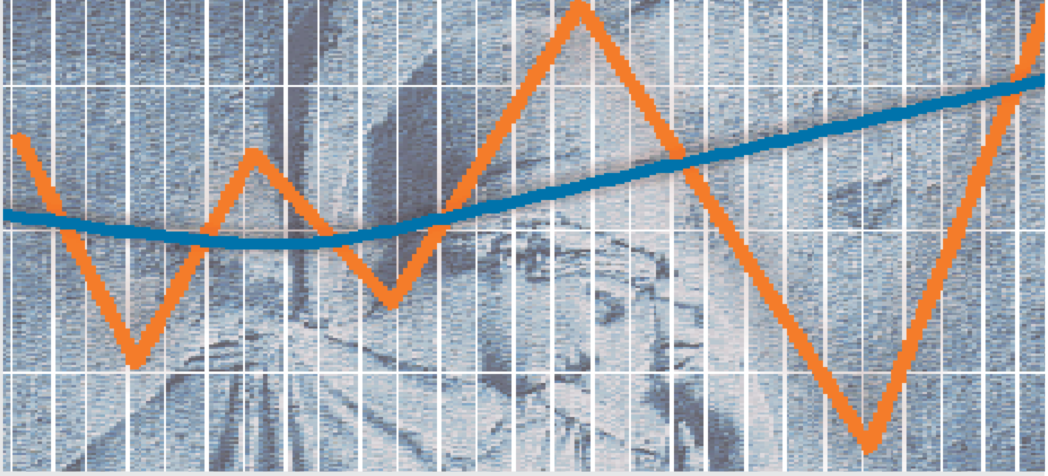

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ifo Beiträge
zur Wirtschaftsforschung

Empirical Essays in the Economics of Ageing and the Economics of Innovation

Janina Reinkowski

ifo Institut
Leibniz-Institut für Wirtschaftsforschung
an der Universität München e.V.

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Preface

This dissertation consists of five distinct empirical papers covering two large areas of research that are rather independent from each other: the economics of ageing and the economics of innovation.

The first three chapters cover the impact of intergeneration interaction on the parents of adult children. Chapter 1 explores the effects of grandchild care on grandparent labour supply. Chapter 2 on the other hand investigates the impact of grandchild care on grandparent health. Chapter 3 analyses the effect of a divorce of an adult child on the parent. The final two chapters take another direction. They evaluate the effects of research and development (R&D) promoting subsidy schemes. Chapter 4 looks at two regionally focused subsidies in the German biotech sector, while Chapter 5 investigates the effect of R&D subsidies from multiple national and international sources on small and medium sized enterprises (SME) in Thuringia.

In an ageing society, factors determining the economic situation and the health of elderly are of high relevance. While previous research has focused on the effects child care has on the labour supply of mothers of young children, little is known about the effect of childcare on those most likely to provide it: the grandparents. This thesis aims at filling this gap.

The following three chapters will be about three generations, where the first generation is called parent or grandparent, the second generation is called child and the third generation is named grandchild or a child's child.

Chapter 1 of this dissertation investigates the effect of grandchild care on grandparent labour supply. If an elderly woman can spend her time on work, leisure or care, an increase in the time spent on care will necessarily lead to less time spent on work and leisure. The question is which of the two domains is affected more. A large body of literature covers the effect of care provided to partners and elderly family members on the labour supply of the provider of such care. A smaller string of literature covers the effect of care provided to co-residing grandchildren and the effect of grandparenthood rather than grandchild care, due to a lack of information about grandchild care outside the household. The first chapter fills a gap in the literature by looking at the effect of grandchild care within and outside the household across Europe using the Survey of Health, Ageing and Retirement in Europe (SHARE), covering a large sample of European countries, and the German Ageing Survey (GAS). The analyses point into the direction of a small negative correlation between grandchild care and labour supply. The effects become even smaller when applying panel data methods and instrumental variable estimation, to overcome endogeneity problems. Thus, grandparents in Europe seem to substitute grandchild care mostly by leisure. In Germany, a country with very low provision of fulltime public child care, we find persistent negative effects.

Chapter 2 looks at the effect of grandchild care on the grandparents' health, i.e. their physical and mental health as well as their cognitive functioning. The existing literature has pointed out that custodial and long hour grandchild care have detrimental effects on grandparent health. Yet, the majority of grandparents provides only occasional grandchild care. The aim of the second chapter of this dissertation is to determine the effect of occasional grandchild care on grandparent health. It seems plausible that the occasional interaction with grandchildren - in contrast to custodial care - has rather a positive influence on grandparent health. Using SHARE-data, we find a significant positive correlation between occasional grandchild care and grandparent health. However, we are confronted with endogeneity, as health is a major factor determining whether a grandparent is providing grandchild care in the first place. Using a set of empirical estimation methods, like panel data analyses and instrumental variable estimation, we find a smaller and insignificant impact of grandchild care on all health outcomes.

Chapter 3 analyses how the divorce of a child influences the parents. While much is known about the detrimental effects of a divorce on the partners and their children, the impact on the elderly parents is rarely studied. The chapter aims to fill that gap. Using SHARE-data, our analysis covers the parents' health and labour supply, and looks at changes in the interaction between the generations. OLS estimates show significant negative correlations between the divorce of a child and the health and labour outcomes of the parents. However, when we apply panel estimations, we find insignificant positive effects of the divorce of one's children. Mental health is insignificantly negatively affected. Hence, the results imply that there are unfavourable unobservable characteristics at work which lead to negative outcomes in the parents of divorced children, rather than a direct negative effect of the divorce itself.

The two papers with a focus on innovation economics look at the effects of policy interventions on innovativeness at the firm and regional level. Chapter 4, which is co-authored by Dirk Engel, Timo Mitze and Roberto Patuelli, examines the effects of two competition based and regionally focused research and development (R&D) subsidies in the German biotech sector on regional innovativeness. Between 1997 and 2001, 7 out of 47 regional biotech clusters were awarded with a total of € 750 Mio by the federal government. The idea to incentivize regional cooperation in R&D through public funding, in order to increase international competitiveness is only a few decades old. Studies investigating the effect of such policies find ambivalent effects. While some cluster policies increased the regional performance of the subsidized sectors, other policies were found to not have increased the performance of already prospering sectors. Studies looking at the effect of the two biotech subsidies we are interested in delivered valuable insights into the regional performance concerning firm formation and new products during, but not after the receipt of the subsidy. This chapter investigates the R&D performance of contest winning regions in comparison to non-winning applicants and non-participating regions, applying Difference-in-Differences estimation techniques on multiple source data. R&D performance is measured as the number of funded R&D projects, cooperative projects and the number of filed patents during and after the funding phase. While we find a positive long-term effect on collaborative R&D projects, only the subsidy recipients (i.e. the competition winners) of one of the two contests were also able to attract more public funding in the post-funding phase.

Chapter 5 is joint work with Björn Alecke, Timo Mitze and Gerhard Untiedt and myself and explores the effect of R&D subsidies from regional, national and international authorities on private sector innovation in small and medium sized firms in the East German federal state of Thuringia. Since reunification, East German firms have been receiving generous publicly funded support for their research and development activities. The existing literature on the effects of publicly funded R&D in Germany has been based on the German section of the Community Innovation Survey (CIS), which observes firms with more than 50 employees. A major share of East German firms are, however, of small and medium size. This chapter fills a gap in the literature by looking at the effect of national and international R&D subsidies on small and very small firms' innovativeness using the GEFRA Business Survey. Our analyses point towards increases in R&D intensity and patent applications, with especially pronounced effects for micro businesses with less than ten employees.

Keywords: Employment; Ageing, Grandparental health; Grandchild care; R&D subsidies; East Germany; SME; Cluster-policy; Biotech; Causality.

JEL-No: I1, J13, J14,C14, C21, O32, O38.

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Chapter 1
Does Grandchild Care Conflict with Grandparents' Employment?[1]

1.1 Introduction

Maternal labour supply has increased significantly over the last decades, and has led to a higher demand for childcare. Rather than using just one source of care, parents tend to have their children looked after by both, public child providers and private persons like friends and family. As Wheelock and Jones (2002) show for Britain, grandparents are the most important providers of private childcare. But how does grandchild care affect the labour supply of those providing it, grandparents? If a grandparent can spend his or her time on three activities - work, leisure, or grandchild care - which of the two alternatives - work or leisure - will suffer from an increase in the time spent on grandchild care?

This question has been little studies so far, in large part because the main U.S. survey in this area (the PSID) does not report care provided to grandchildren living outside the household. For this reason, the literature focuses on care provided to co-residing grandchildren (Wang and Marcotte, 2007) or uses grandparenthood as a proxy to overcome this lack of information (Rupert and Zanella, 2011). The care provided to elderly partners and other family members is a more established field of research and is known to reduce labour supply (Ettner, 1996; Heitmüller, 2007; Bolin et al., 2008; Meng, 2009).

This article fills a gap in the literature by examining the impact of grandchild care provided within and outside the household on grandparents' labour supply and early retirement. We use data from the Survey of Health, Ageing and Retirement in Europe (SHARE), which covers a large sample of European countries, and the German Ageing Survey (GAS) as Germany is especially known for its shortcomings in the provision of public child care. We look at regional variation in the impact of the provision of grandchild care across Europe, and investigate the impact on both part-time and full-time work of grandmothers. Determining causality is a challenge when investigating the relation between labour force participation and the provision of grandchild care. To tackle this problem, we exploit the panel structure of the data and make use of an instrumental variable.

