uses the GLS estimator. Estimators which are unbiased, consistent and more efficient than the OLS and RE estimates are derived.

Another possibility to account for individual correlated effects in panel data is the approach proposed by Hausman and Taylor (1981). The Hausman-Taylor (HT) model is an instrumental variable model with the advantage that it does not require model-external instruments. These are usually difficult to find because they underlie strong assumptions. The model is identified as long as there are at least as many time-varying exogenous regressors as time-invariant endogenous regressors. It is based on the RE transformation, i.e. the HT instrumental variable estimator is a GLS estimator. As mentioned before, the GLS estimator is consistent and efficient if all regressors are uncorrelated with the idiosyncratic error term ν and only a subset of regressors is correlated with the unobservable fixed effects (Cameron and Trivedi, 2005). The HT approach usually leads to very high coefficients of education variables. Hence, the interpretation on the education coefficients will be made carefully, if at all.

Furthermore, this study is less concerned with the level of wage differentials but more with the development of wage differentials. To allow the coefficients to vary over time, time period dummy variables are included in the models and multiplied with the education variable, the variable which measures innovative activity and the interaction term of both. This step enables to explicitly test the SBTC hypothesis. If the wage differential between graduates and lower educated workers has increased over time and if the differential is associated with higher levels of

innovative activity, i.e. if there is an individual innovation wage premium, this suggests that SBTC was prevalent. Moreover, if the coefficients resulting from the models in which it is possible to account for individual time-invariant unobserved effects are lower than the coefficients from models where the coefficients on education are likely to be upward-biased, this indicates that ability is driving the large wage premia for graduates in innovative industries. This suggests that there is a sorting of highly educated and highly able individuals into innovative industries which would support the ABTC hypothesis.

Since industry information is an aggregate measure and is added to the individual data, conventional standard errors may be downward biased due to common disturbances within industries (Moulton, 1990). Hence, standard errors are clustered by industry-time, allowing for 128 clusters.[9]

5.5 Data

This study uses the first 16 waves of the British Household Panel Survey (BHPS) from 1991 to 2006. The BHPS is a nationally representative random sample of about 5,500 British households, containing approximately 10,000 interviewed individuals. The survey provides a rich source of socio-economic information on the household and individual level (Taylor et al., 2007). For the presented investigation it contains the necessary data on educational attainment of individuals, their income and the industry affiliation of their job classified at the national Standard Industrial Classification (SIC 80/SIC 92), as well as a large number of social, economic and job characteristics. The investigation is restricted to the manufacturing industry as data that relates to innovative activity is mainly available for the manufacturing sector and is also mostly reasonable in this sector.

Industry level data, i.e. the amount of R&D expenditure, the number of patent applications and the value of production output, is extracted from the OECD StatsExtract website[10], where industries are classified at the International Standard Industrial Classification (ISIC 2 and 3.1). All four classifications are standardised to one classification which resulted in 8 two-digit industries (see Table 5.A.2 in the Appendix). The remaining manufacturing industries are (1) Food, Beverages and

[9] Only in the Hausman-Taylor model standard errors are not clustered.
[10] http://stats.oecd.org/index.aspx

Tobacco, (2) Textiles and Leather, (3) Wood, Paper, Publishing, (4) Chemicals, Coal, Plastics, (5) Non-metallic Minerals, (6) Basic Metals, (7) Machinery and Equipment and (8) Other Manufacturing industries. The information on patent applications, based on the International Patent Classification (IPC), has also been made consistent with the developed classification. Production output, patent applications and the amount of R&D expenditure per industry are divided by the number of employees in the respective industry, i.e. the industry levels of the indicator variables are per employee values. All monetary indicators are deflated using the consumer price index to the base year 1991. The industries which spend large sums on R&D are the chemicals, coal, petroleum and plastics manufacturing industries and the 'other' industries which include the manufacturing of electrical equipment. The former is also active in patent applications, headed by the manufacture of fabricated metal products, machinery and equipment (see Figure 5.A.1).

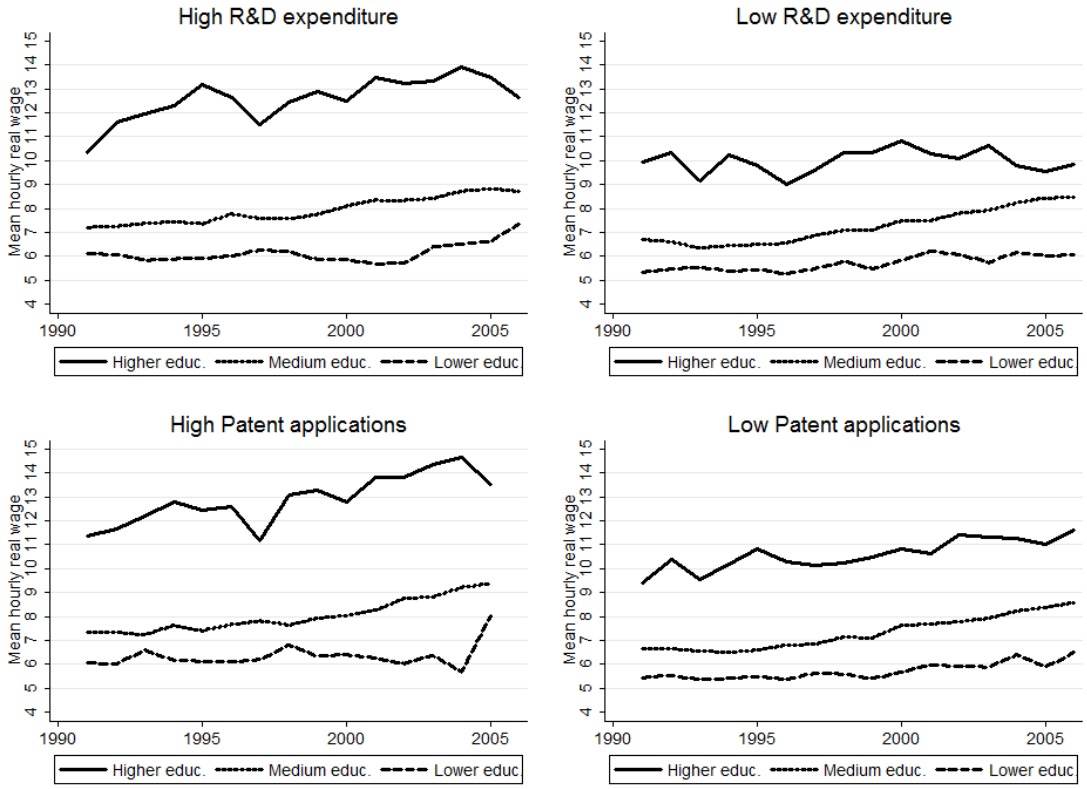
The sample used[11] is an unbalanced panel of male and female workers aged 20 to 64. Only individuals that are salaried in the private sector and are not self-employed are included. The final sample contains about 14,000 person-year observations over 16 years.

The dependent variable is log real hourly wage. It is calculated using usual gross pay per month (a derived variable that measures usual monthly wage or salary payment before tax and other deductions in the current main job) divided by usual standard weekly hours. Graduates are defined as individuals who obtained a university degree. Tenure is measured in years, children counts the number of children in the household and health status is self-assessed.

Figure 5.5.1 shows the development of average wages in industries which are innovative, meaning they have a high level of R&D expenditure and a high level of patent applications, respectively. A high level of a certain activity means that the activity is greater than the mean of the whole manufacturing sector. It can be seen that mean wages are higher if the level of innovative activity is high irrespective of the indicator used.

[11] The data used were extracted using the Add-On package PanelWhiz v2.0 (Nov 2007) for Stata. PanelWhiz was written by Dr. John P. Haisken-DeNew (john@panelwhiz.eu). The PanelWhiz generated DO file to retrieve the BHPS data used here and any PanelWhiz plugins are available upon request. Any data or computational errors in this paper are my own. Haisken-DeNew and Hahn (2006) describe PanelWhiz in detail.

Figure 5.5.1: Wages by Education and Innovative Activity over Time



Source: Own calculations based on BHPS and OECD data.
Notes: High R&D expenditure includes those industries which spend more than average on R&D and low R&D expenditure includes those industries which spend less than average on R&D. High Patent applications includes those industries which apply more than average for patents and low Patent applications includes those industries which apply less than average for patents.

Descriptive statistics on the independent variables can be found in Table 5.5.1 for all time periods separately. The time periods are $t_1 = 1991-1994$, $t_2 = 1995-1998$, $t_3 = 1999-2002$ and $t_4 = 2003-2006$ ($t_4' = 2003-2005$ in the case of patents as there is currently no more recent data available). The amounts of R&D expenditure per employee and the value of production output per employee have increased over the investigated period. Solely the amount of patent applications per employee has decreased in the last period after it had increased significantly beforehand. 18 Regional dummies are included since it has been shown that relative wages and industry structure vary considerably across regions in the UK (Bernard et al., 2008). Other characteristics do not change largely over time.

Table 5.5.1: Descriptive Statistics

	1991-1994		1995-1998		1999-2002		2003-2005	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Industry characteristics								
R&D expenditure	0.17	(0.18)	0.18	(0.18)	0.22	(0.23)	0.25	(0.26)
Patents	0.08	(0.10)	0.09	(0.12)	0.12	(0.17)	0.11	(0.17)
Production	7.89	(2.52)	8.83	(2.33)	9.15	(2.25)	10.68	(2.66)
Job characteristics								
Hourly wage	6.96	(3.35)	7.29	(3.57)	7.86	(3.58)	8.60	(3.76)
Tenure	10.06	(11.27)	9.24	(11.12)	9.80	(11.57)	10.63	(11.86)
1-24 employees	0.16	(0.37)	0.18	(0.38)	0.19	(0.39)	0.20	(0.40)
25-99 employees	0.22	(0.41)	0.23	(0.42)	0.24	(0.43)	0.22	(0.42)
99- employees	0.62	(0.49)	0.59	(0.49)	0.57	(0.49)	0.58	(0.49)
Union member	0.15	(0.36)	0.27	(0.44)	0.28	(0.45)	0.26	(0.44)
Personal characteristics								
High education	0.09	(0.29)	0.10	(0.30)	0.09	(0.28)	0.11	(0.32)
Medium Education	0.71	(0.45)	0.75	(0.43)	0.78	(0.42)	0.79	(0.41)
Low Education	0.20	(0.40)	0.15	(0.36)	0.13	(0.34)	0.10	(0.30)
Age 20-29	0.27	(0.45)	0.28	(0.45)	0.24	(0.43)	0.21	(0.41)
Age 30-39	0.28	(0.45)	0.29	(0.45)	0.30	(0.46)	0.26	(0.44)
Age 30-49	0.27	(0.44)	0.24	(0.43)	0.26	(0.44)	0.30	(0.46)
Age 50-64	0.18	(0.39)	0.18	(0.39)	0.19	(0.40)	0.23	(0.42)
Married	0.65	(0.48)	0.58	(0.49)	0.60	(0.49)	0.60	(0.49)
Children	0.38	(0.48)	0.36	(0.48)	0.40	(0.49)	0.37	(0.48)
Health status	1.96	(0.81)	2.00	(0.82)	2.10	(0.86)	2.03	(0.80)
N	3471		3435		4412		2246	
$\sum$N	13564							

Note: Author's calculations based on BHPS and OECD data. The sum of all observations including the year 2006 (excluding patent information) is 14247.

