Three Essays in Applied Economics

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Summary

This thesis comprises three essays. The first one focuses on the effect of a change in the labour market conditions induced by a trade shock on crime at the US local level. Using US Census data, I provide evidence that the increasing exposure to Chinese competitiveness has indirectly contributed to the change in the propensity to commit crime through a reduction of the expected labour market earnings. The second essay, which is co-authored with Vincenzo Bove and Roberto Nisticò, addresses the reasons why countries decide to transfer weapons only to specific recipients. We present novel empirical models of the arms trade and concentrate on the role of energy dependence, in particular of oil, in explaining the trade of weapons between countries. We find strong empirical support for the hypothesis that oil-dependent economies have incentives to provide security by selling or giving away arms to oil-rich countries and reduce their risk of political instability. Finally, the last essay, joint with Emanuele Ciani, has a specific focus on family economics. We provide evidence that parents who helped their adult children in the past are rewarded by higher chances of receiving informal care later in life. To this purpose we use Italian data containing retrospective information about help with housing received from parents at the time of marriage. We show a positive association with their current provision of informal care to them, which is robust to controlling for a large set of individual and family characteristics, and is confirmed by an IV regression using house prices as instrument. The results are in line with theories based on the presence of a third generation of grandchildren, such as those involving a demonstration effect or a family constitution.

Declarations

No part of this thesis has been submitted for another degree. All errors are mine. The second essay is with Dr. Vincenzo Bove (currently Associate Professor in the Department of Politics and International Studies at the University of Warwick) and Dr. Roberto Nisticò (currently at the Center for Studies in Economics and Finance, namely CSEF, within the Department of Economics and Statistics of the University of Naples Federico II). The third essay is a joint work with my former colleague Dr. Emanuele Ciani (currently at the Bank of Italy).

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Abstracts

First Chapter: This paper analyses the effect of a change in local labour market conditions induced by a trade shock on crime in the US. Over the last three decades, the US economy has been gravely shaped by international trade shocks, and China played a crucial role as a major global exporter. This study documents that the increasing exposure to Chinese competitiveness has indirectly contributed to the change in the propensity to commit crime through a reduction of the expected labour market earnings. I exploit the cross-market variation in import exposure stemming from initial differences in industry specialisation as an instrument for the local labour market conditions. The empirical evidence from the current study suggests a more than proportional elasticity of crime with respect to a decrease in labour earnings originated by Chinese import penetration.

Second Chapter: The arms trade is a controversial issue with many economic and strategic implications, yet we still know little about why countries decide to transfer weapons only to specific recipients. Against this background, we provide a novel empirical model of arms trade and focus on the role of energy dependence, in particular of oil, in explaining the trade of weapons between countries. Dramatic geopolitical events such as wars can cause significant disruptions in the supply of oil and increase oil prices. Oil-dependent economies have therefore incentives to provide security by selling or giving away arms to oil-rich countries and reduce the risk of instability. We find strong empirical support for this claim using data on international transfers of major weapons and information on global and local oil dependence, oil reserves and oil discoveries.

Third Chapter: The empirical literature on the relation between intergenerational transfers of assets and services has mostly focused on contemporary exchange. Differently, we provide evidence that parents who helped their adult children in the past are rewarded by higher chances of receiving

informal care later in life. To this purpose we use Italian data containing retrospective information about help with housing received from parents at the time of marriage. We show a positive association with current provision of informal care to them, which is robust to controlling for a large set of individual and family characteristics, and is confirmed by an IV regression using house prices as instrument. Although the results may be explained by standard models of either altruism or exchange, we provide additional evidence that is more in line with theories based on the presence of a third generation of grandchildren, such as those including a demonstration effect or a family constitution. However, not all their predictions are borne out in our data, suggesting that a single motive is not prevailing.

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Chapter 1

The Bitter Side of Trade Shocks: Local Labour Market Conditions and Crime in the US[1]

1.1 Introduction

Economists and policy-makers have long been interested in the relationship between labour market opportunity and crime. Since the seminal contributions both by Becker (1968) and Ehrlich (1973), deteriorating labour market conditions have been identified as one of the most significant risk factors for criminal activity. Nevertheless, the existing studies on this link still face considerable challenges to causal inference due to omitted variable bias and reverse causality (see Draca and Machin, 2015, and Mustard, 2010, and references therein).

This paper contributes to the literature on labour market conditions and crime by taking advantage of a trade shock induced by the extraordinary growth in China's exports. The connection between trade-induced labour market shocks and crime has never been explored before in such a

[1]This paper has been presented at the Royal Economic Society Conference at the University of Brighton (2016), at the XXX National Conference of Labour Economics (2015) and at the internal seminar at the University of Essex. I would like to thank Giovanni Mastrobuoni and Matthias Parey for their support and guidance. I am in debt to Andrea Geraci for the fruitful conversations and his invaluable advices. Moreover I thank Ludovica Giua, Roberto Nisticó, Emanuele Ciani, Alberto Tumino, Stefano Alderighi and Marco Nieddu for their comments. I thank the FBI for the crime data. Opinions expressed herein are those of the author only. They do not necessarily reflect the views of, or involve any responsibility for, the institutions to which he is affiliated. Any errors are the fault of the author.

context.[2] I thus document that the US exposure to Chinese imports - in a context in which China has unexpectedly emerged as a major global economic power - indirectly contributes to the worsening condition of the US Local Labour Market (LLM hereafter) and then impacts the propensity to commit crimes.[3] I use a simple theoretical model to obtain a labour market opportunity measure defined as the logarithm of wages multiplied by (average) employment rate. Consequently, I investigate how crime reacts to changes in expected labour market earnings driven by international trade shocks. In order to do that, I exploit the cross-market variation in import exposure stemming from initial differences in industry specialisation to instrument the local labour market condition measure. The result of the first-stage regression points in the direction of a clear negative effect of trade shock on the labour market opportunities. Larger Chinese penetration is associated with lower local labour market earnings. The second-stage results highlight a more than proportional effect of trade induced labour market conditions on crime. Additionally, I directly regress changes in local crime rates on the trade shock finding a strong reduced-form effect.[4]

Over the period 1990-2007, the US economy has been dramatically shaped by international trade shocks, which have brought about impressive structural changes in the US LLMs (Autor et al., 2013). During the same period, China's transition from a central planning to a market-oriented economy and the reduction of its trade costs through the World Trade Organization (WTO) accession played a crucial role in the success of Chinese exports. Under these circumstances, US spending on Chinese goods quickly increased from 0.6% in the early 1990s to 4.6% in 2007, with an even faster tendency after 2000, when China joined the WTO.[5] The greater US exposure to Chinese products depressed the US local labour market between 1990 to 2007 (Autor et al., 2013) and it currently represents a relevant issue for economists and policy makers who should provide structural adjustment programmes to possibly limit such a detrimental effect.

In addition to the factors mentioned so far, the effect of trade on crime is interesting in and of itself, since it highlights a dimension of adjustment costs beyond those directly associated with labour market re-allocation, an aspect so far overlooked in the literature. As a matter of fact,

[2]The only other papers considering a somewhat similar aspect are Iyer and Topalova (2014) and Dix Carneiro et al. (2016) for India and Brazil, respectively. Sequeira (2016) provide a new evidence on corruption and trade.

[3]In the paper, the terms labour market conditions and opportunities are considered interchangeable with labour market earnings.

[4]In Table 1.C.1, I also analyse the complement of the main labour market conditions measure, namely NIUN, which includes all the people not-working that can be both unemployed and not in the labour forces. The evidence produces similar conclusions to the main results of this study.

[5]Figure 1.A.1 in Appendix 1.A shows this extraordinary growth.

illegality may be considered as an additional *collateral* cost of trade through a deterioration of the local labour market conditions. Furthermore, crime *per se* imposes tremendous economic and social costs on the society. The public expenditure on criminal justice amounts to approximately $630 per capita, which is about 2.5% of GDP, and private expenditure on crime prevention is at least as large (US Census, 2007). The aggregate cost of crime to society exceeds $1 trillion, which is approximately the size of the US healthcare sector (Anderson, 1999).[6] Despite its economic relevance, the relationship among labour market opportunities, trade shocks and crime remain a relevant and open empirical question for economists.

The empirical literature on crime and labour market conditions (see Freeman, 1999), suggests that, at the margin, participation in criminal activity is the result of the potential earnings from successful crime exceeding the value of legitimate work, where the earnings from delinquency are discounted according to the risk of apprehension and subsequent sanctions. Over the years there has been a long debate on the potential measures of labour market opportunities. The great majority of studies in the literature analyse the link between crime and unemployment, which is considered the main channel through which an individual engages in criminal activities.[7] Other studies (Lin, 2008), focus on the earnings-crime relationship. Generally, scholars find an inconsistent weak positive relationship between slowdowns and illegality (Cullen and Levitt, 1999; Chiricos, 1987). As discussed by Freeman (1983), the effect tends to be modest and it typically fails to take into account the endogeneity between these two phenomena. In addition to this branch of the literature, the range of analyses that relates crime rates to specific measures of earnings seems to provide more robust evidence (see Draca and Machin, 2015, and references therein). Some recent contributions, such as Raphael and Winter-Ember (2001) and Gould et al. (2002), explicitly tackle the potential endogeneity of this relationship. Their evidence, mostly based on national surveys, suggests a positive significant effect on property crimes (Lin, 2008) and on the subgroups more at risk of committing crime, e.g. low-skilled, young men (Gould et al., 2002).

Conceptually, it is difficult to rationalise how a 'shock' in a local labour market could affect one of the two previous margins but not the other. As a consequence, I present a simplified theoretical

[6]For example, Cohen et al. (1996) estimate the annual cost of crime in the United States at about $450 billion, which is equivalent to $1,800 per capita per year. Additionally, the prison population has doubled since the early 1990s and currently stands at over 2.2 million inmates, putting further pressure on the US welfare State.

[7]Mustard (2010) offers a detailed discussion of the most recent papers on the crime and socio-economic conditions relationship.

model which helps to frame how labour market conditions are related to crime and justifies the use of one instrument (Subsection 1.3.1). Differently from the above-mentioned studies, I construct an alternative measure of LLM opportunities, which incorporates both the average wages and the probability to be employed. This proposed measure is defined as "expected labour market earnings" and is related to the index in Dix Carneiro et al. (2016). To begin with, I estimate a first difference specification in order to wipe out the time-invariant heterogeneity. Second, to mitigate the omitted-variable bias, I extensively control for observable demographic and economic variables at the local level. Finally, I exploit the cross-market variation in Chinese imports exposure, which is due to initial differences in industry specialisation, to instrument the US LLM conditions. To the best of my knowledge, this study provides the first causal test of the long-term change of labour opportunities induced by trade shock on crime rates at the local level. To perform this test, I identify the trade shocks to local labour markets considering the cross-industry and the cross-LLM variations in imports competition that is favoured both by China's spectacular rising productivity and falling barriers to trade after its admission in the WTO. This represents a unique attempt to explain how crime rates react to global competition. This paper reveals that the exogenous rise in foreign competition with Chinese products explains the change in arrest (and offence) rates in spite of the worsening status of labour prospects for workers over the period of 1990-2007.[8]

I empirically map the industry-specific trade shocks into a specific geographical unit. Thus, I define the US LLMs as sub-economies subject to heterogeneous trade shocks according to their initial industry specialisation. The Commuting Zone (hereafter CZ), which includes all metropolitan and non-metropolitan areas in the United States, is the logical geographic unit for defining a LLM area (Tolbert and Sizer, 1996; Autor et al., 2013, 2016). The analysis by CZ is motivated by the notion that employers and workers interact within a space bounded by places of work and places of residence. This kind of residents-workers interaction limits, to some extent, the migration flows. Due to the lack of precise geographical information, empirical studies on crime often consider the 50 US States (Raphael and Winter-Ember, 2001) and/or the US counties as LLM (Gould et al., 2002). The latter approach provides a substantially more detailed geographic structure than States. However, both geographical units raise similar methodological concerns, mainly that there is no

[8] A comprehensive literature review can be found in the Handbook on the Economics of Crime (Benson and Zimmerman, 2010). The only other studies which acknowledge a possible link among trade, labour conditions and crime are Iyer and Topalova (2014) and Dix Carneiro et al. (2016) but with completely different settings with respect to the current study.

economic motivation for why the boundaries of LLM should coincide with those of States/counties, provided that the latter are merely administrative definitions. The possibility of mapping the crime phenomenon across US CZs represents a further contribution to the current crime literature.[9]

The main findings of this study suggest that the downturn stemming from an increase in imports from China is accompanied by substantial increases in those criminal activities to which individuals can easily turn when their economic conditions worsen. The first-stage estimation shows a negative effect of trade shock on labour market opportunities which is similar to those previously documented in the literature (Autor et al., 2013). The regions specialised in industries exposed to larger Chinese penetration face a deterioration in labour market earnings relative to their counterparts. The second-stage estimation shows that worsening local labour market opportunities led to an increase in crime rates. In contrast with previous research, this study finds significant and sizable negative effects of worsening labour market earnings on crime, thus leading to more than a one-to-one elasticity. This means that a one per cent decrease in labour market opportunity increases the total crime rate by two per cent. In addition, the reduced-form estimate suggests an effect of global competition on the propensity to commit crime. It is, therefore, somewhat surprising that so little is known by economists and policy-makers about how crimes react to trade shocks as a result of the disruptive effects on LLM structure and job opportunities.

The remainder of the paper is organized as follows: Section 1.2 briefly discusses the background in crime, labour market conditions and trade shocks. Section 1.3 illustrates the theoretical framework, the identification strategy and the empirical specification. The data sources and the descriptive statistics are provided in Section 1.4. Results and robustness checks are presented in Section 1.5. The discussion of the mechanism is in Sections 1.6. To conclude the paper, I summarize the empirical findings and I briefly discuss some policy implications in Section 1.7.

[9] CZs are clusters of counties that are characterised by strong commuting ties within each CZ, and weak ones across CZs. The CZ's boundaries are appropriate when analysing the relationship between local economic conditions and the change in crime since CZs have been created to exactly capture, more than any other administrative definition would do, the economic notion of local labour markets in the US (Tolbert and Sizer, 1996). The most popular concepts for LLM in recent research are Metropolitan Statistical Areas, which are used by Card (2001), for example. Those concepts, however, only cover areas of the US with a major urban population and their geographic definition changes over time (Autor et al., 2013, 2014).

1.2 Background: Crime, Labour Market Conditions and Trade Shock

The past three decades have seen an abundant debate on the impact of international trade shocks on US LLM opportunities and on how these external forces have reshaped the developed economy. Over the same period, China has played a role of guidance as emerging leader in the export sector (Rodrik, 2006; Amiti and Freund, 2010). In particular, the general interest of trade scholars in China relies on possibility of having a credible "exogenous variation". Three peculiarities of China's experience are useful for overcoming the challenges in identifying the casual effects of trade shocks on LLM conditions. First, China's export growth was completely unexpected and it caught academics and economists by surprise (Autor et al., 2016). Second, the isolation under Mao's regime created generous opportunities for a successive catch up (Zhu, 2012). A final important key feature of China's rise is its distinctive and overwhelmingly comparative advantage in producing industrial goods. All these factors - the opening to market economy, which involved rural-to-urban migration of over 150 million workers, and reducing the trade barriers with the WTO accession - determines the remarkable growth in China's exports.

These mentioned elements create an "artificial" setting to test different implications.[10] Depending on the differences in the initial industry specialisation, the impact of Chinese penetration asymmetrically affects the US LLM economies by causing a decline in their labour market conditions.[11] Bernard et al. (2006) find that US industries facing greater increases in exposure to trade from low-wage countries, attributable in the large to China, are subject to higher rates of plant exits. Similar effects are observed for other countries: growing Chinese import competition increases plant closures and reduces firm growth in Mexico, according to Iacovone et al. (2013) and Utar and Ruiz (2013). Additionally, greater exposure to Chinese competition reduces employment growth in Belgian firms (Mion and Zhu, 2013), Danish firms (Utar, 2014), and in a panel of firms from twelve European countries (Draca et al., 2015). A novel study examines the impact of trade on the structure of marriage and child rearing in US households (Autor et al., 2014).

The evidence so far suggests that trade may be a costly and slow process and that, further-

[10] According to Rodrik (2006), the great success of China as the most relevant exporter around the world is again determined by a combination of its comparative advantage in producing tradable goods, the opening to free markets and above all the Chinese government itself playing a crucial guide for this prodigious growth.

[11] Balsvik et al. (2015), Donoso et al. (2015) and Autor et al. (2013) come to similar conclusions.

more, it may not be beneficial for some areas depending on the economic structure of a local labour market.[12] Hence, it follows naturally to ask whether this increasing exposure to Chinese competitiveness has indirectly contributed to the propensity of committing crimes through the deterioration of labour market conditions.

In the Becker (1968) model (and that of Ehrlich, 1973, which I adapt in Subsection 1.3.1), individuals choose to commit an illegal act by simply evaluating the expected benefits from crime with the expected costs. In their theoretical framework, they claim that economic incentives affect crime participation in a number of ways and legal labour market opportunities represent an important factor in determining whether crimes are committed or not. In this context, a deteriorated economy provides higher incentives for individuals to switch into the illegal sector. It is clear, from a theoretical point of view, that declining labour market outcomes worsen legal income opportunities, therefore making crime more attractive and less costly.[13] Consistently with such a hypothesis, trade-induced supply shocks have a negative effect on labour market opportunities, especially for LLMs that are more exposed to the rise in Chinese penetration (as demonstrated by Autor et al., 2013), thus determining an increase in the propensity to offend.

Most empirical analyses so far fail to show a consistent and strong association between downturns and crime, as highlighted by Mustard (2010). The majority of the early empirical works, which focus on the unemployment rate as a measure of labour market opportunity, tend to find small and positive effect on property crime but not on violent ones (Freeman, 1983; Piehl, 1998). Chiricos (1987) reviews more than 60 studies on the crime literature and concludes that the evidence appears to be "inconsistent" and "weak". This relates to the fact that it is complicated to tackle the issue of endogeneity between crime rate and labour market conditions. Conversely, the most recent literature generally finds a stronger, positive and significant effect on property (but not violent) crimes (Lin, 2008). The significant change in the estimated effect of unemployment on crime has to be attributed to a more appropriate list of controls or sub-group analyses of individuals who can be considered at "risk" of committing crimes (Gould et al., 2002). Additionally, the recent need to control for endogeneity caused by omitted variables, reverse causation and measurement

[12] Recently, Autor et al. (2016) study whether the rise in trade integration between the US and China has an effect on the polarization of US politics. They find that congressional districts, which are more exposed to larger increases in import competition, removed moderate representatives from office in the 2000s.

[13] Other scholars focus on the idea of time allocation between legal and illegal activities and its influence on the decision of whether or not to participate in criminal activities (Grogger, 1998).

error determines a notable improvement in the estimation process (Raphael and Winter-Ember, 2001; Lin, 2008). No study yet analyses the role of people who are not-working (Table 1.C.1).

Raphael and Winter-Ember (2001) represent the first attempt in providing an instrumental variable estimate of the link between unemployment and crime. The authors exploit an arguably exogenous variation across States in unemployment due to the closing of military bases and the shocks to oil prices. They discuss the validity of both sets of instruments, which are unrelated to crime, once other observable factors, such as the imprisonment rate, demographic composition and percentage in poverty have been controlled for. They find that a one percentage point increase in unemployment leads to an increase in property crime between 2.8% and 5%.

Gould et al. (2002), using a US panel of counties from 1979 to 1997, provide one of the few pieces of evidence with an earnings measure. They focus on those individuals at the margin of committing crime: young, unskilled, and low-educated males. During the analysed period, they record that a 23 per cent fall in unskilled wages predicted 43 per cent of the total increase in property crime, and that a 3 percentage point increase in unemployment predicted 24 per cent of the change in total crime rate.[14] Lin (2008) analyses the same association using a panel of US States from 1974 to 2000. In order to instrument the unemployment, the author exploits the changes in the real annual exchange rates as an exogenous variation in the economy. In his 2SLS estimates, one percentage point rise in unemployment leads to a rise in crime rate by about 4% to 6%, which is about three times larger than the OLS estimate.

Some authors demonstrate that recession may lead to substantial and persistently higher rates of crime (de Blasio and Menon, 2013). Using a range of US and UK data, Bell et al. (2015) conclude that recessions lead to short-term job loss, lower levels of happiness and decreasing income levels. Rege et al. (2009) focus on the effect of exposure to plants closure on crime using an individual-level panel data set containing criminal charges for all unmarried and employed Norwegian men of under 40 years of age. Men originally employed in plants that subsequently closed are fourteen per cent more likely to be charged of a crime than comparable men in stable plants. Using detailed employer-employee Danish data, Bennett and Ouazad (2015) study the impact of job loss on an individual's probability to commit a crime. Displaced workers are more likely to deviate into the illegal sector leading to convictions for property crimes and for alcohol-related traffic violations in

[14] Also Grönqvist (2011) examines the relation between youth unemployment and crime. His results suggest that joblessness explains a meaningful portion of why male youths are over-represented among criminal offenders.

the two years following displacement. In her recent work, Bindler (2015) provides evidence on the relationship between downturn and crime in the light of increasing unemployment durations and temporary benefit extensions in the United States. It is interesting to note that most of the crime papers listed above employ State-level data, which suffers from the problem of aggregation bias that has been discussed in the crime literature since Cornwell and Trumbull (1994).

1.3 Theoretical and Empirical Framework

Subsection 1.3.1 presents the theoretical model which provides some useful insights for the empirical analysis Dix Carneiro et al. (2016). The main objective of this model is to illustrate how labour market conditions can directly affect the propensity to commit crime by comparing the corresponding utilities.[15] Hence, the model helps to incorporate in a single variable the labour market opportunity at the CZ level. In Subsections 1.3.2 and 1.3.3, I delineate in detail the empirical strategy. To start with, I estimate the model in first difference in order to wipe out the time-invariant heterogeneity. Next, I exploit the unprecedented rise in the Chinese exports across the world to instrument the local labour market conditions. I finally emphasize the reduced-form effect between trade shocks and crime which directly describes to the adjustment costs following a trade shock.

1.3.1 A simple model on local labour market conditions and crime

Following Ehrlich's seminal model (1973) on participation in illegitimate activities, I deliver a statistic of how the labour market opportunity can influence the crime behaviour. The framework provides a guideline to the empirical estimation and do not theoretically contribute to the relation between work opportunity and crime. To do so, I use a simple partial equilibrium model, which is crucial for understanding how crime reacts to labour market conditions as in Dix Carneiro et al. (2016).

In this framework, the individual can only choose to work or committ a criminal act. If s/he finds a job (with probability E), s/he receives a wage, w; otherwise (with probability *1-E*) s/he gets zero. In case an individual engages in criminal activity and s/he is arrested (with probability C), s/he loses all the illegal income receiving zero. On the contrary, if s/he is not caught (with probability *1-C*), s/he enjoys the illegal money, m. In addition to that, individuals are risk-neutral and they care about their expected earnings. To conclude, their inclinations towards work or committing a crime also depend on some idiosyncratic preference shocks: ϵ_i^w and ϵ_i^c, respectively. The individual who looks for a job or commits a crime faces the following utilities:

$$U_i^w = V_w + \upsilon\epsilon_i^w \tag{1.1}$$

[15] The theoretical framework is based on both Dix Carneiro et al. (2016) and Ehrlich (1973).

$$U_i^c = V_c + \upsilon\epsilon_i^c \tag{1.2}$$

V_w describes the $log(w \times E)$, namely the "expected labour market earnings" as defined by Dix Carneiro et al. (2016), while V_c is the potential gain in crime, which is equal to $log(m \times (1 - C))$. The preference shocks follow a standard Gumbel distribution and they are independent from each other. The scale parameter ($\upsilon > 0$) establishes the dispersion of these preference shocks. To conclude, an individual decides to switch to the illegal sector if $Pr(U_i^c > U_i^w)$ which can also be formulated as:

$$CR = Pr(U_i^c > U_i^w) = Pr(V_c + \upsilon\epsilon_i^c > V_w + \upsilon\epsilon_i^w) \tag{1.3}$$

Using the properties of a Gumbel distributions, the equation (1.3) can be formulated as:

$$CR = \frac{e^{\frac{1}{\upsilon}V_c}}{e^{\frac{1}{\upsilon}V_c} + e^{\frac{1}{\upsilon}V_w}} \tag{1.4}$$

The fraction of individuals choosing crime over work determines the crime rate:

$$\frac{CR}{1 - CR} = exp\left\{\frac{1}{\upsilon}(V_c - V_w)\right\} \Longrightarrow log\left(\frac{CR}{1 - CR}\right) = \frac{1}{\upsilon}(V_c - V_w) \tag{1.5}$$

Due to the fact that CR$\ll$1, it is possible to approximate $log\left(\frac{CR}{1-CR}\right)$ with $log(CR)$. Finally, assuming constant returns to crime over time, equation (1.5) can be rewritten in changes as follows:

$$\Delta log(CR) = -\frac{1}{\upsilon}\Delta log(w \times E) = -\frac{1}{\upsilon}\Delta log(LMC) \tag{1.6}$$

This simple model predicts how expected labour earnings in the legal sector, also called Labour Market Conditions (LMC), are related to the propensity to commit crimes. The main theoretical result is based on the fact that changes both in earnings and in the probability of finding a job determine changes in crime rates (Dix Carneiro et al., 2016). Bearing in mind that w and E are generally correlated, any specification that relates changes in just one of these variables to changes in crime rates - a common practice in labour markets and crime literature - indirectly captures the effect of the omitted variables.[16]

[16]For a matter of clarity, it is assumed that the gain from criminal activities does not depend on labour market conditions. If this does not hold, then the estimate of the effect of labour market conditions on crime rates captures both a direct effect and an indirect effect through the payoff of crime. Due to the fact that criminals look for not only

1.3.2 From the theory to the first difference estimation

Following the theoretical prediction outlined earlier in Section 1.3.1, I initially focus on the relationship between crime and expected labour earnings by estimating the model in first difference. Hence, the time-invariant heterogeneity for the long-term change interval between 1990-2000 and 2000-2007 is eliminated. Hence, I stack the ten-year equivalent of first differences for the two periods, 1990 to 2000 and 2000 to 2007, which include separate time dummies for each decade. Due to the fact that the model is estimated in first difference, the decade-specific model is directly comparable to fixed effects regressions, while the stacked first difference models are similar to a three-period fixed effects model with slightly less restrictive assumptions made on the error component. This procedure should minimize any concerns related to the time-invariant unobserved heterogeneity between crime and labour market conditions. For instance, if cultural characteristics across the sampled regions systematically affect crime and LLM behaviour, one local area may display higher crime rates and worse LLM conditions independently from the effect of interest of this analysis. Hence, I rule out all the variation in crime rates caused by factors that vary within regions and are constant over time, but, on the other hand, I include time effects in order to eliminate the influence of factors that cause time-to-time changes in crime rates common to all areas. I then fit the models in first difference of the following form:

$$\Delta log(CR^{k}_{c,t}) = \beta_1 \Delta log(LMC_{c,t}) + \gamma_t + \Delta X^{'}_{c,t}\beta_2 + \Delta\varepsilon_{c,t} \tag{1.7}$$

where Δ is the (decade) first difference operator.[17] $CR^{k}_{c,t}$ is the crime rate, measured as the number of arrests and offences over working-age population, in area c, for the category of crime k, and in the decade t, which is equal to 0 and 1 over the periods of 1990-2000 and 2000-2007, respectively.[18] Additionally, γ_t indicates the dummies for each time decade and $\varepsilon_{c,t}$ is the residual. Standard errors

income, but accumulated wealth as well, I believe that the direct effect of the labour market (through opportunities of employment and legal earnings) is more relevant than the indirect effect (through potential targets for criminal activity). See Dix Carneiro et al. (2016), for further details.

[17] Following Autor et al. (2013), the 2000-2007 change in import growth is multiplied by 10/7 to place it in ten-year equivalent terms. I consider the period of 1990-2007 because data on trade are available from 1991 onwards, and I explicitly do not analyse the period of Great Recession in order to avoid possible confounding factors to the identification strategy.

[18] Applying the logarithm in 1.7, I lose some observations with crime equal to zero. Therefore, I run a lin-log specification and I provide identical conclusions. I do not modify the data (e.g. adding 1 when I observe zero crime) since it produces measurement errors which can lead to selection bias. This is explained in detail in Silva and Tenreyro (2006).

are clustered at the State level to account for spatial correlations across local areas.[19] The main regressor $LMC_{c,t}$ measures the average weekly wage in a local area weighted by the manufacturing and non-manufacturing employed as a ratio to the working-age population.[20]

The vector of Xs contains a rich set of economic and demographic variables at regional level with the aim of capturing any time-varying and confounding factors in the crime-labour market relationship (Cook and Zarkin, 1985). First, in order to control for the changes in demographic or racial structure compositions, I include three distinct age-group categories in the main specification: the share of people in 15-34, 35-49, and 50-64 age bands, which are identified in order to measure the change in age distribution at the CZ level (Fougere et al., 2009). Second, for each age category, I define the proportion of CZ residents in terms of race: White, Black, Indian or Asian. These race divisions are included to identify the decade differences across race distributions for the population subgroups that have higher offending rates compared to other Americans (**?**). Third, I control for the share of individuals with low, medium and high level of educational attainment. The latter levels are defined as less than high school diploma, high school diploma or higher but no bachelor degree, and finally with bachelor degree or higher, respectively. The predicted influence of the educational level variable on crime is difficult to determine a priori. The level of education can affect crime through three main mechanisms, namely the income effect, short-sightedness and self-incapacitation.

For instance, education increases the payoff to legitimate work which, in turn, makes working more worthwhile than criminal activity. However, this relationship may also work in the other direction, as education can also increase the earnings from certain crimes, e.g. white-collar crime such as fraud (Dix Carneiro et al., 2016). As for the effect of short-sightedness, young people who leave education earlier tend to care more about today than they do about tomorrow.[21] In other

[19] Estimating the model in fixed effect assumes that the errors are serially uncorrelated, while the first difference specification is more efficient if the errors are a random walk (Wooldridge, 2010). I cluster the standard errors at US State level in all models. I do not observe any change whether I cluster a lower geographical level or do not.

[20] Due to a lack of complete data on prices at the local level, the wages are in nominal terms and are rescaled in the robustness check by the consumer price index at the national level, which led to obtaining similar results with respect to the main ones in Table 1.4. Wages are inflated to the year 2007 using the Personal Consumption Expenditure Index.

[21] The literature on the relationship between education and crime is growing fast and Machin et al. (2011); Fella and Gallipoli (2014) represent notable examples of such work. (Machin et al., 2011) show that investing in education can yield significant social benefits and a key factor in reducing criminal activities. As discussed by Lochner (2004) and Lochner and Moretti (2004) human capital increases the opportunity cost of crime from foregone work, and the expected costs associated with incarceration. In particular, Lochner and Moretti (2004), who use Census and FBI data, find that schooling significantly reduces the probability of incarceration and arrest.

words, they prioritise short-term gratification in favour of long-term benefits. Such an attitude makes them more likely to undertake risky activities, such as crime. Time spent in school means less time on the streets committing crime and, therefore, less influence of the self-incapacitation mechanism. Following Lin (2008), I additionally characterize each local labour market by including a measure of federal income assistance, which comprises a set of governmental information: SSI (Supplemental Security Income); $TANF$ (Temporary Assistance for Needy Families) and $SNAP$ (Supplemental Nutrition Assistance Program), the share of Democratic and Republican voters in each presidential election over the period 1990-2007 and the fraction of police forces over the population. Finally, in the robustness analysis, I include other three factors which are relevant in the literature on the effect of labour market conditions on crime (Levitt, 1996, 1997): the prison population rate, a measure of income inequality and the unemployment benefit. A complete list of the variables with the corresponding sources is given in Subsection 1.4.2.

1.3.3 IV strategy and the role of trade shock

As previously discussed, the relationship between labour market earnings and crime may be biased by omitted variables, simultaneity or, simply, measurement error concerns. Consequently, the estimated correlation between the expected labour earnings and crime behaviour might be flawed, which means that *ex ante*, the causation of LMC on CR, is not obvious. For instance, individuals commit crimes based on unobservable characteristics, which may be associated with the ones determining the labour market conditions. If the unobservable characteristics are negatively (or positively) correlated with the local labour market opportunity but they are at the same time positively (negatively) correlated with participation in the illegal market, such as alcohol consumption, the estimated correlation is downward-biased. Additionally, reversed causation (i.e. that criminal activity reduces the employability of offenders, or that economic growth is harmed by a high crime rate in the region) may also bias the relation under analysis. Recent IV analyses, mainly using unemployment rate as a measure of the labour market conditions, show that the endogeneity generally produces an underestimated effect (Raphael and Winter-Ember, 2001; Fougere et al., 2009; Lin, 2008).

Since the results may contain bias coming from simultaneity or simple measurement error, and knowing that the list of potential omissions is never complete, correctly identifying the effect

of labour market condition on crime without an instrumental variable approach appears to be complicated. Therefore, an instrument Z becomes necessary to obtain a consistent estimator. As a consequence of this necessity, and in order to capture the correct effect of a long-term change in labour market conditions on crime, an exogenous source of variation is needed, that only affects crime rate through a change in labour market opportunity. This measure should not be determined by endogenous factors that contemporaneously affect the outcome variable (crime).

Thus, I exploit the unprecedented rise in Chinese exports across the world as an instrument for LMC. Recently, the scholars focus on the extraordinary case of Chinese exports because it helps to identify an exogenous shock of the local labour market economy. China's experience is decisive in identifying the casual effects of labour market conditions on crime due to three factors: first, China's export growth is completely unexpected by both the academics and economists (Autor et al., 2016). Second, the isolation under Mao creates generous opportunities for successive catch up (Zhu, 2012). Third, the overwhelmingly comparative advantage in producing industrial goods. All these factors create the conditions for China being a large positive net global supplier of tradable goods and its impact for the US local economies is likely to vary across regional areas according to the industry specialisation structure.

The strategy used to identify the effect of labour market opportunities on crime, in fact, relates to the changes in the exposure to international trade shocks in US CZs with the growth in US imports from China between 1990 and 2007, by exploiting a cross-market variation in import exposure stemming from initial differences in industry specialisation.[22] I concentrate on the trade with China because it is responsible for nearly all of the expansion in US imports from low-income countries since the beginning of the 1990's. As described by Chen et al. (2010), China's spectacular increase in exports is primarily determined by its internal reforms, which triggers the transition to a market-oriented economy and involves a migration from rural to urban areas of around 150 million workers.[23] This radical change co-occurs with China's accession to the WTO in the early 2000's. These transformations largely determine China's leadership in the exports to the US, and among the other high-income countries. In the globalization context, trade with middle-income nations may also play a role and can be used as an alternative unexpected shock to the LLMs. An

[22]The identification strategy is related to the one used by Autor et al. (2013).

[23]Autor et al. (2014) report some other important channels through which China had this incredible penetration in the world market, gaining access to long-run banned foreign technologies, capital goods and intermediate inputs being permitted to operate in the country.

evident case of the latter, is that of Mexico, which can be historically considered as one of the most notable exporters to the US economy.