We find little evidence of a conflict between time spent providing grandchild care and the labour supply of grandmothers. Our ordinary least square (OLS) results show a very small negative correlation between grandchild care and labour force participation and a small

[1] This paper uses data from SHARE wave 4 release 1, as of November 30th 2012 or SHARE wave 1 and 2 release 2.5.0, as of May 24th 2011 or SHARELIFE release 1, as of November 24th 2010. The SHARE data collection has been primarily funded by the European Commission through the 5th Framework Programme (project QLK6-CT-2001-00360 in the thematic programme Quality of Life), through the 6th Framework Programme (projects SHARE-I3, RII-CT-2006-062193, COMPARE, CIT5- CT-2005-028857, and SHARELIFE, CIT4-CT-2006-028812) and through the 7th Framework Programme (SHARE-PREP, N° 211909, SHARE-LEAP, N° 227822 and SHARE M4, N° 261982). Additional funding from the U.S. National Institute on Aging (U01 AG09740-13S2, P01 AG005842, P01 AG08291, P30 AG12815, R21 AG025169, Y1-AG-4553-01, IAG BSR06-11 and OGHA 04-064) and the German Ministry of Education and Research as well as from various national sources is gratefully acknowledged (see www.share-project.org for a full list of funding institutions).

positive correlation with early retirement. The causal analyses mostly reveal even smaller effects. Thus, even though grandchild care is crucial for the labour supply of young mothers, grandmothers do not seem to adjust their employment patterns to their caring responsibilities.

The remainder of this paper is organized as follows. Section 1.2 contains an overview of the extant empirical literature. Section 1.3 describes the data we use and provides some descriptive statistics. Estimation results are shown in Section 1.4. Section 1.5 concludes.

1.2 Previous Literature

Public child care is one of the most important policy measures for increasing the labour supply of young mothers. Much research has been done on how public child care affects mothers' labour supply (see, e.g., Havnes and Mogstad, 2011a; Cascio, 2009; Schlosser, 2011; Lundin et al., 2008) and child outcomes (Felfe and Lalive, 2012; Havnes and Mogstad, 2011b). Informal childcare is an attractive alternative to formal childcare, given potential advantages like flexibility and accessibility on short notice. For Britain, qualitative studies show that most informal child care is provided by grandparents (Wheelock and Jones, 2002). Grandchild care is known to increase the labour supply of young mothers (see, for the United States, Posadas and Vidal-Fernandez, 2012; and for Germany, Garcia-Moran and Kuehn, 2012).

Very few studies investigate the impact of grandchild care on the labour supply of grandparents. Because the main U.S. survey in this area, the PSID, does not accurately record care provided for grandchildren living outside the household, the existing literature concentrates on grandchild care within households (Wang and Marcotte, 2007), or uses grandparenthood as a proxy for the provision of grandchild care available for all elderly (Rupert and Zanella, 2011). In general, grandchild care provided to co-residing grandchildren does not change the labour supply of grandparents. If, however, at the same time they have to provide economically for their grandchildren, they increase their labour supply (Wang and Marcotte, 2007). As grandparenthood might be endogenous (if the presence of grandparents and their likely provision of grandchild care increases the probability of the middle generation's fertility), Rupert and Zanella (2011) use the gender of the firstborn child as an instrument. They find the number of working hours to be significantly lower for grandparents compared to elderly persons without grandchildren.[2]

A more thoroughly researched field is the impact of the provision of care for elderly partners or relatives on the labour supply of the care provider. Wolf and Soldo (1994), using cross-section data, find no effect of care provided to elderly parents on the employment status and working hours of married daughters. Carmichael and Charles (1998, 2003) find that those who provide care for less than 20 hours a week are more likely to be employed but, compared to otherwise similar non-caring employees, they work fewer hours. Meng (2009) finds that

[2] Zamarro (2011) models the simultaneous decision on labor force participation of the mother and the grandmother. He argues that a woman decides on her labor force participation long before she becomes a grandmother and that thus the effect works from employment to grandchild care. He finds that the labor force participation of elderly women impacts their care provision.

eight hours of care provided per week reduces time in paid employment by about half an hour. Pavalko and Artis (1997) use panel data to investigate causation. They find that starting care provision is not influenced by a person's employment status. However, once a person is providing care, she becomes more likely to reduce working hours and to retire. Bolin et al. (2008) use SHARE data and find that a 10% increase in weekly hours of informal elderly care is related to a 2.6% decrease in weekly working hours.

Several of these studies use instrumental variable approaches to cope with the endogeneity of the provision of elderly care. Instruments used in this context include education (used as a proxy for health of the care recipient, Ettner, 1995), the health and age of the care recipient and the number of siblings the care provider has (Ettner, 1996; Heitmüller, 2007; Bolin et al., 2008), marital and socioeconomic status of the care recipient (Ettner, 1996), house ownership, the number of sick in the household, and the age of the three closest friends of the care provider (viewed as potential care recipients) (Heitmüller, 2007), as well as the geographical distance between care provider and recipient (Bolin et al., 2008). All these studies find a negative impact of care provision on labour force participation and working hours. Heitmüller (2007) distinguishes between several types of care recipients and finds the strongest negative impact for care provided to neighbours and friends.[3]

Another, albeit less studied, aspect is the impact of the provision of care for elderly people on the retirement decision of the caregiver. Dentinger and Clarkberg (2002) use a time-hazard rate model and find a reduced likelihood of retirement for care providers. Meng (2012) finds that providing care increases the likelihood to retire. Debrand and Sirven (2009) also find a positive impact of care on the retirement decision. Schneider et al. (2001) include both elderly care and child care in their analyses and find that the probability of leaving the labour force increases with elderly care. Child care, however, is more likely to be combined with part-time employment.[4]

1.3 Data and Descriptives

We use two datasets to see how the provision of grandchild care affects the labour supply of grandparents: the Survey of Health, Ageing and Retirement in Europe (SHARE) and the German Ageing Survey (GAS). SHARE includes a large set of countries: Austria, Belgium, Czechia, Denmark, Estonia, France, Germany, Greece, Hungary, Ireland, Israel, Italy, the Netherlands, Poland, Portugal, Slovenia, Spain, Sweden, and Switzerland. It covers the non-institutionalized (i.e., not living in nursing homes, etc.) population aged 50 and older and their spouses. The multi-disciplinary dataset consists of three panel waves from 2004/2005, 2006/2007, and 2011/2012. The 2008 questionnaire focuses on retrospective life history.

[3] The demand for informal care also depends on the availability of care alternatives. Viitanen (2007) investigates the relationship between formal and informal elderly care. She finds that an increase in public spending on formal care can significantly increase the labour supply of care providers.

[4] The decision to reduce working hours in order to provide care is also likely to correlate with the wage a person is able to earn. Nizalova (2012) looks at the wage elasticity of informal care supply to elderly. When instrumenting for these unobserved demand-side factors of employment with a set of industry- and employment-related regional variables, the negative wage elasticity of informal care becomes even stronger.

We look at three outcome variables, employment, working hours and early retirement. The questionnaire asks for the current job situation; respondents may answer "retired," "employed or self-employed (including working for family business)," "unemployed," "permanently sick or disabled," "homemaker," or "other." For our employment measure we generate a dummy variable that takes the value 1 for "employed or self-employed (including working for family business)" and 0 otherwise. As all observations in our sample are younger than the country specific official retirement age, for early retirement we generate another dummy variable with the value 1 for all those indicating to be retired and 0 otherwise. When a respondent reports being employed, but not having done any paid work during the last four weeks or that he or she is temporarily away from work, the questionnaire also asks for the usual weekly working hours excluding meal breaks but including any paid or unpaid overtime. For those who do not respond to this question, we use the contracted working hours.

Unlike the PSID data used by Wang and Marcotte (2007) and Rupert and Zanella (2011), SHARE and GAS both have the advantage of providing detailed information about the provision of care to all grandchildren. For grandchild care, the SHARE questionnaire asks all who report having grandchildren whether they provided grandchild care within the last 12 months. Those who answer "yes" are then asked for the frequency of care (less than monthly, almost every month, almost every week, almost daily). In Wave 1 and 2, respondents were also asked for the number of hours based on that frequency of care. The third wave provides only the care frequency. From this information we calculate the weekly caring hours for the first two waves. To optimize interpretability, we then replace the standard values of the categorical variable with the mean weekly hours of grandchild care these categories had in the first two waves. Thus we do not need to assume these categories to have a linear impact on labour supply and, also, interpretation of the coefficients becomes more intuitive. Ghysels (2011) shows that those who report providing grandchild care at more frequent levels consistently indicate a higher number of hours of grandchild care per week.

Germany can be viewed as representative of those countries with low provision of public child care, making informal child care relatively more important. As the subsamples for specific countries in SHARE vary widely in size and are limited in their representativeness, we use the German Ageing Survey (GAS). The GAS is a German longitudinal panel covering the population 40 and older in three waves from 1996, 2002, and 2008. From 2011 on, the survey will be conducted every three years. The topics covered by SHARE and GAS are very similar, but there are small variations in the variables of interest. For example, the job situation can be derived from a variable, generated by the provider of the dataset, that indicates whether a respondent is employed, retired, or in another non-working situation. The weekly working hours including overtime are reported for those indicating they are employed.

The GAS asks about several types of child care provided to other than the respondent's own children: grandchildren and the children of siblings, neighbours, friends, and others. One amount of child care in hours is given for all these types of care. The amount of care provided by respondents providing only other types of child care is significantly smaller than the amount of care provided by those who provide grandchild care (5.8 hours per week for non-grandchild caring compared to 14.4 hours for grandchild caring respondents). As our focus is on grandchild care, we set the caring hours to zero for all 162 respondents reporting that they provide child care but no grandchild care. For 48 respondents reporting that they provide child care on less than a monthly basis and who do not report the number of caring hours, we set the number to 1.8 hours per week, which is the average amount of care provided by Germans in the first two SHARE waves. To increase legibility of the result tables, the weekly hours of grandchild care are then divided by ten, so that all results can be interpreted as the impact of 10 more hours of grandchild care.

We include control variables such as age and education (dummies for medium and high education, with low education as the reference group), marital status (dummies indicating whether a person is currently married or is widowed; the reference group consists of singles and the divorced as both show similar patterns), and the number of children. To increase comparability, we restrict both samples to respondents aged between 45 and the official national retirement age. Table 1.1 provides descriptive statistics for the two samples.