5.6 Results

5.6.1 Levels

The results are presented in two different tables, one for each of the innovation indicators, including the OLS, Random Effects, Mundlak and Hausman-Taylor model results. Separate tables for the Fixed Effects results are presented and discussed below as they are not directly comparable with the other estimation results. Starting with the impact of R&D investments per employee in levels, Table 5.6.1 shows the effect of R&D expenditure on wages for graduates and lower educated workers combined and then separately when the interaction term of R&D expenditure and the education variable is included. In all regressions, the indicator variables measure the semi-elasticity between log wages and level of innovative activity.

According to the OLS results, having a university degree is rewarded with an average wage premium of 20.5 percentage points which is statistically significant at

Table 5.6.1: Pooled OLS and Panel Regressions with R&D Expenditure

	OLS		Random Effects		Mundlak		Hausman-Taylor	
Higher Education	0.205***	0.132***	0.321***	0.274***	0.151***	0.131***	0.634***	0.572***
	(0.020)	(0.029)	(0.025)	(0.038)	(0.024)	(0.039)	(0.113)	(0.114)
R&D exp.	0.199***	0.172***	0.144***	0.127***	0.083***	0.067**	0.104***	0.086***
	(0.055)	(0.055)	(0.035)	(0.036)	(0.027)	(0.027)	(0.018)	(0.019)
HE×R&D exp	–	0.269***	–	0.180***	–	0.199**	–	0.208***
		(0.063)		(0.063)		(0.079)		(0.050)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14247	14247	14247	14247	14247	14247	14247	14247
R^2	0.455	0.457	0.408	0.410	0.488	0.489	–	–
Chi^2	–	–	3300	3370	3431	3482	4155	4179

Note: Standard errors in parentheses. Standard errors are clustered by industry-years. *,** and *** denote significance level of 10%, 5% and 1%, respectively. 18 regional dummies, 9 occupational and 15 year dummies included. Charcatersitics include production output by industry, a female dummy, tenure and tenure squared, two firmsize dummies, a dummy for union membership, a dummy for being married, having kids, self-rated health and three age dummies.

the 1% level. The graduation premium is higher when controlling for unobserved industry-specific effects: the Random Effects model estimates a premium of 32 percentage points. In the Mundlak model the premium is 15 percentage points and in the Hausman-Taylor model 63 percentage points. A much higher premium resulting from the Hausman-Taylor model has been found as well by Hausman and Taylor (1981) and should be interpreted with caution. The coefficient of R&D expenditure is 0.199 in the OLS regression model, 0.144 in the Random Effects model, 0.083 in the Mundlak model and 0.104 in the Hausman-Taylor model. A coefficient of 0.199 implies that an increase in R&D expenditure per employee per year in average industries by 10,000 GBP leads to an increase of the average wage of all workers by 19.9 percentage points. Seeing that the whole manufacturing sector spend on average 2,060 GBP per employee per year on R&D between 1991 and 2006, this impact is economically significant. The decrease in the coefficient from 19.9 to 14.4 when controlling for industry-specific heterogeneity shows that the coefficient estimating the return to additional R&D spending is upward biased. The impact is even more reduced when controlling also for individual ability. This implies that unobserved heterogeneity at both the individual and industry level and correlated with both wages and R&D expenditure is present. When comparing the OLS results with the RE results, it can be seen that industry-specific heterogeneity leads to a downward bias of the Higher Education coefficient. This industry-specific heterogeneity may be the different distributions of degree types among the high-educated workers employed in the industry. For example, the share of Masters or

PhD graduates is higher in the Chemical, Coal and Plastics industry (3.2% of the sample) than in the Machinery and Equipment industry (1.9% of the sample), as engineers more often only obtain a Bachelor degree whilst many chemists and biologists obtain a PhD[12].

When the interaction term between R&D expenditure and Higher Education is included, the base R&D expenditure regressor, which now measures only the effect of R&D expenditure on low-educated workers' wages, drops by about 2 percentage points in all estimation models. The base education coefficient drops even more in all models. The interaction term measures the effect of an increase in R&D expenditure for graduates only and thus estimates the wage premium differential for additional R&D expenditure between graduates and lower educated workers – the individual innovation wage premium. It is 26.9 percentage points according to the OLS models, 18 percentage points in the Random Effects model, and 19.9 percentage points and 20.8 percentage points in the Mundlak and Hausman-Taylor models, respectively. The results suggest that graduates profit much more from additional R&D expenditure than low-educated workers. Furthermore, controlling for industry-specific ability and individual-specific ability lowers the interaction term by about 7 percentage points and raises the graduation coefficient significantly. This suggests that OLS results for the effect of R&D expenditure for graduated workers are upward biased due to ability, implying a high demand of high-ability high-educated workers in industries which are R&D intensive.

As Bartel and Sicherman (1999) mention, R&D expenditure is an input related factor for technological change, while the indicator for patent use is an output related factor. In their study, they find a higher impact of input related factors of technological change on wages than of output related factors. The here used output related measure is the amount of patent applications per employee by industry. A measure of patent applications as compared to patent use is a more precise measure of innovative activity because it covers inventions of a new product or process rather than the grants of patents only. Several problems arise when using patent application data, though. First, the use of patents and its correlation with innovative activity is highly heterogeneous across industries (Malerba and Orsenigo, 1999). Second, patents possess highly different economic values, and third,

[12]Due to small number of observations it is not possible to further differentiate First and Higher degrees in the models.

there might be a time lag between patent application and the actual invention, which implies that the innovative activity measured with patent applications at time t has been achieved before t. However, although not a perfect measure of innovation intensity, the indicator at least proxies innovation output and can, in the present study, at least be used as a robustness check. Indeed, the correlation coefficient between R&D and patent applications is rather small (18.9%) but significant (Table 5.A.1). All regression equations include production output as an additional regressor. Production output proxies average firm size and related industry characteristics.

Table 5.6.2: Pooled OLS and Panel Regressions with Patent Applications

	OLS		Random Effects		Mundlak		Hausman-Taylor	
Higher Education	0.213***	0.191***	0.326***	0.301***	0.160***	0.144***	0.692***	0.658***
	(0.019)	(0.028)	(0.023)	(0.027)	(0.023)	(0.032)	(0.125)	(0.125)
Patents	0.232***	0.214***	0.129***	0.109***	0.100***	0.078**	0.106***	0.084***
	(0.050)	(0.050)	(0.040)	(0.041)	(0.028)	(0.031)	(0.019)	(0.020)
HE×Patents	–	0.182	–	0.224**	–	0.259**	–	0.262***
		(0.121)		(0.100)		(0.113)		(0.065)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13564	13564	13564	13564	13564	13564	13564	13564
R^2	0.454	0.454	0.406	0.406	0.487	0.487	–	–
Chi^2	–	–	3102	3148	3135	3176	3732	3754

Note: Standard errors in parentheses. Standard errors are clustered by industry-years. *,** and *** denote significance level of 10%, 5% and 1%, respectively. 18 regional dummies, 9 occupational and 15 year dummies included. Charcatersitics include production output by industry, a female dummy, tenure and tenure squared, two firmsize dummies, a dummy for union membership, a dummy for being married, having kids, self-rated health and three age dummies.

The effect of patent applications on wages in levels is documented in Table 5.6.2. When the interaction term is not included the coefficients are very similar to the R&D results. The premium for being a HE graduate is almost exactly the same as in the table above. The coefficient for patent applications is 0.232 according to the pooled OLS regression. This means that an increase in patent applications by 1 per 100 employees per year increases the average hourly wage by 23.2 percentage points. In other words, applying for one more patent per year increases a worker's wage on average by 0.23 percentage points. This is also an economically relevant effect, as the manufacturing sector applied for approximately 1 patent per year per 1000 employees between 1991 and 2005. The inclusion of the interaction term of patent applications and Higher Education also changes the coefficients of the base regressors in a similar way as the inclusion of the R&D expenditure interaction term does. The coefficients of the interaction terms are large and statistically sig-

nificant. However, the coefficient of the interaction term itself is higher (between 0.22 and 0.26) when controlling for individual and/or industry-specific unobserved heterogeneity, than in the OLS regression (0.18) where it is even statistically insignificant. This implies that the application of patents is negatively correlated with ability. Whilst the coefficient can still be interpreted as evidence for a high demand for HE graduates, it strongly rejects the hypothesis that a specifically high demand for high-ability HE graduates exists. Bartel and Sicherman (1999) find similar effects with regard to the differentiation between innovation input and innovation output related measures, i.e. the correlation between higher wages and higher innovative activity is high when using input related measures of innovation and relatively low when using output related measures of innovation. This already indicates that patent applications are a poor measure of innovative activity at the two-digit industry level and the results using this indicator need to be interpreted with caution.

5.6.2 Changes over Time

The previous results show that there is a significant and large individual innovation wage premium for all workers pooled over the period 1991-2006. The intention of this study is to analyse the development of the individual innovation premium to allow inference to be made about skill-biased and ability-biased technological change. Therefore, time period dummies are included in the regressions and multiplied by the innovation indicators, the education variable and the interaction term of these variables.

Table 5.6.3 displays the estimated coefficients from the models that include R&D expenditure s an indicator for innovation. The OLS results without the interaction terms suggest that the average graduation premium is constant over time with a small drop towards the end of the investigated period from about 20-22 percentage points before 2003 to 18 percentage points on average for the period 2003-2006. This is in line with the recent findings on stagnating skill premia in the UK (Purcell et al., 2005; Silles, 2007).

The return to additional R&D expenditure is on average about 26 percentage points in the first period (1991-1994) according to the OLS regression results. This return decreases over time and reaches the lowest average return of about 13 percentage points in 2003-2006 where the coefficient is statistically significant only

Table 5.6.3: Regressions Including Time Interactions with R&D Expenditure

	OLS		Random Effects		Mundlak		Hausman-Taylor	
Higher Education								
1991-1994	0.214***	0.153**	0.289***	0.295***	0.116***	0.114**	0.744***	0.747***
	(0.034)	(0.063)	(0.029)	(0.053)	(0.030)	(0.046)	(0.124)	(0.124)
1995-1998	0.205***	0.127***	0.278***	0.270***	0.105***	0.089**	0.738***	0.733***
	(0.041)	(0.043)	(0.024)	(0.035)	(0.028)	(0.040)	(0.123)	(0.123)
1999-2002	0.222***	0.162**	0.356***	0.341***	0.193***	0.173***	0.843***	0.836***
	(0.037)	(0.059)	(0.024)	(0.040)	(0.025)	(0.036)	(0.123)	(0.123)
2003-2006	0.180**	0.050	0.358***	0.268***	0.192***	0.105*	0.852***	0.772***
	(0.065)	(0.080)	(0.048)	(0.065)	(0.051)	(0.063)	(0.123)	(0.124)
R&D expenditure								
1991-1994	0.261**	0.244**	0.109	0.114	-0.002	0.012	0.041	0.049
	(0.108)	(0.115)	(0.090)	(0.085)	(0.073)	(0.072)	(0.030)	(0.031)
1995-1998	0.268**	0.234**	0.179***	0.179***	0.096***	0.105***	0.120***	0.126***
	(0.094)	(0.103)	(0.041)	(0.044)	(0.031)	(0.034)	(0.028)	(0.029)
1999-2002	0.203**	0.187**	0.143***	0.141***	0.078**	0.080**	0.090***	0.094***
	(0.077)	(0.080)	(0.042)	(0.042)	(0.036)	(0.035)	(0.022)	(0.022)
2003-2006	0.129*	0.081	0.124***	0.095**	0.084**	0.060*	0.091***	0.070***
	(0.065)	(0.065)	(0.040)	(0.039)	(0.035)	(0.031)	(0.020)	(0.021)
HE×R&D exp								
1991-1994	–	0.264	–	-0.018	–	-0.090	–	-0.036
		(0.164)		(0.144)		(0.122)		(0.099)
1995-1998	–	0.375***	–	0.048	–	-0.029	–	-0.001
		(0.110)		(0.117)		(0.101)		(0.092)
1999-2002	–	0.219*	–	0.060	–	0.027	–	0.006
		(0.120)		(0.076)		(0.075)		(0.069)
2003-2006	–	0.372**	–	0.253**	–	0.222**	–	0.200***
		(0.133)		(0.109)		(0.100)		(0.061)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14247	14247	14247	14247	14247	14247	14247	14247
F	273	261	–	–	–	–	79	74
p	0.000	0.000	0.000	0.000	0.000	0.000	–	–
R^2	0.454	0.456	0.407	0.408	0.489	0.492	–	–
Chi^2	–	–	3250	3426	3420	3714	3894	3920