Unfortunately, in this case, finding a credible exogenous source of variation in Mexico's exports growth is much more complicated. For example, the rise of US imports from Mexico may be caused by changes both in the supply and the demand shock jeopardising the identification of the Mexican increase in productivity or competitiveness. Moreover, a recent contribution by McLaren and Hakobyan (2010) shows no evidence of North American Free Trade Agreement (NAFTA) effects on US LLMs. In a different manner, China experiences an incredible productivity growth over the period 1990-2007, and, arguably, in the case of China, the simultaneity in the joint determination of trade barriers, trade itself and investment flows are less of an issue for the identification strategy. In addition, I also describe the reduced-form relation studying how the increase import from China changes the propensity to commit an illegal act. The analysis of the reduced-form regression provide useful insights on the total effect of the trade shocks without regard to the assumptions needed in the IV specification.

In this context, it is problematic to justify how a trade shock can impact the economy at the local level because trade shocks may play out in general equilibrium contexts.[24] Therefore, one needs to empirically map many industry-specific shocks into a small number of aggregate outcomes. Using (national) labour market units at annual frequencies, it is possible to have very few observations left in the sample and many confounding factors. I use the Commuting Zone (CZ) as the unit of analysis, and I bypass the degrees-of-freedom problem endemic of estimating the labour market consequences of trade. Therefore, it is possible to identify the consequences of trade for the labour market as long as (i) CZs differ in their pattern of industry specialisation, and (ii) frictions in labour markets allow regional differences in the LLM conditions to persist over the medium run. A greater exposure to trade with China affects the local labour market structure by decreasing the legal opportunity in CZs most exposed to foreign competition.

Following the trade literature, I define a general measure of trade shock based on the increase in Chinese competitiveness. This indicator measures the LLM exposure to imports competition, which is the change in Chinese import exposure per worker in a CZ. With respect to this measure, imports are apportioned to each region according to its share of national industry employment, as

[24] See Section 1.4.1 for the details on the geographical units.

the equation in (1.8), below, illustrates:

$$\Delta import_{uit} = \sum_{j} \frac{L_{ijt}}{L_{jt}} \frac{\Delta M_{ucjt}}{L_{it}} \tag{1.8}$$

In this expression, L_{it} is the start of period employment (year t) in CZ i, and ΔM_{ucjt} is the observed change in US imports from China in industry j between the start and end of the period. To put it in more detail, I need to allocate to each CZ a share of total national import growth and divide this import value by a CZ's total employment value. Hence, equation (1.8) yields a measure of import growth per worker (in 1,000's of US$). The variation arises from two sources: differential concentration of employment in manufacturing versus non-manufacturing activities, and specialisation in import intensive industries within the CZ. Local economies that are specialised in industries whose outputs compete with Chinese imports react more strongly to the growth of these imports.[25] The variable $\Delta import_{uit}$ measures the overall trade exposure experience. Furthermore, it is relevant to mention that the CZ exposure variable is by nature a proxy of imports that are not shipped to imports competing CZs for redistribution, but are rather distributed broadly to wholesalers, retailers, and consumers (Autor et al., 2013).

A potential source of concern for this study may be the fact that US imports from China could be affected by US demand shocks rather than just by China's growing productivity and falling trade costs (the latter may be correlated with LMC). In order to correctly identify only the *supply-driven* component of Chinese imports, which is proposed to be the cause of the job displacement at CZ level, I use the contemporaneous composition and growth of Chinese imports in eight other developed countries and ten year lagged employment levels with the aim of ruling out or at least drastically mitigating simultaneity bias.[26]

$$\Delta import_{oit-10} = \sum_{j} \frac{L_{ijt-10}}{L_{jt-10}} \frac{\Delta M_{ocjt}}{L_{it-10}} \tag{1.9}$$

Equation (1.9) is similar to (1.8) and it only differs from it in two aspects. First, I apply the realized imports from China to other high-income markets (ΔM_{ocjt}), which substitutes the ΔM_{ucjt}

[25] Information on industry employment structures by CZs, including employment in 397 manufacturing industries Lijt, is derived from the County Business Patterns data following Autor et al. (2013).

[26] Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland are the other eight high income countries with comparable trade data over the period 1990-2007.

in equation (1.8); and, second, in place of start-of-period employment levels by industry and region, I lag the variable by ten years to avoid any simultaneity.[27]

[27]In Subsection 1.5.3, I run some robustness checks while maintaining a fixed propensity to import at the beginning of the first decade. The results of those checks are similar to the main ones presented in Section 1.5.2.

1.4 Data

1.4.1 Local labour market geographical units

Looking at long-term change relationship between crime and local labour market conditions requires a time-consistent definition of the US LLM economy. Hypothetically, in this area, i.e. the US LLM economy, both the employers and workers interact within a space bounded by places of work and places of residence (Topel, 1986). The ideal geographical definition should be determined by strong commuting ties within the LLM, and weak commuting ties across the LLM in order to alleviate any migration spillovers and mobility, among other things. Given the lack of precise geographical information or data sources, empirical studies often consider each State in the US as a labour market area (Raphael and Winter-Ember, 2001, is a notable example). However, this broad definition of geographical unit presents several drawbacks. To start with, there is no credible economic reason for why the LLM dynamics should coincide with State boundaries, which, indeed, appear to be too large for a single LLM.[28] On top of this, the unit of observation might be characterised by large within-state heterogeneity which may confound the relationship between crime and labour market opportunity. Gould et al. (2002), using the counties as the LLM, made a considerable improvement in the crime literature, although this geographic structure presents similar methodological concerns as the States. In fact, counties represent too-small geographical units and suffer from migration spillovers. In recent studies, the Metropolitan Statistical Areas (hereafter MSAs) have been believed to be the natural location when identifying LLMs (Card, 2001; Mazzolari and Ragusa, 2013). On the one hand, MSAs have a more economic appeal in the sense that they typically cover areas with commutable distances and they may overlap State boundaries. This means MSAs are suitable for studying the relationship between labour market conditions and crime. Nevertheless, MSAs do not cover rural areas and their geographical definition differs over time, which prevents mapping the phenomena under study.

For all the above reasons, I pursue an alternative approach for the definition of LLMs based on the concept of Commuting Zones, which do not reflect any political boundaries and have been created with the explicit aim of capturing the economic notion of LLMs.[29] This feature is ex-

[28] In particular, there are many urban areas overlapping with State lines (e.g. , New York City/Jersey City, Washington D.C./Arlington, Kansas City MO/Kansas City KS), notably because cities developed on both sides of rivers that serve as State boundaries (Dorn, 2009).

[29] By taking these regional economies as the units of analysis, I circumvent the degrees of freedom problem endemic

tremely relevant because it limits to a large extent the possibility of spillovers across market areas including, among others, commuting from other counties, short range county-to-county migration and firms location choices. Tolbert and Sizer (1996) divide the US into 741 clusters of counties. In this paper, I focus on the 722 mainland CZs which include both metropolitan and rural areas.[30] CZs are particularly suitable for measuring job opportunities because they cover the entire area and workforce of the United States where employers, workers and residents are located within commutable distances. As a consequence, it is likely that the effects of Chinese imports will vary across CZs due to the considerable geographic variation in industry specialisation across different economic structures.[31] CZs specialized in industries whose outputs compete with Chinese imports should react more strongly to the growth of these imports, inducing structural changes in the labour market opportunities; these, in turn, trigger a rise in crime rate through the worsening of labour market conditions in the most exposed sectors.

1.4.2 Data and summary statistics

In the current Section, I describe the data sources and discuss some descriptive statistics that covers the period of 1990-2007. I aggregate the county data at the CZ level to estimate the link between the labour market conditions and the criminal rate at the same geographical unit. In order to match the information contained in the IPUMS data to Commuting Zones, I use the crosswalk file developed by Autor et al. (2013).[32]

Crime data come from the master file of the Uniform Crime Reporting programme, or UCR hereafter. Since 1930, law enforcement agencies in the United States have been participating in gathering crime statistics through the UCR programme. The FBI administers the programme and the participation, which is voluntary for all agencies at county level. County-level crime data consider both less serious and more frequent property criminal activities, on the one hand, and more

that results from estimating the labour market consequences of trade (Autor et al., 2013).

[30] 1.A.2 shows the 722 US CZs that cover the 48 mainland States. I follow Tolbert and Sizer (1996) who define the CZs based on commuting patterns in the 1990 Census; the latter are not fully matched with the 1980 definitions (Tolbert and Killian, 1987). The crosswalk is obtained from David Dorn in the URL: *http* : *//www.ddorn.net/data.htm*.

[31] The largest export growth has been in machinery. Within this broad category, telecoms, electrical machinery, and office machines have experienced the highest growth and they make up the largest shares within machinery sector (Amiti and Freund, 2010). Differently from Rodrik (2006), the export growth was accompanied by increasing specialisation and it was mainly accounted for by high export growth of existing products rather than of new varieties (Amiti and Freund, 2010).

[32] In order to group the counties into a single CZ, I use the crosswalk available in the Integrated Public Use Microdata Series projects (IPUMS) at this URL: *https* : *//usa.ipums.org/usa/volii/*1990*lma.shtml*.

serious and less frequent violent crimes, on the other. Using the standard definition in the UCR programme, I split the *total* crime category into two main components: (i) *violent*, which includes murders, rapes, robberies and aggravated assaults; (ii) *property*, which covers burglaries, larcenies, motor vehicle thefts and arson. Weapon violations, fraud, drug possession and family assaults are (iii) *other* crimes I look at. Arrest rates are calculated as the number of arrests aggregated at CZ level, then divided by the working-age population in the observational geographical unit. Illegality is often measured by arrests but not all of the felonies are detected by the police and translate in arrests. For this reason, I also collect data on the offences which are divided into similar standard categories as I previously defined. Using the same data source, I additionally collect information on the police forces and the total number of prisoners.

Trade data are recovered from the UN Comtrade Database on US imports at the six-digit Harmonized System (HS) product level and then aggregated up to four-digit SIC industries.[33] Due to delays in countries implementing the HS classification, 1991 is the first year for which I can obtain data across many high-income economies (Autor et al., 2013a). The annual value of US imports for the years 1991, 2000, and 2007 (with all values in 2007 in US$) is reported in Table 1, Panel A. The import value exponentially increases over the period 1990-2007, as it jumps from $26 to $121 billion in 2000 and it reaches its peak in 2007 ($330 billion). In the second column, I show the value of annual US exports to China in 1992, 2000, and 2007. Comparing the results in Table 1.1, it is plausible to conclude that the main change in trade between China and the United States (over the period of 1990-2007) is due *to* an astounding increase of US imports *from* rather than exports to China.

Table 1.1: Values of the Trade with China for the US and Other High-Income Countries

	Trade with China (in billions 2007 US$)			
	Panel A: United States		**Panel B**: Other developed countries	
	Imports from China	Exports to China	Imports from China	Exports to China
1991-1992	26.3	10.3	28.2	26.6
2000	121.6	23.0	94.3	68.2
2007	330.0	57.4	262.8	196.9
Growth 1991-2007	1156%	456%	832%	639%

Notes: Trade data is reported for the years 1991, 2000, and 2007, except for exports to China, which are all first available in 1992. The set of "other developed countries" in panel B comprises Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

Panel B shows the trade flows from the same exporters to a group of eight high-income countries

[33]The data are available at this URL: *http* : *//comtrade.un.org/db/default.aspx* and in order to match these data to four-digit SIC I use the crosswalk both in Pierce and Schott (2012) and in Autor et al. (2013).

located in Europe, Asia, and the Pacific (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). Like the United States, these countries experienced a dramatic increase in imports from China between 1991 and 2007, especially after China's WTO accession, and a more modest growth of imports from other medium- or low-income countries.[34] The high-income regions are useful to isolate the foreign supply-driven component of changes in Chinese import penetration. As showed by Autor et al. (2016), annual US imports from China increased by $304 billion between 1991 and 2007, while Chinese imports grew by $235 billion across the eight other high-income countries offering comparable trade data for the full sample period. Moreover, the pattern of import growth across industries is highly correlated among the US and the other high-income countries, with correlation coefficients ranging from 0.55 (Switzerland) to 0.96 (Australia). The fact that China made comparable gains in penetration by detailed sectors across numerous countries in the same time interval suggests that China's falling prices and diminishing trade tariff costs are the basis for its success.[35] The potential Chinese exposure comes from detailed information on local industry employment structures in the years 1980, 1990 and 2000, which is taken from the County Business Patterns (CBP) data.[36] CBP is an annual data series that provides information on employment, firm size distribution, and payroll by county and industry and it covers all US mainland.

Employment and **wages** are defined by selecting the individuals (aged between 16 and 64) who were working in the year preceding the survey. I drop from the data residents of institutional group quarters such as prisons and psychiatric institutions along with unpaid family workers and self-employed people.[37] I then measure the labour supply via multiplying the number of weeks worked by the (usual) number of hours per week, while making sure I adjust top-coded values by a factor of 1.5 as in Autor et al. (2013). Unemployment, duration data, individuals not in the labour force (hereafter NILF) and population structures are again recovered from two sources: the Census Integrated Public Use Micro Samples for the years 1990 and 2000 (Steven et al., 2010), and the

[34] As discussed in detail by Autor et al. (2013), these countries have been selected because they are the richest nations for which disaggregated HS trade data are available back to the early nineties.

[35] All imports are inflated to 2007 US$ using the Personal Consumption Expenditure deflator.

[36] CBP data is extracted from the Business Register, a file of all known US companies, that is maintained by the US Census Bureau, and it is available for download at this URL: *http* : *//www.census.gov/econ/cbp/index.html*. I follow the online material available at this URL: *http* : *//www.ddorn.net/data.htm* and in Autor et al. (2013) to build the propensity to import for each CZ.

[37] Following Autor et al. (2013), all calculations are weighted by the Census sampling weight multiplied by the labour supply weight.

American Community Survey (hereafter ACS) for 2006 through to 2008.[38] The 1980, 1990 and 2000 Census samples include 5% of the US population, while the pooled ACS samples include 3% of the population. Federal income assistance comprises Unemployment Insurance benefits, Social Security Disability Insurance (SSDI) benefits, income assistance benefits from SSI (Supplemental Security Income), Temporary Assistance for Needy Families (TANF), all of which are from the Regional Economic Accounts of the Bureau of Economic Analysis (hereafter REA). The REA data provides the exact amount of annual transfers and transfer type by county, unless the transfer is very small (i.e. positive amounts of transfers that are below $50,000 in a given county and year). All transfer amounts are inflated to 2007 US$ using the Personal Consumption Expenditure deflator. Finally, the share of Democrats and Republicans are collected from American National Election Studies. I select the presidential elections in 1988, 1996 and 2004 which are a proxy of the elections in 1990, 2000 and 2007, respectively.

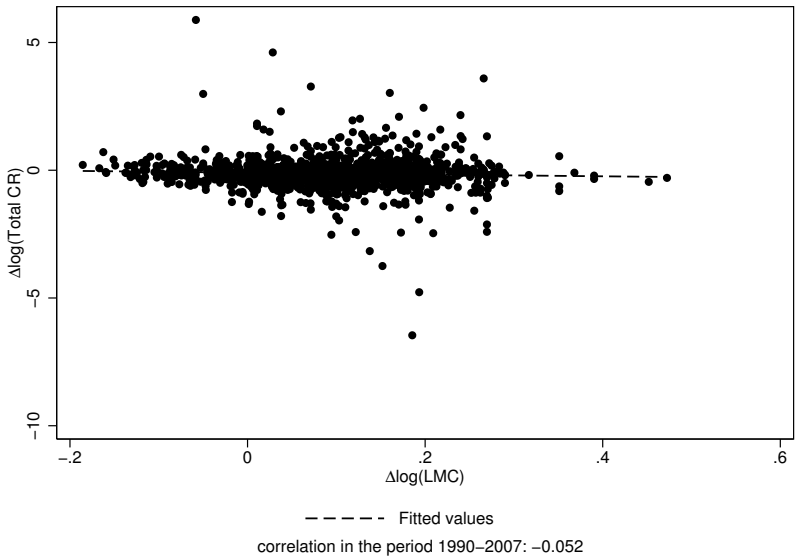
The summary statistics provided in Table 1.B.1 show that, approximately, 650 crimes per 100,000 residents were committed over the period 1990-2007 in the United States, albeit these are property crimes in the great majority of cases. As expected the number of offences is higher with respect to the arrests. Furthermore, there are approximately 400 prisoners and 790 police force members per capita (100,000 residents).

On the one hand, the raw data in Figure 1.1 reveal a weak negative correlation between the two main variables of interest (expressed in changed): higher crime rates occur in the presence of poorer labour market conditions at CZ level. Apparently, there are numerous factors that could potentially change the nature of this correlation, but it is still informative for the expected results from the empirical analysis. This correlation sheds light on the reason why economists typically conclude that a decline in labour market conditions may lead to an increase in crime (Ehrlich, 1973).

On the other hand, Figure 1.2 maps the main variables of this study across the CZs (1990-2007); these variables are: the average (of the change of log) in crime rate, the expected labour market earnings and the instrument, namely the exposure to China's products. In particular, this picture

[38]The CZs' sample is selected from the individuals aged between 16 and 64 who were working in the year preceding the selected survey, as in Autor et al. (2013). The population composition comes from an excellent survey for recent 1969-on US population at the county level that takes into account age, race, sex, and more recently Hispanic origin. This survey is available at this URL: $http://www.nber.org/data/seer\_u.s.\_county\_population\_data.html$. The level of educational attainment at CZ level is derived from Eckhardt (2011) and is freely downloadable at this URL: $https://dataverse.harvard.edu/dataset.xhtml?persistentId = hdl : 1902.1/15351$.

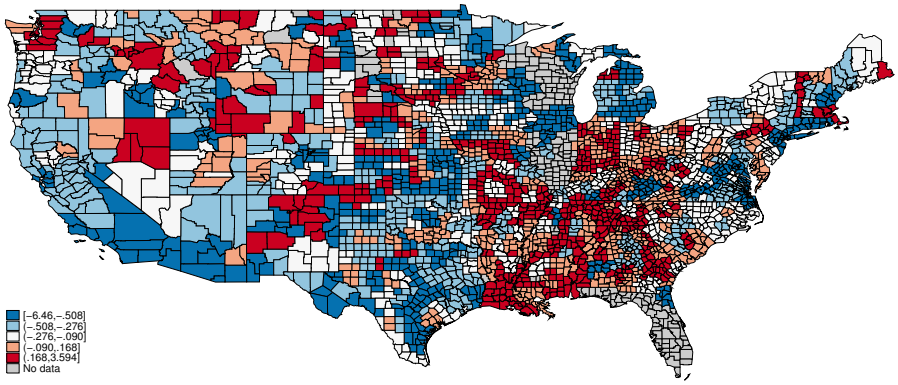
Figure 1.1: Correlation between the Change in both Crime Rate and Labour Market Condition, 1990-2007



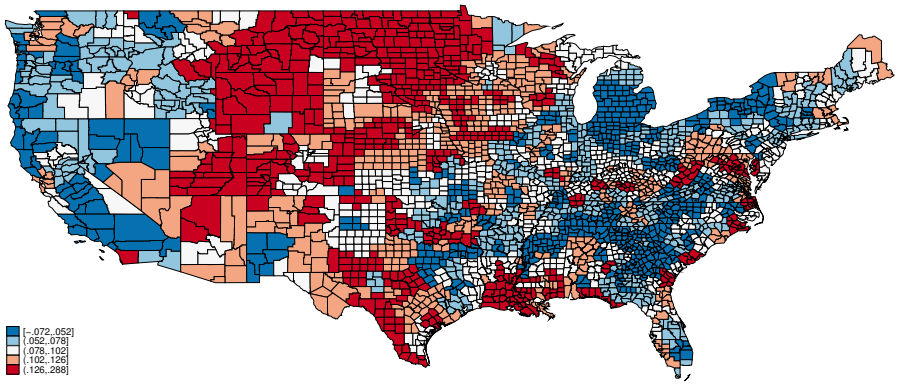
shows the geographical distribution of crime rate (in the Top Panel), local labour market opportunities (in the Middle Panel) and Chinese import exposure per worker (in the Bottom Panel). The different colours help to immediately distinguish the heterogeneous effects across regions. The warmer (darker red) the area, the stronger the positive effect is. Vice versa, the local areas depicted with a colder (darker blue) colour are characterised by a stronger negative impact. The three maps can be easily overlapped. An approximated visual first-stage is obtained by overlapping the Middle Panel with the Bottom one. The maps are mirror images of each other with a clear negative correlation across the different areas, so that a larger positive effect of Chinese import competition is associated with a stronger negative impact on labour market opportunities. To conclude, I graphically present a reduced-form effect in case the Bottom Panel overlaps with the Top one. Here, the evidence is less strong than before but it shows a fairly positive relation between trade shocks and the propensity to commit an illegal act. In Section 1.5.2, I discuss both effects in detail.

Figure 1.2: United States Maps at CZ Level, over the Period 1990-2007

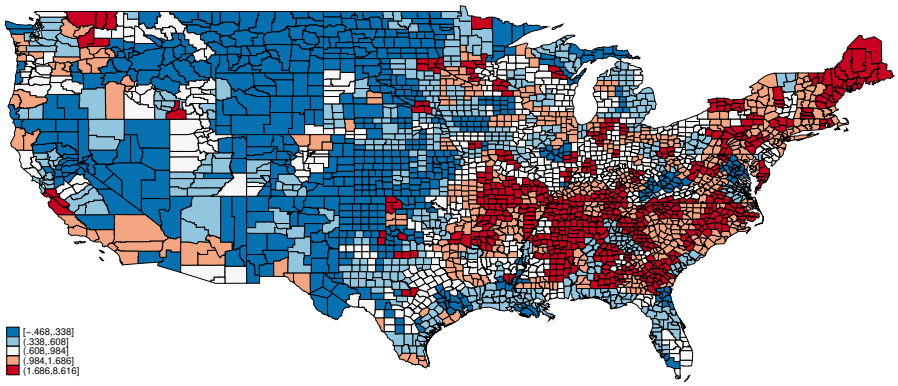
Top Panel: Average Δlog(CR)



Middle Panel: Average Δlog(LMC)



Bottom Panel: Average ΔImport Exposure per worker (in kUSD)



Notes: All the variables are expressed in changes between 2000-2007. The (log of) total crime is the sum of violent and property crimes. Import exposure per worker (in kUSD) is the instrument and it relates to the import from China to eight high income countries, namely Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

1.5 Results

In this Section, I first empirically test the prediction of the model on the relationship between labour market earnings and criminal activities both in terms of arrest and offence rates. Depending on the extent that the omitted variables from the regression are correlated with the measure of labour market condition, there is a scope for omitted variable bias. A relevant development in mitigating the bias from unobserved variables is the use of the panel data estimation technique that allows controlling for the time-invariant heterogeneity. As long as the heterogeneity is constant over time, it is possible to wipe out the omitted variables by taking the model in first difference (FD). In Subsection 1.5.1, I estimate the model in FD using the repeated observations over time (1990, 2000 and 2007).[39]

Still, *ex ante*, the direction of causality is not guaranteed due to potential time-varying unobservable factors, which may bias the results. Hence, an exogenous source of variation is needed in order to identify the causal effects of worsening labour market conditions on crime. I exploit the cross-market variation in Chinese import exposure, stemming from initial differences in industry specialisation, to instrument local labour market conditions. This identification strategy predicts that the rise in Chinese imports within a given industry (e.g. apparel, footwear, furniture, luggage and toys), which occurs simultaneously in the US and other high-income countries, are predominantly driven by the surge in Chinese productivity that have accompanied its transition to a market economy (Brandt et al., 2012) and by the reduction of trade barriers resulting from China's accession to the World Trade Organization. As discussed by Autor et al. (2015), China's rising penetration of specific industries results in sharp disparities in the change in import exposure across CZs, a situation that triggers the fall in expected labour market earnings. Then I use the exogenous variation in trade to explain the crime behaviour at local level.

Consider two almost identical US economies, for instance with similar GDP per capita, population and density, e.g. Buffalo, New York and Orlando, Florida, which hypothetically only differ from each other in their initial industry specialisation. These two counties belong to the highest and the lowest 10^{th} percentile of the exposure to Chinese imports distribution, respectively. Thus, I expect that Buffalo, NY faces, *ceteris paribus*, a major increase in crime rates caused by a (greater)

[39] As I explain in Subsection 1.3.2, the decade-specific model in equation (1.7) is equivalent to a time-fixed effects regression, while the stacked first difference model is similar to a three-period fixed effects model with slightly less restrictive assumptions made on the error term (Wooldridge, 2010).

decline of LLM opportunities, deteriorated by an increase in Chinese import competition. The following Subsections discuss the IV empirical findings (1.5.2) and some robustness checks (1.5.3).

Finally, I discuss some possible mechanisms of the relationship under analysis and present some interesting results on the complement of the labour market earnings measure, namely the "not-working" variable which consists of individuals who are both unemployed and/or not in labour forces (Table 1.C.1). Interestingly this alternative measure yields similar evidence in terms of elasticity to crime with respect to the main results in Subsection 1.5.2.

1.5.1 Labour market conditions and crime: first difference estimations

Table 1.2 presents the regressions in FD where the dependent variable is the logarithm of the total crime rate at CZ level; illegal acts here include both violent and property crime. In column (1), I show the main estimate controlling only for the specific decade effects. The evidence is clearly in favour of a stable negative relationship between crime and labour market conditions once the time-invariant unobserved heterogeneity is taken into account. The effect is significant at the one per cent level of confidence and it suggests an elasticity of -0.37. A ten per cent increase in the labour market earnings decreases the total crime rate by almost four per cent.

I start adding a long set of controls which are meant to capture the US population structural changes. For each age class, I define the change in the proportions of Whites, Blacks, Asians and Indians (baseline). The idea is to capture the observable differences in age and racial composition, which may bias the results. Moreover, I consider the educational attainment, namely the fraction of individuals with no diploma but with at least high school degree. Overall, the results are still in line with the model proposed by this paper: a negative change in the labour market earings yields a positve change in the crime rate. I observe a positive (not significant) correlation between crime and the fraction of individuals in the young and intermediate age-groups, and a negative correlation for individuals in the older groups. The results are also coherent with the recent studies on the ethnic minorities. Some authors interpret this results as a consequence of a greater upward mobility and a better social standing among African Americans during the past decades. Nevertheless, "[...] there may be a growing affluent black middle class, but at the same time, the black underclass appears to have become even more disenfranchised and more segregated from the rest of society," as discussed by Steffensmeier et al. (2011). At last, in line with the expectations, Table 1.2 shows

a negative effect of the elderly characteristics (aged 50-64 years) on the propensity to commit a crime.

Table 1.2: Log-Changes in Crime Rate and Labor Market Condition, FD Regressions, 1990-2007

Arrests	Δlog(Total CR)			
	(1)	(2)	(3)	(4)
Δlog(LMC)	-0.719**	-0.705**	-0.575*	-0.574*
	(0.312)	(0.345)	(0.335)	(0.336)
γ_t	-0.096**	0.112	0.215	0.214
	(0.043)	(0.078)	(0.153)	(0.154)
ΔAge 15-34				
White		3.579***	4.442***	4.427***
		(1.244)	(1.188)	(1.196)
Black		-4.940	-4.793	-4.775
		(4.388)	(4.436)	(4.424)
Asian		4.122	0.297	0.128
		(12.608)	(11.746)	(12.274)
ΔAge 35-49				
White		-0.002	-0.444	-0.413
		(2.274)	(2.424)	(2.468)
Black		-0.924	-0.697	-0.714
		(5.607)	(5.771)	(5.773)
Asian		-34.554	-30.012	-29.904
		(22.084)	(21.746)	(22.015)
ΔAge 50-64				
White		-4.304**	-5.307***	-5.289***
		(1.693)	(1.646)	(1.700)
Black		-6.276*	-8.835**	-8.848**
		(3.505)	(3.661)	(3.623)
Asian		4.704	-1.583	-1.607
		(26.556)	(26.421)	(26.524)
ΔNo Diploma		0.283	0.277	0.259
		(1.513)	(1.548)	(1.571)
ΔHigh School		3.229**	3.030**	3.023**
		(1.486)	(1.379)	(1.397)
ΔFederal Assistance			0.001	0.001
			(0.001)	(0.001)
ΔRepublicans			-0.746	-0.743
			(0.451)	(0.455)
ΔPolice Forces				0.178
				(1.584)
Clusters	48	48	48	48
R^2	0.010	0.064	0.072	0.073

Notes: N = 1342, 671 CZ x 2 time periods. The dependent variable is the (change in) log of the total crime rate which includes both violent and property crime. All the variables are expressed in first-difference rates. All regressions include a dummy for the 2000-2007 period (γ_t). Indians, fraction of individuals with bachelor degree and percentage of people who voted Democratic party are the reference category for the race profile, the level of education and the voters, respectively. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

As extensively discussed in the literature (Machin et al., 2011; Lochner and Moretti, 2004), there are a number of reasons to believe that education may affect subsequent crimes. The results are similar to the previous one and they are only mildly affected by the inclusion of the controls. Following Lin (2008) and Raphael and Winter-Ember (2001), I additionally include other relevant covariates, namely the change in percentage of Republican voters, which is used as a proxy of the criminal-justice system, and the government expenditure in SSI, AFDC/TANF and SNAP programs. These last controls include social security disability insurance, temporary assistance for needy families and food-purchasing assistance for low and no-income people. These sets of variables are meant to

pick any variation in the benefit claims, which may be associated with a decline in the economic conditions. As a consequence, it increases *de facto* the relative payoff of criminal activity, thus inducing workers to diverge away from the legal sector towards the illegal sector. Results are similar to those from the previous ones and they are shown in columns (2) and (3). Finally, in column (4), I include the police forces (per capita) at CZ level as a measure of deterrence effects (Lin, 2008). Deterrence plays a crucial role in economic models of crime. Police forces deter crime by increasing the perception that criminals will be caught and punished. The variable of deterrence effects does not appear to have any impact on the estimates. Another measure of deterrence effects, which is frequently used in empirical analysis, is the incarceration rate (Raphael and Winter-Ember, 2001).

The total crime index is a combination of violent and property crimes. In Table 1.B.2, I study the relationship between the labour market conditions and crime rate at CZ level focusing on two main components: violent crime rates (Panel A) and property crime rates (Panel B). The former is the "more aggressive" component in which an offender uses or threatens force upon a victim. Violent crimes may or may not be committed with weapons but it always implies the use of force. On top of this, some crimes, such as robberies which are defined as violent may depend on economic need: this relates to the action of taking or attempting to take anything of value from the care, custody, or control of a person. Violent crime includes murder, rape, robbery and aggravated assault.

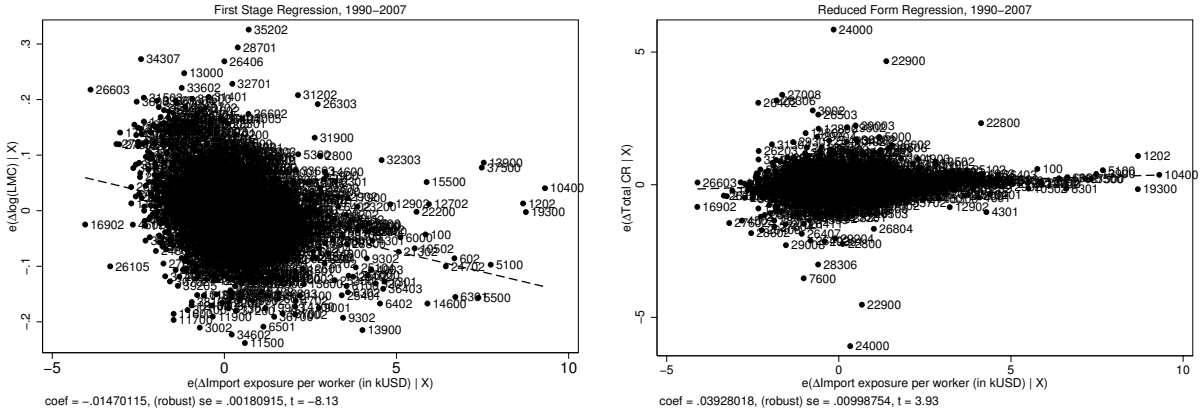
Conversely, property crime involves taking the property of other people, and it does not generally involve the use or threaten to use force against a victim. Property crimes are divided into two groups: destroyed property and stolen property. When property is destroyed, it is called arson or vandalism. An example of the act of stealing property is burglary. Table 1.B.2 illustrates that expected labour market earnings are negatively associated with the propensity of committing a property crime (burglary, larceny, vehicle thefts and arson). I also do not find a clear link between labour market opportunities and violent crime rates. The magnitude of this last effect is small and not statistically significant at any conventional level. By the same token, the evidence suggests a negative stronger relation between labour earnings and property illegal acts. The correspondent elasticity for property crime goes from -0.921 (column 1) to -0.570 (column 4), which is significant at the ten per cent level. To conclude, it should be noted that these results may still bias that could potentially plague the estimates when the endogeneity is not adequately treated.

1.5.2 Labour market conditions, crime and trade shock: reduced-form and IV

As discussed above, the empirical findings reported in Subsection 1.5.1 may still be affected by omitted confounding factors that are not captured by the first difference specification. As a consequence, an instrumental variable approach is needed to tackle the endogeneity concerns arising in the relation between crime and labour market opportunity. In this paper, I exploit the unprecedented rise in Chinese exports across other developed countries as an instrument for LMC during the period 1990-2007 at CZ level. The instrumental variable strategy, discussed in Subsection 1.3.3, identifies the component of US import growth that is due to Chinese productivity and falling trade costs and how this supply shock affects the local labour market conditions. Recall that if the model specifications leave out crime-determining factors, which are correlated with labour market conditions and that are not picked up by the first difference, the previous results (in Subsection 1.5.1) would suffer from downward bias. Moreover, if crime rates reverse the direction of the causation with local labour market earnings, OLS inference will not be appropriate.

Using CZ level data, it is possible to map the trade exposure from China at local level. This approach is valid for identifying the labour market consequences of trade to the extent that CZs differ in their pattern of industry specialisation and frictions in labour markets, which allow regional differences to persist over the medium-long run. Therefore, before discussing the second-stage results, it is useful to visualise both the first-stage relationship and the reduced-form effect.

Figure 1.3: 2SLS Regression, 1990-2007



Notes: Added variable plots of First-stage and reduced-form estimates. The sample of countries used in the IV approach considers the import exposure per worker for Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland.

Figure 1.3 depicts the estimation strategy. On the one hand, the picture on the left reveals the substantial strong predictive power of the instrument for changes in US local labour market earnings. An increase in import exposure per worker corresponds to a negative effect on the labour market earnings of about -0.015 at CZ level. A $1,000 predicted increase in import exposure per CZ worker corresponds to a 1.5 per cent decrease in labour market earnings. On the other hand, the picture on the right plots a reduced-form regression of the change in crime rate on the instrument. Figure 1.3 shows a substantial increase in (total) crime in the CZs facing large increases in exposure to Chinese imports. The results suggest that there is indeed a reduced-form effect of the increase in Chinese competition on crime rates. This evidence is striking and it demonstrates an intended and distorting effect of trade shocks on the propensity to offend in that the areas facing higher exposure to foreign competition are characterised by an increase in crime rate.[40] Table 1.3 shows the evidence from the reduced-form effect of the Chinese import penetration on crime in the US. I observe a significant positive relation between change in crime rates and trade shock, which indicates that CZs that undergo larger exposure to foreign competition also display relative increase in crime rates. The effect is particularly strong in the case of property crime while it is less pronounced for the violent ones.