1.3.1 Estimation Designs

We first use pooled OLS estimation to measure the partial correlation between grandchild care and grandparent employment. We control for all these by including a vector of control variables (X_{it}) in the regression equation for the dependent variable $employment_{it}$:

$$(1.1) \quad employment_{it} = \alpha + \beta \times grandchild\ care_{it} + \gamma \times X_{it} + u_{it}$$

Where $i=1,\dots,N$ denotes the cross-sectional dimension and $t=1,2$ is the time index for the different waves of the data. The regressor $grandchild\ care_{it}$ measures the influence of grandchild care; u_{it} is the residual term of the regression equation, α, β, and γ are coefficients to be estimated.

Fixed effects and lagged dependent variable estimation both make use of the time dimension of our data sets and allow us to control for time fixed characteristics influencing grandchild care and grandparent employment. Fixed effect estimation makes use of the deviation from the individual mean over time.

We control for this individual mean by including an observation fixed intercept α_i

$$(1.2) \quad employment_{it} = \alpha_i + \beta \times grandchild\ care_{it} + \gamma \times X_{it} + u_{it},$$

while the lagged dependent estimation uses the outcome in an earlier period, $employment_{it-1}$, as a proxy for unobserved individual fixed characteristics.

$$(1.3) \quad employment_{it} = \alpha + \beta \times grandchild\ care_{it} + \gamma \times X_{it} + employment_{it-1} + u_{it}$$

Our estimates might, however, still be biased, if there are time-varying unobservables correlated with the variables of interest. We thus use exogenous variation in the amount of grandchild care to cope with this issue.

We use an instrumental variable that leads to a change in the provision of grandchild care but which is expected to be otherwise unrelated to the employment of a grandmother: the gender of the firstborn child. This instrument relies on the random distribution of a child's gender. Its influence on grandchild care has been shown in previous literature (see Rupert and Zanella, 2011).

The instrumental variable approach makes two assumptions. First, the instrumental variable has significant impact on the endogenous grandchild care, also called the

relevance assumption. And second, the exclusion restriction, says that the instrument is as good as randomly assigned and grandchild care is the only channel through which the instrumental variable affects the outcome.

$$(1.4) \quad grandchild\ care_{it} = \delta + \theta \times gender\ of\ the\ firstborn_{it} + \vartheta \times X_{it} + u_{it}$$

This approach assumes the effect of grandchild care to consist of two parts, one part being endogenous and the other variation not suffering from endogeneity – the instrument. The IV thus isolates in a first stage the part of the variation in the treatment variable that can be attributed to an observed third variable which is not otherwise correlated with the outcome.

$$(1.5) \quad employment_{it} = \alpha + \beta \times \overline{grandchild\ care_{it}} + \gamma \times X_{it} + u_{it}$$

In the second stage the outcome variable is regressed on all right hand side variables and the predicted values $\overline{grandchild\ care_{it}}$ from the first stage.

1.4 Results

Our main interest is in whether providing care for grandchildren affects the labour supply of the caregiver. We begin by using OLS and then estimate an ordered logit model to see whether it is easier to combine grandchild care with part-time than with full-time employment. Further, we look at regional variation in the care impact across Europe (North vs. South Europe). To overcome potential endogeneity issues, we next use the panel structure of our data and apply instrumental variable estimation to arrive at a better sense as to whether our correlations can be interpreted as causal.

Table 1.1 Sample descriptives

		SHARE					GAS				
Variable	Definition	Obs	Mean	StdDev	Min	Max	Obs	Mean	StdDev	Min	Max
Employed	1 if employed	27757	0.5054	0.5	0	1	3969	0.5369	0.4987	0	1
Working hours	working hours per week	27757	17.684	19.366	0	168	3969	17.682	19.533	0	100
Early retirement	1 if retired before official retirement age	27757	0.1667	0.3727	0	1	3969	0.1827	0.3864	0	1
Grandchild care	weekly hours of grandchild care/10	27757	0.5245	1.051	0	3.99	3969	0.292	1.07	0	17.5
Age	age in years	27757	56.106	4.5073	45	66	3969	54.943	5.9089	45	65
Education	low education (isced1/2)	27757	0.3759	0.4844	0	1	3969	0.1282	0.3344	0	1
	medium education (isced3/4)	27757	0.3854	0.4867	0	1	3969	0.5868	0.4925	0	1
	higher education (isced5/6)	27757	0.2387	0.4263	0	1	3969	0.285	0.4515	0	1
Married	1 if married	27757	0.8	0.4	0	1	3969	0.7778	0.4158	0	1
Widowed	1 if widowed	27757	0.0588	0.2352	0	1	3969	0.0804	0.2719	0	1
#Children	number of children	27757	2.3618	1.1637	1	17	3969	2.1444	1.0345	1	10
Elderly care	hours of weekly elderly care	26431	2.7124	5.8681	0	21.6	2253	2.3205	10.204	0	168
Self-rated health	poor health	26431	0.0653	0.2471	0	1	2253	0.0151	0.1219	0	1
	fair health	26431	0.2092	0.4068	0	1	2253	0.0737	0.2613	0	1
	good health	26431	0.3792	0.4852	0	1	2253	0.3134	0.464	0	1
	very good health	26431	0.232	0.4221	0	1	2253	0.486	0.4999	0	1
	excellent health	26431	0.1143	0.3181	0	1	2253	0.1119	0.3153	0	1
Closest child	same house/household	26431	0.4796	0.4996	0	1	2253	0.1602	0.3669	0	1
	within a 5-km radius	26431	0.2504	0.4333	0	1	2253	0.2765	0.4474	0	1
	5–25 km	26431	0.1331	0.3396	0	1	2253	0.3946	0.4889	0	1
	25–100 km	26431	0.0742	0.262	0	1	2253	0.1425	0.3496	0	1
	over 100 km	26431	0.0628	0.2425	0	1	2253	0.0262	0.1597	0	1
Working partner	1 if partner is employed	26431	0.6598	0.4738	0	1					
#Daughters	number of daughters	27440	1.1536	0.9493	0	10	3780	1.0651	0.8969	0	7
#Other daughters	number of daughters apart from firstborn	27440	0.6608	0.8047	0	9	3780	0.5582	0.7401	0	6
Firstborn a daughter	1 if firstborn child a daughter	27440	0.4928	0.5	0	1	3780	0.5069	0.5	0	1

Table 1.2 OLS estimations

	SHARE						GAS					
	Employment		Working hours		Early retirement		Employment		Working hours		Early retirement	
Grandchild care	-0.0341***	-0.0217***	-1.222***	-0.733***	0.00562**	0.00671***	-0.0233***	-0.0148**	-0.891***	-0.482*	0.00634	0.00500
	(0.00279)	(0.00277)	(0.109)	(0.108)	(0.00225)	(0.00226)	(0.00737)	(0.00714)	(0.260)	(0.251)	(0.00770)	(0.00776)
Medium education		0.119***		4.407***		0.0171***		0.0946***		3.062***		-0.0354**
		(0.00788)		(0.300)		(0.00542)		(0.0225)		(0.790)		(0.0167)
High education		0.256***		10.00***		0.00677		0.232***		9.410***		-0.0581***
		(0.00869)		(0.342)		(0.00612)		(0.0254)		(0.963)		(0.0176)
Married		-0.0279***		-2.241***		0.00330		-0.0531***		-5.020***		-0.00997
		(0.00909)		(0.369)		(0.00612)		(0.0194)		(0.853)		(0.0135)
Widowed		-0.0196		-2.018***		0.0509***		-0.0663**		-5.570***		0.0190
		(0.0151)		(0.596)		(0.0119)		(0.0300)		(1.193)		(0.0241)
#Children		-0.0208***		-0.679***		-0.00978***		-0.0168**		-0.838***		-0.00107
		(0.00266)		(0.108)		(0.00179)		(0.00741)		(0.294)		(0.00465)
Age dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	27,757	27,757	27,757	27,757	27,757	27,757	3,969	3,969	3,969	3,969	3,969	3,969
R-squared	0.204	0.241	0.183	0.221	0.240	0.242	0.257	0.282	0.207	0.244	0.467	0.469

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for country (SHARE)/East and West Germany (GAS), year dummies, marital status with divorced and singles as reference group, education with low education as reference group, and a constant.

1.4.1 Ordinary Least Square Estimates

In our pooled estimation, we control for year effects, country effects in SHARE, and employ dummies for East and West Germany in GAS. From regressions not shown here, we know that men's labour supply does not respond to caring responsibilities, except for those 3.9% (775 of 20,007 male SHARE observations) providing almost daily care. As this small sample of daily caring men demonstrates effects on their labour supply similar to those of women, we concentrate on female respondents in the following.

The results shown in Table 1.2 reveal that when controlling for country and year effects, as well as for age dummies (in Column 1 of Table 1.2), an increase in weekly grandchild care by 10 hours correlates with a reduced probability of employment of 3.41 percentage points. When controlling for education, marital status, and the number of children – which will be our standard specification from here on – we find the correlation attenuates to 2.17 percentage points. For the weekly working hours, once we control for socio-demographic characteristics, we find that 10 more hours of grandchild care correlates with a reduction in weekly working hours of about (.733*60) 44 minutes. This is about the size of the impact that Meng (2009) finds for elderly care, and suggests that grandchild care mostly substitutes for time spent on leisure. For early retirement, the correlations are even smaller compared to employment, with ten more hours of grandchild care, the likelihood of early retirement increases by .67 percentage points.

The estimated correlation with working hours represents about 4.1% of the average working hours (.733/17.684), which is very similar to the 4.3% impact on average employment rate (.023/.5054). This suggests that most of the impact of grandchild care happens at the extensive margin and so is more likely to reduce the employment share rather than the average working hours of those in the workforce.

For the GAS data, in our standard specification, a grandmother is 1.48 percentage points less likely to be employed if she increases her grandchild care by 10 hours a week; working hours decrease by about 29 minutes and the likelihood for early retirement increases insignificantly by .5 percentage points. As in the European sample, the impact of grandchild care seems to be occurring at the extensive margin. The estimated impact on working hours represents about 2.7% of the average working hours (.482/17.682), and the impact on the average employment rate amounts to 2.9% (.0148/.4987).