Note: Standard errors in parentheses. Standard errors are clustered by industry-years. *,** and *** denote significance level of 10%, 5% and 1%, respectively. 18 regional dummies, 9 occupational and 15 year dummies included. Charcatersitics include production output by industry, a female dummy, tenure and tenure squared, two firmsize dummies, a dummy for union membership, a dummy for being married, having kids, self-rated health and three age dummies.

at the 10% level. This suggests that the average return for additional investment in R&D expenditure at the industry level decreased over time. The coefficients of the interaction terms of Higher Education and R&D expenditure are large in all periods (but they are not significant in all periods). The coefficients of the Higher Education premium decrease and are rendered insignificant in the last period, indicating an increase in the demand for high educated workers in R&D intensive industries. However, the development of the premium seems to be quite uneven according to OLS results and is not described in further detail here. Rather, the focus will be laid on the models which account for individual and/or industry-specific unobserved heterogeneity as they provide less biased results.

In the RE, Mundlak and HT models, the inclusion of the interaction terms of R&D expenditure and Higher Education leads to a drop in the Higher Education coefficient in the last period. In the same period, the interaction term is large and significant (between 1% and 5% significance level) in all models, suggesting an average return to additional R&D expenditure for higher educated workers is between 20 and 25.3 percentage points depending on the model, and only 6 to 9.5 percentage points for low-educated workers, if statistically significant at all. The development of the interaction term over time reveals that the average wage return for additional R&D expenditure increased and is most pronounced in 2003-2006. In all three models which control for unobserved effects the interaction term increases from a negative but insignificant coefficient in the first period to a positive but insignificant coefficient in the third period and is large and significant in the last period. This suggests that graduates did not gain from innovative activity in the 1990s but do so in the 2000s. At first sight this seems to contradict the earlier finding by Taylor (2002) who finds an increasing effect of technological change on wages for high-skilled workers. However, he uses data for the period 1973 to 1994 and averages over this time span. Hence, his results are driven by the computer revolution that characterised the UK in the 1970s and 1980s. Evidence for the 1990s does not exist so far, and it could be the case that after the computer revolution, technological change, as measured in Taylor's study or in the present study, was low and therefore did not induce a skill-bias. The results of this study imply an increase in the demand for graduates in R&D intensive industries in the early 2000s and thereby support the SBTC hypothesis.

The indirect test of ABTC is made by comparing the models. Whilst the coefficients from the pooled OLS estimations are upward biased due to unobservable individual and industry-specific ability, the RE model coefficients are only biased due to individual ability. In fact, the coefficients of R&D expenditure in the RE models are smaller than in the OLS models, suggesting that there is a demand for industry-specific ability in R&D intensive industries. In the Mundlak and HT models, the coefficients are even smaller, as they correct for both industry-specific and individual ability. These results indicate that there is a relatively higher demand for ability in innovative industries. The size of the ability bias seems to be relatively constant over time, given one allows inferring this conclusion from comparing the models. All in all, the findings suggest that both industry-specific ability and individual ability seem to be rewarded more in industries which pos-

sess a high level of R&D expenditure than in industries with a low level of R&D expenditure. This suggests that an ability bias is induced by innovative activity, but it cannot be inferred whether this changed over time.

Table 5.6.4: Regressions Including Time Interactions with Patent Applications

	OLS		Random Effects		Mundlak		Hausman-Taylor	
Higher Education								
1991-1994	0.217***	0.188***	0.289***	0.256***	0.116***	0.092**	0.804***	0.753***
	(0.036)	(0.053)	(0.030)	(0.040)	(0.031)	(0.039)	(0.134)	(0.134)
1995-1998	0.208***	0.203***	0.281***	0.280***	0.111***	0.115***	0.803***	0.785***
	(0.043)	(0.055)	(0.025)	(0.024)	(0.028)	(0.037)	(0.133)	(0.133)
1999-2002	0.225***	0.192***	0.361***	0.342***	0.199***	0.194***	0.910***	0.889***
	(0.037)	(0.056)	(0.023)	(0.027)	(0.025)	(0.033)	(0.133)	(0.133)
2003-2006	0.196***	0.180**	0.373***	0.339***	0.210***	0.191***	0.933***	0.891***
	(0.062)	(0.082)	(0.045)	(0.051)	(0.047)	(0.067)	(0.133)	(0.133)
Patents								
1991-1994	0.320**	0.289*	0.237***	0.202**	0.155**	0.123*	0.207***	0.162***
	(0.151)	(0.166)	(0.083)	(0.082)	(0.068)	(0.071)	(0.046)	(0.049)
1995-1998	0.330***	0.326**	0.219***	0.218***	0.182***	0.179**	0.197***	0.187***
	(0.111)	(0.120)	(0.077)	(0.080)	(0.066)	(0.071)	(0.034)	(0.036)
1999-2002	0.217***	0.196**	0.145***	0.132***	0.124***	0.111***	0.127***	0.117***
	(0.073)	(0.073)	(0.050)	(0.049)	(0.035)	(0.036)	(0.023)	(0.024)
2003-2006	0.163*	0.148	0.077	0.048	0.060	0.024	0.063**	0.034
	(0.079)	(0.094)	(0.058)	(0.071)	(0.042)	(0.047)	(0.029)	(0.031)
HE×Patents								
1991-1994	–	0.297	–	0.361*	–	0.361*	–	0.483***
		(0.308)		(0.196)		(0.209)		(0.153)
1995-1998	–	0.049	–	0.037	–	0.081	–	0.142
		(0.326)		(0.097)		(0.112)		(0.120)
1999-2002	–	0.222	–	0.150**	–	0.155	–	0.130*
		(0.155)		(0.075)		(0.096)		(0.079)
2003-2006	–	0.143	–	0.288	–	0.332**	–	0.298***
		(0.312)		(0.200)		(0.160)		(0.096)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13564	13564	13564	13564	13564	13564	13564	13564
F	257	238	–	–	–	–	72	67
p	0.000	0.000	0.000	0.000	0.000	0.000	–	–
R^2	0.452	0.453	0.406	0.406	0.487	0.488	–	–
Chi^2	–	–	3064	3167	3110	3256	3516	3540

Note: Standard errors in parentheses. Standard errors are clustered by industry-years. *,** and *** denote significance level of 10%, 5% and 1%, respectively. 18 regional dummies, 9 occupational and 14 year dummies included. Charcatersitics include production output by industry, a female dummy, tenure and tenure squared, two firmsize dummies, a dummy for union membership, a dummy for being married, having kids, self-rated health and three age dummies.

The analysis is repeated using patent application data. The development of the HE variable is similar to the effects found with R&D expenditure data, both when the interaction term between patent applications and Higher Education is not included and when it is included (see Table 5.6.4). The patent application coefficients decrease continually between 1991 and 2006 and are significant in all periods. Only the patent application coefficient in the first period is slightly smaller when the interaction term is included. This drop is balanced out by the coefficient of the

interaction term between patent application and Higher Education in the first period. In both the RE and the HT models, an increase in patent applications raises the average wage premium for graduate workers significantly. In the next period, the coefficients are significant, and they increase again from the second to the third period. They are highest in the last period. This would imply that the skill-bias existed in the early 1990s, then disappeared and later occurred again and increased since 2000. These results provide only weak evidence for SBTC in the UK manufacturing industry. Different to the R&D results, using patent applications does not provide evidence for ABTC. However, as mentioned earlier, measuring innovation output in terms of patent applications is a worse measure for innovative activity than R&D expenditure.

Another method to identify SBTC is the estimation of a Fixed Effects model, which eliminates the effect of unobserved ability in the most comprehensive way. By multiplying time period dummies the change of the graduation premium over time can be identified. Using the first period as the base period (excluded from the model), the results show that the graduation premium in the second period was not significantly different from the first period. In the third and the fourth period the premium is 10 and 12 percentage points higher than in the first two periods (Table 5.A.2). This validates the results that have been found using the other models. When including the interaction terms, the individual innovation premium for higher educated workers increases significantly and the average innovation premium decreases over time (Table 5.A.3). Hence, also the Fixed Effects regression results support the SBTC hypothesis.

As further robustness checks, all models have been estimated including both R&D expenditure data and patent application data and their interaction terms with Higher Education simultaneously. The coefficients do not change qualitatively and results do not lead to different conclusions than with estimating separate models. This implies that both indicators measure two independent kinds of innovative activity. Otherwise, the size of at least one set of coefficients would decrease. Furthermore, all models including R&D expenditure data are estimated for the period 1991 to 2005 instead of 1991 to 2006 for better comparison with the patent data results. The concern that the year 2006 may be responsible for the large coefficients found for the last period can be ruled out.

Combining the findings with the existing literature, three novel insights can be de-

duced from the findings in this study. Whilst the constant higher education wage premia found for the 1990s and early 2000s by, e.g., Purcell et al. (2005) and Silles (2007) are reproduced using the BHPS, new is that wage inequality seems to be increasing again after 2002. In the last period of observation, i.e. 2003 to 2006, the overall wage premium for graduates shows a new upturn. This can be seen by adding the coefficient of Higher Education and HE $\times$ R&D expenditure of the last period in Tables 5.6.3 and 5.6.4. The linear combination of the coefficient implies that an increase in R&D expenditure of the employing industry increases the wage premium for graduates twice as much as for non-graduates. Only in 2003-2006 this effects is particularly large and statistically significant. The second novel result is that the premium for innovation is still high for both low- and high-educated workers although the UK was one of the first countries experiencing computerisation and fast technological change, and a decrease of the premium could have been expected. The study shows that the average return to R&D expenditure is higher for graduates, most significantly between 2003 and 2006. This adds further evidence to the discussion on the existence of SBTC in the UK (Taylor, 2002; Corsini, 2008; Berman et al., 1998). The third novel result is that there is a high demand for ability, over and above a Higher Education degree. This result is inferred from the various panel models which account for different sources of ability bias. The findings regarding ABTC however, are inconclusive.