Table 1.3: Log-Changes in Crime Rate and Labor Market Condition, Reduced-Form, 1990-2007

Arrests	Δlog(Total CR)	Δlog(Violent CR)	Δlog(Property CR)
Panel A	(1)	(2)	(3)
ΔImports China-other	0.039***	0.020*	0.035***
	(0.008)	(0.011)	(0.008)
All controls	√	√	√
Clusters	48	48	48
Observations	1342	1314	1337
RMSE	0.605	0.665	0.630

Notes: in Column (1), N = 1342 (671 CZ x 2 time periods); in Column (2), N=1314, 671 CZ x 2 time periods; in Column (3), N=1337, 662 and 675 CZ in 1990-2000 and 2000-2007, respectively. The dependent variables are the log of the total crime, violent crime and property crime rate in Column (1), (2) and (3) respectively. All the variables are expressed in first-difference rates. All regressions include a dummy for the 2000-2007 period (γ_t) and a constant term for trend in the regressors. Indians, fraction of individuals with bachelor degree and percentage of people who voted Democratic party are the reference category for the race profile, the level of education and the voters, respectively. The main variable in all the regressions is Chinese imports in eight other developed countries. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table 1.4 presents the IV estimates of the labour market earnings effects, induced by the increase in Chinese import competition, on total, violent and property crime rates at CZ level. In Panel B, I report the first-stage statistics which integrate the previous information in Figure 1.3. The result from first-stage regression suggests that Δ*Imports China-other* is a strong predictor of US

[40] For an easier visualization, Figure 3 shows the results without 4 Commuting Zones which are Calloway County, KY (25402), Edwards County, IL (14801), Chase County, KS (29402) and McLeod County, MN (21201). The main analysis includes all the sampled 722 CZs.

labour market earnings with an F-statistic of around 52, which is much larger than the rule-of-thumb threshold of 10 proposed by Staiger and Stock (1997). I reject the null hypothesis of weak instrument problem using both the Kleibergen-Paap LM test and Cragg-Donald Wald F statistic (Kleibergen and Paap, 2006). It is worth clarifying what the estimated model identifies and how the IV estimates should be interpreted. Following Imbens and Angrist (1994), the Local Average Treatment Effect (LATE) measures the effect for those workers who are affected by the instrument; although this requires a suitable monotonicity assumption. This means that, while the instrument may have no effect on some workers, all those who are affected are influenced in the same way. In this context, I identify the LATE for those whose labour market status is affected by the change in exposure to China's products. Hence, the compliers are in the regions where the individuals more likely lose their job (mostly in the manufacturing sector) or suffer from a wage reduction (mostly in the non-manufacturing sector) triggered by the increase in global competitiveness (Autor et al., 2013).[41] I generally find the IV estimates to be larger in magnitude than the OLS ones, a result consistent with Imbens and Angrist (1994) who demonstrate that in the presence of heterogeneous effects, the IV estimates may well exceed the OLS estimates.[42]

The evidence from Table 1.4 suggests a sizable impact of Chinese trade shocks, passing through a change in labour market conditions, on crime rate among US CZs. The effect of the labour market earnings has a more than proportional effect on the propensity to commit a crime. The 2SLS estimation then yields a -2.47 elasticity of the total arrest rate with respect to the labour market opportunity, a value that is statistically significant at the 1% level. Therefore, one per cent decrease in labour market earnings, induced by an increase of Chinese competition, increases the crime rate by almost 2.5 per cent. In column (2), the result for violent crime is statistically significant at 10% level and the effect is half with respect to the previous effect. In Column (3), I find the biggest effect for property crime. The fact that IV estimates are higher than their OLS counterparts suggests that, among the sources of bias, those that deliver attenuation (such as the measurement error) are likely to play a prominent role.[43]

[41] Furthermore, I explore the complement measure of the labour market earnings, namely the "individuals not-working" measure, in Table 1.C.1.

[42] According to Imbens and Angrist (1994), the IV estimator is a weighted average of local average treatment effects, with higher weights attributed to those parts of the support of the IV for which changes in the instrument have greater effects on the endogenous variable.

[43] In Table 1.B.3 in Appendix 1.B, I show the results using a line-log specification in order to overcome the presence of a zero value in some crime categories at local level. The results are identical. Moreover, the main evidence is also confirmed when I focus on the offence instead of the arrest rate (Table 1.B.4 in Appendix 1.B).

Table 1.4: Log-Changes in Total, Violent, Property Crime Rate and Labor Market Condition, IV Regressions, 1990-2007

Arrests	Δlog(Total CR)	Δlog(Violent CR)	Δlog(Property CR)
Panel A: 2nd Stage	(1)	(2)	(3)
Δlog(LMC)	-2.472***	-1.605*	-2.770***
	(0.602)	(0.869)	(0.626)
γ_t	0.449**	0.079	0.489***
	(0.175)	(0.197)	(0.184)
ΔAge 15-34			
White	2.903**	3.989*	2.775*
	(1.359)	(2.131)	(1.437)
Black	-5.195	-0.856	-6.192
	(4.644)	(6.705)	(4.300)
Asian	13.444	2.609	19.399
	(12.077)	(15.633)	(13.585)
ΔAge 35-49			
White	1.436	0.450	0.889
	(2.421)	(1.968)	(2.364)
Black	0.478	-3.950	1.574
	(5.342)	(7.535)	(5.352)
Asian	-45.470**	-57.663**	-45.485*
	(22.940)	(28.294)	(26.367)
ΔAge 50-64			
White	-2.945	-2.138	-2.202
	(1.924)	(2.106)	(2.125)
Black	-13.387***	-9.754**	-13.603***
	(4.129)	(4.582)	(4.270)
Asian	5.272	20.321	-5.729
	(25.442)	(24.961)	(29.433)
ΔNo Diploma	-3.113	-0.549	-4.034*
	(2.130)	(2.425)	(2.201)
ΔHigh School	1.137	1.547	0.714
	(1.874)	(1.873)	(1.999)
ΔFederal Assistance	0.000	-0.001*	0.000
	(0.001)	(0.001)	(0.001)
ΔRepublicans	-0.638	-0.476	-0.642
	(0.407)	(0.441)	(0.409)
ΔPolice Forces	-0.584	-3.257	0.267
	(1.798)	(2.310)	(1.985)
Clusters	48	48	48
RMSE	0.621	0.674	0.650
Panel B: 1st Stage	(1)	(2)	(3)
ΔImports China-other	-0.013***	-0.013***	-0.013***
	(0.001)	(0.001)	(0.001)
All controls	√	√	√
First-stage	52.66	56.26	52.28
Kleibergen-Paap LM test (p-value)	0.000	0.000	0.000
C.D.W. F-stat	137.498	126.79	136.81

Notes: in Column (1), N = 1342 (671 CZ x 2 time periods); in Column (2), N=1314, 671 CZ x 2 time periods; in Column (3), N=1337, 662 and 675 CZ in 1990-2000 and 2000-2007, respectively. The dependent variable is the log of the total crime rate which includes both violent and property crime. All the variables are expressed in first-difference rates. All regressions include a dummy for the 2000-2007 period (γ_t) and a constant term for trend in the regressors. Indians, fraction of individuals with bachelor degree and percentage of people who voted Democratic party are the reference category for the race profile, the level of education and the voters, respectively. First-stage estimates in Panel B also include the control variables that are indicated in the second-stage. The instrument in all the regressions is Chinese imports in eight other developed countries. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

I further investigate the effect of local labour market earnings on different types of crime, focusing on a variety of violent, property and some other illegal acts. Table 1.5 shows a clear and strong association between the worsening of LLM opportunities and economic crimes. In Panel A, murders and aggravated assaults, which are the illegal acts with the weakest pecuniary motives, show the weakest relationship between crime and economic conditions. Differently from murders and aggravated assaults, I observe a highly statistical significance for robberies. On the one hand, they imply the use of the force and this is the main reason why it is generally categorized under the

violent group. On the other hand, UCR defines robbery as the taking or attempting to take anything of value from a person. It appears to be the case that robbery is mostly driven by economic needs, which are triggered by worsening labour conditions exacerbated by the increase of Chinese competition. The effect shows an elasticity of -3.53 suggesting a more than proportional effect. This result is unprecedented in the literature and it implies that one per cent decrease in labour market earnings causes 3.5 per cent rise in arrests for robberies.

To conclude, Table 1.5 presents a significant impact of worsening labour market opportunities on the propensity to commit rapes, which is not unheard of in the literature (Gould et al., 2002; Lin, 2008). Moreover, there has been considerable research in recent times on the role of cognitive variables among the set of factors that can lead to rape crimes. Studies mostly in the psychological and sociological literature show that the major motive for rape is power. Furthermore, according to Black et al. (2010), among rape victims, perpetrators are reported to be intimate partners (51.1%) or family members (12.5%), and only around 10% are strangers. This corroborates the idea of how adverse employment shocks induced by increasing Chinese competition have a disruptive effect on marriage which it is demonstrated by Autor et al. (2014).

Table 1.5: Log-Changes in Different Types of Crime and Labor Market Condition, IV Regressions, 1990-2007

Arrests	Δlog(Murder)	Δlog(Rape)	Δlog(Robbery)	Δlog(A. Assault)
Panel A: Violent Crimes	(1)	(2)	(3)	(4)
Δlog(LMC)	-1.908	-2.846**	-3.530***	-1.151
	(1.584)	(1.306)	(1.060)	(0.965)
All controls	√	√	√	√
Clusters	47	48	48	48
Observations	824	1058	999	1312
RMSE	0.892	0.848	0.800	0.741
F-statistic (first-stage regression)	48.91	56.53	62.17	56.25
Arrests	Δlog(Burglary)	Δlog(Larceny)	Δlog(Vehicle thefts)	Δlog(Arson)
Panel B: Property Crimes	(1)	(2)	(3)	(4)
Δlog(LMC)	-3.321***	-2.728***	-1.978*	-2.592**
All controls	√	√	√	√
	(0.831)	(0.667)	(1.012)	(1.316)
Clusters	48	48	48	47
Observations	1299	1330	1249	953
RMSE	0.688	0.721	0.781	0.861
F-statistic (first-stage regression)	53.96	52.28	55.13	47.57
Arrests	Δlog(Weapons)	Δlog(Fraud)	Δlog(Other Drug)	Δlog(Family A.)
Panel C: Other Crimes	(1)	(2)	(3)	(4)
Δlog(LMC)	-0.871	-4.350**	-4.389***	-3.282**
	(0.956)	(1.829)	(1.379)	(1.322)
All controls	√	√	√	√
Clusters	48	48	48	48
Observations	1249	1285	1014	1198
RMSE	0.701	1.156	1.210	1.169
F-statistic (first-stage regression)	61.26	54.35	59.76	63.06

Notes: All the controls as in Table1.4. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

The findings concerning property crimes are fairly substantial (Panel B). The 2SLS results on burglaries and larcenies are negative and significant at one per cent, while motor vehicle thefts

are negative and significant at a five per cent confidence interval. Again, when instrumenting, the results yield stronger effects compared to the previous ones in Table 1.2. Also in the case of arson, which is shown in Column (4), I observe a negative effect (statistically significant at five per cent level) with an elasticity equal to -2.59. At first glance, this kind of crime may be considered to be more of a violent than a property crime. UCR defines arson as any wilful or malicious burning or attempting to burn a personal or public property, whether with or without the intent to defraud. It is not rare that individuals set fire to property. More and more, the motives for committing an arson act is related to profit or similar economic reasoning. Arson for profit, or economic arson, (which is included in the same category with arson) refers to when businesses or individuals set fire to reduce financial loss, recoup initial investments, or dispose of depreciated assets usually for a payout from insurance companies. It is a straightforward way of obtaining money from a fire loss policy (US Fire Administration, 2009). Based on the above argument, it is legitimate to believe that the decrease in labour market opportunities triggers crimes that are more related to the fulfilment of economic needs.

Finally, Panel C provides some further evidence using other relevant criminal activities. Weapons possession crime, which primarily involves the use of violence, does not seem to be responsive to changes in labour market opportunities stemming from an increase in Chinese competitiveness. Conversely, the frauds are highly significant at one per cent, as shown in Column (2). The case of fraud requires intentional perversion that involves inducing another person or entity in reliance upon it to part with something of value or to surrender a legal right. Fraudulent conversion and appropriation of money or property by false pretences can be considered as a more "sophisticated" way to relax the financial constraints in the case of (legal) labour market deterioration. Embezzlement, which is the act of withholding assets for the purpose of conversion (theft) by one or more persons to whom the assets were entrusted to be held or used for specific purposes, is not responsive (results are not shown). Differently to simple fraudes, the embezzlement needs more advanced "criminal skills", in fact, it is a type of financial fraud which is more frequent for white-collar workers who are less likely to be affected by the Chinese trade shocks.

It is worth noting that I do not observe any significant effect of drug possession (marijuana, morphine, heroin, cocaine, demerol and methadones) with the exception of non-narcotic drugs such as barbiturates and benzedrine in Column (3). Barbiturates, in particular, are generally used to

lower anxiety levels and relieve tension. Benzedrine is marketed as a valuable choice that assists people amplifying serotonin levels (hormone responsible for energy and mood) to raise mood and repress hunger. Worsening labour market opportunities induced by trade shocks increase the usage of substances like barbiturates and benzedrine, which has a clear anti-depressive effect. In other words, these cheap drugs are known to be often taken to alleviate the distress ensuing from job loss. However, the long-term effects of addiction to non-narcotic drugs encompass: strained interpersonal relationships, irritability and other risky behavior. All this reasoning, together with the evidence shown by Autor et al. (2014), can potentially explain the increase in crime against the family and children, which includes: desertion, abandonment (or non-support of spouse or child) and the abuse of a spouse (which is correlated with rape crimes as well).

To conclude, the marginal worker, who is more likely to commit an economic crime, is the one who switches to the illegal sector in order to primarily satisfy his/her economic needs once the labour market conditions worsen. As expected, I find no effect for the category of crimes, which involves only violence (murders or weapons possession), while I observe an increase in violent crimes that are not solely driven by aggressive behaviour. On the opposite side, the results for economic-related crimes can be seen as a further reinforcement of the idea that displaced workers - due to a rise in China competitiveness - may commit crime to primarily fulfil their economic needs.[44]

1.5.3 Robustness checks and further results

In this Subsection, I conduct some robustness checks to the main specification. I start by including the prison population rate at CZ level (Table 1.6). This is a different measure of deterrence used in the literature, by for example Raphael and Winter-Ember (2001), and it plays a crucial role in economic models of crime. The result is shown in Panel A and it does not suggest any difference with respect to the baseline evidence in Table 1.4. The coefficient of the change in prison population is significant at 1% level only in Column (2), and it has the expected negative sign. In Panel B, I include as a new covariate the unemployment benefits which incorporate the State benefits and federal unemployment benefits for civilian federal employees, railroad employees, and veterans, as in Autor et al. (2013). The effect on the point estimates is minimal and this potential confounding

[44]The results in Table 1.4 are identical in the case I include the fraction of males at the CZ level. The estimated coefficient of this variable is always not significant possibly because this quantity appears constant in the decades and the first-difference takes into account this effect.

factor does not seem to be working. In Panel C, I further control for a measure of income inequality at household level (Gini coefficient).[45] One could, therefore, expect labour market conditions to have more severe effects on crime in the areas where the inequality is larger. The evidence illustrates no significance and a general small magnitude impact of this variable. The main results in Table 1.4 are unaffected. Another concern may arise if the initial industrial composition and earnings are somehow associated with the initial level of crime and, vice versa, if the change in crime is correlated with the initial crime level, as would occur in the case of mean reversion in crime rates. In the following step of the test, I introduce the initial local labour conditions for each decade as a new independent variable. Panel D (Table 1.6) shows the results, which appear to be identical to the main ones reported in Table 1.4.

A further concern relates to the fact that US exposure to Chinese products may be correlated with pre-existing trends in the outcome of interest. For this reason, I introduce the initial (total, violent and property) crime level for each decade as a new independent variable to rule out the possibility that the estimated effects in the main table 1.4 are driven by a (coincidental) correlation between pre-existing trends and (future) US imports from China. The results demonstrate that pre-trends have almost no effect on the estimates, indicating that pre-existing trends are not likely to be a challenge to the identification strategy (Panel E). In addition, I conduct a falsification exercise where I regress the changes in (total, violent and property) crime rates on future US exposure to Chinese products. In the case of pre-existing trends, the regression would yield statistically significant results. The results for the falsification exercise are presented in Table 1.B.5 in Appendix 1.B. All coefficients are very small in magnitude with respect to those in Table 1.4. None of them appears to be statistically significant at any conventional level, no matter what the specifications are (both for the IVs and the reduced-forms, in Column (1)-(2) and (3)-(4), respectively). Indeed, pre-existing trends do not seem to be a challenge to the identification strategy.[46]

Next, I check whether the main empirical evidence is not driven by any outlier in the distribution of change in trade shocks, crime or labour market opportunities. For this check, I control whether an

[45] The Gini Index is a summary measure of income inequality and it summarizes the dispersion of income across the entire income distribution. The Gini coefficient ranges from 0, indicating perfect equality (where everyone receives an equal share), to 1, which is perfect inequality (where only one recipient or group of recipients receives all the income). This Index is based on the difference between the Lorenz curve (the observed cumulative income distribution) and the notion of a perfectly equal income distribution.

[46] As a further robustness check, I change the empirical specification and I estimate the main regression by including all the controls at the beginning of each decade. The results are in Table 1.B.6 in Appendix 1.B and they are similar to the baseline in Table 1.4.

Table 1.6: Robustness Check I

Arrests	Δlog(Total CR)	Δlog(Violent CR)	Δlog(Property CR)
Panel A	(1)	(2)	(3)
Δlog(LMC)	-2.478***	-1.662*	-2.755***
	(0.602)	(0.861)	(0.626)
ΔPrisoners pc	-0.172	-1.532***	0.409
	(0.341)	(0.260)	(0.363)
All controls	√	√	√
Clusters	48	48	48
Observations	1342	1314	1337
RMSE	0.621	0.674	0.649
F-statistic (first-stage regression)	52.85	56.43	52.45

Arrests	Δlog(Total CR)	Δlog(Violent CR)	Δlog(Property CR)
Panel B	(1)	(2)	(3)
Δlog(LMC)	-2.554***	-1.758**	-2.826***
	(0.601)	(0.873)	(0.629)
ΔUnemp. Benefit	-0.001	-0.001*	0.000
	(0.001)	(0.001)	(0.001)
All controls	√	√	√
Clusters	48	48	48
Observations	1342	1314	1337
RMSE	0.622	0.675	0.651
F-statistic (first-stage regression)	51.64	55.49	51.09

Arrests	Δlog(Total CR)	Δlog(Violent CR)	Δlog(Property CR)
Panel C	(1)	(2)	(3)
Δlog(LMC)	-2.038***	-1.566*	-2.368***
	(0.653)	(0.951)	(0.687)
ΔGini Index of Income Inequality	0.133	1.002	-0.413
	(1.522)	(1.773)	(1.619)
All controls	√	√	√
Clusters	48	48	48
Observations	1186	1172	1184
RMSE	0.603	0.674	0.626
F-statistic (first-stage regression)	49.41	50.14	49.30

Arrests	Δlog(Total CR)	Δlog(Violent CR)	Δlog(Property CR)
Panel D	(1)	(2)	(3)
Δlog(LMC)	-2.566***	-1.667*	-2.899***
	(0.640)	(0.928)	(0.666)
log(LMC), at initial t	-0.227	-0.146	-0.304*
	(0.202)	(0.314)	(0.180)
All controls	√	√	√
Clusters	48	48	48
Observations	1342	1314	1337
RMSE	0.525	0.535	0.554
F-statistic (first-stage regression)	55.45	60.78	54.20

Arrests	Δlog(Total CR)	Δlog(Violent CR)	Δlog(Property CR)
Panel E	(1)	(2)	(3)
Δlog(LMC)	-3.153***	-1.737	-3.492***
	(0.783)	(1.063)	(0.763)
log(CR), at initial t	-0.602***	-0.579***	-0.603***
	(0.070)	(0.054)	(0.066)
All controls	√	√	√
Clusters	48	48	48
Observations	1342	1314	1337
RMSE	0.525	0.535	0.554
F-statistic (first-stage regression)	55.45	60.78	54.20

Notes: All the controls as in Table1.4. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

extraordinary decade change in one of these variables may have deteriorated the main conclusions. To do that, I drop from the sample the top and bottom 1 (5) percentile of their distributions. The results are almost identical to the baseline as it is shown in Table 1.7, columns (1) to (6).

An additional exploration focuses on the heterogeneous effects across macro local economies in order to understand whether some areas suffer more than others. Accordingly, I split the sample

Table 1.7: Robustness Check II

Arrests	Δlog(Total CR)					
	(1)	(2)	(3)	(4)	(5)	(6)
Δlog(LMC)	-2.244***	-2.539***	-2.430***	-1.510***	-2.504***	-4.079***
	[0.739]	(0.909)	(0.545)	(0.519)	(0.735)	(1.203)
Drop in import from China	p1/p99	p5/p95				
Drop in total CR			p1/p99	p5/p95		
Drop in LMC					p1/p99	p5/p95
All controls	√	√	√	√	√	√
Cluster	48	48	47	47	48	48
Observations	1315	1209	1315	1207	1314	1201
RMSE	0.619	0.613	0.458	0.314	0.624	0.641
F-statistic (first-stage regression)	69.89	49.51	53.22	73.37	41.49	48.87

Notes: All the controls as in Table1.4. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

into the South-Atlantic zone versus the Central-West zone. This split-line coincides roughly with the Mississippi river as a dividing line between Eastern and Western "halves" of the US, and this strategy also represents the only way to balance the trade-off between the number of observations and capturing the heterogeneous effects across CZs. In Table 1.8, there is no clear evidence of heterogeneous responses across geographic regions. In fact, the point estimate is similar in both cases in columns (1) and (2). A further piece of evidence, shown in the last two columns, points in the direction that trade-induced labour market conditions and crime are almost identical both in the metropolitan and in the rural areas.

Table 1.8: Robustness Check III

Arrests	Δlog(Total CR)					
	(1)	(2)	(3)	(4)	(5)	(6)
Δlog(LMC)	-2.490***	-2.642**	-2.560**	-2.325***	-2.008**	-2.475***
	(0.837)	(1.200)	(1.194)	(0.764)	(1.004)	(0.801)
Sample	South-Atlantic	Central-West	Metropolitan	Small/Rural	Metropolitan	Small/Rural
Reference year			1990	1990	2000	2000
Population			>=49999	<49999	>=49999	<49999
All controls	√	√	√	√	√	√
Cluster	48	48	42	44	44	43
Observations	629	713	322	1020	420	922
RMSE	0.446	0.729	0.629	0.606	0.576	0.627
F-statistic (first-stage regression)	41.83	36.83	15.57	62.95	28.21	68.29

Notes: All the controls as in Table1.4. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

To conclude, I replicate the main analysis by running some sensitivity tests both on the instrument itself and on the method of estimate. To do that, I define equation (1.10) as the Chinese import exposure in a CZ, keeping the propensity to import fixed at the beginning of the first decade (1990).[47] The alternative instrument follows from this redefinition:

$$Import_{uit} = \sum_j \frac{L_{ij1990}}{L_{j1990}} \frac{\Delta M_{uct}}{L_{i1990}} \tag{1.10}$$

[47]Moreover, notice that Table 1.9 (Panel B) shows the results using a slightly different version of equation (1.10) where I compute the exposure to Chinese product per-capita instead of per-worker.

In this expression L_{i1990} is the employed in the 1990 in CZ i and ΔM_{ucjt} is the observed change in US imports from China in industry j between the start and end of the period. I then estimate the model in fixed effects (FE) assuming that the errors are serially uncorrelated, while the first difference specification (see Subsection 1.5.2) is more efficient in the case of random walk errors. The empirical evidence from columns (1) to (3) is similar to the baseline model and the effect of labour market conditions on crime is larger than the effects in Table 1.4.

Table 1.9: Robustness Check IV

	Panel A: the instrument is per-worker Chinese exposure (1990)					
Arrests	log(Total CR)	log(Violent CR)	log(Property CR)	log(Total CR)	log(Violent CR)	log(Property CR)
	(1)	(2)	(3)	(4)	(5)	(6)
log(LMC)	-5.041***	-4.787**	-5.124***	-7.575***	-7.352**	-7.219***
	(1.255)	(2.007)	(1.257)	(2.832)	(3.029)	(2.753)
All controls	√	√	√	√	√	√
Number of CZs	695	683	694	695	683	694
Observations	2049	2013	2043	2049	2013	2043
RMSE	0.504	0.575	0.519	0.503	0.509	0.495
F-statistic (first-stage regression)	20.74	19.2	20.46	11.53	11.55	11.52
	Panel B: the instrument is per-capita Chinese exposure (1990)					
Arrests	log(Total CR)	log(Violent CR)	log(Property CR)	log(Total CR)	log(Violent CR)	log(Property CR)
	(1)	(2)	(3)	(4)	(5)	(6)
log(LMC)	-4.420***	-3.883**	-4.571***	-5.541***	-4.880**	-5.493***
	(1.037)	(1.550)	(1.045)	(2.051)	(2.083)	(2.066)
All controls	√	√	√	√	√	√
Number of CZs	695	683	694	695	683	694
Observations	2049	2013	2043	2049	2013	2043
RMSE	0.485	0.549	0.502	0.439	0.432	0.442
F-statistic (first-stage regression)	32.56	30.29	32.26	18.11	18.11	18.11

Notes: Fixed-effect estimates using three time periods (1990, 2000 and 2007). All the controls as in Table1.4. Robust standard errors in parentheses. * p<.10 ** p<.05 *** p<.01.

Furthermore, in columns (4) to (6) in both Panels A and B, I consider the use of population weights and, following the recent discussion on the topic (Solon et al., 2015b; Durlauf et al., 2014), I weigh the regression by the share of CZ population (the average over the periods). According to Durlauf et al. (2014), the use of population weights to control for heteroskedasticity in crime rates has almost little evidentiary support in many model specifications. The past literature justifies the use of the weights with different assumptions, which range from the specification of the nature of the policy effect to choices of control variables; and from heteroskedasticity corrections to formulations of potential parameter heterogeneity and the choices of instrumental variables. The use of population weights has become standard practice in empirical crime studies (Raphael and Winter-Ember, 2001; Lin, 2008). There are various reasons for including weights, but the usual argument is based on concerns regarding heteroskedasticity of the residuals. However, it ignores the possibility that location-time-specific unobservables, such as unmeasured demographic and socio-economic factors, are present (Durlauf et al., 2014). Consequently, the use of population weights will overweigh obser-

vations from more populous counties, thus leading to invalid confidence intervals, and potentially misleading point estimates. In other words, models with weights are more likely to find larger effects on crime. The results in Table 1.9 confirm this possibility. In sum, the analysis in the current Subsection supports the previous findings that worsening labour market conditions, triggered by an unexpected rise in Chinese competition, affect the long-run change propensity to commit a crime at CZ level.

1.6 Possible Mechanism

To the best of my knowledge, this is one of the first studies that estimate the effect of a long-term change in trade-induced labour market conditions on the crime rate at US CZ level. Differently from the previous literature, the 2SLS empirical evidence in this paper yields a larger elasticity of crime rates, which is robust to different specifications and statistically significant at the 1% level. The most recent studies that focus on the unemployment or earnings and crime relationship generally find smaller elasticity (Lin, 2008; Raphael and Winter-Ember, 2001). The strategy in this paper highlights the long-term change variation in the crime and LLM structure following a large trade shock that occurred in the US in the last decades. Given the consequences of criminal activity, which includes human capital investments specific to the illegal sector and the potential for extended periods of incarceration, crime should be more responsive to low-frequency changes in the conditions of CZs'. Due to the measurement error in the independent variables, especially when measured at State-level, the changes may suffer less from attenuation bias than the estimates based on annual data, a case discussed by Gould et al. (2002).

Although the comparison with previous contributions is not obvious, mainly due to a lack of general consensus about the elasticity of crime-labour market conditions, I further discuss the implication of the results presented in Section 1.5.2. In cases where responses to treatment varies across CZs, Imbens and Angrist (1994) point out that using linear IV gives an estimate of the local average treatment effects for "compliers" (those induced to get treatment by assignment to the treatment group). Following Imbens and Angrist's (1994) LATE interpretation, the subpopulation of compliers would reveal the causal effect of being in a region where the changes in exposure to Chinese products decrease the probability of being employed and/or reducing the labour market earnings due to initial structure specialization (Autor et al., 2013). On the one hand, this is likely to be referred to workers in the manufacturing sector who face the adverse shock of global competition and lose their job. On the other hand, reducing the demand for local non-traded services (due to the loss in earnings) and increasing the available supply of workers, it creates downward pressure on wages in the non-manufacturing sector.[48]

Moreover, it is interesting to note that, with relatively lower possibility to migrate to other CZs, the increase of Chinese imports has a negative effect on the employment spells. This interpretation

[48]Note that there is no large gender differences (Autor et al., 2013).

would also reasonably explain why the IV results are larger in magnitude than OLS results, which also suffer from well-known attenuation bias. As argued by Becker (1968), the probability of engaging in criminal activities depends on how long an individual stays outside the labour market. At the margin, an individual who remains in employment is less likely to become a criminal than his/her hypothetical counterpart who is unemployed. Local labour market conditions become more severe the longer an individual is out of employment, and human capital depreciation further decreases expected future employability and potential legal returns. In this study, the instrument is likely to pick up the marginal individual who will dramatically decrease his/her employability by undergoing a shorter employment duration.

Table 1.10: Employment Duration and Imports from China, 1990-2007

	Employment Duration (weeks)			
	Average	Short-term ($\leq$ 14)	Medium-term (15-26)	Long-term ($\geq$ 27)
	(1)	(2)	(3)	(4)
ΔImport China-other	-0.001***	0.008***	0.004**	-0.001***
	(0.000)	(0.002)	(0.002)	(0.000)
All controls	$\surd$	$\surd$	$\surd$	$\surd$
Clusters	48	48	48	48
Observations	1444	1444	1444	1444
R^2	0.512	0.787	0.177	0.690

Notes: N = 1444 (722 CZ x 2 time periods). Controls are the same as in Table 1.4. The dependent variable in column (1) is the (log of change of) average duration in employment at CZ level. From Columns (2) to (4), the dependent variables are the (log of change of) percentage of individuals in short, medium and long-term employment. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table 1.10 corroborates this hypothesis. The evidence in column (1) suggests a negative correlation between the (log) change in average employment duration and the change in exposure to Chinese products. The Table clearly shows that an increase in import competition from China is associated with a decrease in the average employment duration at CZ level. Thus, using the same example as before (Subsection 1.5), Buffalo, NY is likely to face, *ceteris paribus*, a larger decrease in the average employment duration with respect to Orlando, FL due to a worsening of LLM opportunities. This happens as a result of the dramatic structural changes that ensue from the rise in Chinese exports. The latter are likely to be associated with shorter employment spells, and that may constantly decrease the returns to legal markets and determine an (expected) increase in the risk of undertaking criminal activities. Following this line of reasoning, Table 1.10 shows other results in terms of employment duration. I define three different categories: short, medium and long-term durations (Krueger et al., 2014) with the aim of shedding light on the differential effect of trade.[49] On the one hand, there is strong evidence in favour of a positive association between the instrument

[49]The results in Table 1.10 column (2), (3) and (4) provide similar evidence estimating a seemingly unrelated regression (SUR) conditioning on the same set of covariates.

and the (change in the) share of individuals in short-term employment, as displayed in column (2). This suggests that the trade shock increases the chances of an individual being employed for a short period. A ten per cent increase in import competition from China increases the chances of being in a short-employment spell by eight per cent. I find similar but weaker results for the medium-term workers in column (3). On the other hand, the exposure to Chinese competition is statistically significant and negatively correlated with long-term employment at the 1% level. The larger the import from China, the lower the likelihood of being in long-term employment is. A ten per cent increase in import exposure per CZ worker decreases the likelihood of having long employment spells.

All the above arguments are valid in the case of weak migration responses. In order to correctly identify the effect of labour market earnings on crime rate, I need to avoid any significant change in the working-age population in each decade. Logically, a serious concern for the above-described identification stems from the fact that if labour is highly mobile across regions, trade may affect workers without its consequences being identifiable at the regional level. Nevertheless, the literature on regional adjustment to labour-market shocks suggests that mobility responses to labour demand shocks across US cities and States are slow and incomplete (Topel, 1986; Autor et al., 2013).

Table 1.11: Imports from China and Change of Working-Age Population, 1990-2007

	ΔLn Pop$_{it}$		
	(1)	(2)	(3)
Δlog(LMC)	0.047	-0.269	
	(0.126)	(0.176)	
ΔImports China-other			0.004
			(0.003)
γ_t		✓	✓
Observations	1444	1444	1444

Notes: N = 1444 (722 CZ x 2 time periods). Columns (1) and (2) show the 2SLS estimations. Column (3) shows the direct impact of import from China on the change in population. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

It is, therefore, plausible that the effects of trade shocks on regional labour markets will be evident over the medium term; indeed, the current analysis does not find significant population adjustments for local labour markets with substantial exposure to imports. The sluggish response of regional labour supply to import exposure may be related to the costly mobility of labour between sectors, as documented by Artur et al. (2010) with respect to the case in the United States. In columns (1) and (2), I control whether the change in import competition, which passes through an increase in labour market conditions, has any impact on the change of the (logarithm) working-age population.

Due to the inclusion of the decade dummy, the coefficient turns negative. There is, however, no statistical significant evidence showing that local labour market shocks lead to substantial changes in population composition (Table 1.11). Moreover, there is no direct significant impact of increasing exposure to Chinese products on the change in population size showed in column (3). These results are in line with what similar work in the literature shows, thus underlining the claim that mobility responses are slow.

1.7 Conclusions

This study presents a novel empirical evidence on the effect of a long-term change in labour market earnings on crime rates, with this change being triggered by the increase in Chinese import exposure per worker at the US CZ level. I provide evidence on the causal effect of labour market conditions on crime while exploiting the exogenous variation in import exposure to China's products by CZ. Rising import competition has a large LLM effect in terms of decreasing labour market opportunities. The results presented here consistently indicate that the worsening labour opportunities in the legal sector trigger the rise in crime rates.

By focusing on CZ areas, I provide new evidence on the impact of global trade shocks on crime rate through a negative effect on local labour earnings in the US. The use of this specific geographical unit allows the mapping of the crime phenomenon on the US mainland including both metropolitan and rural areas. Adverse shocks to local employment opportunities, stemming from rising competition from China, increase the propensity to commit economic-related crimes. The local areas that are largely hit by trade shocks face increasing declines in labour earnings over time. However, I find no evidence that inter-regional migration responds to these trade-induced local shocks. The absence of substantial effects on migration in this context leads to question whether the labour market responses indeed represent welfare losses in terms of increasing the propensity to commit an illegal act.