Despite the significant negative correlation between employment and grandchild care, caution must be exercised in interpreting this relation as causal; we are facing several endogeneity issues. Grandmothers who provide grandchild care might differ from non-caring ones in unobserved characteristics other than the provision of care. Also, reverse causality might be an issue if non-working grandmothers are more willing to look after their grandchildren. This would lead to an overestimation of the negative impact of grandchild care on grandparental labour supply.

Table 1.3 Further OLS estimations

	SHARE						GAS					
Dependent	Employment		Working hours		Early retirement		Employment		Working hours		Early retirement	
Grandchild care	-0.0223***	-0.0210***	-0.736***	-0.676***	0.00630***	0.00543**	-0.0087	-0.00917	-0.381	-0.449*	0.00290	0.00184
	(0.00283)	(0.00281)	(0.110)	(0.110)	(0.00230)	(0.00232)	(0.0071)	(0.00689)	(0.262)	(0.263)	(0.0082)	(0.0076)
Elderly care		-0.00242***		-0.0966***		0.00118***		-0.0024***		-0.0943***		-0.000397
		(0.000484)		(0.0191)		(0.000369)		(0.000780)		(0.0280)		(0.00079)
Fair health		0.164***		5.782***		-0.0313***		0.161**		5.087*		-0.0238
		(0.0118)		(0.446)		(0.0109)		(0.0706)		(2.682)		(0.0749)
Good health		0.292***		10.40***		-0.0466***		0.302***		10.15***		-0.162**
		(0.0114)		(0.438)		(0.0105)		(0.0649)		(2.459)		(0.0704)
Very good health		0.336***		11.92***		-0.0736***		0.370***		12.65***		-0.248***
		(0.0123)		(0.471)		(0.0109)		(0.0645)		(2.445)		(0.0696)
Excellent health		0.349***		12.66***		-0.0709***		0.357***		11.51***		-0.234***
		(0.0137)		(0.531)		(0.0117)		(0.0687)		(2.617)		(0.0709)
Closest child within 5 km		0.0233***		1.006***		-0.00508		0.000643		-0.395		-0.00664
		(0.00777)		(0.304)		(0.00583)		(0.0265)		(1.034)		(0.0227)
5–25 km		0.0195**		1.025***		0.00690		0.00339		-0.764		-0.0211
		(0.00939)		(0.369)		(0.00722)		(0.0259)		(1.036)		(0.0215)
25–100 km		-0.0121		-0.260		0.0117		-0.0205		-2.536*		-0.0199
		(0.0120)		(0.456)		(0.00905)		(0.0329)		(1.296)		(0.0254)
Over 100 km		-0.0304**		-0.566		0.00450		-0.0279		-2.524		-0.00229
		(0.0130)		(0.534)		(0.00984)		(0.0582)		(2.525)		(0.0373)
Non-working partner		-0.0710***		-2.531***		0.0395***						
		(0.00710)		(0.282)		(0.00450)						
Age dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Socio-demographics	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	26,431	26,431	26,431	26,431	26,431	26,431	2,253	2,253	2,253	2,253	2,253	2,253
R-squared	0.240	0.278	0.222	0.254	0.239	0.244	0.323	0.344	0.287	0.305	0.438	0.463

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for country (SHARE)/East and West Germany (GAS), year dummies, marital status with divorced and singles as reference group, self-rated health with poor health as reference group, partner's employment status with singles and retired partners as the reference group, distance to closest child with living in the same house or household as reference group, and a constant.

However, healthier grandmothers might be more able to both work and provide grandchild care, which would bias our OLS estimates upward. It is thus difficult to determine in which direction and to what extent our estimates might be misleading us.

To further reduce the variation in grandchild care, we control for several variables. As pointed out in the literature review, elderly care is a major factor in reducing the labour supply of the elderly. By adding the weekly hours of elderly care to our equation, we compare grandmothers having the same socio-demographic characteristics and providing a similar amount of elderly care, but differing in the weekly number of hours of grandchild care they provide. From including the variables stepwise, we know that the point estimate of the grandchild care coefficient decreases slightly when controlling for elderly care.

Good health is positively correlated with employment (Schuring et al., 2007) and grandchild care (Ku et al., 2012). On the other hand, if a sick person stopped working, she might have more time that could be used to care for her grandchildren. Also, employment is known to have a positive impact on people's health (Ross and Mirowsky, 1995). Despite these endogeneity issues, we include self-rated health in our extended specification (ranging from excellent to very good to good, with fair to poor as the reference group). This allows us to reduce the variation in grandchild care caused by variation in self-rated health.

Whether or not a married grandmother works should be influenced by the employment status of her husband. Pienta (2003) finds a positive correlation between the retirement of the male and the female partner. Also, grandchild care can be a demanding task and having another adult around could alleviate some of the burden. We therefore add a dummy variable indicating whether a woman lives with a non-working partner; the reference group consists of singles and women with working partners.

Finally, the distance between a grandmother and her children is known to be a strong determinant of the amount of grandchild care (Ghysels, 2011). Controlling for the distance to the closest child allows us to compare the impact of grandchild care on grandmothers living at equal distance to their closest child. Of course, a child's location choice is highly endogenous due to children anticipating their parents' need for support (Rainer and Siedler, 2009) and, also, the parents' likely provision of grandchild care. In this case, the geographical distance might be co-determined with expected care exchange and including it would be what Angrist and Pischke (2009, p.64) call a bad control. We show the results when controlling for the geographical distance only in our extended specification. In the standard specification, we allow for variation in geographical distance to drive the provision of grandchild care. There may, of course, be other factors influencing grandchild care and grandparent labour force supply. Nevertheless, we believe that this set of controls includes the most important ones.

Adding the amount of elderly care, self-rated health, and geographical distance in SHARE (Table 1.3) attenuates the negative employment impact of 10 more hours of grandchild care to 2.1 percentage points, and attenuates the impact on working hours to 41 minutes. In the GAS, when we add our further controls, working hours decrease by 27 minutes instead of by the 29 minutes we find for the standard specification in this sample of observations. We do not show the results when controlling for the employment status of the partner, as only respondents in the third year were asked that question. Adding the partners' employment status for the third-wave observations, however, hardly changes the coefficient of grandchild care; these results are available on request. Thus, in both datasets, the negative impacts of grandchild care are relatively robust to alternative specifications.

1.4.2 Full- or Part-time Employment

The impact of grandchild care might vary by the number of working hours. A full-time employed grandmother will almost certainly have to reduce her working hours if she wants to provide grandchild care, whereas a part-time working grandmother is more likely to be able to provide grandchild care during her leisure time and is less likely to have to cut back working hours.

Table 1.4 shows the average marginal effects for employment intensities: not working, working 1 to 19 hours per week, 20 to 29 hours per week, 30 to 39 hours per week, and more than 40 hours. For SHARE, we see that increasing grandchild care by 10 hours a week increases the likelihood of not working by 1.92 percentage points, while it reduces the likelihood of working 30 to 40 hours a week by .92 percentage point. For Germany, we see a similar pattern: 10 more hours of grandchild care increase the likelihood of not working by .16 percentage points, while the strongest impact, .77 percentage points, is on the likelihood of working more than 40 hours.

Table 1.4 Ordered logit average marginal effects for categories of employment

Working hours	SHARE	GAS
Not working	.0192***	.0016**
	(.0029)	(.0078)
1 to 19 hours per week	-.0003***	.0006*
	(.00006)	(.0003)
20 to 29 hours per week	-.0015***	-.0014**
	(.0002)	(.0007)
30 to 40 hours per week	-.0092***	-.0076**
	(.0014)	(.0037)
More than 40 hours	-.0082***	-0.0077**
	(0.0012)	(.0037)
Wald chi2	5039.05	804.06
Prob> chi2	.0000	.0000
Observations	27757	3969

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Controlling for country (SHARE)/East and West Germany (GAS), and year and age dummies, education, marital status: married, widowed, with divorced and singles as reference group, and the number of children.

1.4.3 Regional Variation

Europe is characterized by a great deal of cultural and demographic variation. For example, female labour force participation is high in the northern countries and low in the south, where labour markets seem to be less flexible (Gauthier, 2002). People living in Southern European countries often are described as having strong family ties, while those living in Northern Europe demonstrate relatively weak family ties (Bolin et al., 2008). Albertini et al. (2007) see co-residence as the "South European way of transferring resources"; grandmothers living alone are less likely to exchange help with their offspring but, when they do, the amount exchanged is relatively high. Grandchild care on an at least weekly basis occurs most often in the south, while the Scandinavian countries show the lowest rate of regular grandchild care, and Western Europe, albeit with some variation, has an overall distribution of time transfers that falls between these two extremes (Dimova and Wolff, 2011). Ogg and Renaut (2006) look at the support elderly receive from their children and find patterns similar to those for grandchild care: the share of those providing help to the elderly generation is high in the northern countries and low in the southern, while the share of regular care providers is low in the north and high in the south. Only a very small share of elderly received financial support.

Table 1.5 shows the country means of the variables of interest. In line with other work, we find that the North European countries show a pattern of high labour force participation. The average working hours of the elderly in this region are in excess of the international mean of 17.7 hours per week. Early retirement rates are above the international average of 16.7%. The share of caring grandmothers is relatively high, but they provide only 3.43 hours of weekly care in Denmark and 3.57 hours in Sweden. In the South European countries, only a relatively small share of grandmothers are employed or retired and only about a quarter of all grandmothers provide grandchild care. However, those who are involved, care, on average, for 4.37 hours a week in Greece and 6.65 hours a week in Italy.

Western Europe shows more variation in employment and caring patterns. In Ireland, for example, only 41.8% of grandmothers work; in Switzerland, 67.9% do. The mean working hours vary from 12.0 hours per week in the Netherlands to 23.0 hours in France. The share of grandmothers providing care to grandchildren in Western European countries shows some variation as does the number of hours of care provided, with 6.2 hours being provided in Belgium and 2.7 in Switzerland. Grandmothers in Post-Communist countries show strong variation in employment share (31.6% in Poland and 68.5% in Estonia), and the shares of caring grandmothers in these countries are above the European average.