5.7 Conclusion

A large strand of the literature has tried to shed light on the complex wage patterns and the increasing wage inequality between graduates and lower educated workers in recent decades in the UK. Many authors have shown that wage inequality can partly be explained by industry and firm characteristics, especially technological change (Katz and Murphy, 1992; Autor et al., 1998; Haskel and Slaughter, 2002; Levy and Murnane, 2006; Bartel and Sicherman, 1999). Whilst most studies focus on the U.S., this analysis concentrates on the UK and contributes to the existing literature in many ways. First, it extends the study by Bartel and Sicherman (1999), who investigated the 'technological change premium' in the U.S., in at least two respects. One is the use of additional panel data estimation methods, which allow controlling for both individual and industry-specific ability and reduces biases in the estimated premia. The other extension is the inclusion of time variables to the model, making it possible to investigate changes over time and

hence, to identify SBTC explicitly. Second, it provides an indirect empirical test of the ABTC hypothesis modelled by Galor and Moav (2000), which has not been done so far. Third, this is the first study to look at wage differentials between high- and low-educated workers using a combination of individual level data, which controls for a set of socioeconomic characteristics, and industry level data after the mid 1990s, i.e. after the computer revolution in the UK.

Using individual level data from the British Household Panel Survey (BHPS) and industry level data from the OECD statistical database, wage regressions are estimated to identify the effect of innovative activity at the industry level on average individual wage premia for university-educated workers compared to lower educated workers. Innovative activity is defined by the amount of R&D expenditure and the number of patent applications, measuring innovation input and innovation output, respectively. Using different estimation methods for panel data, such as Fixed Effects, Random Effects, Mundlak and Hausman-Taylor models, in addition to pooled OLS regressions allows controlling for both industry-specific ability and individual ability which are correlated with earnings as well as with education and thus lead to an upward bias in the graduation premium in OLS regressions.

The results for the wage differentials in levels show that an increase in innovative activity raises wages for graduates much more than low-educated workers' wages. For example, additional R&D expenditure of 10,000 GBP per employee per year raises wages for graduated workers by up to 27 percentage points on average. The effect is smaller but still large and statistically significant when controlling for unobserved ability. This implies the existence of an ability-bias in the estimation of the individual innovation premium for graduates. Including time period dummies in the regressions allows looking at the development of the premia. The innovation premium for graduates increased significantly over time by up to 25 percentage points and did not do so for low-educated workers. As such, the results provide evidence for SBTC. Using R&D expenditure as a measure for innovative activity additionally indicates the existence of ABTC, while patent applications do not support this hypothesis. Overall, looking at manufacturing industries and distinguishing industries by their innovation activity provides strong evidence that an increase in wage inequality occurred in the UK again in the mid-2000s.

It can be concluded that graduates with the highest ability have sorted into jobs which are associated with a high rate of innovative activity. Graduates with lower

ability are likely to be over-educated as is indicated by studies such as Dolton and Vignoles (2000); Chevalier (2000); Chevalier and Lindley (2009). An increase in the number of graduates has been an explicit policy goal by the British government. By 2010 it aimed at raising the share of university educated individuals to 50% of school leavers which has been achieved. Whilst past secondary school reforms in England have had positive outcomes on achievements for pupils from a poorer family background (Bradley and Taylor, 2010; Taylor et al., 2007), the expansion of the higher education system has disproportionally benefited people from richer family backgrounds than those from poorer family backgrounds (Blanden and Machin, 2004). As this study shows, the gain from technological change is also disproportionally distributed among the population as high-ability high-educated workers profit more from technological change than low-ability high-educated individuals.

Finally, the increase in wage inequality between high- and low-educated workers as defined in this study does not differentiate between graduates and postgraduates due to a low number of observations of individuals with postgraduate education in the data. Recently, based on data from the Labour Force Survey it has been shown that the expansion in Higher Education in the UK has also produced more postgraduates and that those benefit even more from technological change in terms of wages (Lindley and Machin, 2011). Taken this into consideration, the impact that technological change has on the wage differential between graduates (which includes also postgraduates) and non-graduates is probably even higher between postgraduates and non-graduates. The results of this study should be viewed in light of this.

5.A Appendix

Table 5.A.1: Correlation between Indicators

	R&D exp.	Patents	Production
R&D exp.	1.000		
Patents	0.189***	1.000	
Production	0.647***	-0.081***	1.000

Note: Significance in parentheses. *** denote significance level of 1%.

Table 5.A.2: Fixed Effects Regressions

	Fixed Effects
HE×1995-1998	-0.001
	(0.024)
HE×1999-2002	0.109***
	(0.017)
HE×2003-2006	0.121***
	(0.031)
Constant	1.777***
	(0.083)
Characteristics	Yes
Regional dummies	Yes
Occup. dummies	Yes
Year dummies	Yes
N	14247
F	67
p	0.000
R^2	0.212

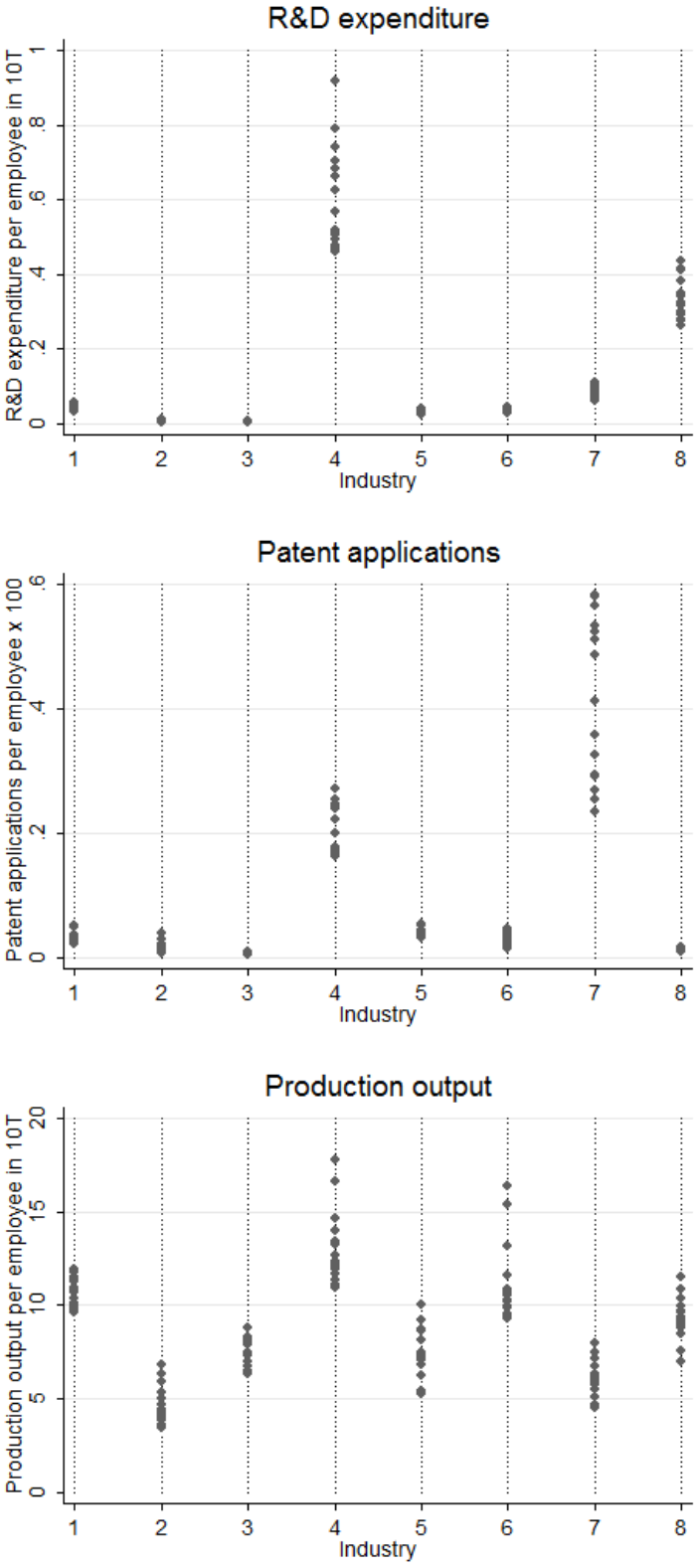
Note: Standard errors in parentheses. Standard errors are clustered by industry-years. *,** and *** denote significance level of 10%, 5% and 1%, respectively. 18 regional dummies, 9 occupational and 15 year dummies included.

Table 5.A.3: Fixed Effects Regressions incl. Time Interactions

	Indicator			
	R&D expenditure		Patents	
Indicator				
1991-1994	-0.001	0.016	0.174***	0.168***
	(0.054)	(0.056)	(0.055)	(0.055)
1995-1998	0.091**	0.111***	0.181***	0.194***
	(0.032)	(0.033)	(0.030)	(0.032)
1999-2002	0.082***	0.071***	0.118***	0.097***
	(0.025)	(0.025)	(0.021)	(0.019)
2003-2006	0.093***	0.065**	0.057**	0.010
	(0.024)	(0.025)	(0.027)	(0.033)
Higher Education×*Indicator*				
1991-1994	–	-0.102	–	0.100
		(0.079)		(0.178)
1995-1998	–	-0.118	–	-0.070
		(0.094)		(0.097)
1999-2002	–	0.140**	–	0.246**
		(0.059)		(0.088)
2003-2006	–	0.203***	–	0.423**
		(0.052)		(0.151)
Constant	Yes	Yes	Yes	Yes
Characteristics	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes
Occupation dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
N	14247	14247	13564	13564
F	65	60	58	54
p	0.000	0.000	0.000	0.000
R^2	0.210	0.213	0.201	0.203

Note: Standard errors in parentheses. Standard errors are clustered by industry-years. *,** and *** denote significance level of 10%, 5% and 1%, respectively. 18 regional dummies, 9 occupational and 15 year dummies included. Charcatersitics inlcude prodiction output by industry, a female dummy, tenure tenure squared, two firmsize dummies, a dummy for union membership, a dummy for being married, having kids, self-rated healh and three age dummies. The patent data only covers 1991 to 2005, hence the last period is 2003-2005.

Figure 5.A.1: Variation in Indicators



Source: Own calculations based on OECD data.