Moreover, most of the studies in the literature implement some identification strategies to investigate the relationship between either unemployment rates and crime, or earnings and crime, but never the relationship among the labour market conditions and crime. Conceptually, it is difficult to assume that labour market shocks would affect one of these dimensions but not the other. This is precisely what motivates the theoretical model, which frames expected labour market earnings as a sufficient statistic for labour market conditions and allows the use of a single instrument to analyse the impact of overall labour market conditions on crime.

The main finding of the paper is that trade shocks to labour market outcomes have strikingly and surprisingly parallel impacts on crime both in terms of arrests and offences. Although the comparison with previous contributions is not straightforward, mainly because of the peculiar geographical units employed and of the different LATE interpretations, I generally estimate greater

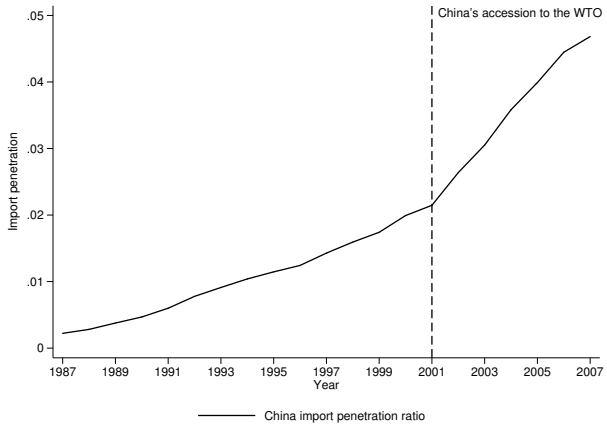
elasticity of crime with respect to changes in labour market earnings.

Additionally, as argued by Becker (1968), the probability of engaging in criminal activity depends on how long an individual stays out of the labour market. In this study, an increase in import competition from China is also associated with a decrease in the average employment duration at CZ level. Two almost identical US CZs (Buffalo, NY and Orlando, FL) which are hypothetically homogeneous in the socio-economic aspects and only differ in their initial industry specialisation, are differently affected. Furthermore, in addition to what has been found by Autor et al. (2013), rising imports correspond to shorter employment durations. Thus, Buffalo, NY is likely to face, ceteris paribus, a major increase in the average employment duration due to a worsening of LLM opportunities. This interpretation would also suggest the motivation why the IV results are larger, in magnitude, than OLS estimates. The evidence and arguments made above are valid in the case of weak migration responses, which are not significant at any conventional level. The robustness checks confirm the main results.

Developing effective tools to regulate and alleviate the costs of trade adjustments should be a high priority on the agenda of policy-makers and economists. This is especially true when these costs translate into criminal activities. Policy-makers should consider the collateral cost of trade shocks associated with job displacement. A possibility would be to develop effective tools in order to limit the chances of individuals staying out of work for long. Another potential solution would point in the direction of vocational courses, which should be designed to help the employed to switch from a more exposed sector to a less exposed one. In this way, individuals who work in sectors that are most exposed to Chinese products may reduce the probability of being fired, increase their mobility across-sectors and avoid, *de facto*, engaging in criminal activity to satisfy their economic needs. A further possibility would be to invest in sectors characterised by high intensive technological and organizational innovations that increase productivity and raise wages, which might in turn raise the cost of switching to the illegal sector.

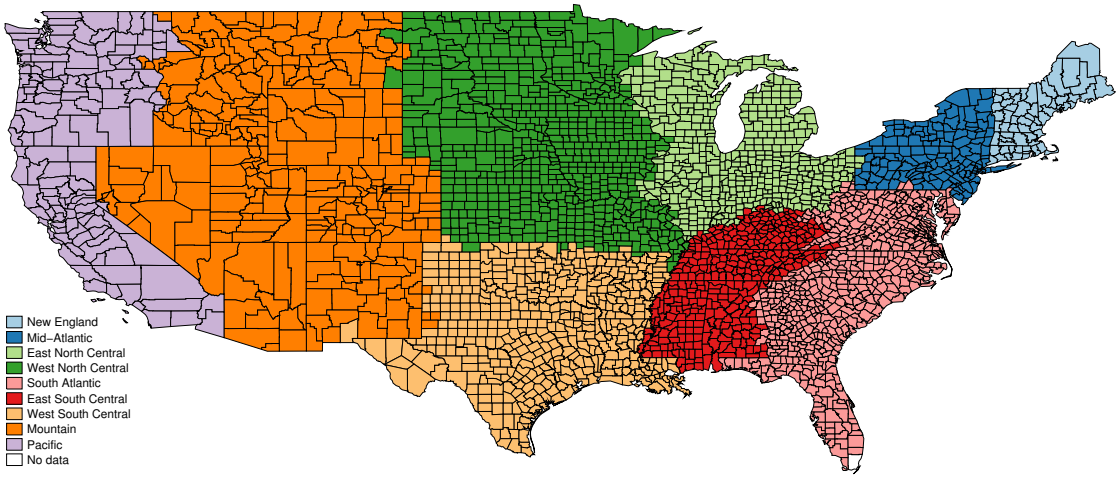
Appendix 1.A: Figures 1.A

Figure 1.A.1: Import Penetration Ratio for US-China



Notes: Import penetration is computed as US imports from China divided by total US expenditure on goods, measured as US gross output plus US imports minus US exports (Autor et al., 2013).

Figure 1.A.2: 722 US Commuting Zones, by Interstate Regions



Appendix 1.B: Tables 1.B

Table 1.B.1: Summary Statistics, 1990-2007

	Panel A: Levels			Panel B: Changes		
Arrests:	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Total crime (A+B)	2166	0.006	0.004	1342	-0.128	0.622
Violent crime (A)	2166	0.001	0.001	1314	0.006	0.682
Property crime (B)	2166	0.005	0.003	1337	-0.155	0.648
A. Violent						
Murder	2166	0.000	0.000	824	-0.197	0.884
Rape	2166	0.000	0.000	1058	-0.178	0.825
Robberies	2166	0.000	0.000	999	0.074	0.769
Aggravated Assault	2166	0.001	0.001	1312	0.019	0.759
B. Property						
Burglaries	2166	0.001	0.001	1299	-0.186	0.682
Larcenies	2166	0.004	0.002	1330	-0.135	0.720
Vehicle thefts	2166	0.000	0.000	1249	-0.196	0.780
Arson	2166	0.000	0.000	953	-0.145	0.856
C. Others						
Weapons possession	2166	0.000	0.000	1249	-0.071	0.708
Fraud	2166	0.001	0.002	1285	-0.067	1.151
Other Drugs	2166	0.000	0.001	1014	0.810	1.260
Family Assault	2166	0.000	0.001	1198	0.194	1.206
Offenses						
Total	2166	0.029	0.016	1369	-0.092	0.510
Violent	2166	0.002	0.002	1291	0.729	1.024
Property	2166	0.027	0.015	1369	-0.137	0.507
log(LMC)	2166	5.957	0.187	1444	0.096	0.090
Average Employment Duration	2223	43.964	1.773	1482	0.017	0.023
Employment duration (short)	2223	0.077	0.021	1482	-0.005	0.019
Employment duration (medium)	2223	0.074	0.016	1482	-0.009	0.009
Employment duration (long)	2223	0.849	0.035	1482	0.014	0.025
Wage manufacturing (log)	2166	6.461	0.186	1444	0.085	0.067
Wage non-manufacturing (log)	2166	6.302	0.134	1444	0.088	0.097
NIUN	2166	0.306	0.064	1444	-0.037	0.112
Import China-Others (kUS$)	2166	1.058	0.700	1444	1.755	2.085
Age: 15-34						
Asian	2166	0.231	0.052	1444	-0.022	0.020
Indian	2166	0.027	0.039	1444	0.000	0.005
Black	2166	0.004	0.006	1444	0.001	0.001
Age: 35-49						
Asian	2166	0.183	0.033	1444	-0.002	0.024
Indian	2166	0.016	0.024	1444	0.002	0.006
Black	2166	0.002	0.004	1444	0.001	0.001
Age: 50-64						
Asian	2166	0.148	0.035	1444	0.023	0.015
Indian	2166	0.010	0.016	1444	0.002	0.005
Black	2166	0.001	0.002	1444	0.001	0.001
Republicans (share)	2166	0.541	0.118	1444	0.027	0.144
Low educated	2166	0.220	0.099	1444	-0.065	0.063
Medium educated	2166	0.617	0.073	1444	0.039	0.053
Federal assistance pc (kUS$)	2166	269.498	158.485	1444	20.136	69.476
Prisoners pc	2166	0.004	0.027	1444	0.001	0.026
Police force pc	2166	0.004	0.027	1444	0.001	0.026
Unemp. Benefit	2166	91.403	56.896	1444	7.151	38.800
Gini Index of Income Inequality	2048	0.431	0.030	1307	0.004	0.020

Table 1.B.2: Log-Changes in Violent, Property Crime Rate and Labor Market Condition, FD Regressions, 1990-2007

Arrests	Panel A: Δlog(Violent CR)				Panel B: Δlog(Property CR)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Δlog(LMC)	0.524	0.206	0.136	0.101	-0.921***	-0.753**	-0.574*	-0.570*
	[0.318]	[0.301]	[0.346]	[0.350]	[0.328]	[0.316]	[0.309]	[0.310]
γ_t	-0.119***	0.021	0.225	0.237	-0.086*	0.089	0.164	0.159
	[0.040]	[0.074]	[0.150]	[0.150]	[0.044]	[0.073]	[0.141]	[0.141]
ΔAge 15-34								
White		2.923*	3.196**	3.412**		3.961***	4.952***	4.842***
		[1.649]	[1.574]	[1.548]		[1.382]	[1.317]	[1.334]
Black		0.537	0.177	-0.246		-6.086	-5.813	-5.678
		[6.084]	[6.236]	[6.335]		[4.085]	[4.091]	[4.048]
Asian		-8.431	-10.052	-6.907		8.838	4.582	3.308
		[15.584]	[15.343]	[15.385]		[14.006]	[13.042]	[13.460]
ΔAge 35-49								
White		0.934	1.414	0.950		-1.290	-1.944	-1.711
		[1.644]	[1.703]	[1.648]		[1.988]	[2.144]	[2.263]
Black		-2.551	-3.096	-2.724		-0.530	-0.082	-0.210
		[8.441]	[7.906]	[7.908]		[5.310]	[5.616]	[5.601]
Asian		-39.174	-38.894	-40.076		-33.360	-27.945	-27.104
		[25.692]	[27.469]	[28.326]		[25.109]	[24.635]	[25.101]
ΔAge 50-64								
White		-1.562	-2.232	-2.561		-4.150**	-5.240***	-5.102***
		[1.501]	[1.671]	[1.687]		[1.900]	[1.804]	[1.867]
Black		-4.704	-6.007	-5.809		-5.367	-8.221**	-8.312**
		[3.189]	[3.744]	[3.678]		[3.671]	[3.668]	[3.651]
Asian		34.026	22.215	21.626		-10.585	-15.286	-15.495
		[26.125]	[27.995]	[27.343]		[30.152]	[31.274]	[31.685]
ΔNo Diploma		-0.369	0.209	0.532		0.408	0.249	0.115
		[1.404]	[1.434]	[1.492]		[1.547]	[1.578]	[1.597]
ΔHigh School		2.218	2.477*	2.584*		3.361**	3.041**	2.984**
		[1.386]	[1.286]	[1.293]		[1.546]	[1.446]	[1.464]
ΔFederal Assistance			-0.001	-0.001			0.001*	0.001*
			[0.001]	[0.001]			[0.001]	[0.001]
ΔRepublicans			-0.666	-0.692			-0.757*	-0.734
			[0.476]	[0.478]			[0.445]	[0.443]
ΔPolice Forces				-3.727				1.346
				[2.450]				[1.736]
Clusters	48	48	48	48	48	48	48	48
R^2	0.018	0.046	0.051	0.056	0.051	0.101	0.111	0.112

Notes: in Panel A, N=1314, 671 CZ x 2 time periods. In Panel B, N=1337, 662 and 675 CZ in 1990-2000 and 2000-2007, respectively. The dependent variable is the (change in) log of the violent and property crime rates in Panel A and B, respectively. All the variables are expressed in first-difference rates. All regressions include a dummy for the 2000-2007 period (γ_t). Indians, fraction of individuals with bachelor degree and percentage of people who voted Democratic party are the reference category for the race profile, the level of education and the voters, respectively. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table 1.B.3: Changes in Total, Violent, Property Crime Rate and Labor Market Condition, IV Regressions, 1990-2007

Arrests	Δlog(Total CR)	Δlog(Violent CR)	Δlog(Property CR)
	(1)	(2)	(3)
Δlog(LMC)	-0.014***	-0.002	-0.011***
	(0.005)	(0.001)	(0.003)
Elasticity	*[-2.157]*	*[-1.400]*	*[-2.173]*
All controls	√	√	√
Cluster	48	48	48
Observations	1444	1444	1444
F-statistic (first-stage regression)	36.60	36.60	36.60

Notes: All the controls as in Table1.4. The specifications consider as a dependent variables, the changes in crime (total, violent and property) rate. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table 1.B.4: Log-Changes in Different Types of Offenses and Labor Market Condition, IV Regressions, 1990-2007

Offenses	Δlog(Total CR)	Δlog(Violent CR)	Δlog(Property CR)
	(1)	(2)	(3)
Δlog(LMC)	-2.316***	-0.860	-2.539***
	(0.566)	(1.089)	(0.562)
All controls	√	√	√
Cluster	48	48	48
Observations	1369	1291	1369
F-statistic (first-stage regression)	62.90	64.83	62.90

Notes: All the controls as in Table1.4. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table 1.B.5: Falsification Tests

Arrests	Δlog(Total CR)			
Panel A	(1)	(2)	(3)	(4)
	IV	IV	OLS	OLS
Δlog(LMC)	0.681	0.790		
	(0.522)	(0.668)		
ΔImport China-other			-0.009	-0.009
			(0.007)	(0.007)
All controls		√		√
Clusters	48	48	48	48
Observations	1379	1379	1379	1379
RMSE	0.705	0.682	0.701	0.681
F-statistic (first-stage regression)	33.83	34.58		

Arrests	Δlog(Violent CR)			
Panel B	(1)	(2)	(3)	(4)
	IV	IV	OLS	OLS
Δlog(LMC)	-0.080	-0.220		
	(0.727)	(0.821)		
ΔImport China-other			0.001	0.002
			(0.010)	(0.009)
All controls		√		√
Clusters	48	48	48	48
Observations	1348	1348	1348	1348
RMSE	0.709	0.702	0.71	0.707
F-statistic (first-stage regression)	34.34	34.71		

Arrests	Δlog(Property CR)			
Panel C	(1)	(2)	(3)	(4)
	IV	IV	OLS	OLS
Δlog(LMC)	0.544	0.683		
	(0.465)	(0.620)		
ΔImport China-other			-0.007	-0.008
			(0.006)	(0.007)
All controls		√		√
Clusters	34	34.65		
Observations	1378	1378	1378	1378
RMSE	0.584	0.579	0.585	0.584
F-statistic (first-stage regression)	25.66	26.88		

Notes: All the controls as in Table1.4. Change in Total, Violent and Property crime rates are computed between 1975-1980 and 1980-1990. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table 1.B.6: Log-Changes in Total, Violent, Property Crime Rate and Labor Market Condition, IV Regressions, 1990-2007 (All controls at initial t)

Arrests	Δlog(Total CR)	Δlog(Violent CR)	Δlog(Property CR)
	(1)	(2)	(3)
Δlog(LMC)	-2.626***	-2.116**	-2.560***
	(0.620)	(0.944)	(0.603)
All controls at initial t	√	√	√
Cluster	48	48	48
Observations	1342	1314	1337
F-statistic (first-stage regression)	64.56	66.44	65.38

Notes: All the controls as in Table1.4 at the beginning of the decade. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Appendix 1.C: Other Labour Market Conditions Measure

In this Section, I analyse the complement of the labour market earnings measure, namely the NIUN (not in labour forces and unemployed), so that the wage component becomes less relevant. This category encompasses all individuals who do not have a job, hence defining themselves as unemployed (UN) and/or not in the labour force (NILF). Differently from other studies in the current literature, which only look at the group of the unemployed, I also consider the NILF individuals. Residents of institutional groups such as prisons, psychiatric institutions and unpaid family workers are excluded from NILF.

The attractiveness of the NIUN is in the fact that it includes both the unemployed and, possibly, the discouraged jobseekers who do not technically belong to the unemployed but, nevertheless, are among those who may potentially commit crimes in order to primarily satisfy economic needs. In other words, this subset of "hidden unemployed" who are willing and able to work but have given up searching due to their belief that no jobs are available or to them lacking the necessary skills to get a job, may be incentivised, all other things being equal, to perpetrate a criminal activity.

Table 1.C.1: Log-Changes in Total, Violent, Property Crime Rate and NIUN, IV Regressions, 1990-2007

Arrests	Δlog(Total CR)	Δlog(Violent CR)	Δlog(Property CR)
Panel A: 2nd Stage	(1)	(2)	(3)
Δlog(NIUN)	1.691***	1.093*	1.906***
	(0.405)	(0.593)	(0.435)
Clusters	48	48	48
RMSE	0.621	0.674	0.650
Panel B: 1st Stage	(1)	(2)	(3)
ΔImports China-other	0.019***	0.019***	0.019***
	(0.003)	(0.003)	(0.003)
All controls	√	√	√
First-stage	40.78	41.00	40.92
Kleibergen-Paap LM test (p-value)	0.000	0.000	0.000
C.D.W. F-stat	163.834	154.356	161.505

Notes: in Column (1), N = 1342 (671 CZ x 2 time periods); in Column (2), N=1314, 671 CZ x 2 time periods; in Column (3), N=1337, 662 and 675 CZ in 1990-2000 and 2000-2007, respectively. All the controls as in Table1.4. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table 1.C.1 shows the results of the relation between the change in NIUN and the propensity to commit illegal acts. The evidence is in line with the main findings in Table 1.4. The first-stage statistic (Panel B) underlines the strong predictive power of the instrument which is close to 41, a larger value than the rule-of-thumb threshold of 10 proposed by Staiger and Stock (1997). Also in this case, I reject the null hypothesis of weak instrument problem using both the KleibergenPaap LM test and Cragg-Donald Wald F statistic (Kleibergen and Paap, 2006). In contrast with the position mentioned in Section 1.5.2, an increase in Chinese import competition is related to a

rise in the (log of) change of NIUN. The effect in the second stage is substantial and it yields an elasticity of almost two for the total and the property crime categories and of one in the case of violent crimes (which, however, do not seem to be responsive to induced trade shocks). Thus, the evidence suggests that a one per cent increase in the NIUN increases the crime rate by almost two per cent. The result for economic-related crimes can be interpreted as a further reinforcement of the idea that displaced workers - due to a rise in China competitiveness - may commit crime to primarily satisfy their economic needs. This result highlights the importance of also taking into account the discouraged workers (NILF) who may easily switch from the legal to the illegal sectors to principally fulfil their essential needs.

Chapter 2

Energy (In)Security and the Arms Trade[1]

2.1 Introduction

The international transfers of major conventional weapons is one of the most dynamic sector of international trade. Although the 2008 financial crisis has affected many industries worldwide and has caused a general reduction in government spending, the global volume of transfers has grown by 14% between 2004-08 and 2009-13, according to the 2014 report by the Stockholm International Peace Research Institute (Wezeman and Wezeman, 2014). Most of the countries in the world import weapons, and between 2004-2008 and 2009-13 imports increased by a staggering 53% in Africa, by 34% in Asia, by 10% in the Americas, by 3% in the Middle East, and decreased by 25% in Europe.[2]

The arms trade is a very controversial issue with many economic and strategic implications on both sides of the transaction. On the demand side, countries import weapons for reasons of national security, but a combination of prices, income and international political relations affects the optimal bundle of domestic production - sometimes in collaboration with other partners - and import of weapon systems. Using network analysis, Akerman and Seim (2014) show that in the

[1]We are grateful to Ludovica Giua, Tullio Jappelli, Giovanni Mastrobuoni, Tommaso Oliviero, Marco Pagano, Matthias Parey, Saverio Simonelli, Ron Smith, Joao Santos Silva and Tiziana Venittelli for their helpful insights. We thank seminar participants at the University of Naples Federico II, University of Sheffield, University of Warwick, as well as participants at the 56th Italian Economic Association (SIE) conference for valuable comments on earlier versions of the manuscript. The usual disclaimer applies.

[2]In the period 2009-2013, the top ten major suppliers of weapons were the US, Russia, Germany, China, France, UK, Spain, Ukraine, Italy and Israel while the top ten recipients were India, China, Pakistan, the United Arab Emirates (UAE), Saudi Arabia, US, Australia, South Korea, Singapore and Algeria.

last six decades, the global arms trade network has become more dense, clustered and decentralized over time. Particularly since the end of the Cold War, the market has become more globalized, with increasing interdependence and cooperation. Today, virtually no states are self-sufficient in arms production, including the US, and self-produced arms need to be complemented by imported weapons or components (see Brauer, 2007). As such, arms import is an essential component of the defense budget.

On the supply side, countries sell weapons for economic reasons, and defence industries are economically strategic in terms of R&D intensity, spin-offs and decreasing unit costs (Sandler and Hartley, 1999; Garcia-Alonso and Levine, 2007). Although producing weapons can be inefficient for some countries, many developed economies maintain a domestic defense industrial base for economic and strategic needs, i.e., to protect and promote the so-called "national champions" and ensure a level of autonomy. At the same time, subsidies to the domestic arms manufacturers often increase their international market share. Yet, economic motivations are frequently accompanied by political interests; in fact, by exporting weapons, countries also seek to improve the military capabilities of the recipient states. As a necessary adjunct of national policy and strategic doctrine, weapons are often given only to close allies and it is not unusual to observe arms transferred free to allies, under the umbrella of military aid. By the same token, the absence of trade between pairs of country can reflect arms denial and constraints on transfers to specific recipients so as to safeguard national security.[3]

The arms trade has both a political and economic component, and the question of which factors are more likely to affect the bilateral flows of weapons is a timely and important issue. Given its size and scope, there is surprisingly little empirical research on the the arms trade, particularly on its determinants (see Bergstrand, 1992; Smith and Tasiran, 2005, 2010; Comola, 2012; Akerman and Seim, 2014). Against this backdrop, we show that the arms trade lies at the intersection of foreign policy and economic concerns and it is an active tool of both geopolitical and economic competition; we use the most economically and politically prominent energy source, oil, and demonstrate how oil interdependence is a critical determinant of the volume of the arms trade between countries. A recent theoretical model by Garfinkel et al. (2015) explores the consequences of interstate disputes over contested resources, such as oil, for defence spending and trade flows. Contestation of natural

[3]Interestingly, however, arms exports may generate negative externalities when e.g., the importing nation becomes a future threat (see Garcia-Alonso and Levine, 2007).

resources plays a big role in many interstate disputes and shapes the security policies of the countries involved. Oil, in particular, is a highly "politicized" commodity and responds to international political relations even in times of peace (Mityakov et al., 2013). Civil wars, violent regime changes, and regional instabilities have long been a significant cause of oil shocks, in particular when involving oil-abundant regions. Since the end-use of arms export concerns the security of the recipients, we claim that oil-dependent economies have strong incentives to sell or give away arms to reduce the risk of instability in oil-rich and potentially unstable regions. Specularly, oil-rich countries are more likely to receive weapons by oil-dependent economies.

We estimate the effects of oil interdependence using a gravity model of international trade and explore the extent to which the economic and political characteristics of the client and the supplier, and the connections between them, affect the bilateral arms trade. Deciphering the impact of oil dependence on the arms trade is complicated by the fact that oil and weapons could be simultaneously determined.

On the one hand, establishing a relationship between the two variables leaves open the question of whether "oil causes weapons" or vice versa. We strive to include plausibly exogenous variables, such as indicators for the known amount of oil reserves and information on the discoveries of new oil fields. Moreover, we estimate leads of the dependent variable running from one to five years ahead to further circumvent the risk of causality running both ways. On the other hand, there are a number of important confounding factors, whose omission could bias the estimates. For example, countries with a developed manufacturing sector are more likely to be arms producers and at the same time to import oil. We control for multilateral resistance terms i.e., importer-time and exporter-time fixed effects (see e.g., Anderson and van Wincoop, 2003), which flexibly account for time-varying country-specific unobservables. We also include country-pair fixed effects to capture all time-invariant unobservable bilateral factors influencing arms trade flows. We implement a battery of robustness checks to support our identifying assumption.

To anticipate, our empirical analysis paints a clear picture and supports our claim that oil is a crucial factor affecting the volume of arms flows on both sides of the transaction. We proceed as follows: section 2.2 provides a brief overview of the latest theoretical and empirical literature on the arms trade and elaborate on our hypothesized mechanism. Section 2.3 presents the data and the empirical strategy. Section 2.4 discusses our main empirical results. Section 2.5 concludes.

2.2 Energy security and the demand and supply for weapons

The majority of scholarly research on the arms trade takes the form of theoretical models, which usually focus on the strategic interactions between exporters and importers, and the implications for arms races and arms proliferation - see, e.g., the seminal dynamic models offered by Levine and Smith (1995, 1997, 2000b), who also discuss possible common control regimes. Levine and Smith (2000a), in particular, integrate economic and strategic incentives within a unified framework, and analyze national and international regulatory regimes and market structures. They find that whereas prices have dampening effects on arms race, regulatory regimes can have either positive or negative effects on domestic production and arms imports. Garcia-Alonso and Levine (2007) build on the above models to discuss the main strategic characteristics of the arms trade and to examine the determinants of market structure in the military sector. Sandler (2000) explores collective action failures in relation to arms control and security. Kollias and Sirakoulis (2002) model the effects that arms imports have on the military balance between two antagonistic regional players. Finally, Seitz et al. (2015) provide a model of trade, conflict and defence spending with an arms race and determine the magnitude of welfare gains due to reductions in the likelihood of conflict and defense spending cuts.

Empirical works on the decision-making processes behind the arms trade and on the characteristics and relations between suppliers and recipients are scant at best.[4] Bergstrand (1992) estimates the effects of arms reduction on world trade using data for 17 OECD countries over the 1975-1985 period. He also uses a gravity model for gaining insight in the economic determinants of the arms trade and finds that the model is limited in its capacity to explain this sort of trade, as it is "determined largely by political, military or other non-economic factors" (Bergstrand, 1992, p.137). Blanton (2000, 2005) explores the impact of human rights and democracy on the eligibility of a country to receive weapons from the USA. Smith and Tasiran (2005, 2010) examine the factors affecting the elasticity of arms imports with respect to military expenditure, per capita income and the price of arms imports, and address issues of measurement errors, non-linearity and dynamic specification. Yet, they focus solely on the characteristics of the importers. Comola (2012) explores the existence of political cycles in arms exports using data on the top 20 major exporters over the

[4] A number of empirical studies reverse the causal arrow and look at the effects of arms transfer on several outcomes, such as interstate conflict, ethnic uprisings and repression; Kinsella (2011) offers a comprehensive and recent review of this strand of the literature.

period 1975-2004; she finds that right-wing incumbents increase arms exports, whereas higher concentration of power and incumbents serving the last year of their term and potentially running for re-election have the opposite effect. Finally, Akerman and Seim (2014) find a negative relationship between differences in the polity and the likelihood of the arms trade during the Cold War.

We advance the relevance of geo-economic and geo-strategic considerations and suggest that energy interdependence is a major factor explaining the volume of arms transfers between states. In doing so, we expand the range of perspectives on the arms trade beyond questions of economic and political determinants at the national level to issues of energy dependence at the international level. The arms trade, security and energy dependence are heavily interconnected. On the demand side, recipients receive weapons mainly for reasons of national security as the acquisition of new equipments improve their defense capabilities (e.g., Levine and Smith, 2000b). Although other reasons for importing weapons exist, security is usually the main objective. On the supply side, arms are exported to support the security needs of friends and allies, and to strengthen security links. Moreover, many countries receive military aid to buy weapons and equipment from the donor country. The US is the largest supplier of military aid to over 150 foreign countries in the world, with the explicit goal of contributing to regional and global stability, strengthening military support for democratically elected governments and containing transnational threats (see US Greenbook, 2012).[5]

Therefore, the end-use of the arms trade concerns the security of the recipients. We claim that this is particularly crucial when the recipient state is a main supplier of energy and when the arms exporter is dependent on it. Conspiracy theorists have long insisted that modern wars revolve around oil, the main energy source worldwide. The post-WWII period has many instances of military intervention in oil-rich states, such as in Angola, Chad, Guatemala, Indonesia, Mali, Nigeria, Sudan and the Philippines. Recent examples include the military intervention in Libya in 2011 by a coalition comprising most of NATO oil-dependent economies, or the US campaign against Isis in northern Iraq. Bove et al. (2015) finds that the likelihood of a third-party intervention in civil war increases when the country at war has large reserves of oil and such interventions are more likely to be carried out by countries that highly depend on oil imports. Yet, military intervention is expensive and risky and can easily cause domestic backlash if the benefits are not clear-cut. To

[5]USAID Economic Analysis and Data Services (2012): US Overseas Loans and Grants, Obligations and Loan Authorizations Greenbook (`http://gbk.eads.usaidallnet.gov/`)

support the security needs of allies and strategic partners, countries can resort to alternative, less invasive, foreign policy tools.

We argue that the provision of security extends beyond direct military intervention and war times and that the export of arms is an effective substitute for costlier forms of assistance. The arms trade is therefore a factor to counter local threats, to inhibit or reduce the risk of political instabilities and, as a result, the chances of disruption in the oil trade. Violent events such as civil wars or terrorist incidents are often accompanied by surging oil prices, or more generally insecurity in the supply of oil; this was the case in many recent wars, such as during the Gulf War, 9/11, the Iraq War, the Lebanon Conflict and the political unrests in Venezuela in 2003. Political instabilities do not necessarily cause disruptions in oil production, yet they can affect prices and/or future supplies. Kilian (2009) explores exogenous political events in the Middle East and find that wars or revolutions affect the real price of oil through "their effect on precautionary demand for oil. The latter channel can produce immediate and potentially large effects on the real price of oil through shifts in the uncertainty about future oil supply shortfalls, even when crude oil production has not changed" (Kilian, 2009, p. 1064). The prospects of energy supply disruptions and increases in oil prices can easily put at risk fragile economies while posing significant costs for more developed countries. Disruptions in the oil industry and higher oil prices may in fact negatively affect the real GDP growth, the real wages and increase the short-term interest rates (e.g., Kilian, 2008; Lippi and Nobili, 2012). These negative effects are more likely to materialize in oil-importing countries, which therefore have incentives to reduce the risk of instabilities in oil-rich countries.

A seminal study by SIPRI (1971), identifies, among the purposes of arms supply, a "hegemonic" aim: countries can use arms transfers to "support a particular group in power, or to prevent the emergence of an alternative group" (SIPRI 1971, p. 17). This is consistent with recent studies which provide convincing evidence that military aid can be effective at keeping terrorist groups out of power (see Bapat, 2011). Therefore, the deliveries of major conventional weapons can be put forward as evidence of the supplier's commitment to the security and military advantage of the recipient state. In most of the wars fought in the last few decades and in most of the confrontations between states and terrorist groups, foreign arms, or restraints on arms supplies, have played a central role in determining the fortune of the combatants. Ensuring the military advantage of a country against domestic and external threats is all the more important when this country is a

key supplier of oil and when the arms supplier is dependent on oil. Improving the security of the oil-rich economies makes them more reliant in the supply of oil and, at the same time, reduces the uncertainty about shortages in future oil supplies, which is a critical determinant of oil prices (Kilian, 2009).

Note, however, that we are not suggesting the sole existence of a direct oil-for-weapons mechanism. By providing weapons, the oil-dependent country seeks to contain the risk of instabilities in a oil-rich country; yet, the latter does not necessarily need to be its *direct* oil supplier, because disruptions in the production of oil in this country are very likely to affect oil prices worldwide. In sum, we seek to test two related expectations, or hypotheses:

> **H1 (local dependence)**: The larger the amount of oil imported from a country, the higher the volume of arms exported to the same country
>
> **H2 (global dependence)**: The larger the level of global oil dependence, the higher the volume of arms exported to oil-rich countries

Although theoretically intertwined, the two mechanisms require two substantially different empirical models, the issue considered next.

2.3 Data and Empirical Strategy

To measure the volume of international transfers of arms we use the SIPRI Arms Transfers Database, which contains information on all transfers of major conventional weapons since 1950. SIPRI has developed a unique system that uses a common unit, the trend-indicator value (TIV), to permit comparisons between deliveries of different weapons. The TIV is based on the known unit production costs of a core set of weapons and is useful to estimate the transfer of military resources rather than the financial value of the transfer. The TIV fits well with the purpose of our analysis, explaining the quantities of arms transfers rather than the contracted prices, which can be as low as zero in the case of military aid.[6]

To measure oil dependence, we assemble a very comprehensive dataset on stock variables such as oil reserves and new oil discoveries, as well as on flow variables, in particular oil imports and

[6]More information is available on SIPRI's website (`http://www.sipri.org/databases/armstransfers`).

exports. Data on oil reserves and on new oil discoveries in thousand million barrels come from Cotet and Tsui (2013), who draw information from the Association for the Study of Peak Oil and Gas, the BP Statistical Review of World Energy, and the Oil & Gas Journal.

To test Hypothesis 1, we first construct a measure of net oil import, using disaggregated bilateral trade flows from Feenstra et al. (2005). This measure indicates the volume of net import of oil of the arms exporter (i.e., the oil-dependent country) from the arms importer (i.e., the oil-rich country). Note that this variable can be thought of as being made by two components. The first is whether the country-pair includes an oil-producing and an oil-dependent country, otherwise net imports would be zero; the second is whether the pair of countries actually has an established trading relationship, which is related to whether they are economic partners and/or political allies. The data are organized by 4-digit SITC Revision 2, and cover trade flows reported by 149 countries (98% of world exports) for the period from 1962 to 2000. The availability of data on oil flows limits our study to the same period.[7]

We then estimate the effect of net oil import on the arms trade between countries using a gravity equation model and the Poisson Pseudo Maximum Likelihood (PPML) estimator developed by Silva and Tenreyro (2006). The gravity equation takes the following form:

$$Y_{ijt} = \alpha \, exp(\beta \, Net\ oil\ import_{ijt} + X_{1it} \, \delta + X_{2jt} \, \zeta + D_{ijt} \, \lambda) \, \epsilon_{ijt} \tag{2.1}$$

where Y_{ijt} is the volume of major weapons transfers from country i to country j at time t, and $Net\ oil\ import_{ijt}$ is our variables of interest, the degree of oil dependence of country i from country j at time t.

X_{1it} is the vector of country i's characteristics, including the real GDP to capture the economic size of the country (larger countries should import higher volumes of weapons); the level of democracy (the Polity IV indicator) to capture the degree of institutional development; the level of military spending in % of the GDP and the number of armed forces in % of the population; and the membership in NATO or the Warsaw pact. X_{2jt} is the vector of country j's characteristics, which includes all the above variables and additional controls to account for any form of intra-state

[7]Note that the limit of the sample is not particular to our study, and most other studies use the Feenstra et al.'s data for similar analyses. According to Baier et al. (2014, p.344), Feenstra et al. (2005) is "the most disaggregated publicly available data set for bilateral trade flows for a large number of years and a large number of country pairs, constructed on a consistent basis".

and inter-state conflict involving country j; the number of wars in its neighbourhood to pick up additional security threats; and the presence of an international arms embargo on j.