When estimating country-specific care effects, we interact every control variable with the country dummies and estimate without a constant (see Table 1.6). The fact that most of the country-specific care coefficients are insignificant is no doubt due to the fact that the number of observations per country is relatively small (for example, for Ireland we have only 337 observations).

Maps showing the regional distribution of the variables of interest are provided in Figure A.1 to A.4. Figure A.5 to A.7 show the mean and the 95% confidence intervals of the country-specific care effects on employment, working hours and early retirement. We see that compared to the coefficient for the whole sample (from a regression without any country interactions), the confidence intervals for the country-specific coefficients are very large. The country-specific coefficients are all very similar. There is hardly any significant difference. In Table A.5 we see significantly negative correlation between employment and grandchild care in Sweden, Greece, Belgium, France and Czechia. The correlation with the working hours (Table A.6) is significant in Austria, Belgium and Czechia. While for early retirement and grandchild care (Table A.7), Belgium, Germany and Czechia show significant positive correlation.

Table 1.5 Country characteristics grouped by socio-cultural regions (SHARE)

	Employment	Working hours	Early retirement	Grandchild care dummy	Caring hours	Obs
Northern Europe						
Sweden	0.6897	25.6753	0.2120	0.4736	3.5669	1953
Denmark	0.6545	23.4565	0.1808	0.4834	3.4270	1864
Southern Europe						
Greece	0.3558	12.9206	0.1252	0.1918	4.3704	1366
Italy	0.3823	12.9971	0.0999	0.2566	6.6455	1551
Spain	0.3068	11.4833	0.0598	0.2717	5.3703	1822
Portugal	0.4058	6.2783	0.2397	0.3048	6.4082	584
Western Europe						
Austria	0.4860	17.3215	0.2656	0.3128	4.6117	1397
Belgium	0.4362	14.0470	0.1767	0.4803	6.7023	3090
France	0.6456	22.8500	0.0837	0.3844	3.7841	2305
Germany	0.4765	15.8158	0.2122	0.3549	4.5065	1744
Ireland	0.4184	12.9000	0.1187	0.4273	5.8214	337
Switzerland	0.6736	19.7480	0.0621	0.2802	3.1197	1449
Netherlands	0.4378	11.8329	0.0798	0.4462	4.2262	2380
Post-Communist countries						
Hungary	0.4048	18.3868	0.3329	0.4554	7.1350	751
Slovenia	0.3922	15.6029	0.4085	0.4412	8.8410	612
Estonia	0.6823	26.8137	0.0691	0.4059	4.5087	1259
Poland	0.3227	13.6889	0.3367	0.5045	11.2714	781
Czechia	0.5482	18.6630	0.1079	0.4460	8.0578	695
Others						
Israel	0.5751	24.6681	0.3170	0.4568	6.2250	1817
Overall	0.5054	17.6836	0.1667	0.3910	5.2453	27757

In a more parsimonious specification, we instead interact every control variable with a categorical variable indicating the cultural background characteristic of each country: Western Europe, Northern and Southern Europe, and Post-Communist (as Israel cannot easily be subsumed into any of these categories, Israeli respondents are dropped for this specification).

Table 1.6 shows the results from regressing grandchild care, cultural region dummies, and the interaction of the two on the employment outcomes. Compared to Western Europe, where 10 more hours of grandchild care have a significantly negative correlation of 3.02 percentage points for employment and reduce working hours by 56 minutes, the effect on Post-

Communist country grandmothers is stronger, leading to a (–3.02 – 1.29) 4.31 percentage point reduction in employment and a (–56 – 50) 106 minute reduction in working hours. The care effects are less pronounced for Southern Europe: 10 more hours of care lead to a reduction in employment of only (–3.02 + 1.60) 1.42 percentage points and working hours decrease by only (–56 + 41) 15 minutes. When we look at early retirement, 10 more hours of grandchild care increase the likelihood of its occurrence by .76 percentage points in Western Europe, by (.76 + 2.66) 3.42 percentage points in Northern Europe, by 3.99 percentage points in Post-Communist countries and in Southern Europe it reduces the likelihood for early retirement by .83 percentage points.

Table 1.6 OLS Country-group-specific correlations

Dependent	Employment	Working hours	Early retirement
Grandchild care	-0.0302***	-0.933***	0.00763**
	(0.00495)	(0.179)	(0.00382)
Grandchild care*Northern Europe	0.00477	-0.165	0.0266**
	(0.0149)	(0.530)	(0.0113)
Grandchild care* Post-Communist countries	-0.0129*	-0.835***	0.0323***
	(0.00687)	(0.275)	(0.00614)
Grandchild care*Southern Europe	0.0160**	0.683***	-0.0159***
	(0.00683)	(0.257)	(0.00541)
Socio-demographics	yes	yes	yes
Observations	27,062	27,062	27,062
R-squared	0.220	0.202	0.199

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for further socio-demographics: year dummies, education: high and medium with low education as the reference group, marital status: married, widowed, with divorced and singles as reference group, employment status: employed, retired, chronically ill, homemaker, with retired as reference group, log of household income, possession of any real estate, number of children, number of grandchildren, and retirement because of bad health.

1.4.4 Panel Data Analyses

One way to further address our endogeneity concerns is to make use of the panel structure of our data and control for the lagged dependent variable. This estimation strategy includes the past labour supply as a proxy for unobserved time invariant personal characteristics. In order to make the results comparable to the fixed effects estimations we are also showing, we restrict the sample to the 1577 observations in SHARE and 104 observations in GAS that have information available for all three periods.

For SHARE data, compared to our standard identification, when we control for the lagged outcome in Table 1.7, i.e. we compare only those grandmothers that have been working in the past, we see that for this smaller sample, the impact of grandchild care on employment is significant at the 5% level when controlling for socio-demographic characteristics. When additionally controlling for past employment status, the coefficient is attenuated and becomes significant at the 10% level only. In the case of working hours, there is also a slight reduction in the size of the coefficient; however, as standard errors decrease even more, we are left with an significant impact at the 5% level. For early retirement even though we do not see significant coefficients, here as well, the size of the impact shrinks when controlling for the lagged outcome. Table A.1 in shows the results for fixed effects estimations. The size of these effects is small and the findings are insignificant and positive. For example, if we look at the point estimates, 10 more hours of grandchild care leads to an increase of the employment probability by .36 percentage points and working hours increase by 3 minutes. Both estimation methods point toward causal effects that are non-existent or at least smaller than the correlations from the OLS.

This is not the case for Germany; compared to the larger OLS sample, we find rather large impact in the baseline specification, as 10 hours more grandchild care lead to a 7.17 percentage point reduction in employment probability and a reduction of 2.81 hours in working time. Controlling for the lagged dependent variable increases the impact on the employment probability to 9.59 percentage points, and the impact on working hours to 3.19 hours. The fixed effects in Table 8 find a significant reduction of 13.4 percentage points in the employment probability and a reduction in working hours by 3.49 hours.

As pointed out in the literature review, for the entrance into retirement often time-hazard models are used (Dentinger and Clarkberg, 2002; Meng, 2012; Debrand and Sirven, 2009). To run what would be as close to survival analyses as possible on a panel with three waves, we use our sample of observations younger than retirement age and restrict it to those who were working in the first period and are observed in all three waves. This leaves us with 922 observations in SHARE and 74 in GAS. On this sample we run the same fixed effects model, as we do on the whole sample in Table A.1.

Comparing these results, we see in Table 1.8 that this approach in SHARE suggests the insignificant impact of an increase in grandchild care on grandparent employment and working hours to be much stronger than the fixed effect estimates on the whole sample do. Increasing the provision of grandchild care by ten hours seems to increase the likelihood of employment by .72 percentage points and working hours by .308 which corresponds to 18 minutes. The likelihood of early retirement increases too, by 1.17 percentage points, the discrepancy between the reduced likelihood in the overall sample and the increased likelihood of early retirement in employed grandmothers points towards a slower transition into early retirement from other groups like unemployed and homemakers. In the GAS we find weaker and insignificant results for the sample of those employed in the first wave.

Lagged dependent estimation and fixed effect estimation both assume the relevant omitted variables to be time invariant. The former uses the past outcome as a proxy for unobserved time-invariant personal characteristics; the latter builds on the variation from the individual mean. With so few waves of data collection, there is very little variation and fixed effect estimates should be interpreted carefully.

When comparing lagged outcome estimation and fixed effects, we need to keep in mind that if we use lagged estimates when, in reality, we are facing a fixed effect problem (i.e., it is the variation in grandchild care driving the variation in the labour supply), we would be underestimating the real impact.

Table 1.7 Lagged dependent estimations

	SHARE						GAS					
Dependent	Employment		Working hours		Early retirement		Employment		Working hours		Early retirement	
Grandchild care	-0.0189**	-0.0121*	-0.583*	-0.557**	0.00559	0.00402	-0.0717**	-0.0959***	-2.811**	-3.191***	-0.0330	-0.0340
	(0.00910)	(0.00642)	(0.322)	(0.243)	(0.00663)	(0.00593)	(0.0326)	(0.0303)	(1.225)	(1.054)	(0.0254)	(0.0248)
Medium education	0.103***	0.0254*	4.114***	1.319***	0.00617	0.0111	0.329**	0.223***	7.061	8.170***	-0.0476	-0.0294
	(0.0255)	(0.0145)	(0.886)	(0.510)	(0.0160)	(0.0132)	(0.147)	(0.0803)	(6.506)	(2.265)	(0.139)	(0.103)
High education	0.230***	0.0797***	9.751***	3.820***	0.0131	0.0194	0.328**	0.172*	7.889	6.926**	0.00146	0.00985
	(0.0255)	(0.0157)	(0.942)	(0.596)	(0.0179)	(0.0149)	(0.158)	(0.0897)	(7.088)	(3.103)	(0.143)	(0.108)
Married	-0.0873***	-0.0331*	-4.764***	-1.846***	0.0287	0.0238	0.0706	0.0950	-0.574	1.122	-0.117	-0.0882
	(0.0285)	(0.0170)	(1.098)	(0.636)	(0.0187)	(0.0161)	(0.108)	(0.0706)	(4.874)	(2.926)	(0.119)	(0.0932)
Widowed	-0.0797	-0.0165	-3.705*	-1.495	0.00365	-0.0106	-0.0766	-0.00483	-10.92**	-6.918*	0.158	0.158
	(0.0505)	(0.0288)	(1.994)	(1.143)	(0.0332)	(0.0299)	(0.129)	(0.0951)	(5.456)	(3.850)	(0.153)	(0.120)
#Children	-0.00948	0.00380	-0.452	-0.0759	-0.0153**	-0.0134***	-0.0624	-0.0429*	-2.078	-1.517*	0.0212	0.0158
	(0.00990)	(0.00585)	(0.364)	(0.208)	(0.00602)	(0.00510)	(0.0377)	(0.0233)	(1.385)	(0.828)	(0.0219)	(0.0177)
Lagged outcome		0.596***		0.583***		0.389***		0.450***		0.448***		0.563***
		(0.0172)		(0.0202)		(0.0377)		(0.0672)		(0.0593)		(0.156)
Age dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	3,154	3,154	3,154	3,154	3,154	3,154	208	208	208	208	208	208
R-squared	0.263	0.534	0.279	0.546	0.190	0.259	0.320	0.473	0.282	0.461	0.373	0.453

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for country (SHARE)/East and West Germany (GAS), year dummies, marital status with divorced and singles as reference group, and a constant.