Figure 5.A.2: List of Industries

Standardisation of ISIC rev.2, ISIC rev. 3, SIC 92 and SIC 80

ISIC-Rev. 2	ISIC-Rev. 3	Standardised Industry Classification	SIC 92*	SIC 80
3 Manufacturing	**D Manufacturing**	**1. Manufacture of Food, Beverages and Tobacco**	**D. Manufacturing**	**4 Other manufacturing Industries**
31 Manufacture of Food, Beverages and Tobacco	**15** Manufacture of food products and beverages		**DA(15,16)** Manufacture of food products, beverages and tobacco	**41/42** Food, drink & tobacco manufacturing industries
	16 Manufacture of tobacco products			
32 Textile, Wearing Apparel and Leather Industries	**17** Manufacture of textiles	**2. Manufacture of Textile, Wearing Apparel and Leather Industries**	**DB (17,18)** Manufacture of textiles and textile products	**43** Textile industry
	18 Manufacture of wearing apparel; dressing and dyeing of fur		**DC (19)** Manufacture of leather and leather products	**44** Manufacture of leather & leather goods
	19 Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear			**45** Footwear & clothing industries
33 Manufacture of Wood and Wood Products, Including Furniture	**20** Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	**3. Manufacture of Wood and Wood Products, Including Furniture, Paper and Paper Products, Printing and Publishing**	**DD (20)** Manufacture of wood and wood products	**46** Timber & wooden furniture industries
34 Manufacture of Paper and Paper Products, Printing and Publishing	**21** Manufacture of paper and paper products		**DE (21,22)** Manufacture of pulp, paper and paper products; publishing and printing	**47** Manufacture of paper & paper products; printing & publishing
	22 Publishing, printing and reproduction of recorded media			
35 Manufacture of Chemicals and Chemical, Petroleum, Coal, Rubber and Plastic Products	**23** Manufacture of coke, refined petroleum products and nuclear fuel	**4. Manufacture of Chemicals and Chemical, Petroleum, Coal, Rubber and Plastic Products**	**DF (23)** Manufacture of coke, refined petroleum products and nuclear fuel	**11** Coal extraction & manufacture of solid fuels
				12 Coke ovens
	24 Manufacture of chemicals and chemical products		**DG (24)** Manufacture of chemicals, chemical products and man-made fibres	**13** Extraction of mineral oil & natural gas
				14 Mineral oil processing
				15 Nuclear fuel production
	25 Manufacture of rubber and plastics products		**DH (25)** Manufacture of rubber and plastic products	**25** Chemical industry
				26 Production of man-made fibres
				48 Processing of rubber & plastics
36 Manufacture of Non-Metallic Mineral Products, except Products of Petroleum and Coal	**26** Manufacture of other non-metallic mineral products	**5. Manufacture of other non-metallic mineral products**	**DI (26)** Manufacture of other non-metallic mineral products	**24** Manufacture of non-metallic mineral products
37 Basic Metal Industries	**27** Manufacture of basic metals	**6. Manufacture of basic metals**	**DJ (27,28)** Manufacture of basic metals and fabricated metal products	**22** Metal manufacturing
				31 Manufacture of metal goods not elsewhere specified
38 Manufacture of Fabricated Metal Products, Machinery and Equipment	**28** Manufacture of fabricated metal products, except machinery and equipment	**7. Manufacture of Fabricated Metal Products, Machinery and Equipment**	**DK (29)** Manufacture of machinery and equipment not elsewhere classified	**32** Mechanical engineering processing equipment
	29 Manufacture of machinery and equipment n.e.c.			**33** Manufacture of office machinery & data
39 Other Manufacturing Industries	**30** Manufacture of office, accounting and computing machinery	**8 Other Manufacturing Industries**	**DL (30,31,32,33)** Manufacture of electrical and optical equipment	**34** Electrical & electronic engineering
	31 Manufacture of electrical machinery and apparatus n.e.c.			
	32 Manufacture of radio, television and communication equipment and apparatus			
	33 Manufacture of medical, precision and optical instruments, watches and clocks			**37** Instrument engineering
	34 Manufacture of motor vehicles, trailers and semi-trailers		**DM (34,35)** Manufacture of transport equipment	**35** Manufacture of motor vehicles & parts thereof
	35 Manufacture of other transport equipment			**36** Manufacture of other transport equipment
	36 Manufacture of furniture; manufacturing n.e.c.		**DN (36,37)** Manufacturing not elsewhere classified	**49** Other manufacturing industries
	37 Recycling			

* SIC92 is given at the 4 digit level in BHPS. The numbers in brackets are the first two numbers of each classified group.

Chapter 6

Reaching High: Occupational Sorting and Higher Education Wage Differentials in the UK

Co-authored with Jan Kleibrink

Abstract The Further and Higher Education Act of 1992 changed the system of Higher Education in the UK by giving all polytechnics university status. Using the British Household Panel Survey and accounting for different sources of selection bias in the econometric specifications, we confirm earlier results on the wage gap between polytechnic and university graduates. We show that wage differentials can be explained by a glass ceiling preventing polytechnic graduates from reaching managerial and professional occupations. We find that after the reform, the glass ceiling disappeared and average wages of post-reform polytechnic graduates are not statistically different from average wages of post-reform graduates of traditional universities. We provide a discussion on the likely determinants of this new result.[1]

[1]An earlier version is published as Ruhr Economic Papers No. 377 (2012). The authors are very grateful to Gerhard Kussel for superb research assistance. We also acknowledge highly useful suggestions and comments by John P. Haisken-DeNew, Mathias Sinning, members of our chair at RUB and participants at the BHPS/Understanding Society Conference in 2011, the EEA/ESEM in 2012 and the RGS Conference in 2013.

6.1 Introduction

Participation in Higher Education (HE) is permanently subject to political discussion because of rapidly changing labour market demands. In the UK, a policy goal since the publication of the Dearing Report in 1997[2] was to raise participation in HE to 50% by 2010. This serves both a societal as well as an individual interest: HE graduates are on average better-skilled than non-graduates and a high share of high-skilled graduates sustains and enhances the competitiveness of an economy. At the individual level, obtaining an HE degree pays off in the labour market as graduates can reach higher positions than non-graduates and earn on average higher wages (Harmon and Walker, 1999; Lange and Topel, 2006; Walker and Zhu, 2008; O'Leary and Sloane, 2011). However, a high participation rate in HE raises the question whether the demand for graduates is large enough to guarantee an adequate occupational position for all graduates. A rising number of participants may lead to an oversupply of high-skilled workers and thereby worsen the situation of graduates in the labour market.[3]

The system of HE in the UK used to be 'two-tier' before 1992 when research-oriented universities were distinguished from more applied polytechnics. This 'two-tier' system was abolished by the Further and Higher Education Act (FHEA) of 1992, which granted polytechnics university status. The particular changes refer to (1) an assimilation of funding schemes between the two types of institutions, (2) the introduced right for polytechnics to award their own Higher Education degrees and (3) the renaming of polytechnics to universities.[4] In how far teaching and research structures have assimilated since the FHEA has not received much attention in the literature (examples are Belfield and Fielding, 2001; Hussain et al., 2009), neither has the analysis of differences in labour market outcomes of graduates from these two different institutions. On the latter issue, empirical evidence is based on cohort studies and suggests labour market disadvantages for polytechnic graduates compared to university graduates (Weale, 1992; Chevalier and Conlon, 2003). This paper examines whether the FHEA has changed the wage differential between polytechnic and university graduates.

[2] https://bei.leeds.ac.uk/Partners/NCIHE/

[3] See the literature on over-education such as Hartog (2000); Sloane et al. (1999).

[4] Former polytechnics are now commonly referred to as 'new universities'.

Whilst former investigations are based on cohort surveys, this paper assesses average wage effects of a representative population of HE graduates. We base our analysis on data from the British Household Panel Survey (BHPS) for the years 1991 to 2008 and restrict the analysis to male graduates, as the female labour supply underwent important changes during the observation period. For instance, female labour market participation has risen significantly and career orientation has gained importance for women (Gutierrez-Domenech and Bell, 2004). Modelling this is beyond the scope of this study.

In the econometric specification we explicitly control for possible selection bias from sorting into polytechnics rather than universities. We address this by using a Heckman (1979) selection model with Wooldridge's (1995) panel approach. Whilst various studies exist which estimate the determinants of school attainment and school choice in Britain (e.g. Hogan and Walker, 2007), no study exists which analyses the determinants of the choice of the Higher Education institution. Hence, our study is the first to do so. Our novel exclusion restriction is based on the geographical distribution of HE institutions at the respondents' age of 17. Furthermore, we control for occupational sorting which crucially influences wages and may bias OLS estimates. In fact, whether someone is able to reach, for example, a managerial position connected to a high degree of responsibility is a major determinant of career success and thereby of wages. Controlling for occupational sorting accounts for an important source of possible heterogeneity. This might be of special importance here because a glass ceiling effect might be present. A glass ceiling effect is well-known from gender studies and defines a situation in which a certain group cannot reach positions in the labour market although being formally qualified (Fisman and O'Neill, 2009; Russo and Hassink, 2011). Such a situation might arise for polytechnic graduates. In doing so, this study is, to our best knowledge, the first study to identify a glass ceiling effect between graduates of different institutions in the UK.

In line with previous studies, we find significant wage differentials for individuals who graduated before the reform. Pre-reform polytechnic graduates earn on average significantly less than pre-reform university graduates. We identify a glass ceiling in reaching 'high positions' for post-reform university and pre-reform polytechnic graduates compared to pre-reform university graduates. For polytechnic graduates, the reform has been beneficial. Graduates from 'new universities' have caught up with their university counterparts in terms of average wages, because

they are more likely to reach managerial and professional occupations than before. However, this catching-up process is only partly explained by a better situation for post-reform polytechnic graduates as the wage gap for graduates after the reform is levelled off at overall lower wages than pre-reform wages. The structure of the paper is as follows: In the next section we briefly describe the HE system in the UK, highlighting the most important changes of the last two decades. A short review of the existing literature is provided. In Section 6.3, the empirical methodology is explained. Section 6.4 describes the data used and summarises descriptive statistics. Section 6.5 reports the results and Section 6.6 concludes.

6.2 Background

In the UK, pupils usually enter the HE system at the age of 17 or 18 with appropriate 'A levels' or equivalent college certificates. By 1960, about 400,000 students were enrolled in the HE system, which consisted almost entirely of universities. Since then, about 20 universities were created as well as a number of polytechnics and university colleges. This meant a remarkable shift in the HE system as polytechnics became an important alternative to traditional universities.

In the early 1990s, the composition of the HE system changed through the Further and Higher Education Act from 1992[5], which granted polytechnics university status in terms of naming and funding schemes. This raised the overall number of universities and hence the number of university students. The reform was mainly conducted over three channels: Firstly, there were different funding schemes for universities and polytechnics before. Secondly, former polytechnics obtained the right to award higher degrees. Thirdly, and most prominently, a renaming process started. In the course of the reform, all former polytechnics changed their names to universities.

Commonly, it is stated that universities are more research-intensive and more academic than polytechnics, in which education is more vocational and oriented directly towards labour market demands. The difference in composition of subjects between the institutions is only minor. At both kinds of institutions, students can obtain natural science, engineering as well as arts and humanities degrees. A larger difference exists between the course structures: At 'new universities', students are

[5] http://www.legislation.gov.uk/ukpga/1992/13/contents

more likely to attend 'sandwich-courses' which lead to bachelor degrees while at traditional universities students are more likely to obtain additional postgraduate degrees. Apart from this, all institutions charge similar amounts of tuition fees. This raises the question whether the abolition of the 'two-tier' system has also equalised labour market opportunities and success of graduates from these (statutory identical) institutions.

So far, empirical evidence is based on cohort studies and suggests labour market disadvantages for polytechnic graduates compared to university graduates (e.g. Weale, 1992; Chevalier and Conlon, 2003). Weale (1992) uses data from the Survey of 1980 Graduates and Diplomats, carried out in 1986, i.e. before the FHEA from 1992 was passed. He compares unemployment experience and benefits from HE based on earnings and educational costs for graduates from both types of institutions by estimating separate equations for both groups. He finds that graduates from both types of institutions possess similar probabilities of unemployment and that university graduates benefit from good 'A levels' while polytechnic graduates' earnings are insensible to 'A level' scores. With this approach, he does not identify a wage differential between the two types.

Chevalier and Conlon (2003) distinguish three types of universities: (a) 'Modern universities' which are the pre-1992 polytechnics, (b) 'prestigious universities', also referred to as the Russell Group[6], and (c) other pre-1992 universities ('old universities'). They use OLS and propensity score matching to estimate the return to HE based on data from three graduate cohort studies. In summary, they find no premium for attending an old university and a small premium (at most 6%) for graduating from a Russell Group university compared to a modern university.