The vector D_{ijt} includes the classical impediments or facilitating factors in a list of gravity controls, in particular: the capital-to-capital distance; a measure of religious distance; a set of binary variables taking value one if i and j have a common currency, language, ethnicity or colonial history; and a dummy that equals one for regional trade agreements in force. To further investigate potential factors affecting the presence and the volume of bilateral arms trade, we also include information on military alliances and on political affinity. The latter measures the preferences of each state, or more precisely, the interest similarity among pairs of states on the basis of voting patterns at the UN General Assembly (see Voeten and Merdzanovic, 2009, for more information). Finally, ϵ_{ijt} is a multiplicative error term with $E(\epsilon_{ijt}|Net\ oil\ import_{ijt}, X_{1it}, X_{2jt}, D_{ijt},) = 1$, assumed to be statistically independent of the regressors. Table 2.A.1 provides information on the name, definition and source of all the above variables, and Table 2.A.2 contains the summary statistics.[8]

To deal with the potential co-evolution of arms transfers and net oil import over time, we include linear time trends or a set of year dummies, whose coefficients are not shown in the tables of results. We report robust standard errors clustered at the country-pair level to allow for the variance to differ across pairs; this further addresses the issue of heteroskedasticity in the error terms and controls for autocorrelation by allowing an unstructured covariance within the clusters. Finally, to address endogeneity bias that might arise from the omission of important determinants of arms export, we estimate a number of models with importer-time and exporter-time fixed effects, which account for important time-varying multilateral variables, as well as models with bilateral fixed effects, as bilateral trade flows are known to systematically depend on country-pair specific factors.[9]

[8]Note that since the algorithm does not converge when the dependent variable has large values, we follow Santos Silva & Tenreyro's (2006) advice and rescale it. Rescaling arms transfers does not affect the substantive interpretation of the coefficients of interest.

[9]There are several advantages of using the PPML over alternative models. First, the value of our dependent variable is most often zero, and the classical log-log gravity model is unsuitable when Y_{ijt} is zero. Dropping all the observation with no trade induces a sample selection issue, and we would lose a number of important information on cases of arms denial and constraints on the export of weapons to specific states. Using the logarithm of $Y_{ijt} + 1$ as the dependent variable generates inconsistency in the parameter of interest (Silva and Tenreyro, 2006). Moreover, our dependent variable is highly heteroskedastic; we have small deviation when i and j are small countries with no political relations, whereas large values and large dispersions around the mean are observed when i and j are powerful and connected. Under heteroskedasticity, estimating log-linearized equation by OLS leads to significant biases. However, the PPML estimator is robust to different patterns of heteroskedasticity, provides a natural way to deal with zeros in trade data, and is resilient to measurement error of Y_{ijt}, which can potentially contaminate our analysis (see Silva and Tenreyro, 2006; Santos Silva and Tenreyro, 2011). A recent article by Fally (2015) also argues

Hypothesis 2 states that oil-dependent countries are more inclined to export arms to oil-rich countries, in order to safeguard its political stability and, as a consequence, prevent oil shocks and higher oil prices in international markets. To test Hypothesis 2, we augment equation (2.1), in the specification with multilateral resistance terms, with an interaction between a dummy indicating whether the arms exporter is an oil-dependent country in the global system and a dummy indicating whether the arms importer is an oil-rich country in the global system. This simple strategy allows us to disentangle the effect on the arms trade of a global oil dependence, when the arms exporter wants to keep global oil prices stable in international markets, from that of a local oil dependence, when the arms exporter wants to safeguard the supply of oil from a particular oil-rich country. We therefore estimate the following model:

$$Y_{ijt} = \alpha \, exp(\beta \, Net \, oil \, import_{ijt} + \gamma \, Oil \, dependent_{it} * Oil \, rich_{jt} + D_{ijt} \, \lambda + \theta_{it} + \tau_{jt}) \, \epsilon_{ijt} \qquad (2.2)$$

where θ_{it} and τ_{jt} serve, respectively, as exporter-time and importer-time fixed effects, accounting for the multilateral resistance terms. $Oil\,dependent_{it}$ is a dummy that takes value one if country i is net importer of oil in the global system, i.e., when the balance of global trade in oil (the difference between global volumes of oil import and oil export) is negative. $Oil\,rich_{jt}$ is a dummy that takes value one if country j is rich in oil. As a proxy for the abundance of oil in country j, we use stock variables such as oil reserves and new oilfield discoveries at time t in lieu of flow variables like oil production which could be potentially endogenous to arms import.

On one hand, the timing and relative size of new oilfield discoveries are mostly random, at least in the short-medium run, as prospecting for oil is highly uncertain, and countries have generally little control over the timing of such discoveries (see e.g., Lei and Michaels, 2014). Moreover, oil discoveries conveys important information about the potential for oil production in the very near future. Cotet and Tsui (2013) and Lei and Michaels (2014), among others, discuss how (unexpected) oil discoveries generate exogenous variation in oil wealth and increase per capita oil production and oil exports. On the other hand, to ensure that our results are not driven by this particular operationalization, we also use alternative definitions of the *Oil rich* dummy, which takes the value one if a country's total amount of oil reserves belongs to the 75th, 90th, 95th or 99th percentile of

in favor of the PPML and gives additional motivation for using it.

the total (global) oil reserves at time t. This stock variable should be less vulnerable to endogeneity concerns than oil production, as reserves depend on geological features and previous exploration efforts. Our parameter of interest is now γ as it speaks to the issue of global oil interdependence (Hypothesis 2), whereas β speaks to the issue of local dependence (Hypothesis 1).

2.4 Empirical results

2.4.1 Arms transfers and net oil import

Tables 2.1 and 2.2 provide the main tests of Hypothesis 1, a direct oil-for-weapons exchange. We start from Table 2.1, which incorporates the baseline models. Column (1) in Table 2.1 provides an initial test of the impact of net oil import on the volume of the arms trade, when no other control variables are included. The estimated coefficients for net oil import is positive and significantly discernible from zero at the 1% level. In column (2) we include the set of monadic controls (i.e., country i- and country j-specific characteristics). In column (3) we add the set of dyadic controls (i.e., country-pair characteristics). In column (4) we control for year dummies, and in column (5) for a linear time trend. Our coefficient of interest, β, is remarkably stable across model specifications and remains positive and statistically significant at the 1% level. The PPML specification allows for direct reading of the coefficients, and the substantive interpretation is similar to a semi-elasticity. Net oil import is measured in 10 million metric tons, this means that a one-unit increase (10 ml metric tons) in the net oil import of country i from country j will lead to an increase of between 136% and 363% in the volume of arms transfers from i to j. These findings provide a first corroboration of the thesis outlined by Hypothesis 1 and demonstrates that the higher is the net oil import of country i from country j, i.e., its local oil dependence on country j, the higher its exports of arms to j.

Table 2.1: Arms Transfers and Net Oil Import, PPML Estimates

	Arms transfers$_{ijt}$				
	(1)	(2)	(3)	(4)	(5)
Net oil import$_{ijt}$	3.625***	1.358**	1.731***	1.662***	1.695***
	(0.535)	(0.653)	(0.600)	(0.601)	(0.594)
Country i's characteristics					
GDP		3.461***	4.325***	5.768***	5.125***
		(0.225)	(0.303)	(0.495)	(0.373)
Democracy		0.026	0.027	0.017	0.014
		(0.022)	(0.020)	(0.017)	(0.017)
NATO		1.557***	1.554***	1.270***	1.293***
		(0.207)	(0.219)	(0.200)	(0.199)
Warsaw pact		-1.274**	-1.215**	-1.488***	-1.482***
		(0.507)	(0.488)	(0.467)	(0.469)
Military burden		0.011***	0.011***	0.009***	0.010***
		(0.001)	(0.001)	(0.001)	(0.001)
Soldiers per capita		-19.478**	-13.968*	-26.424***	-27.176***
		(7.663)	(7.463)	(9.263)	(8.294)
Country j's characteristics					
GDP		2.927***	3.446***	4.582***	4.171***
		(0.626)	(0.413)	(0.555)	(0.488)
Democracy		0.018	-0.007	-0.000	0.003
		(0.021)	(0.016)	(0.014)	(0.015)
NATO		0.414	-0.201	-0.262	-0.249
		(0.422)	(0.383)	(0.307)	(0.343)
Warsaw pact		-1.166	-1.038	-1.257	-1.110
		(0.905)	(0.834)	(0.853)	(0.846)
Military burden		0.002***	0.003***	0.002***	0.003***
		(0.001)	(0.000)	(0.001)	(0.001)
Soldiers per capita		26.928***	22.642***	18.253***	19.595***
		(9.394)	(6.576)	(5.523)	(6.086)
War		0.073	0.071	0.003	0.075
		(0.200)	(0.146)	(0.176)	(0.156)
Neighboring wars		0.164*	0.210***	0.226***	0.234***
		(0.092)	(0.068)	(0.070)	(0.069)
Arms embargo		-0.887	-0.942	-0.699	-0.830
		(0.612)	(0.614)	(0.656)	(0.655)
Country-pairs's characteristics					
Military alliance			1.140***	0.826***	0.935***
			(0.369)	(0.300)	(0.331)
Political affinity			1.268***	1.452***	1.161***
			(0.205)	(0.214)	(0.186)
Year trend					-0.047***
					(0.008)
Gravity controls	No	No	✓	✓	✓
Year fixed effects	No	No	No	✓	No
Clusters	8765	8765	8765	8765	8765
Observations	66037	64531	64531	64531	64531

Note: Robust standard errors in parentheses are clustered at country-pair level. The dependent variable, Arms transfers$_{ijt}$, measures the volume of major weapons transfers from country i to country j at time t. The main explanatory variable, Net oil import$_{ijt}$, measures the net oil import (import - export) of country i from country j at time t. Gravity controls include Distance, Common colony, Common currency, Common ethnicity, Common language, Religious distance and RTAs. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Although we strive to control for a host of determinants of arms trade and get as close of an estimate as possible of a pure "local oil dependence" effect, it is still possible that unobservable factors affect both the transfers of arms and the net import of oil. In such a case, the PPML estimation of equation (2.1) might produce biased estimates. To address these endogeneity concerns, in Table 2.2, column (1), we estimate equation (2.1) with the inclusion of country-specific (i and j) fixed effects to account for time-invariant unobservables at the country level. Furthermore, in column (2) we estimate a specification with the inclusion of it and jt fixed effects (i.e., the multilateral resistance terms) to flexibly capture all the time-varying barriers to trade that each country faces with all its trading partners every year. This specification soaks up all the effects of country i's and country j's characteristics in the it and jt fixed effects. Finally, in column (3) we run a specification with country-pair fixed effects to absorb time-invariant characteristics at the dyadic level. Note that this model requires us to exclude all dyads where we do not observe variation in arms transfers over time, in our case almost half of the total number of observations. Results in Table 2.2 show that our coefficient of interest remains strongly significant when taking into account additional unobservables. Reading across the first row of results in Table 2.2, we find that a 10 million metric tones increase in the volume of net oil import increases the bilateral arms transfer by a minimum of 99%.

Table 2.2: Arms Transfers and Net Oil Import, PPML Estimates with FE

	Arms transfers$_{ijt}$		
	(1)	(2)	(3)
Net oil import$_{ijt}$	1.112***	1.615**	0.987***
	(0.325)	(0.627)	(0.378)
Country i's characteristics			
GDP	0.666		0.516
	(0.560)		(0.632)
Democracy	-0.007		-0.008
	(0.027)		(0.020)
NATO	1.608**		0.743**
	(0.625)		(0.359)
Warsaw pact	0.254		-0.989
	(0.725)		(0.747)
Military burden	-0.002		-0.002
	(0.003)		(0.003)
Soldiers per capita	7.866		15.251
	(23.245)		(20.589)
Country j's characteristics			
GDP	2.099***		2.594***
	(0.661)		(0.777)
Democracy	-0.020		-0.019
	(0.012)		(0.012)
NATO	-0.468		0.245
	(0.325)		(0.302)
Warsaw pact	0.170		0.322
	(0.751)		(0.938)
Military burden	0.002***		0.001
	(0.001)		(0.001)
Soldiers per capita	24.468***		16.122**
	(6.338)		(7.711)
War	-0.143		-0.204
	(0.236)		(0.275)
Neighboring wars	-0.033		-0.148**
	(0.058)		(0.064)
Arms embargo	0.141		-0.438
	(0.317)		(0.458)
Country-pairs's characteristics			
Military alliance	0.911***	0.812**	-0.021
	(0.298)	(0.324)	(0.320)
Political affinity	0.861***	2.245***	0.759***
	(0.192)	(0.322)	(0.275)
Year trend	0.012		
	(0.008)		
Gravity controls	✓	✓	✓
Year fixed effects	No	No	✓
(i) and (j) fixed effects	✓	No	No
(it) and (jt) fixed effects	No	✓	No
(ij) fixed effects	No	No	✓
Observations	64531	63129	32573
Clusters	8765	8919	1112

Note: Robust standard errors in parentheses are clustered at country-pair level. The dependent variable, Arms transfers$_{ijt}$, measures the volume of major weapons transfers from country i to country j at time t. The main explanatory variable, Net oil import$_{ijt}$, measures the net oil import (import - export) of country i from country j at time t. Gravity controls include Distance, Common colony, Common currency, Common ethnicity, Common language, Religious distance and RTAs. $*p < 0.10, **p < 0.05, ***p < 0.01$.

We now briefly turn to our contextual covariates on the supply and demand side of the arms trade. We find that the arms trade is a positive function of both i's and j's real GDP. It is not however associated with the level of democracy in the exporting and importing country. We include the military spending in % of the GDP to capture military capabilities on the supply side, and perception of threats on the demand side, when it is not adequately picked up by the war variables. Military spending display a positive effect, significant at conventional levels, on both sides. We also include the number of armed forces in % of the population for both i and j, a proxy of the labour intensity of a country's force structure (see, e.g., Smith and Tasiran, 2005, 2010). Whereas this is negative on the supply side, it is positive on the demand side, reflecting the modernization of labour-intensive armed forces. Note also that being a member of NATO (or the Warsaw pact) increases (decreases) the volume of arms export, but it does not significantly affect the demand for weapons. As one would expect, the number of wars in the immediate vicinity of j (neighboring wars) increases its import of weapons while domestic war is not significantly different from zero. On the demand side, results are not surprising as the decision to import arms reflects threats, proxied here by wars or military spending, and the size of a country, proxied by the GDP (see Smith and Tasiran, 2010).

The presence of international arms embargo against the importing country reduces its level of arms import, due to possible compliance dynamics, but it fails to achieve statistical significance. Our two measures of connectedness, military alliances and political affinity, display a positive sign; this indicates that arms transfers between two states depend on the presence and strength of cordial diplomatic and military relations. Following the traditional literature on the determinants of bilateral trade, we also include customary control variables, such as the geographic distance, the presence of a common religion, a common ethnicity, a common language, a common colonial history and a regional trade agreement. We omit these additional rows due to space limitations, although the full results can be produced with our replication material.[10]

[10]Note that whereas the effect of most of these variables is in the expected direction, geographic distance is often insignificant or positive. Bergstrand (1992) finds a negative effect of distance on the arms trade, yet he uses only 17 OECD countries. A negative effect could be driven by countries' strategic decision to deny arms transfers to potential regional competitors. Moreover, distance becomes negative in Table 2.5 when we exclude major players.

2.4.2 Arms transfers, net oil import and global oil dependence

Table 2.3 offers a direct test of Hypothesis 2, on the effect of global oil dependence, while keeping local oil dependence (i.e., net oil import) constant. We also control for the full set of country-pair's characteristics and estimate models with multilateral resistance terms. Reading across the first row of results, we find that net oil import continues to exert a positive, significant and substantive effect on the volume of arms transfers; the coefficients are virtually identical to those in Table 2.2, column (2), which makes use of the same conservative specification with multilateral resistance terms.

The second row presents an interaction between the *Oil dependent* dummy, on the supply side, and the *Oil rich* dummy, on the demand side. Whereas defining an oil-dependent economy is quite straightforward (i.e., whether it is a net importer of oil or not), recall that we use alternative definitions of an *Oil rich* economy. In column (1) we look at whether j has a positive discovery of oil at time t and we find that its interaction with *Oil dependent* is associated with a 45% increase in the quantity of arms transfers. Columns (2) to (5) display the results of four alterations of the definition of *Oil rich*, according to the percentile distribution of oil reserves in country j, which provides an additional exogenous source of variation. As one moves across the columns of the table the stringency of this definition gradually builds up, and we find that only countries belonging to the 95th or 99th percentile of oil reserves at time t receive higher amount of arms, and that this effect is conditional on whether the arms exporter is oil-dependent. Interestingly, the size of the marginal effect in column (4) is very similar to that of column (1), around 0.5, although they use quite different operationalizations of *Oil rich*. The other contextual variables all continue to add significantly to the fit of the model in the same direction.

Table 2.3: Arms Transfers, Net Oil Import and Global Oil Dependence

	Arms transfers$_{ijt}$				
	Oil rich$_{jt}$=1 if	Oil rich$_{jt}$=1 if Oil reserves$_{jt}$ >=			
	New oil discoveries$_{jt} > 0$	$p75$	$p90$	$p95$	$p99$
	(1)	(2)	(3)	(4)	(5)
Net oil import$_{ijt}$	1.602***	1.574**	1.530**	1.458**	1.326**
	(0.614)	(0.632)	(0.622)	(0.616)	(0.600)
Oil dependent$_{it}$ * Oil rich$_{jt}$	0.454**	0.232	0.269	0.542**	0.935***
	(0.203)	(0.248)	(0.256)	(0.262)	(0.288)
Country-pairs's characteristics					
Military alliance	0.808**	0.834***	0.810**	0.794**	0.761**
	(0.323)	(0.312)	(0.317)	(0.309)	(0.305)
Political affinity	2.232***	2.240***	2.217***	2.214***	2.147***
	(0.320)	(0.319)	(0.318)	(0.314)	(0.308)
Gravity controls	✓	✓	✓	✓	✓
(it) and (jt) fixed effects	✓	✓	✓	✓	✓
Observations	63129	63129	63129	63129	63129
Clusters	8919	8919	8919	8919	8919

Note: Robust standard errors in parentheses are clustered at country-pair level. The dependent variable, Arms transfers$_{ijt}$, measures the volume of major weapons transfers from country i to country j at time t. Net oil import$_{ijt}$ measures the net oil import (import - export) of country i from country j at time t. Oil dependent$_{it}$ is a dummy variable that takes value equal to 1 if country i is globall oil importer at time t. Oil rich$_{jt}$ is a dummy variable that takes value equal to 1 if country j has a new oil discovery at time t, in column (1). In columns (2)-(5), Oil rich$_{jt}$ is redefined equal to 1 if country j belongs to the 75th, 90th, 95th and 99th percentile of oil reserves at time t, respectively. Gravity controls include Distance, Common colony, Common currency, Common ethnicity, Common language, Religious distance and RTAs. $*p < 0.10, **p < 0.05, ***p < 0.01$.

2.4.3 Robustness Checks

We test the robustness of our findings in a number of additional ways. First, we ask whether the potential failure to fully address reverse causality might introduce simultaneity bias into our estimated models. Therefore, in Table 2.4 we estimate a series of regressions as in equation (2.2) using as dependent variable future arms transfers in year $t + s$, with $s = 1, 2, 3, 4$ and 5. Our results hold up well to this series of specification checks and the size of the coefficients is virtually unaltered, which increases the confidence in our results.

Table 2.4: Future Arms Transfers, Net Oil Import and Global Oil Dependence

	Arms transfers$_{ijt+s}$									
	s=1		*s=2*		*s=3*		*s=4*		*s=5*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Net oil import$_{ijt}$	1.570***	1.556***	1.568***	1.567***	1.521***	1.489***	1.404***	1.370***	1.068**	1.082**
	(0.559)	(0.541)	(0.522)	(0.506)	(0.536)	(0.524)	(0.530)	(0.526)	(0.528)	(0.519)
Oil dependent$_{it}$ * Oil rich$_{jt}$		0.604***		0.622***		0.692***		0.576**		0.425**
		(0.195)		(0.194)		(0.208)		(0.224)		(0.213)
Country-pairs's characteristics										
Military alliance	0.782**	0.762**	0.715**	0.691**	0.649**	0.640**	0.668**	0.664**	0.557*	0.546*
	(0.314)	(0.312)	(0.311)	(0.308)	(0.311)	(0.308)	(0.307)	(0.304)	(0.307)	(0.303)
Political affinity	2.110***	2.128***	2.118***	2.175***	2.054***	2.049***	1.937***	1.919***	1.945***	1.984***
	(0.320)	(0.321)	(0.324)	(0.328)	(0.318)	(0.314)	(0.312)	(0.306)	(0.323)	(0.323)
Gravity controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
(it) and (jt) fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Clusters	8785	8785	8640	8640	8346	8346	8154	8154	7864	7864
Observations	61113	61113	58738	58738	56762	56762	56814	56814	53843	53843

Note: Robust standard errors in parentheses are clustered at country-pair level. The dependent variable, Arms transfers$_{ijt+s}$, measures the volume of major weapons transfers from country i to country$_j$ at time $t+s$, with s varying from 1 to 5. Net oil import$_{ijt}$ measures the net oil import (import - export) of country i from country j at time t. Oil dependent$_{it}$ is a dummy variable that takes value equal to 1 if country i is a global oil importer at time t. Oil rich$_{jt}$ is a dummy variable that takes value equal to 1 if country j has a new oil discovery at time t. Gravity controls include Distance, Common colony, Common currency, Common ethnicity, Common language, Religious distance and RTAs. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Second, we ask whether our results are driven by specific outliers. Top arms exporters in the period under consideration are the two global powers, USA and Russia, while two countries, Saudi Arabia and Iran, are top oil producers and the major importers of weapons. We exclude them in Table 2.5, columns (1) and (2), and, by and large, the results carry over, thus suggesting that they do not rely on outliers. Third, although our hypotheses speak to the issue of oil dependence, it could be easily extended to strategic natural resources, more generally. Gas is an obvious candidate, and we reproduce the baseline models but use gas in lieu of oil. The results are shown in columns (3)-(4) of Table 2.5. The coefficient on the interaction term is overall similar to the ones presented above for the case of oil, yet net gas import is not statistically significant. This last result suggests that global dependence on gas is more crucial than a direct gas-for-weapons relation.

Table 2.5: Robustness Checks

	Arms transfers$_{ijt}$			
	(1)	(2)	(3)	(4)
Net oil import$_{ijt}$	3.084*	3.002*		
	(1.823)	(1.787)		
Oil dependent$_{it}$ * Oil rich$_{jt}$		0.815***		
		(0.208)		
Net gas import$_{ijt}$			1.722	1.504
			(1.247)	(1.254)
Gas dependent$_{it}$ * Gas rich$_{jt}$				0.736***
				(0.249)
Country-pairs's characteristics				
Military alliance	0.231	0.220	0.669**	0.734**
	(0.336)	(0.327)	(0.326)	(0.328)
Political affinity	1.463***	1.381***	2.164***	2.238***
	(0.413)	(0.403)	(0.329)	(0.324)
Gravity controls	✓	✓	✓	✓
(it) and (jt) fixed effects	✓	✓	✓	✓
Countries	No USA, RUS, SAU, IRN		All	All
Observations	43879	43879	63129	63129

Note: Robust standard errors in parentheses are clustered at country-pair level. The dependent variable, Arms transfers$_{ijt}$, measures the volume of major weapons transfers from country i to country j at time t. Net oil import$_{ijt}$ measures the net oil import (import - export) of country i from country j at time t. Oil dependent$_{it}$ is a dummy variable that takes value equal to 1 if country i is a global oil importer at time t. Oil rich$_{jt}$ is a dummy variable that takes value equal to 1 if country j has a new oil discovery at time t. In column (1) and (2) we exclude the major arms' exporters (USA and Russia) and the richest oil countries (Saudi Arabia and Iran). In columns (3)-(4), we re-estimate our main specifications by using Oil in lieu of Gas. Gravity controls include Distance, Common colony, Common currency, Common ethnicity, Common language, Religious distance and RTAs. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Third, the decisions on whether to transfer weapons or not and on how much to trade might not be completely independent, thus leading to selection bias; a common way to correct for this issue is to estimate a sample selection model (see e.g., Egger et al., 2011). We therefore rely on a Heckman model (Heckman, 1979) which, in the first stage, explains whether two countries trade or not using a Probit model and, in the second stage, uses an OLS to explain the quantity of arms flows, conditional on the first stage. Because of space limitations, the results are reported in the Appendix, Table A.3. We find that global and local oil dependence are statistically significant in the selection equations, and that local oil dependence explains also the volume of arms trade after controlling for selection whereas global oil dependence is not significant. There are however several caveats associated with this procedure, and these last results should be interpreted with caution.[11]

2.5 Conclusions

One of the most debated issues in the study of international economics revolves around the question of whether and to what extent the economic ties between nations affect or are affected by the "flag", i.e., the nature and quality of their diplomatic relations. The arms trade is a very sensitive issue as it reveals national interests beyond simple economic considerations; as such, the volume of bilateral arms transfers can be used as a barometer of political relations between the supplier and the recipient states. The empirical literature on the arms trade is remarkably scarce and the aim of this article is to advance the relevance of energy dependence, and in particular of oil, in explaining the volume of arms transfers between countries. We claim that instances of political violence can cause disruptions in the global supply of oil and increasing oil prices. Oil-dependent economies have therefore incentives to provide security by selling or giving away arms to oil-rich countries to lower their risks of political turmoils and instabilities. This indirect military support should in turn ensure that countries maintain crude oil production within a target range. By the same token, countries with proven as well as a potential for oil production are more likely to receive

[11] Selection models require identifying assumptions and the Heckman model is appropriate only when at least one additional explanatory factor influences the selection but not the outcome equation. To identify the parameters in both stages, we follow Helpman et al. (2008) and choose either common religion (models 1 and 2) or common language (models 3 and 4) as the excluded variable. Yet, choosing the right variable to omit from the outcome equation - one that is only correlated to the decision to transfer weapons rather than to the actual level of arms flows - is very difficult. As a consequence, the results are sensitive to the validity and correct specification of the two equations. Moreover, as Silva and Tenreyro (2006) point out, the validity of the estimator hinges critically also on the assumption of homoskedasticity, which is unrealistic when we use trade data.

weapons by oil-dependent economies. We argue for the existence of both a bilateral or local oil dependence as well as a global oil dependence. The former indicates that arms import is positively tied to the quantities of oil exported to the arms supplier. Speculatively, arms export to a specific country is affected by the degree of dependence on its supply of oil. The latter indicates that global dependence on oil is a motivated factor for the arms trade and increases the volume of arms transfers between countries, even in absence of a direct bilateral oil-for-weapons exchange.

To test these hypotheses, we assemble an extensive panel of oil wealth and oil trade data, including stock variables such as the size of reserves and recent discoveries to prove plausibly exogenous sources of variation; we also include flow variables, in particular the bilateral and global balance of trade in oil of each country, to measure the potential damage of regional instabilities to its oil supply. Our hypotheses about the impact of oil dependence on the arms trade are strongly borne out by the empirical results. Overall, the evidence seems to point consistently towards the conclusion that the arms trade can be associated to attempts to securing and maintaining access to oil and stabilizing prices. As such, oil might play an even larger role in influencing economic and political decisions than is generally acknowledged. Because of the limited number of empirical works on the arms trade and the fact that securing future energy supplies remains a major challenge, there is certainly an interesting agenda for future research in this area.

Appendix 2.A: Tables 2.A

Table 2.A.1: Variable Definitions and Sources

Variable	Definition	Source
Arms transfers$_{ijt}$	Trend-indicator value (TIV) of major weapons transfers from country i to country j at time t in 10 million US$	Stockholm International Peace Research Institute (SIPRI) Arms Transfers Database (`http://www.sipri.org/databases/armstransfers`)
Net oil import$_{ijt}$	Volume of net oil import (import - export) of country i from country j at time t in 10 million metric tons	Feenstra *et al.* (2005)
New oil discoveries$_{jt}$	Volume of new oil discoveries in country j at time t in thousand million barrels	Cotet and Tsui (2013)
Oil reserves$_{jt}$	Volume of oil reserves in country j at time t in thousand million barrels	Cotet and Tsui (2013)
Oil dependent$_{it}$	Dummy for global oil importer countries	Authors' own
Oil rich$_{jt}$	Dummy for countries with a new oil discovery at time t	Authors' own
GDP	Real GDP in 10 million US$	Expanded Trade and GDP Data - Gleditsch (2002) (`http://privatewww.essex.ac.uk/~ksg/exptradegdp.html`)
Democracy	Regime authority spectrum on a 21-point scale ranging from -10 to +10 (Polity2 indicator)	The Polity IV Project - Marshall and Jaggers (2013) (`http://www.systemicpeace.org`)
NATO	Dummy for countries belonging to the North Atlantic Treaty Organization (NATO)	Authors' own
Warsaw Pact	Dummy for countries belonging to the Warsaw Pact	Authors' own
Military burden	Military spending as a percentage of Real GDP	The Correlates of War (COW) Project (`http://www.correlatesofwar.org/`)
Soldiers per capita	Number of soldiers per capita (as a percentage of Population)	COW

Table 2.A.1: Variable definitions and sources – continued

Variable	Definition	Source
War	Dummy for countries with a war	Cotet and Tsui (2013)
Neighboring wars	Number of neighboring countries with a war	Authors' own
Arms embargo	Dummy for countries with arms embargo from either UN or EU	SIPRI Arms Embargoes Database (`http://www.sipri.org/databases/embargoes`)
Military alliance	Dummy for pairs of countries with a formal military alliance	COW
Political affinity	Affinity of Nations score ranging from -1 (least similar interests) to +1 (most similar interests)	United Nations General Assembly Voting Data - Voeten *et al.* (2013) (`https://dataverse.harvard.edu/dataverse/harvard?q=affinity`)
Distance	Capital-to-capital distance between countries in a pair (in 10 million km)	CEPII distance database (`http://www.cepii.fr/CEPII/fr/bdd_modele/presentation.asp?id=6`)
Common colony	Dummy for pairs of countries with common colonizer	CEPII distance database
Common currency	Dummy for pairs of countries with common currency	CEPII distance database
Common ethnicity	Dummy for pairs of countries with the same language spoken by at least 9% of the population	CEPII distance database
Common language	Dummy for pairs of countries sharing a common official or primary language	CEPII distance database
Religious distance	Percentage in which both countries share religions	CEPII distance database
RTAs	Dummy for pairs of countries with regional trade agreements in force	CEPII distance database

Table 2.A.2: Summary Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
Arms transfers$_{ijt}$	overall	0.00000	0.00001	0.00000	0.00045	N = 66037
	between		0.00000	0.00000	0.00012	n = 8919
	within		0.00001	-0.00010	0.00038	T-bar = 7.40408
Net oil import$_{ijt}$	overall	0.00283	0.04766	-1.97506	1.77677	N = 66037
	between		0.02698	-0.72296	0.69729	n = 8919
	within		0.02943	-1.24927	1.08231	T-bar = 7.40408
New oil discovery$_{jt}$	overall	0.26076	1.16661	0.00000	26.06000	N = 53104
	between		0.71353	0.00000	26.06000	n = 7141
	within		1.02365	-9.38986	24.38469	T-bar = 7.43649
Oil reserves$_{jt}$	overall	14.42523	37.83175	0.00000	269.29310	N = 53104
	between		32.12553	0.00000	268.07590	n = 7141
	within		3.12478	-21.70162	38.02587	T-bar = 7.43649
Oil dependent$_{it}$	overall	0.69600	0.45998	0.00000	1.00000	N = 66037
	between		0.44685	0.00000	1.00000	n = 8919
	within		0.26219	-0.27066	1.65754	T-bar = 7.40408
Oil rich$_{jt}$	overall	0.61609	0.48634	0.00000	1.00000	N = 66037
	between		0.46654	0.00000	1.00000	n = 8919
	within		0.23486	-0.35688	1.51609	T-bar = 7.40408
Country i's characteristics						
GDP	overall	0.06601	0.13996	0.00031	1.08073	N = 66037
	between		0.09620	0.00031	1.05582	n = 8919
	within		0.04631	-0.37618	0.60003	T-bar = 7.40408
Democracy	overall	4.14505	7.63329	-10.00000	10.00000	N = 65971
	between		7.56390	-10.00000	10.00000	n = 8894
	within		2.99487	-12.29940	19.26270	T-bar = 7.41747
NATO	overall	0.28816	0.45291	0.00000	1.00000	N = 66037
	between		0.36288	0.00000	1.00000	n = 8919
	within		0.10475	-0.65302	1.24970	T-bar = 7.40408
Warsaw Pact	overall	0.04687	0.21136	0.00000	1.00000	N = 66037
	between		0.15541	0.00000	1.00000	n = 8919
	within		0.11335	-0.89758	0.93576	T-bar = 7.40408

Table 2.A.2: Summary statistics – continued

Variable		Mean	Std. Dev.	Min	Max	Observations
Military burden	overall	38.75193	47.23373	1.95592	439.19770	N = 65810
	between		41.61042	2.38771	439.19770	n = 8886
	within		26.69683	-164.80690	320.38360	T-bar = 7.40603
Soldiers per capita	overall	0.01015	0.00973	0.00077	0.05923	N = 65878
	between		0.00990	0.00081	0.05923	n = 8913
	within		0.00294	-0.00952	0.03068	T-bar = 7.39123
Country j's characteristics						
GDP	overall	0.03000	0.09011	0.00004	1.08073	N = 66037
	between		0.07827	0.00004	0.98974	n = 8919
	within		0.02467	-0.48003	0.45698	T-bar = 7.40408
Democracy	overall	0.98150	7.78391	-10.00000	10.00000	N = 65627
	between		7.16601	-10.00000	10.00000	n = 8893
	within		3.32754	-16.20600	15.11483	T-bar = 7.37962
NATO	overall	0.13969	0.34667	0.00000	1.00000	N = 66037
	between		0.29005	0.00000	1.00000	n = 8919
	within		0.05921	-0.73531	1.04879	T-bar = 7.40408
Warsaw Pact	overall	0.00880	0.09339	0.00000	1.00000	N = 66037
	between		0.07576	0.00000	1.00000	n = 8919
	within		0.05281	-0.92454	0.89769	T-bar = 7.40408
Military burden	overall	30.12046	49.15098	0.00000	1122.41000	N = 65388
	between		38.61121	0.00000	1122.41000	n = 8853
	within		35.16985	-327.93680	1054.41900	T-bar = 7.38597
Soldiers per capita	overall	0.00815	0.00850	0.00000	0.07689	N = 66005
	between		0.00823	0.00000	0.07689	n = 8913
	within		0.00297	-0.02325	0.05051	T-bar = 7.40548
War	overall	0.22859	0.41993	0.00000	1.00000	N = 66014
	between		0.36304	0.00000	1.00000	n = 8919
	within		0.24785	-0.73693	1.20156	T-bar = 7.4015
Neighboring wars	overall	0.77941	1.03456	0.00000	7.00000	N = 66037
	between		0.94539	0.00000	7.00000	n = 8919
	within		0.50314	-2.28726	3.94608	T-bar = 7.40408
Arms embargo	overall	0.03344	0.17977	0.00000	1.00000	N = 66037