Table 1.8 Fixed effects estimation on first period employed observations only

	SHARE			GAS		
Dependent	Employment	Working hours	Early retirement	Employment	Working hours	Early retirement
Grandchild care	0.00723	0.308	0.0117	-0.00967	-0.226	-0.00444
	(0.0114)	(0.435)	(0.00952)	(0.00398)	(0.172)	(0.00334)
Married	-0.0578	-1.072	0.0149	0.0890	-13.06	-0.0127
	(0.268)	(10.19)	(0.223)	(0.241)	(10.43)	(0.202)
Widowed	0.0578	2.072	-0.0149	-0.173	-28.68**	0.452*
	(0.268)	(10.19)	(0.223)	(0.286)	(12.34)	(0.240)
Observations	2,766	2,766	2,766	222	222	222
R-squared	0.229	0.152	0.182	0.446	0.360	0.342
Number of individuals	922	922	922	74	74	74

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for year fixed effects, marital status with divorced and singles as reference group, and a constant.

Table 1.9 IV estimation (SHARE); Instrument: Firstborn a daughter

Dependent	Grandchild care	Employment		Working hours		Early retirement	
	First stage	OLS	IV	OLS	IV	OLS	IV
Grandchild care		-0.0220***	-0.0243	-0.731***	-0.535	0.00666***	0.0144
		(0.00278)	(0.0429)	(0.108)	(1.677)	(0.00227)	(0.0302)
Medium education	-0.158***	0.118***	0.118***	4.415***	4.447***	0.0166***	0.0178**
	(0.0176)	(0.00791)	(0.0103)	(0.302)	(0.399)	(0.00545)	(0.00717)
High education	-0.296***	0.256***	0.255***	10.02***	10.08***	0.00634	0.00865
	(0.0169)	(0.00872)	(0.0155)	(0.343)	(0.607)	(0.00617)	(0.0107)
Married	0.115***	-0.0269***	-0.0267***	-2.212***	-2.234***	0.00366	0.00280
	(0.0169)	(0.00912)	(0.0103)	(0.371)	(0.414)	(0.00617)	(0.00702)
Widowed	0.153***	-0.0191	-0.0187	-1.992***	-2.022***	0.0520***	0.0508***
	(0.0357)	(0.0151)	(0.0164)	(0.600)	(0.648)	(0.0119)	(0.0128)
#Children	0.0356***	-0.0253***	-0.0252***	-0.767***	-0.774***	-0.00791***	-0.00819***
	(0.00867)	(0.00374)	(0.00404)	(0.153)	(0.166)	(0.00249)	(0.00270)
#Other daughters	0.0659***	0.00692	0.00707	0.122	0.110	-0.00350	-0.00400
	(0.0123)	(0.00521)	(0.00590)	(0.207)	(0.232)	(0.00361)	(0.00418)
First child a daughter	0.142***						
	(0.0137)						
Age dummies	yes	yes	Yes	yes	yes	yes	yes
Observations	27,440	27,440	27,440	27,440	27,440	27,440	27,440
R-squared	0.082	0.241	0.241	0.222	0.222	0.242	0.241
F-value	108.09						

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Controlling for country and year dummies, marital status with divorced and singles as reference group, and a constant.

If, however, the assumptions of the lagged estimation are correct (i.e., the determinant of grandchild care in the present is labour supply in the past), applying a fixed effect model is likely to overestimate the results. That is, the real impact would be smaller than the impact estimated by the fixed effects model. We cannot prove the validity of either assumption; however, we can consider them both as robustness checks to our OLS results as neither approach contradicts our former findings. Both point in the direction of the causal effect across Europe being smaller than expected, while the German results indicate the causal effect to be larger than indicated by OLS.

These panel estimations allow us to control for time-invariant personal characteristics influencing both grandchild care and labour supply. If, however, there were time-varying unobservables that were correlated with the variables of interest, the lagged dependent estimation would still be biased. In the next section, we thus use exogenous variation in the amount of grandchild care.

1.4.5 Instrumental Variable Estimation

We have an instrument at hand that we believe, as we discuss below, causes variation in the amount of grandchild care and that is otherwise unrelated to labour supply. This allows us to make use of an instrumental variable approach. The instrument is the gender of the firstborn child. It makes use of the random distribution of a child's gender and its effect on grandchild care has been discussed in the literature (see Rupert and Zanella, 2011). We need to reduce the sample to those respondents who indicate the gender and birth year of every child they have. This leaves us with 24,997 observations in SHARE. As for the GAS, we find an insignificant effect in the first stage, and similar results in the second stage, those results are not shown here.

Having a daughter as a first child makes a grandmother provide grandchild care earlier in life, as women have children earlier in life than men. Parents whose firstborn child is a girl are thus likely to become grandparents earlier in life than parents whose firstborn child is a boy. For those 48% (or 8,580) of respondents for whom we have this information, the age of the grandmothers at the birth of their first grandchild was, on average, 50.6 when the grandmother's firstborn child was a girl, and 51.2 years for those whose firstborn was a boy; these values are statistically different from one another. So, when we instrument for the gender of the firstborn while controlling for the number of children and the presence of further daughters, we should be able to use the variation in timing only. The exclusion restriction in this case says that the only reason for the gender of the firstborn to affect the labour supply of grandmothers is through grandchild care provided earlier in life.

As Column 1 of Table 1.9 shows, the first-stage estimate is significantly positive; having a daughter as the firstborn significantly increases the amount of grandchild care a grandmother provides by 1.42 hours. With an F-value of 108.09, there is no concern over weakness of the instrument. The 2SLS results are not significantly different from zero or the OLS results. Nevertheless, when we look at the point estimates, we see that the 2SLS finds a 2.43

percentage point lower employment probability for grandmothers who increase their grandchild care by 10 hours per week; working hours decrease by .535 hours. And the likelihood of early retirement increases by 1.4 percentage points. In line with the panel estimations, this points in the direction of a very small causal impact. However, in the following, we discuss a set of channels that might lead our 2SLS results constituting a lower-bound estimate only, which might also at least partially explain our insignificant results.

Are there direct and indirect ways the gender of the first child could affect the labour supply of grandmothers? Birth order is known to affect a child's educational attainment (Ejrnaes and Pörtner, 2004), and higher education leads to a higher employment propensity. The education and employment of a woman's children should influence her labour supply, mostly through the channel we are interested in – grandchild care – as employed children, and especially daughters, are more likely to rely on their mothers for grandchild care.

Bedard and Deschênes (2005) use the gender of the firstborn to instrument for the endogeneity in the instability of marriages. They use US registry data and find a very small but significant stabilizing impact on couples if the firstborn child is a son. However, even if our instrument increases marital instability, this should not impact our findings, as divorced women have to make a living on their own and are thus more likely to work. A positive impact on labour supply, however, would lead us to underestimate the real impact and might be why we do not find significant results. Thus, to this point we have not been able to discover a channel that could jeopardize this instrument.

Can We Falsify Our Instrument?

If our instrument is valid and it really is grandchild care that is influencing the labour supply of grandmothers, we should thus not find an impact of the gender of the first born child on employment in the group of grandchildless women.

Table 1.10 shows the results of regressing our instrument directly on the outcome variables (reduced form): for employment, the results for grandmothers are in Column 1 and for the grandchildless in Column 2. Even though the coefficients are insignificant, for the elderly with grandchildren, the gender of the firstborn negatively correlates with employment and working hours; for the women without grandchildren, the coefficients are smaller or even change sign, which supports the validity of our instruments. Thus, there does not appear to be another channel leading to negative correlation of the gender of the firstborn on the labour supply of grandmothers.

Also, we can look at the impacts on non-caring grandfathers living in households with caring grandmothers. Table 1.11 shows that the grandchild care of the female partner is positively correlated with the employment of the non-caring partner. There does not appear to be an unobserved factor negatively influencing the employment decision of couples if the female partner is providing grandchild care.

Table 1.10 Reduced form for elderly women with and without grandchildren for number of daughters (SHARE)

Dependent	Employment		Working hours		Early retirement	
	with gc	without gc	with gc	without gc	with gc	without gc
Medium education	0.116***	0.125***	4.536***	4.471***	0.00884	0.0223***
	(0.00984)	(0.0127)	(0.375)	(0.487)	(0.00767)	(0.00719)
High education	0.242***	0.272***	10.16***	10.06***	0.000472	0.0116
	(0.0119)	(0.0130)	(0.464)	(0.513)	(0.00965)	(0.00759)
Married	-0.0237*	-0.0340**	-1.697***	-2.982***	0.00167	0.00325
	(0.0121)	(0.0135)	(0.478)	(0.561)	(0.00909)	(0.00782)
Widowed	-0.0215	-0.0224	-1.964***	-1.960*	0.0566***	0.0344*
	(0.0188)	(0.0251)	(0.721)	(1.044)	(0.0155)	(0.0179)
#Children	-0.0188***	-0.0358***	-0.515***	-1.220***	-0.0110***	2.57e-05
	(0.00443)	(0.00681)	(0.185)	(0.268)	(0.00321)	(0.00379)
#Other daughters	0.00115	0.0163*	-0.148	0.601*	-0.00260	-0.00612
	(0.00616)	(0.00903)	(0.244)	(0.362)	(0.00475)	(0.00491)
First child a daughter	-0.00161	-0.00104	-0.0443	0.0242	-0.000457	0.00330
	(0.00788)	(0.00927)	(0.304)	(0.367)	(0.00625)	(0.00540)
Age dummies	yes	yes	yes	yes	yes	yes
Observations	15,282	12,158	15,282	12,158	15,282	12,158
R-squared	0.234	0.205	0.225	0.192	0.252	0.184

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Controlling for country and year dummies, marital status with divorced and singles as reference group, and a constant.