To our best knowledge, previous studies neither use representative panel data of the UK graduate population, nor analyse the differences in occupational success between both types of graduates. The studies cited above have found significant wage gaps for polytechnic graduates compared to university graduates at a certain period after graduation based on cohort surveys. Rather than estimating wage

[6]Universities belonging to the Russell Group are: University of Birmingham, University of Bristol, University of Cambridge, Cardiff University, University of Edinburgh, University of Glasgow, University of Leeds, University of Liverpool, University of Manchester, University of Newcastle upon Tyne, University of Nottingham, University of Oxford, University of Sheffield, University of Southampton, University of Warwick, Imperial College, King's College London, London School of Economics and University College London.

differentials for a specific cohort at a specific point in time, we are able to estimate the average wage rates of graduates of different cohorts in the overall working graduate population. In the labour economics literature, numerous studies look at the gender differences in job promotion between men and women and show that women commonly, but decreasingly, face a glass ceiling (e.g. Winter-Ebmer and Zweimüller, 1997; McDowell et al., 1999; Russo and Hassink, 2011). In this study, we do not look at gender differences in job promotion but borrow from their identification strategies to identify differences between the types of graduates.

6.3 Estimation Methods

We analyse labour market success of graduates from different institutions by estimating the wage differential. In particular, we estimate one model for all male graduates in which we include a binary regressor which is equal to 1 if an individual graduated from a polytechnic (or 'new university' after 1992) and 0 if an individual graduated from a university. This allows us to interpret the coefficient as the marginal effect of having attended a polytechnic rather than a university, holding all other observable characteristics constant. We are able to control for a large number of job and socioeconomic characteristics, which former studies lack. The basic model underlying the wage (hourly, w_{it}) regressions can be written as

$$ln(w_{it}) = \alpha_0 + Poly_i\alpha_1 + After_i\alpha_2 + x_{it}\beta + s_{it}\delta + \epsilon_{1it}, \tag{6.1}$$

where i and t are subscripts for individuals and time, respectively, *Poly* is the indicator for having attended a polytechnic rather than a university, *After* indicates whether someone graduated after the reform, x and s are vectors of regressors of individual and job characteristics, respectively, α, β and δ are vectors of coefficients to be estimated and ϵ_1 is the error term.

To analyse the impact of the reform, we also apply a different, more detailed model. In this second model, we include dummies for three of the four types of graduates, i.e. graduating from a traditional university before the reform (*Unibefore*), graduating from a polytechnic before the reform (*Polybefore*) and graduating from a traditional university after the reform (*Uniafter*). The reference group are graduates from former polytechnics – now 'new universities' – after the reform (*Polyafter*).

The model becomes

$$ln(w_{it}) = \alpha_0 + Unibefore_i\alpha_1 + Polybefore_i\alpha_2 + Uniafter_i\alpha_3 + x_{it}\beta + s_{it}\delta + \epsilon_{2it}. \quad (6.2)$$

By estimating wage equations for graduates using Ordinary Least Squares (OLS), we are concerned with potential sample selection bias through prior sorting into different HE institutions. It may be that individuals with certain unobservable characteristics decide to attend a polytechnic rather than a traditional university, which would lead to biased estimates. Migali and Walker (2011) take into account that educational choice is endogenous. In this respect, we expect the choice of the HE institution to be endogenous, too. For this reason, we apply a version of the Heckman sample selection model (Heckman, 1979). The original Heckman model is a two-step model in which the first step is a probit model which can be written as

$$p_{it} \equiv \Pr(y_{it} = 1|x_{it}, z_{it}) = x_{it}\beta + z_i\gamma + \epsilon_{2it}. \quad (6.3)$$

z serves as exclusion restriction necessary for the selection model, γ are vectors of coefficients to be estimated and ϵ_2 is the error term. The second step is the wage equation expanded by the inverse Mill's ratio (λ_{HE}) obtained from equation 6.3.

The exclusion restriction applied here is the share of traditional universities in the overall number of HE institutions around a respondent's place of birth. In detail, we use information on the geographic coordinates of all UK universities and polytechnics and match this information with the place of birth of the respondents provided in the BHPS. We count the number of polytechnics and universities within a 150 km radius[7] around the place of birth at their age of 17. We thereby need to make the assumption that individuals did not move between their birth and 17th year of age. By calculating this share we take into account the foundation year of a HE institution, its institutional change and the location of split campus of particular institutions. We then derive the share of traditional universities among all institutions for each year. Figure 6.A.1 in the appendix displays all HE institutions that existed before 1993 and are taken into account to derive the exclusion restriction.

[7] We have also used differently-sized radii without qualitative differences of the results.

This exclusion restriction is valid as it is clearly exogenous to the respondent. The number of HE institutions cannot be directly influenced and the 150 km radius serves two purposes. On the one hand it is big enough to rule out the possibility that a respondent's parents explicitly moved into this radius to be close to a certain institution.[8] On the other hand, the radius is close enough to have a significant influence on the respondents' decision. Choosing an institution of higher education opens the possibility to stay within the parents' household. Moreover, it is not necessary to leave the own social network. We expect a high share of universities in this radius decreases the likelihood of attending a polytechnic. This hypothesis is confirmed in our data. As we base our analysis on panel data, using the Heckman (1979) procedure leads to inconsistent estimates if the selection process is not constant over time. A pooled probit in the first step would then lead to inconsistent estimates due to correlation of the error terms of equations (6.1) and (6.2) over time:

$$(\epsilon_{1it}, \epsilon_{2it}) \sim N[(0,0),(\sigma^2, 1, \rho\sigma)]. \tag{6.4}$$

Wooldridge (1995) suggests estimating single probit models for each period separately and including all calculated inverse Mill's ratios (λ_{HE_t}) interacted with time period dummies in the main equation.[9] This eliminates the possible sample selection bias in a panel context (also explained in Wooldridge, 2002). Basically, this procedure allows the estimation of the main equation regardless of the time series properties of the error terms and does not impose assumptions on the distribution of the error terms and the coefficients in the second step.[10] We bootstrap standard errors in the main equation because of the two-step nature of the model. Finally, conducting a Wald test on the joint significance of the period-specific inverse Mill's ratios offers a test of the existence of sample selection in the model.

The second part of the analysis regards the possible glass ceiling effect, i.e. whether

[8] It is a well-known phenomenon that some people choose their residence to be located close to a certain school to give their children the possibility to attend it. This is very unlikely to be a problem in this application as the university attendance is not attached to catchment areas. It is unlikely that parents choose a residence to influence their children's educational decision nearly 20 years in the future.

[9] We use year-pairs rather than single years due to the small number of observations in our sample.

[10] See, e.g., Dustmann and Rochina-Barrachina (2007) for a discussion of this method and alternative approaches.

the possibility of reaching high occupational positions differs by type of graduate institution and time. We therefore estimate probit models in which the dependent variable is equal to 1 if an individual has a 'high occupation' for each year-pair. The chosen occupational categories are based on the UK Standard Occupational Classification (SOC 2000). The two highest occupational one-digit categories, which are used here, include managerial and professional occupations (SOC 1 and SOC 2). We re-estimate the wage equations additionally including the inverse Mill's ratios obtained from these probit models.

For our exclusion restriction, we lean on an approach used in an education-wage study for Germany by Riphahn et al. (2010), assuming that social background and the educational and occupational success of someone's parents affects the probability of reaching a high occupation but not the wage level directly. To trust the validity of the exclusion restriction, we rely on the work of Delaney et al. (2011), who find that the intergenerational mobility of occupational success mainly works over the channel of children's educational success. In our study, we use the information on parents' labour market status and occupational success at the interviewees' age of 14. At the age of 14, individuals are likely to be influenced by their parents regarding the optimal educational path to follow. However, the wages that these adolescents earn when they finished their educational career is unlikely to be influenced by their parents' characteristics at age 14, over and above the occupation they have achieved. We can therefore assume that the exclusion restriction is valid, although we are aware of the potential weakness of the exogeneity assumption using these variables, already pointed out by Harmon et al. (2003). They estimate wage regressions controlling for a non-random sorting process into self-employment using a Heckman approach on BHPS data. Their exclusion restriction is the parents' self-employment decision as it is likely to influence the child's self-employment decision but not wages directly. We follow their reasoning and apply a similar strategy.

6.4 Data

We use the British Household Panel Survey (BHPS)[11] which consists of a large range of household and individual data, collected yearly since 1991.[12] The data cover a variety of characteristics concerning income and labour market performance as well as family and schooling background. We use data from 1991 to 2008 and restrict the sample to men aged 23 to 64 who obtained an HE degree.[13] The sample consists of 3,759 person-year-observations, of which 28.9% have obtained a degree from a polytechnic (pre- and post-reform). The last wave in the BHPS in which the question about type of university distinguished between former polytechnics and traditional universities is 2002. We have not included individuals who graduated after this wave. Due to our exclusion restriction which is based on the place of birth within the UK, we have to drop all migrants and those individuals who did not report their place of birth.

Table 6.4.1 presents means and standard deviations of personal characteristics and job characteristics differentiated by institutions. It is visible that higher degrees, such as masters and PhDs, are more often obtained from universities (26%) than from polytechnics (11%) and students from universities are more likely to have previously attended private schools. Green et al. (2011) show that a wage differential exists between workers who attended a private school as compared to workers who attended a non-private school in the UK. Furthermore, it has been argued that selection into an HE institution is partly based on the type of school one has attended (Blanden and Machin, 2004). We are aware of possible sorting into institutions in the interpretation of our results. However, we cannot control for this due to data limitations. More importantly, private schooling is not useful as an exclusion restriction as it was found to affect wages directly. Nevertheless, we are confident that selection bias from this source is a minor problem, since we include a large number of controls in both the binary and linear specifications. Furthermore, the share of private school alumni is quite low in our sample (10%

[11] Data are extracted using the Stata add-on PanelWhiz written by John P. Haisken-DeNew (Haisken-DeNew and Hahn, 2006).

[12] We exclude the data on Northern Ireland as we do not have enough observations for the pre-reform period.

[13] We dropped the self-employed (9% of the sample) because their degree does not matter strongly for their earnings. As a robustness check, we included the self-employed. The difference in results is negligible.

Table 6.4.1: Descriptive Statistics by Institution

	University		Polytechnic		Difference	
	Mean	Std.Dev.	Mean	Std.Dev.	Diff	S.E.
Personal characteristics						
Higher degree	0.26	(0.44)	0.11	(0.32)	0.15***	(0.01)
First degree	0.74	(0.44)	0.89	(0.32)	-0.15***	(0.01)
Private school	0.10	(0.30)	0.02	(0.14)	0.08***	(0.01)
Vocational	0.19	(0.40)	0.34	(0.47)	-0.14***	(0.02)
Married	0.63	(0.48)	0.64	(0.48)	-0.02	(0.02)
Age	39.8	(9.47)	38.5	(8.39)	1.3***	(0.3)
Left HE 1992-2007	0.18	(0.39)	0.19	(0.39)	-0.01	(0.01)
Health status	1.81	(0.75)	1.86	(0.76)	-0.05*	(0.03)
Mother prof.	0.15	(0.36)	0.12	(0.33)	0.03**	(0.01)
Mother unempl.	0.43	(0.49)	0.36	(0.48)	0.07***	(0.02)
Father prof.	0.46	(0.50)	0.40	(0.49)	0.06***	(0.02)
Father unempl.	0.03	(0.17)	0.02	(0.13)	0.01**	(0.01)
Uni share 150km	0.57	(0.27)	0.56	(0.24)	0.01	(0.01)
Total institutions	17.3	(12.0)	19.9	(11.2)	-2.60***	(0.42)
Job characteristics						
Hourly wage	12.45	(5.12)	11.97	(4.46)	0.48***	(0.18)
Union member	0.29	(0.46)	0.39	(0.49)	-0.10***	(0.02)
Tenure	7.33	(9.28)	7.02	(7.86)	0.31	(0.32)
Full time job	0.95	(0.21)	0.96	(0.21)	-0.00	(0.01)
1-24 employees	0.20	(0.40)	0.20	(0.40)	-0.00	(0.01)
25-99 employees	0.2	(0.42)	0.3	(0.46)	-0.1***	(0.0)
100- employees	0.58	(0.49)	0.50	(0.50)	0.08***	(0.02)
Manager or professional	0.67	(0.47)	0.60	(0.49)	0.06***	(0.02)
N	2672		1087		3759	

Note: Authors' calculations based on BHPS. S.E.: Standard Errors. *,** and *** denote significance level of 1%, 5% and 10%, respectively.

of university and 2% of polytechnic graduates).