Table 2.A.2: Summary statistics – continued

Variable		Mean	Std. Dev.	Min	Max	Observations
	between		0.19687	0.00000	1.00000	n = 8919
	within		0.10836	-0.88323	1.00566	T-bar = 7.40408
Country-pair's characteristics						
Military alliance	overall	0.08933	0.28522	0.00000	1.00000	N = 66037
	between		0.22412	0.00000	1.00000	n = 8919
	within		0.07503	-0.85512	1.05087	T-bar = 7.40408
Political affinity	overall	0.67944	0.37083	-1.00000	1.00000	N = 66037
	between		0.28779	-0.82718	1.00000	n = 8919
	within		0.19951	-0.86192	1.97075	T-bar = 7.40408
Distance	overall	0.00073	0.00045	0.00001	0.00200	N = 66037
	between		0.00044	0.00001	0.00200	n = 8919
	within		0.00000	0.00073	0.00073	T-bar = 7.40408
Common colony						
	between		0.22744	0.00000	1.00000	n = 8919
	within		0.00000	0.02986	0.02986	T-bar = 7.40408
Common currency	overall	0.00277	0.05257	0.00000	1.00000	N = 66037
	between		0.05052	0.00000	1.00000	n = 8919
	within		0.03547	-0.77501	0.97574	T-bar = 7.40408
Common ethnicity	overall	0.14292	0.34999	0.00000	1.00000	N = 66037
	between		0.34053	0.00000	1.00000	n = 8919
	within		0.00000	0.14292	0.14292	T-bar = 7.40408
Common language	overall	0.10711	0.30925	0.00000	1.00000	N = 66037
	between		0.31498	0.00000	1.00000	n = 8919
	within		0.00000	0.10711	0.10711	T-bar = 7.40408
Religious distance	overall	0.15667	0.25129	0.00000	0.99201	N = 66037
	between		0.25310	0.00000	0.99201	n = 8919
	within		0.00000	0.15667	0.15667	T-bar = 7.40408
RTAs	overall	0.06013	0.23773	0.00000	1.00000	N = 66037
	between		0.15562	0.00000	1.00000	n = 8919
	within		0.12911	-0.89639	1.02167	T-bar = 7.40408

Table 2.A.3: Heckman selection model: two-step estimates

	Arms transfers$_{ijt}$			
	(1)	(2)	(3)	(4)
Outcome Equation:				
Net oil import$_{ijt}$	0.000028***	0.000027***	0.000029***	0.000027***
	(0.000003)	(0.000003)	(0.000003)	(0.000003)
Oil dependent$_{it}$ * Oil rich$_{jt}$		0.000002		0.000002
		(0.000002)		(0.000001)
Country-pair's characteristics				
Military alliance	-0.000002	-0.000000	-0.000000	0.000000
	(0.000002)	(0.000002)	(0.000002)	(0.000001)
Political affinity	0.000010***	0.000010***	0.000011***	0.000011***
	(0.000001)	(0.000001)	(0.000001)	(0.000001)
Common religion			-0.000009***	-0.000009***
			(0.000001)	(0.000001)
Common language	0.000003**	0.000004***		
	(0.000001)	(0.000001)		
Selection Equation:				
Net oil import$_{ijt}$	0.378082***	0.271010**	0.378082***	0.271010**
	(0.135296)	(0.136011)	(0.135296)	(0.136011)
Oil dependent$_{it}$ * Oil rich$_{jt}$		0.154948***		0.154948***
		(0.036572)		(0.036572)
Country-pair's characteristics				
Military alliance	0.479222***	0.469871***	0.479222***	0.469871***
	(0.029376)	(0.029429)	(0.029376)	(0.029429)
Political affinity	0.146970***	0.142814***	0.146970***	0.142814***
	(0.027377)	(0.027439)	(0.027377)	(0.027439)
Common religion	-0.138524***	-0.122744***	-0.138524***	-0.122744***
	(0.034405)	(0.034617)	(0.034405)	(0.034617)
Common language	0.135111***	0.151488***	0.135111***	0.151488***
	(0.036345)	(0.036505)	(0.036345)	(0.036505)
Inverse Mills' ratio	-0.000004	0.000003	-0.000000	0.000002
	(0.000005)	(0.000004)	(0.000004)	(0.000004)
Other gravity controls	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Excluded instrument	Common religion		Common language	
Observations	64531	64531	64531	64531

Note: Robust standard errors in parentheses are clustered at country-pair level. The dependent variable, Arms transfers$_{ijt}$, measures the volume of major weapons transfers from country i to country j at time t. Net oil import$_{ijt}$ measures the net oil import (import - export) of country i from country j at time t. Oil dependent$_{it}$ is a dummy variable that takes value equal to 1 if country i is globall oil importer at time t. Oil rich$_{jt}$ is a dummy variable that takes value equal to 1 if country j has a new oil discovery at time t. In the selection equation, the dependent variable is a dummy equal to 1 if Arms transfers$_{ijt}$ is positive, and zero otherwise. The excluded instrument (i.e. the variable excluded from the outcome equation) is Common religion in columns (1)-(2) and Common language in columns (3)-(4), respectively. The other gravity controls include Distance, Common colony, Common currency, Common ethnicity and RTAs. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Chapter 3

No Free Lunch, Buddy: Housing Transfers and Informal Care Later in Life[1]

3.1 Introduction

Inter-vivos transfers between members of the extended family network are both heterogeneous in type (monetary, in-kind, time) and in motives. In developed countries, upstream transfers are mainly in form of caregiving (time) from adult children to their elderly parents (Arrondel and Masson, 2006). Downstream financial and in-kind transfers usually take place at an earlier stage of the life-cycle, when young individuals are investing in their human capital and when they leave the nest to establish a new family, possibly acquiring their own house. These transfers are particularly important as they affect the process of wealth formation, both influencing the young individuals' decisions and determining the degree of wealth and income mobility.

The relation between downstream financial transfers from parents to adult children and time

[1]This paper has been presented at the 18th IZA European Summer School in Labor Economics, the Royal Economic Society Conference at the University of Manchester (2015), the 2nd CIdE workshop in Econometrics and Empirical Economics (WEEE) and the VII Italian Workshop in Empirical Economics at the Collegio Carlo Alberto, Moncalieri (Turin, Italy). We would like to thank Matthias Parey, David Reinstein, Giovanni Mastrobuoni, Daniel Hamermesh, Giulio Zanella, Claudio Labanca, Effrosyni Adamopoulou, Marco Francesconi, Vincenzo Mariani, Ludovica Giua, Paolo Sestito, Federico Signorini, Raffaello Bronzini and Federico Vaccari for valuable comments. Opinions expressed herein are those of the authors only. They do not necessarily reflect the views of, or involve any responsibility for, the institutions to which they are affiliated. Any errors are the fault of the authors.

transfers flowing in the opposite direction (e.g. attention and caregiving) has been subject to a lively debate in the literature, starting from Bernheim et al. (1985). The motive underlying them is crucial in understanding how they can be affected by different policies. While an altruistic model implies crowding-out of private transfers by public redistribution, one based on exchange allows for the possibility of crowding-in. Other models, which account for the fact that the transfers usually involve reciprocities between more than two generations, imply different predictions for the effect of mandatory retirement schemes on intra-family transfers.

Most of the evidence that tries to directly estimate the relation between downstream transfers and upstream caregiving is focused on the contemporary association. Among the most recent, Norton and Van Houtven (2006) and Norton and Huang (2013) find evidence that caregivers are more likely to receive money from their parents (although there are no differences in terms of amount). Conversely, according to Jimenez-Martin and Prieto (2015), informal caregivers receive less transfers. Few empirical studies provide evidence about the relation between past transfers and in-kind services provided by the adult children later on in life. An exception is Arrondel and Masson (2001), who use French data containing rich information on past and current financial and time transfers. The authors find a mild and not significant association between past transfers and current caregiving, which lead them more recently to conclude that there is limited empirical support for inter-temporal exchange (Arrondel and Masson, 2006). Other studies, in particular Tomassini et al. (2003) and Coda Moscarola et al. (2010), point out that those receiving help with housing are more likely to live near to their parents. Although geographical distance is a good proxy for time transfers, both papers do not directly estimate the relation between them and housing transfers. Brugiavini et al. (2013), in a recent study, provide evidence of reciprocity between the provision of grandchildren care and the receipt of informal care later on.

In this paper we first of all aim at providing evidence that those adult children who received economic help in the past from their parents are more likely to provide them care. This is useful to shed light on how the members of the extended family network enforce implicit agreements of mutual assistance that extend over time. The analysis of contemporary transfers can hardly offer insights about this issue. To this purpose we use data from three cross-sections (1998, 2003 and 2009) of the Italian Multipurpose Survey on Families, which contain a retrospective information on help received from the parents with housing at the time of marriage, as well as information on the

family network and on the current exchange of services, including informal elderly care provided by the adult children to their parents. The 1998 wave of the Multipurpose Survey was already used by Tomassini et al. (2003) to study the relation between past help with housing and geographical distance, but differently from them we directly analyze the link with informal care.[2]

We focus on help with housing at the time of marriage for several reasons. To begin with, housing costs represent a large fraction of income and European households generally perceive them as a heavy burden (Pittini, 2012). Secondly, it involves a quite significant fraction of adult couples, consistently with previous evidence about the fundamental role of the family in supporting entry into home ownership (Mencarini and Tanturri, 2006; Helderman and Mulder, 2007; Modena and Rondinelli, 2011). Thirdly, this help takes place at the moment in which a new household is formed and therefore it makes the distinction between the two generations clearer. This is particularly true in Southern Europe, where liquidity constraints for the young are more severe and households traditionally acquire real estate either using personal savings or through family transfers or inheritance (Chiuri and Jappelli, 2003). Finally, this past transfer is precisely identified in the Multipurpose Survey, while other forms of past economic assistance are collected only with reference to specific moments of economic hardship. Nevertheless we also discuss them in our empirical analysis.

The raw data display a positive correlation between the help with housing received at the time of marriage and the provision of elderly care at the moment of interview. We show that this correlation persists after controlling for heterogeneity in other socio-demographic characteristics, such as employment, education, or other proxies for adult children and parents' wealth. We then try to understand to what extent the parents' choice of providing housing transfers considers its opportunity cost. For this purpose, we relate it to regional house prices at the time of marriage. We find that parents are less likely to provide help with housing when house prices are higher. We then show that this negative relation also translates to a lower probability of receiving informal care in the future.

We then move on discussing whether our results fit the predictions of the different competing models that try to rationalize the motives behind these transfers. A strategic bequest motive is

[2]Cigno et al. (1998) also used some statistics from an earlier wave (1987-1991) to show that also those parents that report to be in excellent financial conditions have a large probability of receiving personal or financial assistance from relatives or friends. This suggests that altruism is not likely to be the only explanation. Unfortunately, the microdata from this earlier wave are not currently available.

at odd with our results. A standard Cox model (1987) with improperly altruistic parents, who care not only about their child's consumption but also desire a service from him/her, requires some mechanism to enforce the implicit agreement of receiving future care. This is more likely to hold if children go to live close to parents who helped them, but we show that increased geographical proximity explains only a fraction of the positive association with care. Furthermore, although both altruism and exchange can explain our main result, both models are hard to reconcile with the fact that house prices at the time of marriage negatively affect both the housing transfer and the future receipt of informal care. We provide additional evidence that the housing transfer increases fertility and that parents who offered it are also more likely to provide care services for their grandchildren. This suggests that they are investing in the presence of a third generation, which is more in line with models such as the demonstration effect of Cox and Stark (2005) or the family constitution of Cigno (2006). However, we find that also couples without children tend to reciprocate the past help. This possibly suggests that no single motive is prevailing in the population.

The remainder of the paper is organised as follows: Section 2 discusses the empirical strategy, data are presented in Section 3. Main results are discussed in Section 4. Section 5 discusses whether our findings are in line with different theoretical models, and provides additional evidence which helps discriminating between them. Section 6 concludes.

3.2 Empirical Strategy

This paper focuses on the relationship between help with house and informal care provided by the adult children (elderly care - *ICP*). We take the married couple of adult children as the unit of observation i, and we define ICP equal to one if at least one of the two partners provides help to at least one of the members of the older generation, i.e. parents and in-laws.[3] We assume that informal care depends on whether the adult children receive any type of help with the purchase of their house at the time of marriage and a set of observable (X) and unobservable characteristics (ε):

$$ICP_i = \beta_0 + \beta_1 Help\ with\ house_{i,tm} + X_i^{'}\delta + \varepsilon_i \tag{3.1}$$

For a matter of clarity, the subscript tm indicates that the housing transfer occurs at the time of marriage, which took place prior to the individual interviews (1998, 2003 and 2009).

The first issue that we face is that the relation between help with housing and services may be simply driven by different individual characteristics. In particular, the association between inter-vivos family transfers and help received with housing may be driven by: (i) differences across cohorts and areas; (ii) correlation between housing help and different demographic characteristics that may influence the exchange of services; (iii) differences in wealth between families with and without housing help. To handle these problems, we make use of the extensive information about the household that are available in the *Multiscopo* survey, assuming that including this set of variables in X_i would be sufficient for the unobservable components ϵ to be uncorrelated with our main regressor, $Helpwithhouse_{i,tm}$. To this purpose, we estimate equation (3.1) using OLS, adding step-by-step different sets of variables.

At first we include socio-demographic variables which are good predictors for the exchange of services and, at the same time, may be correlated with the (past) help with housing. In a second step, we also account for the fact that the relation between help with housing and intra-family services may also be explained by differences in income and wealth. Even if we do not

[3] An alternative strategy could be to compare the two sides of the family, that is parents vs in-laws. Empirically, this strategy requires many observations, because the identification would come only from those who received help from one side only. Unfortunately, the survey does not allow us to do this, because in the last wave we cannot distinguish the two sides. Furthermore, if they answer that they received housing help in-kind, only one set of the older generation can be mentioned, and this may create some mechanical exclusion (for instance, if the other side donated some money for furnishing the flat).

have quantitative information on them, the survey includes several good proxies that can be used to understand how much the estimates are influenced by this wealth channel. Nevertheless, there are still concerns about possible omitted variables. One concern is that our set of proxies, mostly dummies, may not be sufficient to capture all the relevant heterogeneity in wealth and income. Another is that some cultural traits are transmissible from parents to children, so that the two generations may share an altruistic propensity which would explain both transfers. We therefore try to see whether the parental decision to provide an housing transfer is affected by relevant economic factors. To this purpose, we relate it with the average house price in the region of residence at the time of marriage:

$$Help\ with\ house_{i,tm} = \alpha_0 + \alpha_1 House\ Price_{r,tm} + X_i'\sigma + \mu_i \tag{3.2}$$

and we test whether $\alpha_1 = 0$. Notice that α_1 may be negative if parents consider it more costly to provide help when house prices are high, or positive because children are more in need of help. Both may be operative in different subsections of the population, but, empirically, α_1 should capture the prevailing one. This can also help discriminate between different underlying models, as we will discuss in Section 3.5. In the case of $\alpha_1 \neq 0$, we can exploit the induced variation in housing help to estimate the effect of the latter on ICP. In other terms, we can use $House\ Price_{r,tm}$ as an instrument for $Help\ with\ house_{i,tm}$, using a 2SLS estimator for equation (3.1). In order to be consistent for the true effect, we need to assume that the housing prices are not related to the unobservable component ε_i. We further discuss this assumption in the relevant section. In the presence of heterogeneous effects, this IV estimates is likely to capture the effect for the subgroup of families where parents' choice of transfer changes with a marginal variation in *House Price*. The estimate can then be interpreted as Local Average Treatment Effect (LATE) for this group (Imbens and Angrist, 1994).

3.3 Data

3.3.1 Dataset and sample selection

We use data from three waves of *Multiscopo sulle Famiglie, soggetti sociali e condizione dell'infanzia* (Multipurpose Survey on Family and Childhood Conditions), a cross-sectional survey carried out by ISTAT in 1998, 2003 and 2009 on the private household population of Italy. The survey sampled around 30,000 households, to collect information on household structure, family network, unpaid assistance, important life cycle events and labour market conditions. The total sample size includes 152,441 respondents.

The dataset is a stratified sample where strata are defined by region and size of the town/city of residence. In our estimates we do not use sample weights, both because we pool three cross-sections, and because we focus on modelling the relationships among different variables. Nevertheless, we know from Solon et al. (2015a) that, in the case of misspecification, it is not clear whether unweighted estimates produce a good approximation. Given that this is not guaranteed even when using weights, we follow the quite standard approach of including the regional dummies among the covariates.[4]

Table 3.1: Sample Selection

	1998		2003		2009		Total
	Obs	%	Obs	%	Obs	%	Obs
Original sample	59050		49541		43850		152441
Only married cohabiting couples	29750	-49.6	24138	-51.3	20918	-52.3	74806
Only if reference person or partner	29038	-2.4	23574	-2.3	20464	-2.2	73076
Only one observation per couple (wife)	14519	-50.0	11787	-50.0	10232	-50.0	36538
Only if both partners aged between 20 and 70	12993	-10.5	9990	-15.2	8233	-19.5	31216
No previous marriage of the wife	12865	-1.0	9845	-1.5	8055	-2.2	30765
With at least one parent alive on both sides	7466	-42.0	5247	-46.7	4289	-46.8	17002
Not cohabiting with parents or in laws	7143	-4.3	5065	-3.5	4146	-3.3	16354
Excluding those with parents or in laws abroad	6966	-2.5	4863	-4.0	3788	-8.6	15617

Sample selection is reported in Table 3.1. We restrict our analysis to married cohabiting couples and we consider them as the adult children, or "middle" generation. To maintain consistency and distinguish the partners where needed, we refer to them as "adult wives" and "her partner" or "husband". Differently, the older generation is referred to as "parents". Only when necessary, we

[4]To guarantee anonymity, the dataset is released in two versions that cannot be merged: in the first one, the region of residence is provided, but not the size of the town; in the other one, the size is provided but only broader geographical areas are available. We prefer to use the former, as it allows to control for aggregate differences across regions, for instance heterogeneity in the mortgage's accessibility.

distinguish between "parents" for the wife's side and the "in-laws" for the husband's. Finally, the third generation is considered to be the "grandchildren". We restrain the analysis to married couples for several reasons. First of all, we are constrained by the 1998 wave, which asked the questions on housing help at the time of marriage only to married and cohabiting women. Secondly, in those cases in which the partner is dead or living elsewhere, we do not have information on the in-laws. Finally, these are quite different cases, where we should also account for the different dynamic of the marital history.

In order to correctly identify the adult children, we keep only cases where one of the partners is the reference person of the interview, which are anyway the large majority. Given that we are interested both in help received from elderly parents or in-laws and in help provided to them, we select couples aged between 20 and 70 years old.

The information on marriage is collected with respect to the last wedding in 1998, and to the first one in 2003 and 2009, and therefore we exclude cases of previous divorce or widowhood. These were still a minority in 1998, and slightly increased in 2003 and 2009 (Table 3.1). We restrict the sample to couples where there is at least one parent alive on both sides, because our interest lies on inter-vivos exchange of family services. We also exclude those cases where the couple cohabits with parents or in-laws at the time of the interview, because the survey does not allow us to identify elderly care in such cases. This involves only around 3 per cent of the couples. Lastly, we exclude the few cases with parents or in-laws residing abroad, because these are likely to be driven by sensibly different migratory processes. Our final sample contains couples who married between 1956 and 2009. The median is 1988. Excluding the 1 per cent tail married before 1965, the distribution is quite symmetric.

3.3.2 Main variables of interest

In all waves, adults are asked whether they provide any help to non co-resident individuals. They then have to specify the most important kind of help they provide, and who receives it, with possible multiple recipients. Around 85 per cent of those who report that their most important help is directed toward their parents say that it consists of informal care. We define the dummy *ICP* (Informal Care Provided) equal to one for those couples where at least one of the partners reports that this help is directed to a member of the older generation (parents or in-laws), and that it

consists of either medical assistance, adult care, domestic work, company, or paper work. The fact that we observe elderly care only when it is the most important help provided to non co-resident individuals can lead to an underestimate of the total amount of caregivers. Nevertheless, we still find that around 21 per cent of the couples provide informal care to the older generation.

Our main explanatory variable, *Help with house*, is a dummy for help received with housing at the time of the marriage. The assistance could be either a transfer in-kind, where parents from either the wife's or the husband's side donate the house or make it available for free (or for a small sum), or an earmarked monetary transfer for purchasing or building a house. The latter includes both gifts and loans, implicitly assuming that the loan is either more convenient or more accessible compared to the "formal" market.

A fraction of adult children, in particular among the older generations, moved in to live with them. We control for this choice of cohabitation in all the regressions, as this constitutes an important alternative to provide help with housing. We chose to keep it distinct from the "help with house" for three main reasons. First of all, in this case it is impossible to separate geographical distance with housing assistance. Secondly, it may involve sensibly different preferences and, because of the co-residence, a different decision mechanisms. Finally, as discussed in Section 3.3.3, this phenomenon is rather marginal for younger generations.

Among the set of control variables there are no missing values, because ISTAT traditionally provides data where all values have been imputed using multivariate methods. This is clearly a drawback for our analysis, but unfortunately ISTAT do not provide indicators for whether or not a single variable has been subject to imputation or correction. Only for some discrete explanatory variables, such as health or retrospective questions, missing values are explicitly allowed to account for cases where the respondent does not want to answer or does not remember. Instead of dropping them, we add the respective category along with the other dummies.

For house prices we use a database, provided by Nomisma, that contains the prices of the houses per square metre (from 1965 to 2009) in each of the Italian provinces for each year. Given that the province identifier is not available in the public release of the Multipurpose survey, and that not all provinces are always available, we average the price at the regional level. One of the problems is that the number of provinces has changed through time, both for administrative reasons and because the sample was progressively extended. We chose to make use of all available information by simply

averaging across available provinces in each region and each year. Nevertheless, in Appendix 3.A we show that price trends are fairly smooth (apart from a spike in the Lazio region in the 1983), and therefore the change is not likely to significantly alter the dynamics by cohorts. The most expensive regions in terms of housing price are Lombardy and Lazio. In Appendix 3.B we also show other descriptive statistics for this variable.

3.3.3 Is housing help at marriage a relevant transfer?

Table 3.2 shows the incidence of earmarked transfers which appears substantial: about one third of the married couples in our sample received financial support for the purchase of a house at the time of marriage. Similarly, Guiso and Jappelli (2002), using the Bank of Italy Survey on Households Income and Wealth, find that 28 per cent of Italian households have acquired real estate properties through a gift, or with the financial help of relatives, or as a bequest.

Table 3.2: Transfers Earmarked for Home Purchase from Parents or In-laws

Housing transfer	Year			%
	1998	2003	2009	
No	71.3%	71.3%	64.4%	68.9%
[*Obs.*]	[4,967]	[3,466]	[2,429]	[10,862]
Yes	28.7%	28.7%	35.9%	31.1%
[*Obs.*]	[1,999]	[1,397]	[1,359]	[4,755]
Total	6,966	4,863	3,788	15617

Note: the sample has been selected from the Multipurpose Survey on Family and Childhood Conditions Dataset (1998/2003/2009). In squared brackets we show the number of observations.

More recently, Jappelli et al. (2014) show that the proportion of households who received real estate transfers rose from 30 per cent in 1993 to above 35 per cent in 2006, which is similar to the increase over time that we find in this paper. These numbers are large but in line with the evidence available for other countries. For instance, Villanueva (2005) finds that bequests account for 31 per cent of total net worth for the US and slightly less for Germany.

This statistics suggest that the help with housing at the time of marriage is one of the most relevant inter-vivos transfer. The survey also allows us to recover some information on other transfers received by the couple. We build a dummy variable OH equal to one if the couple received further transfers from parents or in-laws after the time of marriage and up to the moment of the interview. The information (available only for 1998 and 2003) is collected through retrospective questions and

refers to monetary help during difficult or particularly demanding economic circumstances.[5] Only around 6 per cent of the couples in the sample received this kind of help, of which some also already received help with the house at the time of marriage. Furthermore, in the sample (still limited to the 1998 and 2003 waves) we also know how many couples are currently helped by parents or in laws with economic transfers.[6] The proportion is quite limited, around 2.4 per cent. The focus on contemporary exchange, therefore, limits the analysis to a limited fraction of the overall transfers, as it neglects that several adult children already received economic assistance in the past.

[5]This can be due to unemployment, eviction, insufficient household income, debts, health related problems or, finally, financial needs to set up or run a business.

[6]This refers to those who report that the main help received by the family is an economic transfer that comes from parents or in-laws.

3.4 Results

3.4.1 The relation between housing help and elderly care

In order to understand whether the association between housing help at the time of marriage and services exchanged later on is simply driven by other differences across couples, we start by including socio-demographic variables that are, according to the literature, good predictors for the exchange of services and may, at the same time, be correlated with the (past) help with housing. For obvious reasons, we include dummies for wave and region of residence in all regressions. As already discussed, at the couple level we control for a dummy for whether the couple moved in with parents or in laws after the marriage. We also consider the number of children in the household, a dummy for their presence in the ICP equation, and the age of the youngest child codified to 0 if no children is present. Both account for the fact that the presence of offspring reduces the available time to dedicate on ICP. For both partners we control for age, in order to account for the stage in the life cycle (we also discuss whether there are strong cohort effects, see Section 3.4.2). We include also the number of siblings and a dummy for their presence, given that they strongly reduce the need for ICP. Dummies for educational attainment and presence of health limitations (interacted with wave dummies to account for a minor change in the questionnaire wording) are considered. The former can influence the preferences towards housework, although they are also good proxies for income, while the latter account for possible problems in helping other persons. For each of the parents and in-laws we include variables that may shape their preference towards caregiving and help, or that may influence their demand for assistance. In particular, we add their age and dummies for (parents') educational attainment when the respondent was 14 and for their health limitations interacted with wave dummies to account for a minor change in the questionnaire wording. Given that it may be that only one parent or in-law is alive, we also add two dummies indicating whether only the father or only the mother is alive. For each of the parents, age is rescaled so that the average age for a living parent is zero. If a parent is dead, age and limitations are set to zero but the relative dummies account for this case. The same variables are included for in-laws.

As for the differences in income and wealth across households, we include as covariates the number of rooms, televisions, mobile phones, motorbikes and cars and, in addition, dummies for the

kind of dwelling and tenure. For both partners we add dummies for employment status, extended to account also for the kind of occupation, and for the main source of income (labour, pensions, wealth). Finally, for all parents and in-laws we include dummies for their employment status when the respondent was aged 14. Summary statistics and the full set of estimated coefficients can be found in Appendix 3.B (Table 3.B.1 and Table 3.B.3, respectively). Here we show only the main results of interest. The coefficients on the various control variables appear in line with the economic theory.

Table 3.3: Linear Probability Model for ICP (informal care provided to parents or in-laws)

	(1) ICP	(2) ICP	(3) ICP	(4) ICP	(5) ICP
Help with house	0.020***	0.033***	0.026***		
	(0.007)	(0.007)	(0.008)		
Monetary help				0.022*	
				(0.012)	
In-kind help				0.029***	
				(0.009)	
Contemp. Monetary help					0.086***
					(0.026)
Observations	15617	15617	15617	15617	11829
R^2	0.006	0.084	0.090	0.090	0.090
Waves, regions	X	X	X	X	X
Demographic characteristics		X	X	X	X
Wealth characteristics			X	X	X

Note: * p<.10 ** p<.05 *** p<.01. ICP is a dummy equal to 1 for the adult couple who provide elderly care to parents or in-laws. The variable Contemporary Monetary Help is not available for the 2009 wave. Waves (1998, 2003 and 2009) and (19) regional dummies are included. The following demographic characteristics are include both for each partner of the adult couple and for each parent and in-law: age, health limitations (reference category: no health problem), dummies for parents and in-laws alive and level of educational attainment (reference category: elementary). For the adult couple we consider a dummy for having a siblings and the number of them; we include a dummy which for having a child, the number of them and the age of the youngest one. The wealth characteristics are: dummies for tenure status (reference category: rent), type of house (reference category: terraced), number of rooms, mobile phones, TVs, motorcycles, cars. We also include job occupations (reference category: clerical worker) both for the adult couple and for each parents and in-laws at the time in which the (current) adult child was 14 years old. We finally control for the main source of earnings (reference category: dependent employee). Robust standard errors in brackets.

Table 3.3 starts from a basic specification which includes only waves and regions dummies. Adult children who have been helped by their parents with the house (at the time of the marriage) are more likely to currently provide them elderly care. The relation is likely to be affected by different demographic characteristics, in particular age, given that there are significant differences in the importance of the housing help over time. Once we add the full set of demographic characteristics (column 2), the estimated coefficient increases to 3.3 percentage points. This is a non-negligible effect, given that the proportion of informal carers in the overall sample is around 21 per cent.

Once we incorporate wealth related covariates (column 3), the estimated coefficient of the housing transfer from parents shrinks to 2.6 percentage points. The estimates for the coefficient on help with house from columns (2) and (3) are statistically different with p-value smaller than 1 per cent, according to the proper Wald test.[7] However, the effect is still quite relevant and the reduction in size is relatively small.

We also distinguished between earmarked monetary transfers for housing and in-kind help. The coefficient on the latter is slightly larger (0.029 vs 0.022), but the difference is not statistically significant. Another important heterogeneity is that, in some cases that we included in the in-kind transfer, the house was only made available for free (or for a small sum), without giving the property rights to the children.[8] We expect this type of help, which accounts for one fourth of the total help with house, to be more strongly related to ICP. The reason is that the parents still have some power to evict their adult children from the house, even if this possibility is limited by social and legal constraints. We also run the main regression by splitting the *Help with house* dummy to separate this kind of help. In line with our a-priori, it displays a stronger coefficient (0.057, s.e. 0.018). The effect of the other forms of *Help with house* is, nevertheless, still in line with the main results (0.020, s.e. 0.008).

In the last column we substitute the past help with a dummy for those couples who are currently receiving economic transfers from their parents (*Contemp. Monetary Help*). This is not available for the 2009 wave.[9] In line with the literature, the effect on the provision of informal care to parents is quite large, amounting to 8.6 percentage points. Although this effect is stronger than the one relative to the help with housing at the time of marriage, it must be recalled that the current monetary help from parents involves, in each year, a significantly smaller fraction of the population (2.4 per cent vs 31.1). In Section 3.5.1 we also discuss the relation between housing help and current economic transfers.

One concern is that parents may have supported their children with other transfers around the time of marriage, for instance by simply transferring them some money. Unfortunately, the questionnaire is not designed to pick up this alternative. The problem is that the dummy variable

[7] Results for sub-sample with stronger care needs (e.g. older parents) can be found in Appendix 3.C.

[8] Indeed, those with *Help with house* equal to one are much more likely, at the time of the survey, to live in a house which does not belong to them but for which they do not pay the rent (26.5 per cent in the sample of those who received help with house vs 7.0 for the others). The difference in the proportion of those who live in their own house is, instead, much smaller (70.0 vs 69.4).

[9] The regression in Column (3), run only on 1998 and 2003, gives a similar positive and significant coefficient.

Help with house may actually capture only the actual use of the transfer (for housing), not the fact that a transfer took effectively place. We believe this is not necessarily a concern in this case. First of all, we have already shown that the housing help at the time of marriage appears to be quite relevant among inter-vivos transfers, and therefore our dummy is likely to be at least a very good proxy also for the presence of an actual transfer. Secondly, we would expect a positive relation also between other forms of economic assistance from the parents to the adult children and in-kind services from the latter generation. If this is the case, we are potentially underestimating the effect of housing transfers, given that also some of the couples in the comparison group may have received assistance in the past. Therefore our results would still support our conclusions. We also check whether results would be sensibly different if we exclude those cases in which the couple may have simply not found it optimal to acquire a house, by excluding those who went to live in a rented flat and those who moved in a house that was already owned by one of the partners. Estimates are very similar (0.020 with s.e. 0.008).

3.4.2 Robustness checks

We carry out several robustness checks (full results are available on request). Firstly, we control for two additional sets of dummies accounting for family contacts. The idea is to capture some observable family ties which may bias our results, and to check whether the results on the exchange of caregiving is actually capturing a simple increase in the number of visits. One of the two sets of additional variables refers to the (categorical) frequency of phone calls (separately for parents and in laws). The other accounts for how often the two generations meet together. In both cases the variables assume six distinct categories: every day, more than once a week, once a week, a few times in a month (less than 4), a few times per year and never. The main results are not affected by the inclusion of these dummies, suggesting that the relation is not simply driven by family tastes or increased contacts.

Secondly, we add two dummies to account for the fact that some individuals had already left the parents' house before marriage. One is a dummy for adult children who were already living in a different house, while the other is equal to one for those who had already had at least one paid job at that time (more than 50 per cent of the sample). Both are meant to capture the possible endogeneity of parental help with housing with respect to employment and residential status before

marriage. The estimated coefficients of interest are, again, virtually unaffected.

Thirdly, we check whether the coefficients of interest are somehow biased by the choice of a linear specification. We run the main regressions by using a Probit, but in all cases the Average Marginal Effects are practically indistinguishable from OLS coefficients.

Last but not least, although all regressions include the partners, parents and in-laws' age, together with wave dummies, cohort effects may bias the results. We statistically test for the presence of this effects both with respect to age and to the year of marriage. We set age groups every ten years from 1930 to 1980, and we do similarly in the case of year of marriage from 1956 to 2009. In both cases we add these cohort dummies as additional regressors and we test the joint significance of the parameters. In both scenarios the p-values are larger than 0.6. Results are similar in case of five years selection. It seems safe to conclude that, once we account for all the set of covariates, the cohort effects are not statistically different from zero. Related to this concern, we also replicate the main regressions by using standard errors clustered at combination between year of marriage and region of residence. The results are still statistically significant.

3.4.3 House prices and IV approach

In order to study how parents react to economic factors that may influence their transfer choice, we regress *Help with house* on *House price* and the whole set of variables. Table 3.4, column (1) shows that when house prices at the time of marriage are larger, children are less likely to receive help in purchasing their first house. The opportunity cost of the transfer seem therefore to be more important than the fact that children may be more in need of help, at least on average. The effect is not negligible: considering that a standard deviation in house prices is 567 euro/sqm, an increase of this magnitude would lower the probability of receiving housing help at marriage by 2.5 percentage points, which is slightly more than one tenth of the proportion of households that actually received it.[10]

Inference is complicated by the fact that the *House price* variable only changes at the regional level, for which we have 19 distinct categories.[11] The correct standard errors should account for this clustering. However, as discussed by Cameron and Miller (2015), these standard errors are

[10] We get similar results in terms of magnitude, for both the first stage and the reduced-form, when we divide the housing prices by the consumer price index.

[11] In the Multipurpose Survey, the Aosta Valley region is aggregate with Piedmont (the Italian regions are 20). Given that the latter is much larger and populated, we always use only its price level.

likely to be distorted when the clusters are few. We therefore calculate p-values implementing the wild-bootstrap method that they suggest.[12] In all cases the coefficient is statistically significant at the 5 per cent level.