Table 1.11 OLS of non-caring husband's labour supply on female grandchild care

Dependent	Employment	Working hours	Early retirement
Wife's care grandchild care	0.000644	-0.00114	-0.000989
	(0.00150)	(0.0759)	(0.00120)
Medium education	-0.0226	0.870	0.0449
	(0.0400)	(2.130)	(0.0320)
High education	0.116***	4.829**	-0.00841
	(0.0446)	(2.346)	(0.0382)
Married	-0.0967	1.200	-0.00330
	(0.0661)	(2.767)	(0.0638)
Widowed	-0.463***	-18.63***	0.447***
	(0.0927)	(4.248)	(0.0919)
#Children	-0.00893	-0.191	0.00865
	(0.0123)	(0.888)	(0.0103)
Observations	954	954	954
R-squared	0.244	0.175	0.250

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Controlling for country and year dummies, marital status with divorced and singles as reference group, and a constant.

1.5 Conclusion

Grandchild care is known to increase young mothers' labour supply (Posadas and Vidal-Fernandez, 2012; Garcia-Moran and Kuehn, 2012). But how does informal child care affect those providing it? Our focus is on how grandchild care impacts the labour supply of the grandmothers. In line with Rupert and Zanella (2011) and the literature on elderly care (Ettner, 1995, 1996; Heitmüller, 2007; Bolin et al., 2008), we find a small negative impact.

Our OLS results indicate a negative correlation between grandchild care and the labour supply of grandmothers and a positive correlation between grandchild care and early retirement. Across Europe, ten more hours of grandchild care correlate to a reduction in the employment probability of 2.17 percentage points and a reduction in weekly working hours of about 44 minutes, as an upper bound. Thus, it seems that it is predominately leisure and not working time that is reduced when grandchild care increases. The negative impact of grandchild care is more pronounced in Post-Communist countries and less pronounced in Southern Europe. To address possible endogeneity issues, we make use of the panel structure of the data and explore a potential instrument. Causal analyses point in the direction of even smaller and mostly insignificant effects.

Grandchild care, even though it is crucial for the labour supply of young mothers, seems to have hardly any impact on the labour supply of grandmothers. However, it is questionable whether this finding holds if policies encouraging this kind of child care were introduced. This would strongly depend on the economic incentives that were implemented along with the policy.