We include the individual's age and its second polynomial. About 35% of the polytechnic graduates have some vocational training, while only 19% of the university graduates have vocational training. In the 'sorting into polytechnics/occupational positions' models we include information on social status. As a proxy, we use information on the parents' labour market status at the individual's age of 14. Graduates from universities more often have a parent who is a professional but also more often have an unemployed mother. Differences in the fathers' unemployment probabilities hardly exist. We see that the share of universities among all institutions in a 150 km radius around a respondent's place of birth at his or her age of 17 is 56% with slightly more total institutions in a 150 km radius for polytechnic than university graduates.

Apart from the average hourly wages[14], job characteristics are quite similar for both

[14]Wages are deflated using the CPI from the Office of National Statics in the UK to the base

groups. On average, graduates from universities receive hourly wages of £12.45 and graduates from polytechnics receive hourly wages of on average £11.97. Furthermore, university graduates are on average more likely to be managers or having another professional occupation than polytechnic graduates. These differences are significant and need to be controlled for in the wage regressions. Furthermore, we will address the question of reaching the highest occupational positions explicitly.

6.5 Results

OLS wage regressions are the natural starting point when estimating wage differences and the results are reported in columns 1 and 2 in Table 6.5.1. The results from the two-stage models including the inverse Mill's ratios from probit models to control for sorting into polytechnics are to be found in columns 3 and 4 and the results from controlling for sorting into polytechnics and sorting into high occupations are displayed in columns 5 and 6.

In the first column, both the polytechnic dummy and the dummy for graduating after the FHEA have negative coefficients. The polytechnic dummy is statistically insignificant but it indicates a wage gap at the disadvantage of polytechnic graduates. Even though we control for age and tenure, we find that average denominated wages are lower for post-reform graduates than pre-reform graduates. This finding is likely to be explained by the high share of graduates working in low-skilled jobs after graduation. For HE graduates, the average duration of finding a job that matches the obtained skills is 9 months.[15] This gives rises to the assumption that the rising share of graduates does not meet an equally rising demand. More meaningful and more telling are the results from the more detailed specification (column 2). The coefficient for graduating from a university before 1992 is positive, indicating that, unsurprisingly, pre-reform university graduates earn on average more than post-reform polytechnic graduates. For the dummy indicating that someone graduated from a traditional university after the reform the coefficient is negative. This implies that post-reform university graduates have an average wage disadvantage over post-reform polytechnic graduates. However, in the OLS specifications, these coefficients are statistically insignificant.

year 1991.

[15] This has economists led to investigate the phenomenon of over-education in the UK (Dolton and Vignoles, 2000; Chevalier and Lindley, 2009; O'Leary and Sloane, 2011).

Table 6.5.1: Wage Regressions

	OLS		OLS Poly-Sel		OLS Poly+Occ-Sel	
	A	B	A	B	A	B
Polytechnic	-0.020	–	-0.021*	–	-0.019	–
	(0.031)		(0.013)		(0.013)	
Left HE 1992-2007	-0.068	–	-0.066***	–	-0.051**	–
	(0.042)		(0.020)		(0.021)	
Uni. before 1992	–	0.062	–	0.062**	–	0.041
		(0.056)		(0.027)		(0.029)
Poly. before 1992	–	0.031	–	0.029	–	0.009
		(0.056)		(0.028)		(0.029)
Uni. after 1992	–	-0.026	–	-0.026	–	-0.034
		(0.055)		(0.028)		(0.029)
Higher degree	0.049	0.049	0.050***	0.051***	0.032**	0.032**
	(0.031)	(0.031)	(0.013)	(0.013)	(0.015)	(0.015)
Vocational	-0.122***	-0.122***	-0.123***	-0.123***	-0.109***	-0.109***
	(0.031)	(0.032)	(0.014)	(0.014)	(0.016)	(0.016)
Private school	0.056	0.054	0.055**	0.052**	0.048**	0.046**
	(0.055)	(0.056)	(0.022)	(0.022)	(0.023)	(0.023)
Tenure	0.002	0.003	0.002	0.003	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure^2	-0.000***	-0.000***	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.094***	0.094***	0.093***	0.093***	0.093***	0.093***
	(0.012)	(0.012)	(0.007)	(0.007)	(0.007)	(0.007)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Health status	-0.031**	-0.031**	-0.031***	-0.031***	-0.027***	-0.027***
	(0.014)	(0.014)	(0.008)	(0.008)	(0.008)	(0.008)
Married	0.102***	0.100***	0.102***	0.100***	0.090***	0.088***
	(0.028)	(0.028)	(0.014)	(0.014)	(0.014)	(0.014)
Full time job	-0.036	-0.035	-0.036	-0.035	-0.036	-0.035
	(0.092)	(0.092)	(0.059)	(0.059)	(0.058)	(0.058)
Union member	0.035	0.035	0.038***	0.038***	0.036***	0.037***
	(0.027)	(0.027)	(0.013)	(0.013)	(0.013)	(0.013)
25-99 employees	0.186***	0.188***	0.186***	0.187***	0.182***	0.184***
	(0.035)	(0.034)	(0.017)	(0.017)	(0.017)	(0.017)
100- employees	0.205***	0.205***	0.204***	0.204***	0.202***	0.203***
	(0.034)	(0.034)	(0.017)	(0.017)	(0.017)	(0.017)
Constant	0.199	0.158	0.236	0.193	0.235	0.217
	(0.281)	(0.278)	(0.176)	(0.172)	(0.178)	(0.175)
Selection Poly	No	No	Yes	Yes	Yes	Yes
Selection Occ	No	No	No	No	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	3759	3759	3759	3759	3759	3759
R^2	0.379	0.379	0.382	0.383	0.386	0.386
Chi^2			3892	3790	3804	3767
p	0.000	0.000	0.000	0.000	0.000	0.000
Wald-χ^2 (Poly)	–	–	20.10	19.94	17.11	17.11
Wald-p (Poly)	–	–	0.01	0.011	0.029	0.029
Wald-χ^2 (Occ)	–	–	–	–	24.91	25.65
Wald-p (Occ)	–	–	–	–	0.002	0.001

Note: Standard errors in parentheses. *,** and *** denote significance level of 1%, 5% and 10% respcetively. Standard errors are bootstrapped with 400 replications.

Controlling for selection into polytechnics, column 3 shows that polytechnic graduates (pre- and post-reform) are on average disadvantaged in terms of wages (2.1

percentage points). The negative wage differential for pre- versus post-reform graduates is also verified in this model and both coefficients become statistically significant. In the more detailed specification in column 4, the positive coefficient for pre-reform university graduates is statistically significant. It is very interesting to note that pre-reform traditional university graduates do also earn significantly more than post-reform graduates from traditional universities (the t-test shows that the coefficients are statistically different from each other.) This allows the interpretation that wages are equalised at traditional university graduates' expenses.

The question that is still to be answered is what drives these results. One channel that could be of importance here is an occupational sorting in the labour market. Managerial and professional positions are accompanied by a higher prestige, responsibility as well as earnings potential. If these positions are more likely to be held by graduates of traditional universities, this may explain the wage difference that we observe for pre-reform graduates.

The wage regressions controlling for occupational sorting in addition to sorting into a specific HE institution show that occupational sorting matters.[16] The model in column 5 shows that the effects go in the same direction as before, but the coefficients become smaller. The more detailed model in column 6 shows the difference more clearly. The coefficient depicting the effect of graduating from a university after 1992 implies that university graduates do no longer earn on average higher wages than polytechnic (or 'new university') graduates, given they have graduated after 1992.

We check whether this finding is explained by a difference in wages at a certain part of the income distribution by estimating quantile regressions at the 25th and 75th quantile and the median. The coefficients do not vary by quantile, but they are also not significant.[17] This can be traced back to the lower precision of quantile regressions and the size of our sample. All in all, we find that post-reform polytechnic graduates have assimilated to post-reform university graduates in terms of wages.

The econometric analysis offers several interesting results. Firstly, established re-

[16] We provide a regression table from first stage probit models in the appendix (6.A.1 and 6.A.2). To calculate the inverse Mill's ratios, the probit models are estimated for each year-pair separately.

[17] Tables are provided by the authors on request.

sults based on cohort surveys are confirmed using the BHPS: Generally, there was a wage benefit for university graduates over graduates from polytechnics. The FHEA, however, has changed the situation drastically. A degree obtained after the reform, regardless from which institution, does not lead to equally high wages as before the reform. The comparison of graduates from traditional universities and polytechnics before and after the reform shows that the overall benefit of graduates from traditional universities is driven by pre-reform graduates. While there is a significant difference between university and polytechnic graduates having graduated before the reform, this difference cannot be seen any longer for post-reform graduates. Controlling for occupational sorting, we show that the wage advantage of pre-reform university graduates over pre-reform polytechnic graduates is partly driven by a previously existing glass ceiling effect and that graduates from 'new universities' have managed to shatter the glass.

We can think of three different explanations of these findings, which are not mutually exclusive. First, as mentioned earlier, the phenomenon of over-education may be responsible for equal wages of post-reform university graduates compared to post-reform polytechnic graduates. Post-reform university graduates may be longer unemployed, or remain longer in low-skill occupations after graduation than post-reform polytechnic graduates. Although we cannot find any evidence for (or against) this hypothesis, we think this may be likely due to the fact that many polytechnic graduates studied 'sandwich-courses' and have therefore practical experience and better connections to employers. Second, combining this argument with the common perception that the 'new universities' are still more vocational and market-oriented (Economist, 2012), it is likely that post-reform polytechnic graduates are on average better matches to labour market demands than post-reform university graduates. Third, referring to the literature on employer learning, (e.g. Altonji and Pierret, 2001; Bauer and Haisken-DeNew, 2001), a possible explanation of our finding may be that the employer's perception of the two types of graduates has changed towards the advantage of 'new university' graduates. All in all, it is likely that the overall rising number of graduates leads to an oversupply. While the reform succeeded in giving equal wage rates to all graduates leaving HE after the reform, this convergence is achieved on an overall lower level.

6.6 Conclusion

In the course of this study we analyse the labour market outcomes of graduates from different types of HE institutions in the United Kingdom. The comparison is of special interest because the system of HE used to be 'two-tier' until 1992. Due to the Further and Higher Education Act of 1992, the system was changed by giving all polytechnics university status in terms of funding and naming. We can therefore compare labour market outcomes of graduates from universities and pre- and post-reform polytechnics and thereby explicitly evaluate the effect of the 1992 reform.

Using the large representative British Household Panel Survey over the period 1991 to 2008, we analyse whether wage differentials exist between pre- and post-reform polytechnic and university graduates. We control for possible bias from selection into polytechnics rather than universities and into professional/managerial occupations in a Heckman (1979) selection bias correction approach for panel data, proposed by Wooldridge (1995). We find wage differentials between polytechnic and university graduates in the baseline regressions, which is in line with previous studies (Weale, 1992; Chevalier and Conlon, 2003). However, post-reform polytechnic graduates earn equal average wages as post-reform traditional university graduates. Hence, the reform has changed relative wage rates between the types of graduates.