Table 3.4: Help with House, House Prices and Informal Care

	All sample			Excluding cases of monetary help		
	(1) Help with house OLS	(2) ICP OLS	(3) ICP 2SLS	(4) Help with house OLS	(5) ICP OLS	(6) ICP 2SLS
House price (1000 euro × sqm)	-0.044	-0.031		-0.076	-0.036	
Help with house			0.693			0.470
P-value (robust)	0.001	0.016	0.044	0.000	0.008	0.012
P-value (cluster region)	0.009	0.045	0.024	0.000	0.041	0.016
P-value (wild bootstrap)	0.021	0.086	0.047	0.000	0.095	0.069
F (robust)	10.7			11.0		
F (cluster region)	8.45			28.0		
Observations	14744	14744	14744	13309	13309	13309

Note: in each column, p-values and F statistics refer to the null that the coefficient associated with the displayed regressor is equal to zero (*House price* in columns (1),(2),(5),(6) and *Help with house* in columns (3),(5)). The 2SLS estimates are obtained by instrumenting *Help with house* by *House price*. All regressions include wave, region dummies, plus demographic characteristics and wealth characteristics, as in Table 3.3, column (2). The sample excluded observations for which we do not have regional house prices for the relative year of marriage. Bootstrap p-values are calculated using 999 replications.

As before, one concern could be that house prices do not necessarily affect the parents' decision about giving economic assistance, but simply their specific choice about helping their children with housing instead of giving them a general (non-earmarked) monetary transfer. To shed light on this issue, we can check whether the estimate is driven by in-kind housing help rather than earmarked transfers, because in the in-kind case it is more likely that the parents already owned the property and therefore the house prices at the time of marriage were the relevant opportunity cost (to be compared with the future gains from informal care). We built the categorical variable Type of help as:

$$\textit{Type of help} = \begin{cases} 0 \text{ if Help with house} = 0 \\ 1 \text{ if Earmarked monetary transfer for housing} = 1 \\ 2 \text{ if In-kind help with housing} = 1 \end{cases} \tag{3.3}$$

and we run a multinomial logit regression, using the category *no help* as a baseline and adding

[12] We thank Claudio Labanca for sharing with us his code for calculating wild bootstrap p-values. We took inspiration from it and from Cameron and Miller (2015). We also inspected the distribution of t-tests generated and we never found particular problems, such as mass points around particular values or missing values. We finally tried with a more standard pair bootstrap, but p-values tend to be smaller than the one obtained using clustered s.e., which is in line with the poor performance of this method when clusters are few.

all the regressors, plus *House price*. The latter is statistically significant only for the in-kind help outcome. Furthermore, in column (4) of Table 3.4 we exclude from the sample those who received a monetary help. The comparison is, therefore, only between couples who were helped with an in-kind transfer and those for which Help with house equal to zero. The association with house prices is much stronger.

The variation in house prices seems, therefore, to induce a change in the choice of parents about whether or not to transfer their children part of their real assets. As long as this variability is not correlated to the unobservable heterogeneity leading to the (future) choice of providing elderly care, we could exploit it to instrument *Help with house* and address the potential omitted variable bias not already accounted for by the inclusion of family and individual characteristics. Notice also that if parents are simply switching to other transfers when house prices are higher, then we would expect no difference from the point of view of the adult children, who is anyway still receiving help. Therefore we would foresee no impact of past house prices on the current provision of informal care.

Table 3.4, column (2) shows the reduced-form regressions of ICP on house prices. The estimated effect of *House price* is negative. If house prices at marriage affect ICP only through their effect on *Help with house*, then this finding corroborates the main results. The estimate is imprecise, but statistically significant at the 10 per cent level also using the wild-bootstrap s.e. The resulting estimate for the effect of *Help with house* on ICP, obtained by 2SLS (i.e. dividing column (2) by column (1)), shows a quite large relation. It is significant at the 5 per cent level according to all methods. However, the first stage F-statistic (column (1)) suggests that the instrument is potentially weak. In this situation, the most robust test for the significance of the endogenous regressor is the t-test on the excluded instrument (help with house; see Davidson and MacKinnon (2010) for a discussion) in the reduced-form for ICP (column (2)), which gives a p-value of 0.086 in the wild-bootstrap case, suggesting therefore that the coefficient is statistically significant at the 10% level. Estimates focusing on in-kind transfers only (columns (5) and (6)) show a similar reduced-form. The IV estimate is smaller, but it is still quite large in economic terms and it confirms our results.[13]

[13]In order to further check whether our IV estimates are simply capturing a switch between different forms of assistance, we tried excluding those couples for which it might have been anyway less convenient to acquire a house, namely those who moved in a rented flat or in a house already owned by one of the partners. The estimates are again in line with our conclusions and even more precise. The first stage is stronger and still shows a negative relation between house prices and the help with house, while the 2SLS estimates of the main effect is around 0.39 and significant at the 5 per cent level.

There are some reasons why *House price* may actually be correlated with unobserved heterogeneity entering the equation for ICP, so that our estimates can be biased. One of the main issues is that prices may be related to other characteristics, and in particular to family wealth. However, our regressions include a full set of controls for current wealth, as expressed by the possession of a list of durable goods, and a quite good proxy of life-time wealth, as expressed by the partners' occupation and education, and by the parents and in-laws education and occupation when the currently adult children were aged 14. Another problem is that we do not know the region of origin, but only the current one (except for the 2003 wave, which does not provide enough observations to perform the IV strategy). This is likely to reduce the predictive power of the instrument, although it is hard to predict whether and how this could bias the result. Nevertheless, although a significant fraction of the couples lives in a different town than their parents, most of them live within 50 km (see Figure 3.1). Finally, the year of marriage could be endogenous with respect to the transfer, because couples may wait for better housing market conditions. However, it is hard to argue that the choice of timing is related to the willingness to provide elderly care in the future. Furthermore, in Section 3.4.2 we already discussed that cohorts effects with respect to age or year of marriage are not significant in the main regressions, after accounting for the complete set of variables.

The large relation between help with housing and ICP recovered by the IV regressions compared to the OLS may have two different explanations. The first is that the unobserved component actually leads to a downward bias. In this case, for instance, the family preference for informal care may be negatively related with *Help with house*. Alternatively, the cost of providing it may be positively related with the transfer. This would imply that parents *negatively* select their adult children when they decide to provide them with help. In other terms, they are more likely to help their children if they know that, otherwise, they would be less willing to care after them in the future.

The second possible explanation is that the effect recovered by IV is a local effect for those parents who take into account the opportunity cost of the transfer when they make a decision, so that they provide it when the prices are lower than usual. This group of parents is likely to be the one for which the choice is more influenced by strategic considerations, and therefore we expect that they use it if they expect larger returns in terms of future elderly care.

3.5 Possible Motivations

Our main result concerns the positive association between the receipt of a downstream housing transfer earlier on in time and the likelihood of an upstream time transfer later on. First of all, this evidence seems to contradict the standard prediction of models based on the strategic bequest motive (Bernheim et al., 1985).[14] In these models, the parent promises a larger fraction of the remaining wealth at death to the child who provides the most help. This implies that a contraction in bequeatable wealth, in this case the housing transfer, should reduce the incentive for siblings to compete for it.

Our finding can, instead, be simply explained by the presence of altruism on both sides. Parents, who value their children's utility or consumption, help them when they are liquidity constrained but they want nevertheless to move out and form a new family. In this way the parents reduce their own wealth and will be more in need of help in the future, so that their child, who is also altruist, will provide more help. However, the simple altruistic model is at odds with our results on house prices. Assuming that parents already own at least their own house but children do not, as it is usually the case in Italy, the older generation's wealth increases while the real income of the younger one drops. Parents should therefore be more likely to help their children.[15]

The model proposed by Cox (1987) can also explain our main result. In his setting, the parent dominates the decision. She cares not only about her child's utility, but also about a personal service provided by the latter for which there is no direct market substitute. For the child, instead, the service only brings about utility costs. Hence the parent provides a transfer in order to compensate for this disutility. One key assumption of this model regards the fact that the dominant parent needs to make sure that the child will provide the service agreed upon. Cox (1987) assumes that this contract is enforced through social control. This, however, may be hard to justify when the service occurs much later in time, as in our case (see Cigno et al., 1998, for a similar comment). One possibility, somehow related to the idea that the old generation uses future transfers strategically, is that the parent promises to later compensate the children who is currently helping. In this case,

[14] For a complete discussion of this and of the other models mentioned in this section, see Laferrere and Wolff (2006).

[15] This may not be true in some more extreme circumstances, in particular when the parents already own a house that could be transferred to the children, but the house is too big for his/her needs and the increase in price is large enough to make the optimal transfer smaller than the income loss for donating the house. In this case the parent could switch from a real estate transfer to a monetary transfer and we may not see it in the data.

it might be that past housing help is just a signal about the future availability of further financial help, so that the actual exchange is between contemporary transfers. In Section 3.5.1 we discuss this hypothesis. Another possibility, discussed and explored by Coda Moscarola et al. (2010), is that the service is not informal care per se, but geographical proximity. Parents buy their children a house nearby, compensating them for possible income or utility losses due to constrained mobility. Given that smaller geographical distance reduces the cost of care, this could explain our findings. In Section 3.5.2 we discuss to what extent our result can be explained by increased proximity alone.

Cox's (1987) model allows for both altruism and exchange. The former arises when the parent more than compensates the child for his/her utility loss, while the latter refers to the case in which there is no extra compensation. Although the two situations lead to different predictions regarding the quantity of the downstream transfers, the prediction regarding the likelihood of the transfer is the same. In both cases, an increase in the parent's income and a decrease in the child's should increase the chances of a transfer. This prediction does not seem to be in line with our results regarding house prices. As in the bilateral altruism case above, we would therefore expect the parent to be more prone to provide a transfer. As a consequence, this should lead to higher chances of receiving a service in the future. On the contrary, we found a negative association of house prices at the time of marriage with both housing help and future informal care. Note that this result cannot be explained by parents simply switching to different forms of help to their children, because in this case we would expect a negative association only with housing help and not with informal care as well.

Some alternative models take into account that inter-vivos transfers usually occur between three generations. Cox and Stark (2005) suggest that elderly parents may invest in their adult children's housing or consumption in order to increase the "production" of grandchildren, hoping that their presence will induce the middle generation to set a good example by providing elderly care in front of their own young offspring. This should generate the so-called "demonstration effect". Another model, suggested by Cigno (2006), assumes that the generations are involved in a strategic game where adult children need to choose whether to follow the rules of an (unwritten) "family constitution" or not. In the first case they have to provide help to their own elderly parents (from which they have received in the past) and to the younger generation. In the other case they do not provide any help, but they will be excluded by the family informal agreement so that they will not

receive any help in the future.

Both models share two common predictions. The first is that providing help to your own children can be interpreted as a kind of investment, which has an internal rate of return given by the chances of receiving care in the future. The higher the opportunity cost of providing this help, the lower are the chances that the parents will opt for this investment, no matter the needs of the children. This is in line with our results showing that when house prices are higher the parents are less likely to transfer real estate to their offspring and to receive care in the future. The second prediction stems from the fact that the past help provided by the parents has no chances of leading to more future elderly care if there is not a third generation. Therefore we should observe that it leads to increase fertility and that parents may provide additional services aimed at the third generation, such as grandchildren care. Notice that the presence of living children, possibly still resident in the household, is crucial for the demonstration effect to work. Differently, for the family constitution it is sufficient that the middle generation plans to have children, or alternatively that there are other young members of the extended family who have the power to decide whether or not to provide them assistance in the future. We discuss this second prediction in Section 3.5.3.

The theoretical and empirical analysis of the motivation for a transfer is relevant in planning optimal public policies. The main message here relates to the fact that both the future of social security and the retirement schemes should be designed not only by looking at the efficiency of the state and the market. Indeed it becomes relevant to understand the family intergenerational relations and the specific motive for a gift when assessing an optimal public intervention.

The main policy implications of standard altruistic model of transfers is that an unexpected redistribution from the elderly parents to the adult children would be compensated by a one to one decrease in downstream private transfers (crowding-out effect). Under the exchange motive the impact on private transfers is ambiguous and it depends on the form and the nature of the exchange. Private transfers, being more likely anti-compensatory, may reinforce public income redistribution. Similarly, an increase in publicly provided assistance to the elderly may strongly reduce the assistance provided by adult children if these are only motivated by altruism, while it may not affect the provision of services if these represent the repayment from previous assistance or are provided in view of future bequests.

Similar conclusions as in the exchange model arise in Cigno's family constitution and in the

demonstration effect model. However, these two cases bear some distinct predictions. In the family constitution, inter-vivos transfers could be reduced even by an actuarially fair change in the compulsory retirement scheme, which increases the social contributions paid by the middle aged but keeps the life-stream income unchanged. The reason is that the individuals are forced to save and therefore they are less likely to abide to the family constitution. In the Cox and Stark's model, transfers to old parents are not sensitive to short term changes in retirement or health policies, while the middle one reacts only to expected changes in the long run, because these would reduce the convenience of the demonstration effect.

3.5.1 Is housing help only a signal for future transfers?

Parents might have used the housing transfer to signal to their children the possibility of further financial transfers, closer or contemporary to the time in which they need informal care. In Table 3.5, column (1) we focus on the dummy variable *OH*, which is equal to one if the couple received further transfers from parents or in-laws during particular moment of economic distress, after the time of marriage and up to the interview. The relation of help with house is non negligible, considering that only approximately 7 per cent of the couples in the sample received this other support from parents or in-laws. This is in line with the idea that parents may use the housing transfer to signal their future wealth availability or some residual family resources to support the adult child. Nevertheless, this is not likely to be the main explanation for the association between housing help and ICP. For instance, for it to explain 10% of the effect (that is 0.26 percentage points), we would need these further transfers to increase the likelihood of providing ICP by around 19 percentage points, a much larger effect than the one found for help with house itself. In column (2) we focus on the relation with a dummy for contemporary monetary help from the older generation (*Contemp. Monetary Help*). The estimate is very small in size and not statistically different from zero, confirming that our main result is not driven by the association of past housing help with further financial transfers.

An alternative but related explanation could be that housing help at marriage is an anticipation of future bequests. In this case, the intertemporal exchange is guaranteed by adult children expectations of larger returns in the future, after the provision of elderly care. Unfortunately, our data do not contain information on bequest expectations. To the best of our knowledge, only the

Table 3.5: Linear Probability Model for OH (other help received from parents or in-laws)

	(1) OH	(2) Contemp. Monetary
Help with house	0.011**	0.002
	(0.005)	(0.003)
Observations	11829	11829
R^2	0.056	0.065
Waves, regions	X	X
Demographic characteristics	X	X
Wealth characteristics	X	X

Note: * p<.10 ** p<.05 *** p<.01. OH is a dummy equal to 1 for the adult couple who receive future (with respect to the time of marriage) other type of help from parents or in- laws. Both dependent variables are not available for the 2009 wave. We include the full set of controls used for the main specification in Table 3.3. In case we run the regressions in Column (1) and (2) with the same sample used for house price (which has some missing values), we do not observe any difference in the point of estimate. Robust standard error in brackets.

Survey of Health, Ageing and Retirement in Europe (SHARE) contains such information. However, its structure and the available information is quite different from the *Multiscopo*. It is, therefore, beyond the scope of the present work to exploit SHARE to provide results about this channel. Furthermore, in Italy the succession law prescribes some minimum shares for each possible heir, in particular for children and partners. There is, therefore, limited scope for a strategic use of bequests, because parents cannot promise to write a strongly unequal will.

3.5.2 Is it only an exchange with geographical proximity?

An important mechanism explaining the result is the fact that those who received help with housing are more likely to live closer to their parents, as already shown by Tomassini et al. (2003). This could imply that the actual exchange is not with future assistance, but with geographical proximity, as suggested by Coda Moscarola et al. (2010). Furthermore, if the positive association does not hold for those living far away, it is more likely that the intergenerational agreement is enforced through social control, which we expect to decrease with distance. This would support one of the key assumptions underlying Cox's (1987) model.

Individuals are also asked about the distance between their residence and that of their parents at the time of the interview. The information is reported as a categorical variable, as reported in Figure 3.1. For each partner we define the distance to parents as the minimum distance from either the mother or the father, in case they live apart. At the couple level we define distance as the minimum between parents and in-laws.

Figure 3.1 reproduces the result by Tomassini et al. (2003), by first fitting a set of linear

probability models for each distance dummy (at the level of the couple) on help with housing and all the other covariates, and then predicting the two counterfactual probability distribution for the overall sample (assuming, respectively, that nobody received help and that everybody did).[16] Receiving help is associated with a strong increase in the chances to live in the same building, and a decrease in the other distances. Nevertheless, most of decrease in probability mass associated with other categories is related to those within 16 km of distance.

Figure 3.1: Predicted Distribution of Current Distance to Parents or In-laws by Help Received with Housing Transfer at the Time of Marriage, Linear Probability Model Fits, Multiscopo 1998/2003/2009

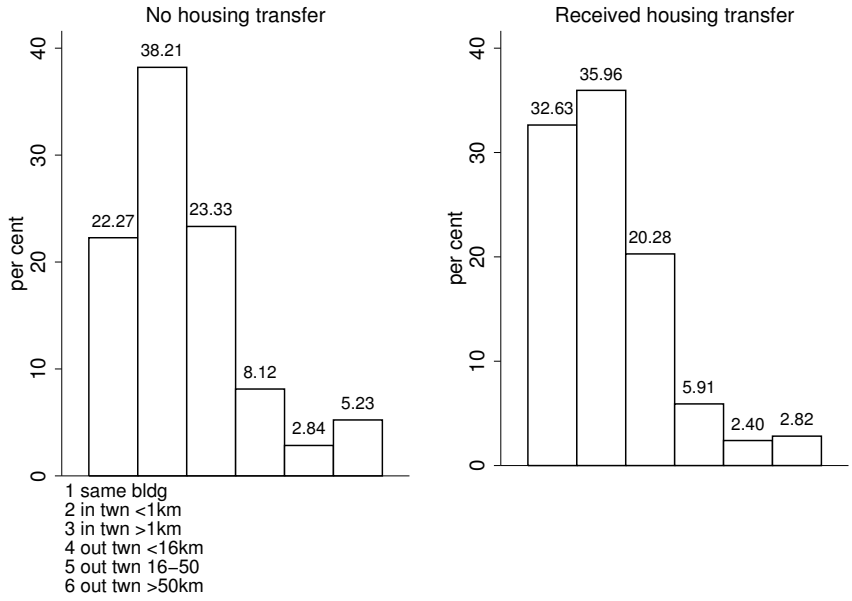


Table 3.6, column (1) shows a regression of ICP on distance dummies, which is are defined as the minimum distance from parents or in-laws. Although geographical distance is generally associated with less parental care, the negative effect of distance becomes substantially large only when adult children are located further than 16 km away. Using the predicted changes in the geographical distribution (Figure 3.1) we can also calculate that around 0.7 percentage points of the effect, approximately one fourth, can be explained by increased proximity.

An alternative way to understand what fraction of the effect can be explained by geographical proximity would be to condition the regressions on distance. If there is no selection on unobservables relative to distance, this strategy should recover the conditional effect of interest (see Cutler and

[16]Each distance bar is the average fitted probability across the whole sample, fixing the *Help with house* dummy either to 0 or 1.

Table 3.6: Linear Probability Model for ICP with Distance Controls

	(1) ICP	(2) ICP	(3) ICP	(4) ICP
Help with house		0.019**	0.022	0.019**
		(0.008)	(0.021)	(0.008)
Minimum distance				
In town <1km	-0.003			
	(0.009)			
In town >1km	-0.027**			
	(0.010)			
Out town <16km	-0.058***			
	(0.014)			
Out town 16-50	-0.117***			
	(0.018)			
Out town >50km	-0.179***			
	(0.013)			
Distance dummies				
Parents: in town <1km				0.009
				(0.012)
Parents: in town >1km				-0.034***
				(0.012)
Parents: out town <16km				-0.024*
				(0.013)
Parents: out town 16-50				-0.059***
				(0.014)
Parents: out town >50km				-0.090***
				(0.014)
In-laws: in town <1km				-0.013
				(0.011)
In-laws: in town >1km				0.004
				(0.011)
In-laws: out town <16km				-0.028**
				(0.013)
In-laws: out town 16-50				-0.032**
				(0.015)
In-laws: out twn <50km				-0.094***
				(0.013)
Sample	All	Within town	Outside town	All
Observations	15617	13329	2288	15617
R2	0.099	0.095	0.193	0.101
Waves, regions	X	X	X	X
Demographic characteristics	X	X	X	X
Wealth characteristics	X	X	X	X

Note: * p<.10 ** p<.05 *** p<.01. We include the full set of controls used for the main specification in Table 3.3, column (2). Robust standard error in brackets.

Lleras-Muney, 2010, for an example in a different context). Hence we would expect no significant effect in the case in which the overall (unconditional) results were simply driven by increased proximity. Columns (2) and (3) split the sample between those who live within 16 km and to who live further apart. The coefficients are very similar in magnitude. They are significant only when we focus on the sample of individuals who live closer to their parents or in-laws. However, the sample size for those living further away is quite small and a proper Wald test cannot, anyway,

reject the null that the coefficients in the two subsamples are equal. Column (4) repeats the main regression, but including the whole set of dummies for distance (in this case separately for parents and in-laws) along with the explanatory variable of interest ICP.[17] Comparing the coefficient on *Help with house* in the last column with the main estimate in Table 3.3, we can say that around 25% of the relation between help with housing and informal care to parents seems to be driven by proximity.

Conditioning the regression on distance is actually problematic if housing help modifies the composition of unobservable characteristics in groups living at the same distance. Specifically, consider only two categories of distance, close ($D_i = 1$) and far ($D_i = 0$). The mean regression conditional on distance becomes

$$E[ICP_i|HwH_{i,tm}, X_i^{'}, D_i = d] = \tilde{\beta}_0 + X_i^{'}\tilde{\delta} + (\beta_1 + E[\varepsilon_i|HwH_{i,tm} = 1, X_i, D_i = d] - E[\varepsilon_i|HwH_{i,tm} = 0, X_i, D_i = d])HwH_{i,tm}. \quad (3.4)$$

The coefficient on *Help with house* (HwH here) includes, therefore, a selection term which accounts for the different unobservable ability or preference in providing elderly care between those who live at a certain distance and received help with housing and those who live at the same distance and did not receive help. Clearly this bias eventually includes also all the endogeneity problems that affect the regression not conditional on distance, which have already been discussed before and addressed in Sections 3.4.1 and 3.4.3.

Nevertheless, this selection term may be different from zero even if $E[\varepsilon_i|HwH_{i,tm}, X_i^{'}] = E[\varepsilon_i|X_i^{'}]$, that is even if the two groups are similar in terms of unobservables (unconditionally with respect to distance but conditionally on other observables). This may happen if, among those who receive help, there is a specific subgroup whose location decision is more influenced by the help itself. We can try to give a sign to this selection term reasoning in an intuitive model where only geographical distance D_i and the individual unobservable willingness to provide elderly care (as summarized by ε_i) matter (see Konrad et al., 2002, for a formal model). In this case there should be a threshold $\bar{\varepsilon}$ such that those with $\varepsilon_i < \bar{\varepsilon}$ should locate further away ($D_i = 0$), conditionally on labour market

[17] We could also include the distance to parents at the time of marriage. However, we statistically test the joint significance of the dummies and we conclude that we cannot reject H_0 with a F-test with prob(0.28).

opportunities and other characteristics (captured by covariates X_i). Assuming that parents act strategically, as suggested by Section 3.4.3, we would expect them to be more likely to help with a house located nearby. This is also in line with the evidence just discussed on the effect on geographical proximity. Therefore, as far as the gift is large enough to compensate for the increased cost of ICP, the threshold $\bar{\varepsilon}$ gets smaller, moving closer to the parents some individuals whose ε_i is in the middle of the distribution. This implies that, among those who received the help, there is a decrease in the average ε_i within each distance group. Therefore the estimates conditional on distance should have a downward bias, which is reassuring given that our results still reveal a positive effect of housing help on ICP.

Overall, we can conclude that the distance mechanism appears to be relevant, but it does not seem to be the only explanation.

3.5.3 Are (grand)parents facilitating the presence of a third generation?

Both the "demonstration effect" proposed by Cox and Stark (2005) and the family constitution advanced by Cigno (2006) suggest that the parent housing help can be interpreted as an investment in the family network, which will increase the care that they will receive in the future. However, this investment will provide a return only if there is a third generation.

In Table 3.7 we find a positive weak correlation between the receipt of an housing transfer and the probability that the couple has at least a child, living in the household or elsewhere. This correlation is still positive when we include the full set of controls, but it becomes smaller and not statistically significant.[18] We observe, however, quite different effects for the "Monetary" and the "In-kind" help. The former is never significant at any conventional statistical level while the latter appears strongly and positively related with the probability of having at least a child.[19] These results suggest that in-kind intergenerational transfers increase, *de facto*, the likelihood to "produce" grandchildren. This is particularly true if we focus on younger women, aged less than 40 (lower panel), suggesting that help with house may also lead to anticipate the decision of having children.

In Table 3.8 we show that those parents who provided help with house are also more likely to

[18] Covariates are similar to those in previous tables, but we obviously exclude those relative to the presence of offspring in the household.

[19] We presumably underestimate the fertility effect because the question ("how many children alive/adopted do you have?") is asked only to people over 25 years old.

Table 3.7: Linear Probability Model for the Probability of Having at Least One Child In or Outside the Household

***Upper panel**: All sample*			
	(1)	(2)	(3)
Help with house	0.016***	0.007	
	(0.006)	(0.006)	
Monetary help			-0.007
			(0.010)
In-kind help			0.015**
			(0.007)
Observations	15617	15617	15617
R^2	0.123	0.148	0.148
***Lower panel**: Women aged less than 40*			
	(1)	(2)	(3)
Help with house	0.021***	0.011	
	(0.008)	(0.008)	
Monetary help			-0.011
			(0.013)
In-kind help			0.023**
			(0.009)
Observations	9309	9309	9309
R^2	0.185	0.212	0.212
Waves, regions	X	X	X
Demographic characteristics	X	X	X
Wealth characteristics		X	X

Note: * p<.10 ** p<.05 *** p<.01. We include the full set of controls used for the main specification in Table 3.3. Robust standard error in brackets.

currently help with grandchildren. When we control for all covariates the effect is still quite large, given that the proportion of couples receiving help with grandchildren is 48 per cent in the selected sample.[20]

Both results suggest that parents who provided help with house seem to try to facilitate the presence of a third generation, which is in line with both the demonstration effect and the family constitution models. Although the presence of a young generation that will provide assistance in the future is crucial for both models, for the demonstration effect to be operative it necessary that a living child assists to the provision of care to the elderly parent, so that his/her preferences will be shaped accordingly. Differently, Table 3.9 shows the relation in the subgroup with living children seems to be at least as large as in the other group, although results tend to be highly imprecise due to small sample size.[21] Results are similar if we split the sample between those with coresident children and those without. This results is at odd with the demonstration effect. On the opposite, the

[20] If we add dummies for distance from parents and in-laws, which are strongly negatively correlated with *ICR*, the coefficient on help received from parents shrinks to 4.6 percentage points and it is still statistically significant at the 1 per cent level.

[21] The results are unchanged once we control for the geographical proximity to parents and in-laws.

Table 3.8: Linear Probability Model for ICR (grandchildren care provided by parents or in-laws)

	(1) ICR	(2) ICR	(3) ICR
Help with house	0.082***	0.058***	
	(0.008)	(0.008)	
Monetary help			0.028**
			(0.013)
In-kind help			0.073***
			(0.009)
Observations	13384	13384	13384
R^2	0.354	0.370	0.370
Waves, regions	X	X	X
Demographic characteristics	X	X	X
Wealth characteristics		X	X

Note: * p<.10 ** p<.05 *** p<.01. The dependent variable is a dummy ICR equal to one if the young offspring (aged less than 13) of the couple are at least sometimes looked after by a grandfather or grandmother. The age threshold of 14 is due to questionnaire design. We restrict the sample to all the individuals with at least a coresident child aged 13 or less. We include the full set of controls used for the main specification in Table 3.3 column (2) with the only obvious exception of the dummy of having a child. Robust standard error in brackets.

family constitution does not require young children to be present. What is necessary is that the middle generation expects a younger generation to assists them in the future. Nevertheless, the last columns of Table 3.9 focus only on the subsample of wives aged 40 or more, for which is less likely to have other children in the future. Results are highly imprecise but still suggest that the positive relation is, if nothing, larger in the sample without children. One possible explanation, that we cannot check in our data, is that the relevant young generation for this (relatively small) subgroup is constituted by other relatives in the extended family network.

Table 3.9: Linear Probability Model for the Probability YES vs NO Children

	(1) ICP	(2) ICP	(3) ICP	(4) ICP	(5) ICP	(6) ICP
Help with house	0.013	0.018	0.033*	0.025*	0.084	0.083
	(0.008)	(0.022)	(0.020)	(0.013)	(0.067)	(0.055)
Child			-0.003			-0.073**
			(0.012)			(0.028)
Help with house X Child			-0.021			-0.059
			(0.021)			(0.057)
Observations	13677	1940	15617	6603	401	7004
R^2	0.024	0.053	0.024	0.023	0.158	0.023
Child	Yes	No	All	Yes	No	All
Mother's age	All	All	All	> 39	> 39	> 39
Waves, regions	X	X	X	X	X	X
Demographic characteristics	X	X	X	X	X	X
Wealth characteristics	X	X	X	X	X	X

We include the full set of controls used for the main specification in Table 3.3. Robust standard error in brackets. * p<.10 ** p<.05 *** p<.01.

3.6 Conclusions

In this paper we contribute to the debate about the economic rationale behind unpaid assistance to aging parents. Using data from three waves (1998, 2003 and 2009) of the Italian Multipurpose Survey, we show a positive effect of downstream housing help received in the past on current informal elderly care. The two generations seem, therefore, to be able to avoid the prisoner dilemma in which neither financial transfers nor elderly care are provided.

Our main result can be explained by different motives, including standard versions of the altruistic and exchange models. In the exchange case, the informal agreement between generations needs to be enforceable over time in order to explain our results. One possible explanation is that parents who provided a housing transfer seem to be more likely to provide further financial transfers in the future. This suggests that help with housing may be understood as a signal of the availability of intergenerational help. In this case, inasmuch as the adults assume to receive more in the future, they may be more willing to currently assist their parents. However, we show that empirically this channel seems to influence only marginally our main result. Another possibility is that the actual exchange occurs between housing help and geographical proximity, which decreases the cost of care and increases social control, leading to a higher likelihood of informal care. However, perhaps surprisingly, only a fraction of the relation is explained by this channel, as the empirical association between past help and current care persists even for children living further away.

The decision to provide help with housing at the time of marriage seems also to be negatively related to regional house prices, in particular with respect to in-kind transfers. The negative relation translates into a lower likelihood of receiving informal care from the adult children. This suggests that parents take into account the opportunity cost of their help when they decide to enter in the implicit agreement. This is not in line with a purely altruistic model, nor with the prediction from Cox's (1987) model with an imperfectly altruist parent. Differently, it is in line with those models where the help provided to the children can be understood as an investment for the future, such as the demonstration effect of Cox and Stark (2005) and the family constitution of Cigno et al. (1998). Both of them predict that the return on this investment is guaranteed only if there is (or there will be for the family constitution) a third generation, the grandchildren. Indeed, we provide additional evidence in line suggesting that the housing help from parents is positive correlated with

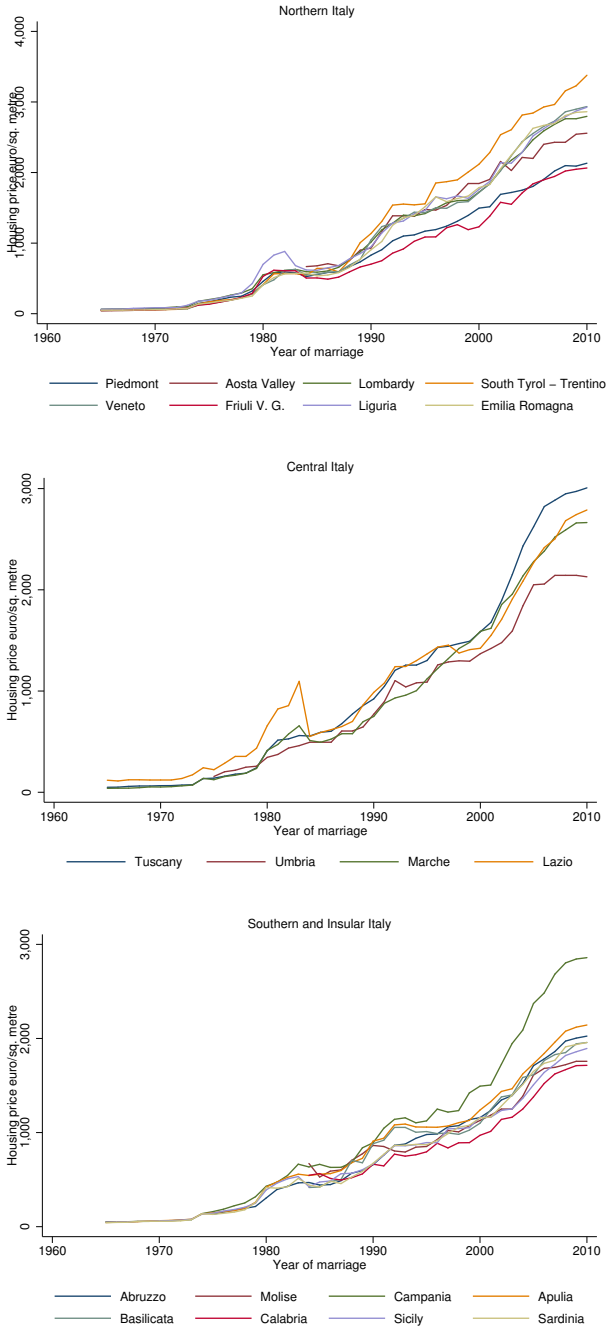
fertility and with them helping to look after grandchildren. However, we also show that the positive correlation is not driven only by couples who have children, but also by those who are childless and also less likely to have children in the future. In this case, it must be that either altruism or exchange explain the results.

To summarize, the evidence suggests that a single motive is not prevailing in the data, as also suggested, for other countries and with other methods, by (Arrondel and Masson, 2006) and Park (2014). Altruism may explain some of the results, but there is evidence that some kind of exchange is taking place. In some families, the past housing help can be understood as a standard exchange with increased proximity. In other cases, the quid-pro-quo seems to be between quasi-contemporary transfers. Some families seem instead to understand the help as an investment in their future, following the rules of an unwritten constitution or the hope that the demonstration effect will take place.

With respect to the theoretical and empirical literature, our results also suggest that more attention should be devoted to past transfers, and not only to bequests and contemporary inter-vivos exchange. One limitation of our study, also due to the survey design, is that we are not fully able to study the differences between past tied transfers, such as the one we analyse, and other forms of economic assistance. Some of the mechanisms that we discuss are relevant only for the housing transfer, in particular the increased geographical proximity. Further research may help to understand whether the positive relation with the current provision of elderly care by the adult children carries over to other forms of past economic assistance provided by the parents, and how this intertemporal exchange is enforced.