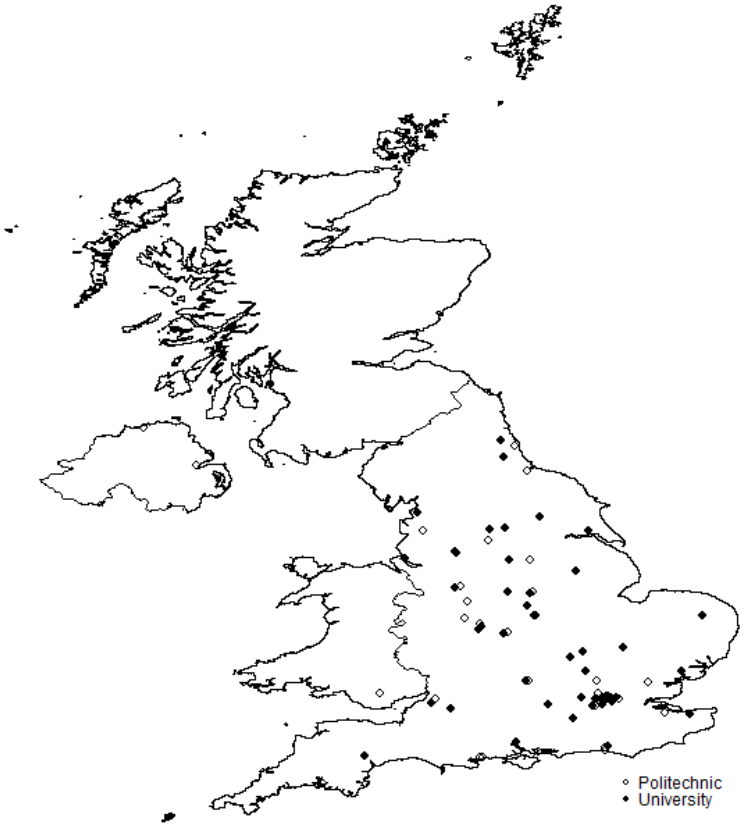
We augment this analysis and investigate, for the first time, whether both types of graduates are able to reach the same level on the occupational ladder. Therefore, we categorise occupations, based on the SOC 2000, into professional occupations and non-professional occupations. In a probit model, we identify a glass ceiling effect for polytechnic graduates compared to university graduates if they graduated before the reform. This glass ceiling is shattered by post-reform polytechnic graduates.

This analysis gives a detailed picture of the effects the Further and Higher Education Act of 1992 has had on graduates in the UK. It shows that the success of graduates on the labour market has significantly changed. This can partly be explained by a change in the education offered at the different institutions. However, this cannot be the complete explanation behind the finding that polytechnic graduates overcome the wage disadvantage. While the harmonisation in terms of funding gives rise to the assumption that education at both institution converges

after the reform, this does not explain why it become worse on a large scale, especially not in a short time period. However, it may be the case that the market orientation of post-reform polytechnics' curricula is paying off, and the supply of graduates from these institutions better meets actual labour market demands. Furthermore, solely the renaming process is a likely explanation when taking into account the strand of literature that investigates employer learning (e.g. Altonji and Pierret, 2001; Bauer and Haisken-DeNew, 2001). Employers may have changed their perception of 'new university' graduates' productivity since the reform and offer them higher positions. It is inconclusive whether this fast change after the reform provides evidence of a sheepskin effect or whether an educational difference has been conducted that quickly.

6.A Appendix

Figure 6.A.1: Higher Education institutions before 1994



Source: Authors' construction.

Table 6.A.1: First-Stage Probit Regressions – Sorting into Polytechnic

	1991/92	1993/94	1995/96	1997/98	1999/00	2001/02	2003/04	2005/06	2007/08
Uni share 150km	-0.743	-0.361	-0.372	-0.190	-0.553*	-0.531	-0.376	-0.680*	0.411
	(0.537)	(0.586)	(0.502)	(0.514)	(0.310)	(0.324)	(0.339)	(0.389)	(0.418)
Total institutions	0.018*	0.009	0.002	0.007	0.012*	0.005	-0.002	-0.002	-0.003
	(0.011)	(0.011)	(0.011)	(0.011)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)
Age	0.016	0.158	0.122	0.238**	0.106*	0.018	0.214***	0.256***	0.273***
	(0.106)	(0.120)	(0.118)	(0.101)	(0.056)	(0.066)	(0.069)	(0.069)	(0.087)
Age^2	-0.001	-0.003*	-0.002	-0.003**	-0.001**	-0.000	-0.003***	-0.003***	-0.003***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Father prof.	-0.610***	0.023	-0.114	-0.229	-0.226*	-0.169	-0.214	-0.574***	-0.538***
	(0.204)	(0.196)	(0.190)	(0.186)	(0.130)	(0.137)	(0.150)	(0.156)	(0.169)
Mother prof.	0.387	-0.325	-0.373	-0.296	-0.304	-0.609***	-0.143	-0.257	-0.135
	(0.279)	(0.311)	(0.288)	(0.276)	(0.199)	(0.219)	(0.221)	(0.243)	(0.239)
Father unempl.	-1.236*	0.000	-0.142	-0.381	-0.488	-0.297	-0.269	-0.308	-0.564
	(0.660)	(0.000)	(0.508)	(0.517)	(0.455)	(0.429)	(0.597)	(0.452)	(0.592)
Mother unempl.	0.402*	0.126	0.009	-0.136	-0.123	-0.304**	-0.276*	-0.077	-0.007
	(0.210)	(0.203)	(0.188)	(0.186)	(0.134)	(0.140)	(0.154)	(0.163)	(0.181)
Constant	0.066	-2.913	-2.144	-4.443**	-2.130*	0.205	-4.130***	-4.616***	-5.841***
	(1.908)	(2.227)	(2.298)	(1.868)	(1.107)	(1.298)	(1.403)	(1.518)	(2.040)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	323	286	307	343	546	471	418	411	364

Note: Marginal effects displayed. Standard errors in parentheses. *,** and *** denote significance level of 1%, 5% and 10% respcetively. Standard errors are bootstrapped with 400 replications.

Table 6.A.2: First-Stage Probit Regressions – Sorting into High Occupation

	1991/92	1993/94	1995/96	1997/98	1999/00	2001/02	2003/04	2005/06	2007/08
Father prof.	-0.058	0.007	0.045	0.026	0.177*	-0.158	0.009	-0.024	-0.080
	(0.147)	(0.150)	(0.146)	(0.139)	(0.103)	(0.108)	(0.122)	(0.121)	(0.130)
Mother prof.	-0.210	-0.200	-0.446*	0.045	-0.332**	-0.194	-0.031	-0.071	0.163
	(0.225)	(0.255)	(0.233)	(0.216)	(0.158)	(0.177)	(0.190)	(0.187)	(0.192)
Father unempl.	0.084	-0.578	-0.198	-0.031	-0.412	-0.098	-0.715*	0.226	0.049
	(0.359)	(0.448)	(0.420)	(0.412)	(0.345)	(0.301)	(0.393)	(0.335)	(0.352)
Mother unempl.	-0.285*	-0.162	-0.551***	-0.291**	-0.250**	-0.166	-0.050	-0.252*	-0.019
	(0.160)	(0.165)	(0.155)	(0.145)	(0.110)	(0.115)	(0.125)	(0.131)	(0.138)
Polytechnic	-0.332**	-0.539***	-0.303*	-0.147	-0.264**	-0.186	-0.172	0.042	0.186
	(0.169)	(0.182)	(0.173)	(0.159)	(0.114)	(0.115)	(0.129)	(0.134)	(0.143)
Higher degree	-0.013	0.493**	-0.134	0.560***	0.111	0.433***	0.315**	0.570***	0.753***
	(0.190)	(0.205)	(0.169)	(0.171)	(0.116)	(0.126)	(0.134)	(0.140)	(0.150)
Vocational	-0.365**	-0.597***	-0.308*	-0.516***	-0.356***	-0.280**	-0.140	-0.347***	-0.495***
	(0.171)	(0.184)	(0.170)	(0.156)	(0.111)	(0.117)	(0.127)	(0.129)	(0.136)
Private school	0.557**	0.245	0.332	0.460**	-0.263*	0.197	0.678***	0.273	0.091
	(0.220)	(0.243)	(0.240)	(0.230)	(0.159)	(0.194)	(0.223)	(0.217)	(0.231)
Tenure	0.043	0.009	-0.040	-0.030	-0.014	-0.013	-0.008	-0.026	-0.045**
	(0.026)	(0.032)	(0.024)	(0.027)	(0.015)	(0.017)	(0.019)	(0.019)	(0.021)
Tenure^2	-0.001	0.001	0.001	0.001	0.001*	0.001	0.001	0.001	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Age	0.136**	0.118	0.003	0.004	0.098**	0.048	0.084*	0.011	0.046
	(0.066)	(0.084)	(0.089)	(0.067)	(0.044)	(0.045)	(0.049)	(0.049)	(0.055)
Age^2	-0.001	-0.001	0.001	0.000	-0.001**	-0.001	-0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Health status	0.054	-0.160	-0.134	-0.182**	-0.090	-0.129*	-0.127	-0.082	-0.110
	(0.097)	(0.101)	(0.087)	(0.092)	(0.056)	(0.068)	(0.077)	(0.080)	(0.082)
Married	0.147	0.557***	0.411***	0.271**	0.226**	0.222*	0.317**	0.441***	0.354**
	(0.153)	(0.160)	(0.146)	(0.137)	(0.108)	(0.113)	(0.128)	(0.129)	(0.138)
Constant	-2.596**	-2.423	-0.200	0.648	-1.384	-0.442	-1.508	0.337	-0.085
	(1.252)	(1.594)	(1.737)	(1.304)	(0.887)	(0.924)	(0.997)	(1.072)	(1.352)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	480	464	458	516	777	689	601	575	535

Note: Marginal effects displayed. Standard errors in parentheses. *,** and *** denote significance level of 1%, 5% and 10% respcetively. Standard errors are bootstrapped with 400 replications.

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OCT 2010:	Universidad Iberoamericana, Mexico City
JUL & SEP 2009:	IAB Nuremberg, Forschungsdatenzentrum

GRANTS

2013:	RUB Research School plus Conference Grant (2x)
2012:	Stipend of Austrian National Bank (conference premium)
2012:	Royal Economic Society Conference Grant
2012:	"Scheme to support special activities of doctoral students" (travel grant) by RUB
2012:	"Going International Travel Grant" by RUB Research School
2012:	1000,- Euro Allowance by RUB Research School
2011:	1000,- Euro Allowance by RUB Research School
2011:	"Equal Opportunities Travel Grant" by Department of Economics, RUB
2010:	1000,- Euro Allowance by RUB Research School

MEMBERSHIP OF PROFESSIONAL ORGANISATIONS

American Economic Association, European Economic Association, Latin American and Caribbean Economic Association, Royal Economic Society, Verein für Socialpolitik

REFEREE ACTIVITIES

Journal of Agricultural Economics

LANGUAGE SKILLS

German:	Native language
English:	Excellent reading, writing and verbal skills
Spanish:	Excellent reading skills, good writing and verbal skills
Latin:	Good reading skills

REFERENCES

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