Appendix 3.A: Figures 3.A

Figure 3.A.1: Regional Housing Price (Euro/sq m) by Year of Marriage, Nomisma



Appendix 3.B: Tables 3.B

Table 3.B.1: Summary statistics

Main variables	Mean	Std.Dev.	Min	Max
ICP	0.213	0.409	0	1
ICR	0.413	0.492	0	1
Help with house	0.304	0.460	0	1
Monetary help	0.095	0.293	0	1
In-kind help	0.210	0.407	0	1
Cohabitation	0.091	0.288	0	1
Year				
1998	0.446	0.497	0	1
2003	0.311	0.463	0	1
2009	0.243	0.429	0	1
Regions				
Piedmont	0.090	0.286	0	1
Lombardy	0.089	0.285	0	1
South Tyrol - Trentino	0.048	0.214	0	1
Veneto	0.061	0.239	0	1
Friuli V. G.	0.032	0.175	0	1
Liguria	0.026	0.160	0	1
Emilia Romagna	0.051	0.220	0	1
Tuscany	0.054	0.226	0	1
Umbria	0.032	0.176	0	1
Marche	0.043	0.203	0	1
Lazio	0.045	0.206	0	1
Abruzzo	0.044	0.205	0	1
Molise	0.032	0.176	0	1
Campania	0.065	0.247	0	1
Apulia	0.077	0.266	0	1
Basilicata	0.033	0.178	0	1
Calabria	0.059	0.236	0	1
Sicily	0.078	0.268	0	1
Sardinia	0.042	0.201	0	1
Wife characteristics				
Age	39.000	8.035	20	68
None/elementary	0.100	0.300	0	1
Middle school	0.353	0.478	0	1

Table 3.B.1: Summary statistics – continued

Main variables	Mean	Std.Dev.	Min	Max
School of vocational	0.089	0.284	0	1
High school	0.341	0.474	0	1
Bachelor or more	0.117	0.321	0	1
No limitations	0.970	0.171	0	1
Limitations (sometimes)	0.024	0.153	0	1
Limitations (most of the time)	0.006	0.077	0	1
Has siblings	0.892	0.310	0	1
n. of siblings	2.089	1.753	0	20
Husband characteristics				
Age	42.242	8.303	20	69
None/elementary	0.102	0.302	0	1
Middle school	0.390	0.488	0	1
School of vocational	0.088	0.284	0	1
High school	0.314	0.464	0	1
Bachelor or more	0.106	0.307	0	1
No limitations	0.970	0.171	0	1
Limitations (sometimes)	0.022	0.148	0	1
Limitations (most of the time)	0.008	0.088	0	1
Has siblings	0.896	0.305	0	1
n. of siblings	2.192	1.818	0	20
Children characteristics				
Presence of Child	0.857	0.350	0	1
n. children	1.536	0.920	0	9
Age of the youngest child	8.046	7.745	0	39
Parents characteristics				
Only father alive	0.060	0.237	0	1
Only mother alive	0.284	0.451	0	1
Mother's age	0.000	9.208	-30.419	34.581
Father's age	0.000	7.471	-28.123	33.877
Father: no limitations	0.874	0.332	0	1
Father: limitations (sometimes)	0.082	0.275	0	1
Father: limitations (most of the time)	0.044	0.205	0	1
Mother: no limitations	0.843	0.364	0	1
Mother: limitations (sometimes)	0.108	0.311	0	1
Mother: limitations (most of the time)	0.049	0.216	0	1
Father: none/elementary	0.659	0.474	0	1
Father: middle school	0.176	0.381	0	1
Father: school of vocational	0.036	0.186	0	1

Table 3.B.1: Summary statistics – continued

Main variables	Mean	Std.Dev.	Min	Max
Father: high school	0.076	0.265	0	1
Father: bachelor or more	0.027	0.162	0	1
Father: does not remember	0.025	0.157	0	1
Mother: none/elementary	0.721	0.448	0	1
Mother: middle school	0.160	0.366	0	1
Mother: school of vocational	0.027	0.162	0	1
Mother: high school	0.060	0.237	0	1
Mother: bachelor or more	0.013	0.113	0	1
Mother: does not remember	0.019	0.136	0	1
In-laws characteristics				
Only father alive	0.068	0.252	0	1
Only mother alive	0.346	0.476	0	1
Age: mother	0.000	9.160	-28.507	31.493
Age: father	0.000	7.057	-29.477	30.523
Father: no limitations	0.871	0.335	0	1
Father: limitations (sometimes)	0.085	0.279	0	1
Father: limitations (most of the time)	0.043	0.204	0	1
Mother: no limitations	0.811	0.391	0	1
Mother: limitations (sometimes)	0.125	0.330	0	1
Mother: limitations (most of the time)	0.064	0.245	0	1
Father: none/elementary	0.690	0.463	0	1
Father: middle school	0.157	0.363	0	1
Father: school of vocational	0.032	0.176	0	1
Father: high school	0.067	0.251	0	1
Father: bachelor or more	0.023	0.151	0	1
Father: does not remember	0.031	0.173	0	1
Mother: none/elementary	0.741	0.438	0	1
Mother: middle school	0.148	0.355	0	1
Mother: school of vocational	0.025	0.156	0	1
Mother: high school	0.048	0.215	0	1
Mother: bachelor or more	0.011	0.105	0	1
Mother: does not remember	0.026	0.159	0	1
Household characteristics				
Rent	0.175	0.380	0	1
Own property	0.696	0.460	0	1
Usufruct	0.130	0.336	0	1
Type of house				
Cottage	0.089	0.285	0	1

Table 3.B.1: Summary statistics – continued

Main variables	Mean	Std.Dev.	Min	Max
Large house	0.091	0.288	0	1
Civil house	0.649	0.477	0	1
Social house	0.125	0.331	0	1
Rural	0.023	0.150	0	1
Improper home	0.003	0.056	0	1
Do not know	0.019	0.136	0	1
Items				
n. rooms	4.814	1.609	1	30
n. mobiles	1.658	1.295	0	9
n. TVs	1.828	0.875	0	9
n. motorcycles	0.114	0.367	0	7
n. cars	1.627	0.666	0	8
Occupation of parents				
Father: white collar	0.292	0.454	0	1
Father: blue collar	0.366	0.482	0	1
Father: clerical workers	0.257	0.437	0	1
Father: employed but does not remember	0.013	0.115	0	1
Father: unemployed	0.028	0.165	0	1
Father: dead	0.027	0.163	0	1
Father: does not remember	0.017	0.129	0	1
Mother: white collar	0.103	0.304	0	1
Mother: blue collar	0.113	0.316	0	1
Mother: clerical workers	0.124	0.330	0	1
Mother: employed but does not remember	0.009	0.095	0	1
Mother: housewife	0.622	0.485	0	1
Mother: unemployed	0.013	0.112	0	1
Mother: dead	0.005	0.067	0	1
Mother: does not remember	0.012	0.107	0	1
Occupation of in-laws				
Father: white collar	0.282	0.450	0	1
Father: blue collar	0.359	0.480	0	1
Father: clerical workers	0.274	0.446	0	1
Father: employed but does not remember	0.015	0.120	0	1
Father: unemployed	0.027	0.163	0	1
Father: dead	0.026	0.160	0	1
Father: does not remember	0.017	0.130	0	1
Mother: white collar	0.087	0.281	0	1
Mother: blue collar	0.101	0.302	0	1

Table 3.B.1: Summary statistics – continued

Main variables	Mean	Std.Dev.	Min	Max
Mother: clerical workers	0.125	0.331	0	1
Mother: employed but does not remember	0.009	0.096	0	1
Mother: housewife	0.647	0.478	0	1
Mother: unemployed	0.012	0.109	0	1
Mother: dead	0.005	0.068	0	1
Mother: does not remember	0.014	0.118	0	1
Occupation of the wife				
White collar	0.288	0.453	0	1
Blue collar	0.130	0.336	0	1
Clerical workers	0.100	0.300	0	1
Unemployed	0.039	0.194	0	1
Housewife	0.398	0.490	0	1
Retired	0.016	0.125	0	1
Student	0.029	0.167	0	1
Occupation of the husband				
White collar	0.318	0.466	0	1
Blue collar	0.304	0.460	0	1
Clerical workers	0.311	0.463	0	1
Unemployed	0.049	0.215	0	1
Retired	0.018	0.132	0	1
Wife's source of income				
Employed	0.418	0.493	0	1
Self-employee	0.100	0.300	0	1
Retirement	0.025	0.155	0	1
Benefits	0.009	0.096	0	1
Estate income	0.006	0.079	0	1
From family of origin	0.442	0.497	0	1
Husband's source of income				
Employed	0.621	0.485	0	1
Self-employee	0.274	0.446	0	1
Retirement	0.055	0.228	0	1
Benefits	0.014	0.116	0	1
Estate income	0.003	0.054	0	1
From family of origin	0.034	0.181	0	1
Phone contacts with parents				
Every day	0.440	0.496	0	1
More than once per week	0.318	0.466	0	1
Once per week	0.064	0.244	0	1

Table 3.B.1: Summary statistics – continued

Main variables	Mean	Std.Dev.	Min	Max
Less than 4 in a month	0.048	0.213	0	1
Sometimes over the year	0.020	0.139	0	1
Never	0.111	0.314	0	1
Visits to parents				
Every day	0.441	0.497	0	1
More than once per week	0.288	0.453	0	1
Once per week	0.104	0.305	0	1
Less than 4 in a month	0.088	0.284	0	1
Sometimes over the year	0.073	0.260	0	1
Never	0.006	0.077	0	1
Phone contacts with in-laws				
Every day	0.253	0.435	0	1
More than once per week	0.352	0.478	0	1
Once per week	0.088	0.283	0	1
Less than 4 in a month	0.086	0.280	0	1
Sometimes over the year	0.041	0.199	0	1
Never	0.180	0.384	0	1
Visits to in-laws				
Every day	0.415	0.493	0	1
More than once per week	0.285	0.451	0	1
Once per week	0.118	0.322	0	1
Less than 4 in a month	0.093	0.291	0	1
Sometimes over the year	0.083	0.276	0	1
Never	0.006	0.078	0	1
Total observations	15617			

Table 3.B.2: Summary Statistics: Regional Housing Prices (euro/sq m), Nomisma

Region name	Region number	Available years	Mean	Std. Dev.	Min	Max
Piedmont	1	1965-2010	854.13	682.88	58.60	2132.14
Lombardy	3	1965-2010	1060.00	899.51	63.70	2796.10
South Tyrol - Trentino	4	1965-2010	1197.73	1092.49	43.68	3378.57
Veneto	5	1965-2010	1050.44	946.61	42.24	2934.69
Friuli V. G.	6	1965-2010	796.44	656.24	44.27	2064.29
Liguria	7	1965-2010	1095.16	912.50	62.71	2925.00
Emilia Romagna	8	1965-2010	1048.10	948.49	49.20	2861.91
Tuscany	9	1965-2010	1032.48	954.58	48.95	3007.14
Umbria	10	1975-2010	1042.22	656.41	156.01	2142.86
Marche	11	1965-2010	919.77	847.43	38.73	2664.29
Lazio	12	1965-2010	1030.66	810.46	111.41	2788.57
Abruzzo	13	1975-2010	911.64	581.36	130.74	2025.00
Molise	14	1984-2010	1086.29	396.25	527.52	1757.14
Campania	15	1965-2010	964.85	866.25	51.72	2858.57
Apulia	16	1965-2010	798.08	650.35	44.60	2142.86
Basilicata	17	1984-2010	1140.13	471.27	416.12	1957.14
Calabria	18	1984-2010	972.26	400.94	496.17	1714.29
Sicily	19	1965-2010	699.70	564.45	48.19	1893.65
Sardinia	20	1965-2010	708.81	598.79	41.54	1957.14

Table 3.B.3: Linear Probability Model for ICP and ICR with All Controls

	(1)	(2)	(3)	(4)
	ICP	ICP	ICR	ICR
Help with house	0.026***		0.058***	
	(0.008)		(0.008)	
Monetary help		0.022*		0.028**
		(0.012)		(0.013)
In-kind help		0.029***		0.073***
		(0.009)		(0.009)
Cohabitation	0.013	0.013	0.006	0.006
	(0.012)	(0.012)	(0.012)	(0.012)
2003	0.018*	0.018*	-0.034***	-0.034***
	(0.010)	(0.010)	(0.012)	(0.012)
2009	0.003	0.003	0.020	0.020
	(0.014)	(0.014)	(0.016)	(0.016)
Lombardy	-0.011	-0.011	-0.014	-0.012
	(0.015)	(0.015)	(0.017)	(0.017)
South Tyrol - Trentino	0.024	0.024	0.002	0.002
	(0.019)	(0.019)	(0.020)	(0.020)
Veneto	0.024	0.024	-0.022	-0.020
	(0.017)	(0.018)	(0.018)	(0.018)
Friuli V. G.	0.038*	0.038*	-0.030	-0.029
	(0.022)	(0.022)	(0.023)	(0.023)
Liguria	-0.030	-0.030	-0.031	-0.029
	(0.021)	(0.021)	(0.025)	(0.025)
Emilia Romagna	0.013	0.013	-0.034*	-0.032*
	(0.018)	(0.018)	(0.019)	(0.019)
Tuscany	-0.010	-0.009	-0.015	-0.013
	(0.017)	(0.017)	(0.018)	(0.018)
Umbria	-0.009	-0.009	-0.035	-0.033
	(0.021)	(0.021)	(0.022)	(0.022)
Marche	0.000	0.000	-0.017	-0.014
	(0.019)	(0.019)	(0.019)	(0.020)
Lazio	-0.048***	-0.048***	-0.037*	-0.036*
	(0.018)	(0.018)	(0.021)	(0.021)
Abruzzo	-0.028	-0.028	-0.022	-0.021
	(0.018)	(0.018)	(0.020)	(0.020)
Molise	-0.036*	-0.036*	-0.012	-0.012

Table 3.B.3: Linear probability model for ICP and ICR with all controls – continued

	(1) ICP	(2) ICP	(3) ICR	(4) ICR
	(0.021)	(0.021)	(0.022)	(0.022)
Campania	0.001	0.001	-0.055***	-0.055***
	(0.017)	(0.017)	(0.019)	(0.019)
Apulia	0.022	0.022	-0.029	-0.029
	(0.016)	(0.016)	(0.018)	(0.018)
Basilicata	0.002	0.002	-0.019	-0.019
	(0.021)	(0.021)	(0.023)	(0.023)
Calabria	-0.028*	-0.029*	0.012	0.011
	(0.017)	(0.017)	(0.019)	(0.019)
Sicily	-0.002	-0.002	-0.032*	-0.033*
	(0.016)	(0.016)	(0.018)	(0.018)
Sardinia	-0.016	-0.016	0.010	0.011
	(0.019)	(0.019)	(0.022)	(0.022)
Wife characteristics				
Age	-0.003**	-0.003**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Middle school	0.025*	0.025*	0.011	0.010
	(0.013)	(0.013)	(0.013)	(0.013)
School of vocational	0.039**	0.038**	0.026	0.025
	(0.017)	(0.017)	(0.017)	(0.017)
High school	0.041***	0.041***	0.025	0.024
	(0.015)	(0.015)	(0.015)	(0.015)
Bacheor or more	0.037*	0.037*	0.017	0.016
	(0.019)	(0.019)	(0.020)	(0.020)
Limitation (sometimes) * 1998	-0.010	-0.010	0.030	0.031
	(0.048)	(0.048)	(0.051)	(0.052)
Limitation (sometimes) * 2003	0.087	0.086	0.061	0.060
	(0.064)	(0.064)	(0.066)	(0.066)
Limitation (sometimes) * 2009	0.017	0.017	0.013	0.013
	(0.029)	(0.029)	(0.026)	(0.027)
Limitation (most of the time) * 1998	-0.226***	-0.226***	0.166*	0.165*
	(0.039)	(0.039)	(0.100)	(0.100)
Limitation (most of the time) * 2003	0.095	0.095	-0.071	-0.070
	(0.120)	(0.120)	(0.123)	(0.123)
Limitation (most of the time) * 2009	-0.092	-0.092	0.125***	0.126***
	(0.060)	(0.060)	(0.046)	(0.046)
Brother	0.005	0.005	0.025**	0.024**

Table 3.B.3: Linear probability model for ICP and ICR with all controls – continued

	(1) ICP	(2) ICP	(3) ICR	(4) ICR
	(0.011)	(0.011)	(0.012)	(0.012)
# brothers	0.001	0.001	-0.012***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)
Husband characteristics				
Age	0.001	0.001	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Middle school	0.014	0.014	0.017	0.016
	(0.013)	(0.013)	(0.013)	(0.013)
School of vocational	0.047***	0.048***	0.023	0.023
	(0.017)	(0.017)	(0.017)	(0.017)
High school	0.044***	0.044***	0.015	0.015
	(0.015)	(0.015)	(0.015)	(0.015)
Bacheor or more	0.058***	0.059***	-0.007	-0.007
	(0.019)	(0.019)	(0.020)	(0.019)
Limitation (sometimes) * 1998	-0.004	-0.004	0.057	0.058
	(0.059)	(0.059)	(0.047)	(0.047)
Limitation (sometimes) * 2003	-0.062	-0.062	0.071	0.070
	(0.060)	(0.060)	(0.049)	(0.049)
Limitation (sometimes) * 2009	0.075**	0.075**	-0.011	-0.010
	(0.031)	(0.031)	(0.027)	(0.027)
Limitation (most of the time) * 1998	-0.150***	-0.150***	-0.115	-0.114
	(0.051)	(0.051)	(0.075)	(0.075)
Limitation (most of the time) * 2003	0.049	0.049	0.118	0.114
	(0.111)	(0.111)	(0.093)	(0.093)
Limitation (most of the time) * 2009	-0.057	-0.057	0.037	0.035
	(0.052)	(0.052)	(0.049)	(0.050)
Brother	0.004	0.003	0.030**	0.029**
	(0.012)	(0.012)	(0.013)	(0.013)
# brothers	-0.010***	-0.010***	-0.011***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Children characteristics				
Child	-0.048***	-0.048***		
	(0.014)	(0.014)		
# children	0.003	0.003	-0.006	-0.006
	(0.005)	(0.005)	(0.006)	(0.006)
Age of the youngest child	0.001	0.001	-0.030***	-0.030***
	(0.001)	(0.001)	(0.001)	(0.001)

Table 3.B.3: Linear probability model for ICP and ICR with all controls – continued

	(1) ICP	(2) ICP	(3) ICR	(4) ICR
Parents characteristics				
Only father alive	0.031**	0.031**	-0.096***	-0.096***
	(0.015)	(0.015)	(0.016)	(0.016)
Only mother alive	0.020**	0.020**	-0.005	-0.006
	(0.009)	(0.009)	(0.010)	(0.010)
Age: mother	0.002***	0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Age: father	0.002***	0.002***	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Father limitation (sometimes) * 1998	0.072***	0.072***	-0.004	-0.004
	(0.027)	(0.027)	(0.025)	(0.025)
Father limitation (sometimes) * 2003	0.084**	0.084**	-0.016	-0.016
	(0.037)	(0.037)	(0.032)	(0.032)
Father limitation (sometimes) * 2009	-0.020	-0.020	-0.015	-0.015
	(0.021)	(0.021)	(0.020)	(0.019)
Father limitation (most of the time) * 1998	0.177***	0.177***	0.021	0.021
	(0.032)	(0.032)	(0.029)	(0.029)
Father limitation (most of the time) * 2003	0.056	0.056	-0.029	-0.029
	(0.038)	(0.038)	(0.038)	(0.038)
Father limitation (most of the time) * 2009	0.070**	0.070**	-0.050*	-0.051*
	(0.027)	(0.027)	(0.028)	(0.028)
Mother limitation (sometimes) * 1998	0.082***	0.082***	-0.020	-0.020
	(0.024)	(0.024)	(0.022)	(0.022)
Mother limitation (sometimes) * 2003	0.083***	0.083***	-0.028	-0.027
	(0.031)	(0.031)	(0.026)	(0.026)
Mother limitation (sometimes) * 2009	0.055***	0.055***	-0.021	-0.020
	(0.020)	(0.020)	(0.018)	(0.018)
Mother limitation (most of the time) * 1998	0.197***	0.197***	-0.065***	-0.066***
	(0.030)	(0.030)	(0.025)	(0.025)
Mother limitation (most of the time) * 2003	0.228***	0.228***	0.045	0.047
	(0.036)	(0.036)	(0.028)	(0.028)
Mother limitation (most of the time) * 2009	0.160***	0.160***	-0.050**	-0.050**
	(0.030)	(0.030)	(0.025)	(0.025)
Father: middle school	-0.003	-0.003	-0.005	-0.005
	(0.011)	(0.011)	(0.012)	(0.012)
Father: school of vocational	0.037*	0.037*	0.013	0.015
	(0.020)	(0.020)	(0.021)	(0.021)

Table 3.B.3: Linear probability model for ICP and ICR with all controls – continued

	(1) ICP	(2) ICP	(3) ICR	(4) ICR
Father: high school	0.013	0.013	-0.033*	-0.033*
	(0.017)	(0.017)	(0.019)	(0.019)
Father: bacheor or more	-0.007	-0.006	0.034	0.035
	(0.025)	(0.025)	(0.029)	(0.029)
Father: No remember	0.021	0.021	-0.066*	-0.065*
	(0.031)	(0.031)	(0.038)	(0.038)
Mother: middle school	-0.017	-0.016	-0.015	-0.015
	(0.011)	(0.011)	(0.013)	(0.013)
Mother: school of vocational	0.001	0.001	-0.029	-0.030
	(0.023)	(0.023)	(0.026)	(0.026)
Mother: high school	-0.018	-0.018	-0.024	-0.025
	(0.019)	(0.019)	(0.022)	(0.022)
Mother: bacheor or more	-0.060*	-0.060*	-0.055	-0.054
	(0.032)	(0.032)	(0.042)	(0.042)
Mother: No remember	-0.055	-0.055	0.108**	0.109**
	(0.035)	(0.035)	(0.042)	(0.042)
In-laws characteristics				
Only father alive	0.046***	0.046***	-0.061***	-0.062***
	(0.014)	(0.014)	(0.015)	(0.015)
Only mother alive	0.026***	0.026***	-0.006	-0.006
	(0.008)	(0.008)	(0.010)	(0.010)
Age: mother	0.002***	0.002***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Age: father	0.002***	0.002***	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Father limitation (sometimes) * 1998	0.065**	0.066**	0.006	0.006
	(0.026)	(0.026)	(0.027)	(0.027)
Father limitation (sometimes) * 2003	0.109***	0.109***	-0.020	-0.019
	(0.033)	(0.033)	(0.034)	(0.034)
Father limitation (sometimes) * 2009	0.009	0.009	-0.016	-0.017
	(0.019)	(0.019)	(0.019)	(0.019)
Father limitation (most of the time) * 1998	0.188***	0.188***	-0.005	-0.005
	(0.031)	(0.031)	(0.029)	(0.029)
Father limitation (most of the time) * 2003	0.121***	0.121***	-0.010	-0.010
	(0.038)	(0.038)	(0.032)	(0.031)
Father limitation (most of the time) * 2009	0.017	0.017	0.025	0.026
	(0.027)	(0.027)	(0.029)	(0.029)

Table 3.B.3: Linear probability model for ICP and ICR with all controls – continued

	(1) ICP	(2) ICP	(3) ICR	(4) ICR
Mother limitation (sometimes) * 1998	0.042*	0.042*	-0.041*	-0.041**
	(0.022)	(0.022)	(0.021)	(0.021)
Mother limitation (sometimes) * 2003	-0.017	-0.017	0.012	0.011
	(0.026)	(0.026)	(0.026)	(0.026)
Mother limitation (sometimes) * 2009	0.047**	0.047**	0.014	0.014
	(0.019)	(0.019)	(0.018)	(0.018)
Mother limitation (most of the time) * 1998	0.135***	0.135***	-0.071***	-0.071***
	(0.027)	(0.027)	(0.023)	(0.023)
Mother limitation (most of the time) * 2003	0.131***	0.131***	-0.049**	-0.047**
	(0.029)	(0.029)	(0.024)	(0.024)
Mother limitation (most of the time) * 2009	0.129***	0.129***	-0.008	-0.009
	(0.028)	(0.028)	(0.024)	(0.024)
Father: middle school	0.005	0.005	-0.009	-0.008
	(0.011)	(0.011)	(0.013)	(0.013)
Father: school of vocational	0.011	0.011	-0.051**	-0.050**
	(0.020)	(0.020)	(0.023)	(0.024)
Father: high school	0.035**	0.035**	-0.008	-0.008
	(0.018)	(0.018)	(0.020)	(0.020)
Father: bacheor or more	0.015	0.015	-0.023	-0.024
	(0.027)	(0.027)	(0.030)	(0.030)
Father: No remember	-0.030	-0.030	-0.035	-0.035
	(0.029)	(0.029)	(0.036)	(0.036)
Mother: middle school	-0.018	-0.018	-0.031**	-0.031**
	(0.012)	(0.012)	(0.014)	(0.014)
Mother: school of vocational	-0.008	-0.008	0.017	0.017
	(0.023)	(0.023)	(0.028)	(0.028)
Mother: high school	-0.037*	-0.037*	0.032	0.031
	(0.020)	(0.020)	(0.023)	(0.023)
Mother: bacheor or more	-0.011	-0.011	0.024	0.025
	(0.037)	(0.037)	(0.041)	(0.041)
Mother: No remember	0.017	0.017	0.036	0.037
	(0.032)	(0.032)	(0.039)	(0.039)
Household characteristics				
Rent	0.016*	0.016*	0.067***	0.068***
	(0.009)	(0.009)	(0.011)	(0.011)
Own property	0.030**	0.029**	0.101***	0.093***
	(0.012)	(0.012)	(0.015)	(0.015)

Table 3.B.3: Linear probability model for ICP and ICR with all controls – continued

	(1) ICP	(2) ICP	(3) ICR	(4) ICR
Large house	-0.014	-0.014	0.009	0.009
	(0.015)	(0.015)	(0.016)	(0.016)
Civil house	0.002	0.002	0.003	0.003
	(0.012)	(0.012)	(0.012)	(0.012)
Social house	-0.009	-0.009	-0.025	-0.026
	(0.015)	(0.015)	(0.016)	(0.016)
Rural	-0.004	-0.004	-0.009	-0.011
	(0.023)	(0.023)	(0.025)	(0.025)
Improper home	0.015	0.015	-0.034	-0.033
	(0.055)	(0.055)	(0.067)	(0.067)
Do not know	-0.021	-0.021	-0.085***	-0.086***
	(0.025)	(0.025)	(0.027)	(0.027)
# rooms	0.003	0.003	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
# mobile	0.003	0.003	-0.024***	-0.024***
	(0.004)	(0.004)	(0.004)	(0.004)
# TVs	0.011***	0.011***	0.007*	0.007
	(0.004)	(0.004)	(0.004)	(0.004)
# motorcycles	0.004	0.004	-0.010	-0.010
	(0.009)	(0.009)	(0.009)	(0.009)
# cars	0.009	0.009	0.010*	0.010*
	(0.006)	(0.006)	(0.006)	(0.006)
Occupation parents				
Father: blue collar	0.015	0.014	0.000	-0.001
	(0.010)	(0.010)	(0.011)	(0.011)
Father: clerical workers	-0.013	-0.013	0.012	0.011
	(0.010)	(0.010)	(0.011)	(0.011)
Father: employed but don't remember	0.000	0.000	0.011	0.011
	(0.029)	(0.029)	(0.033)	(0.033)
Father: unemployed	0.018	0.018	-0.033	-0.034
	(0.022)	(0.022)	(0.023)	(0.023)
Father: dead	-0.022	-0.022	-0.002	-0.002
	(0.022)	(0.022)	(0.024)	(0.024)
Father: don't remember	-0.096***	-0.096***	-0.032	-0.032
	(0.026)	(0.026)	(0.039)	(0.039)
Mother: blue collar	-0.011	-0.011	0.022	0.023
	(0.016)	(0.016)	(0.018)	(0.018)

Table 3.B.3: Linear probability model for ICP and ICR with all controls – continued

	(1) ICP	(2) ICP	(3) ICR	(4) ICR
Mother: clerical workers	0.016	0.016	-0.003	-0.004
	(0.016)	(0.016)	(0.017)	(0.017)
Mother: employed but don't remember	0.002	0.002	0.016	0.014
	(0.040)	(0.040)	(0.042)	(0.042)
Mother: housewife	0.000	0.000	0.003	0.003
	(0.013)	(0.013)	(0.014)	(0.014)
Mother: unemployed	-0.028	-0.028	0.003	0.003
	(0.030)	(0.030)	(0.031)	(0.031)
Mother: dead	0.042	0.042	-0.016	-0.018
	(0.054)	(0.054)	(0.057)	(0.057)
Mother: don't remember	0.019	0.019	-0.022	-0.022
	(0.035)	(0.035)	(0.047)	(0.047)
Occupation in-laws				
Father: blue collar	0.013	0.012	0.002	0.002
	(0.010)	(0.010)	(0.011)	(0.011)
Father: clerical workers	0.010	0.010	0.005	0.005
	(0.011)	(0.011)	(0.012)	(0.012)
Father: employed but don't remember	-0.010	-0.010	0.014	0.013
	(0.029)	(0.029)	(0.035)	(0.035)
Father: unemployed	0.029	0.029	-0.007	-0.008
	(0.022)	(0.022)	(0.024)	(0.024)
Father: dead	0.004	0.004	0.057**	0.057**
	(0.022)	(0.022)	(0.023)	(0.023)
Father: don't remember	0.035	0.035	-0.027	-0.028
	(0.034)	(0.034)	(0.038)	(0.038)
Mother: blue collar	0.015	0.015	-0.005	-0.005
	(0.017)	(0.017)	(0.019)	(0.019)
Mother: clerical workers	0.031*	0.031*	-0.009	-0.010
	(0.017)	(0.017)	(0.018)	(0.018)
Mother: employed but don't remember	0.045	0.045	-0.012	-0.012
	(0.039)	(0.039)	(0.045)	(0.044)
Mother: housewife	0.009	0.009	-0.016	-0.017
	(0.013)	(0.013)	(0.015)	(0.015)
Mother: unemployed	-0.007	-0.007	-0.049	-0.049
	(0.032)	(0.032)	(0.037)	(0.037)
Mother: dead	-0.003	-0.003	0.062	0.062
	(0.052)	(0.052)	(0.051)	(0.051)

Table 3.B.3: Linear probability model for ICP and ICR with all controls – continued

	(1) ICP	(2) ICP	(3) ICR	(4) ICR
Mother: don't remember	-0.021	-0.021	0.022	0.022
	(0.039)	(0.039)	(0.044)	(0.043)
Occupation wife				
Blue collar	-0.014	-0.014	-0.049***	-0.049***
	(0.012)	(0.012)	(0.013)	(0.013)
Clerical workers	0.011	0.011	-0.043	-0.044
	(0.034)	(0.034)	(0.038)	(0.038)
Unemployed	-0.011	-0.011	-0.129**	-0.130**
	(0.058)	(0.058)	(0.062)	(0.061)
Housewife	-0.049	-0.049	-0.152**	-0.152**
	(0.057)	(0.057)	(0.060)	(0.060)
Retired	-0.073	-0.073	-0.096	-0.096
	(0.066)	(0.066)	(0.065)	(0.065)
Student	-0.045	-0.045	-0.121**	-0.121**
	(0.058)	(0.058)	(0.061)	(0.061)
Husband source of income				
Blue collar	-0.004	-0.004	0.007	0.006
	(0.009)	(0.009)	(0.011)	(0.011)
Clerical workers	-0.035	-0.035	-0.026	-0.025
	(0.041)	(0.041)	(0.042)	(0.042)
Unemployed	-0.089	-0.089	0.043	0.047
	(0.059)	(0.059)	(0.055)	(0.055)
Retired	-0.082*	-0.082*	0.012	0.015
	(0.048)	(0.048)	(0.050)	(0.050)
Wife source of income				
Self-employee	-0.025	-0.026	-0.005	-0.005
	(0.034)	(0.034)	(0.038)	(0.038)
Retirement	0.063	0.063	0.037	0.036
	(0.062)	(0.062)	(0.063)	(0.063)
Benefits	0.046	0.046	0.050	0.048
	(0.060)	(0.060)	(0.064)	(0.064)
Estate income	0.016	0.016	0.059	0.059
	(0.063)	(0.063)	(0.066)	(0.066)
From origin family	0.044	0.044	0.043	0.042
	(0.057)	(0.057)	(0.059)	(0.059)
Husband source of income				
Self-employee	0.014	0.013	0.057	0.055

Table 3.B.3: Linear probability model for ICP and ICR with all controls – continued

	(1)	(2)	(3)	(4)
	ICP	ICP	ICR	ICR
	(0.041)	(0.041)	(0.042)	(0.042)
Retirement	0.112*	0.111*	0.046	0.043
	(0.057)	(0.057)	(0.054)	(0.054)
Benefits	0.089*	0.089*	0.026	0.024
	(0.049)	(0.049)	(0.050)	(0.050)
Estate income	-0.010	-0.010	-0.059	-0.061
	(0.065)	(0.065)	(0.083)	(0.083)
From origin family	0.044	0.044	0.036	0.034
	(0.045)	(0.045)	(0.046)	(0.046)
Constant	0.105*	0.107*	1.010***	1.016***
	(0.055)	(0.055)	(0.062)	(0.062)
Observations	15617	15617	13384	13384
R-squared	0.090	0.090	0.370	0.370

We include the full set of controls used for the main specification in Table 3.3, column (2). Robust standard error in brackets.
* p<.10 ** p<.05 *** p<.01.

Appendix 3.C: Heterogeneity in the Care Needs

The effects may be limited to those families where the need of care is stronger.

Table 3.C.1: Sensitivity:Linear Probability Model for ICP

Upper panel: *parents aged more than 65*			
	(1)	(2)	(3)
	ICP	ICP	ICP
Help with house	0.034***	0.027***	
	(0.008)	(0.008)	
Monetary help			0.025*
			(0.013)
In-kind help			0.029***
			(0.010)
Observations	13628	13628	13628
R^2	0.081	0.087	0.087
Lower panel: *at least one parent with health-related limitations or aged 85+*			
	(1)	(2)	(3)
	ICP	ICP	ICP
Help with house	0.048***	0.037***	
	(0.013)	(0.014)	
Monetary help			0.019
			(0.022)
In-kind help			0.045***
			(0.016)
Observations	6241	6241	6241
R^2	0.080	0.091	0.091
Waves, regions	X	X	X
Demographic characteristics	X	X	X
Wealth characteristics		X	X

We include the full set of controls used for the main specification in Table 3.3. Robust standard error in brackets. * p<.10 ** p<.05 *** p<.01.

In the Upper panel of Table 3.C.1, we select the couples whose parents are aged 65 or older. The coefficient is actually only slightly bigger than the main estimates. We then focus on those whose parents or in-laws suffer from health-related limitation or are aged more than 85 (Lower panel). Estimates are bigger by around one percentage point. Also in these subgroups, the association is mainly driven by the in-kind help as Table 3.C.1 shows in column (4) and (5).

Additionally, the results are robust also in the case we only include relatively younger parents (aged 65-). The estimated effect of help with house on the informal care provided is around 0.020 with standard error of 0.01.

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