Appendix A Figures

Figure A.1 Regional distribution of employment

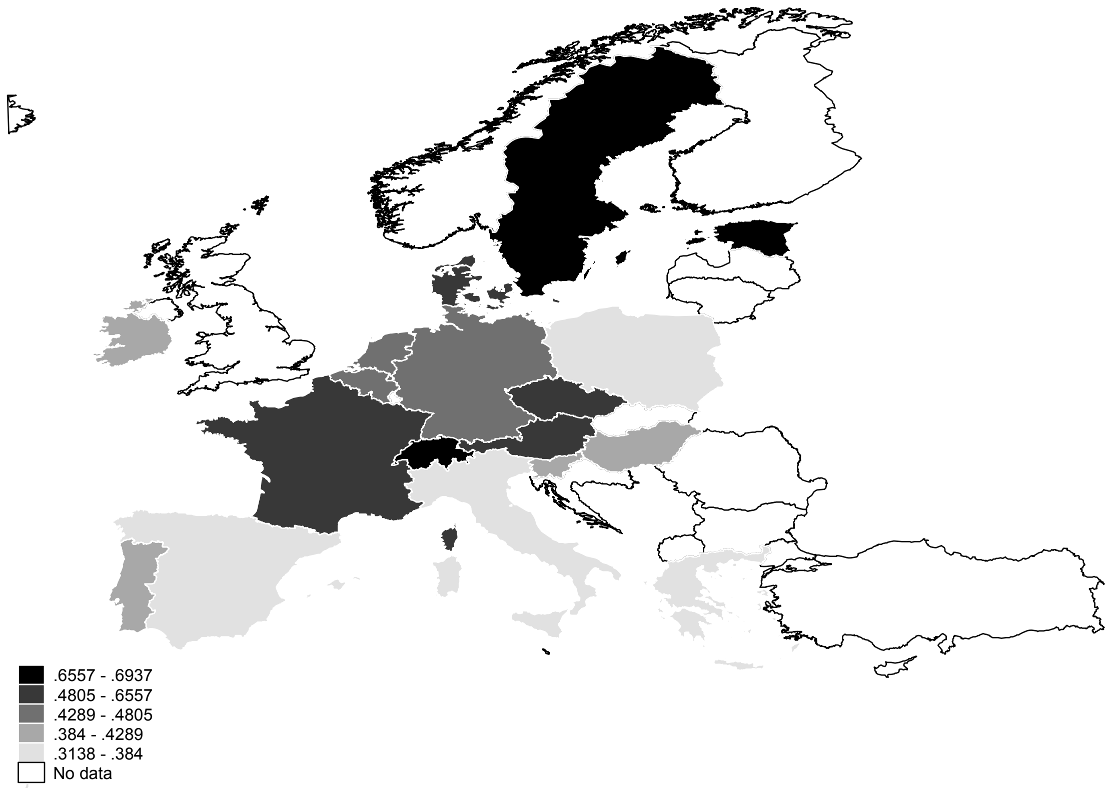

Figure A.2 Regional distribution of working hours

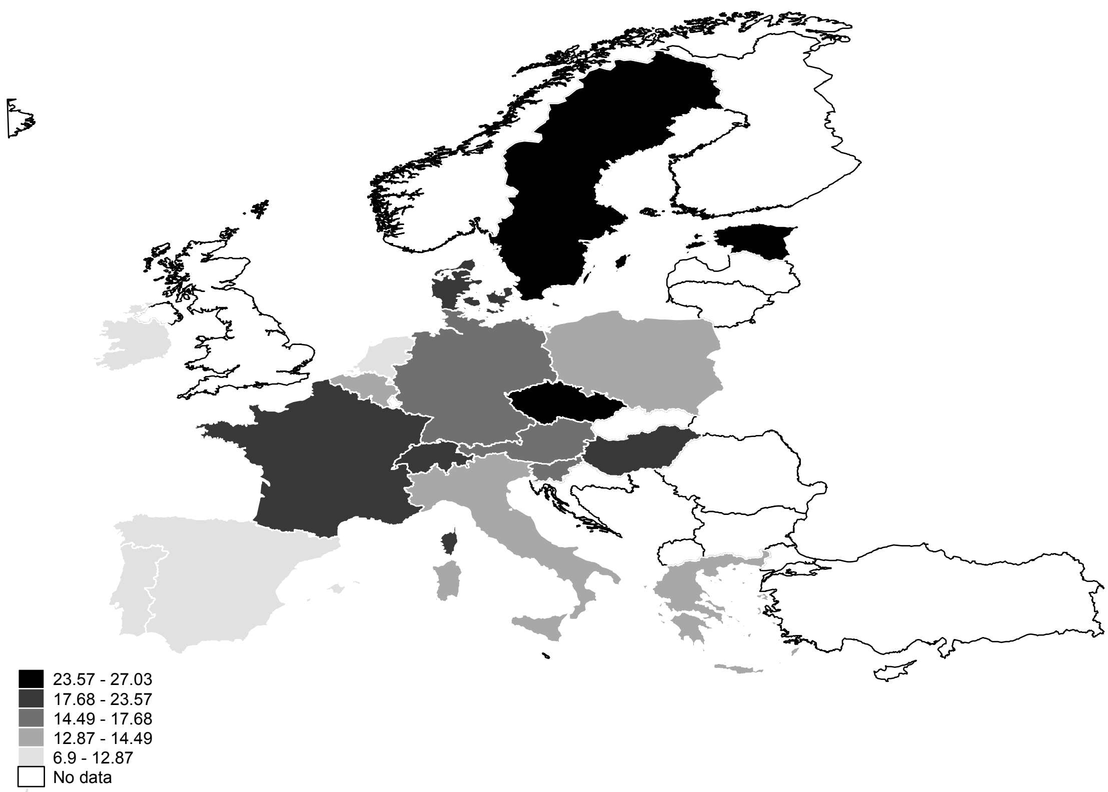

Figure A.3 Regional distribution of early retirement

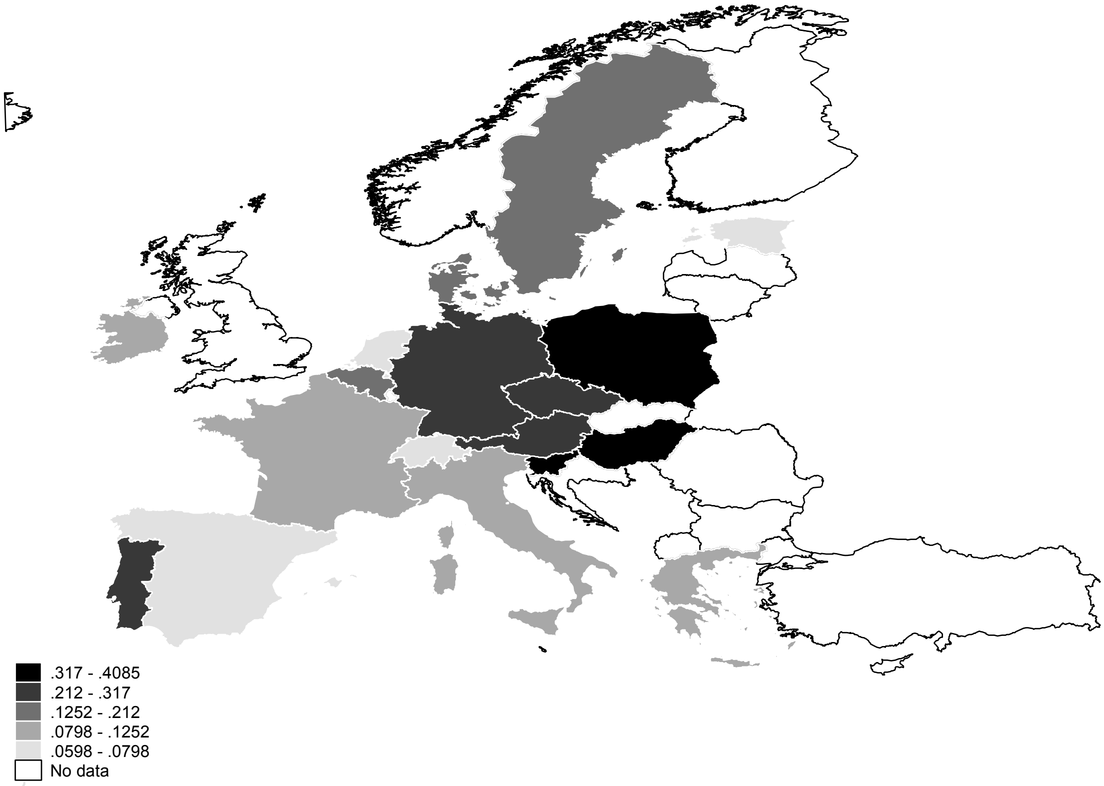

Figure A.4 Regional distribution of grandchild care intensity (hours per week)

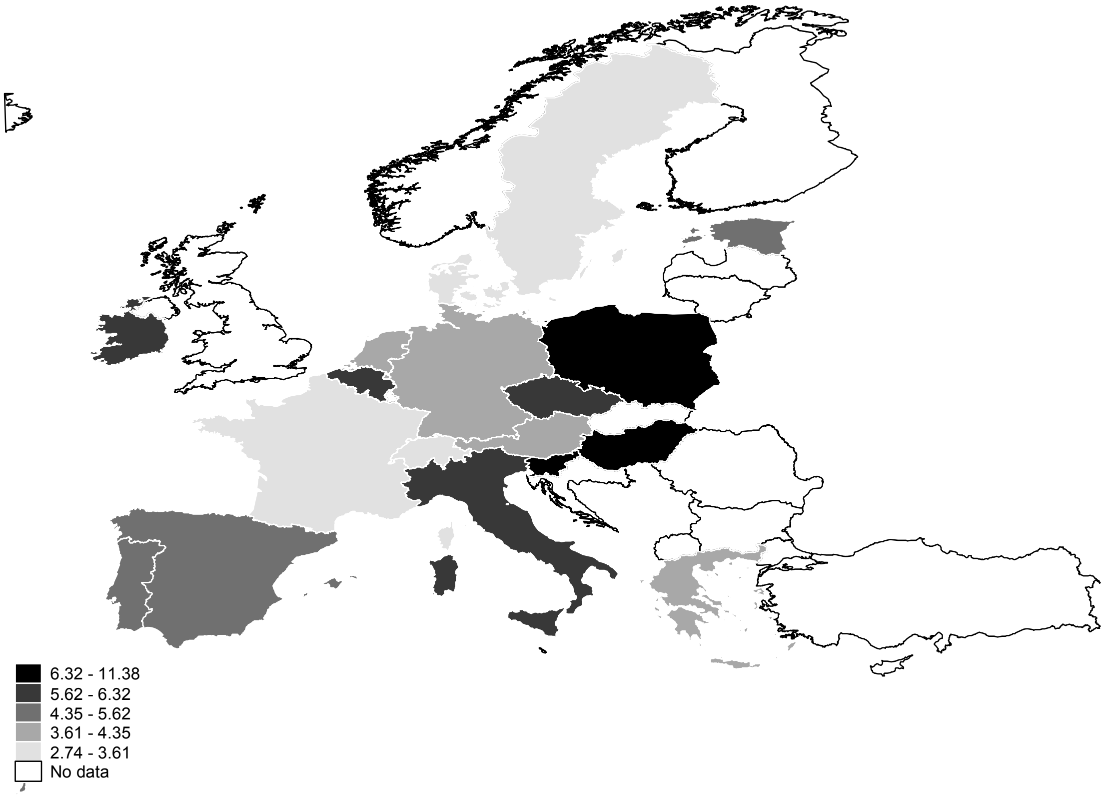

Figure A.5 Country-specific correlation of grandchild care and employment

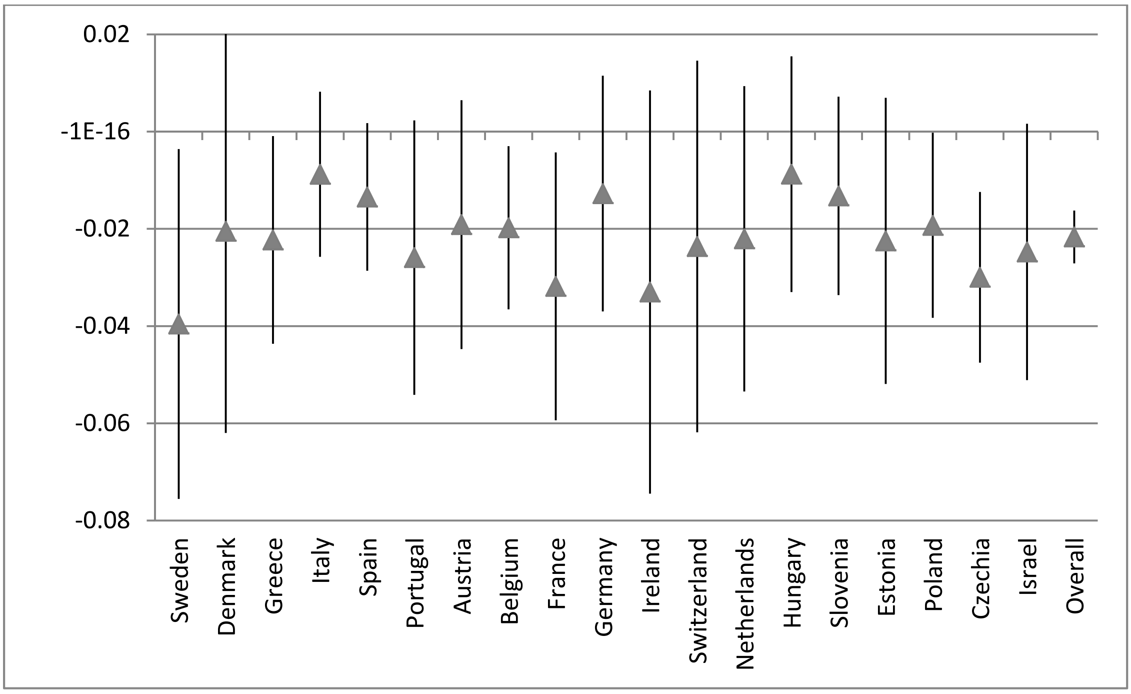

Figure A.6 Country-specific correlation of grandchild care and working hours

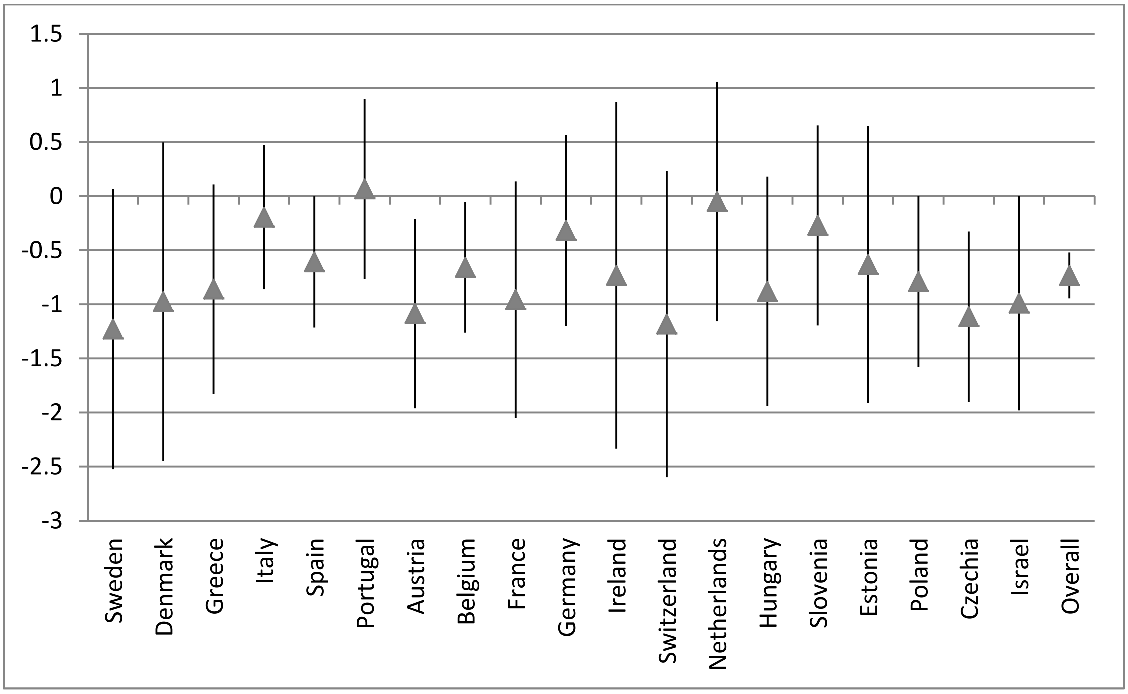

Figure A.7 Country-specific correlation of grandchild care and early retirement

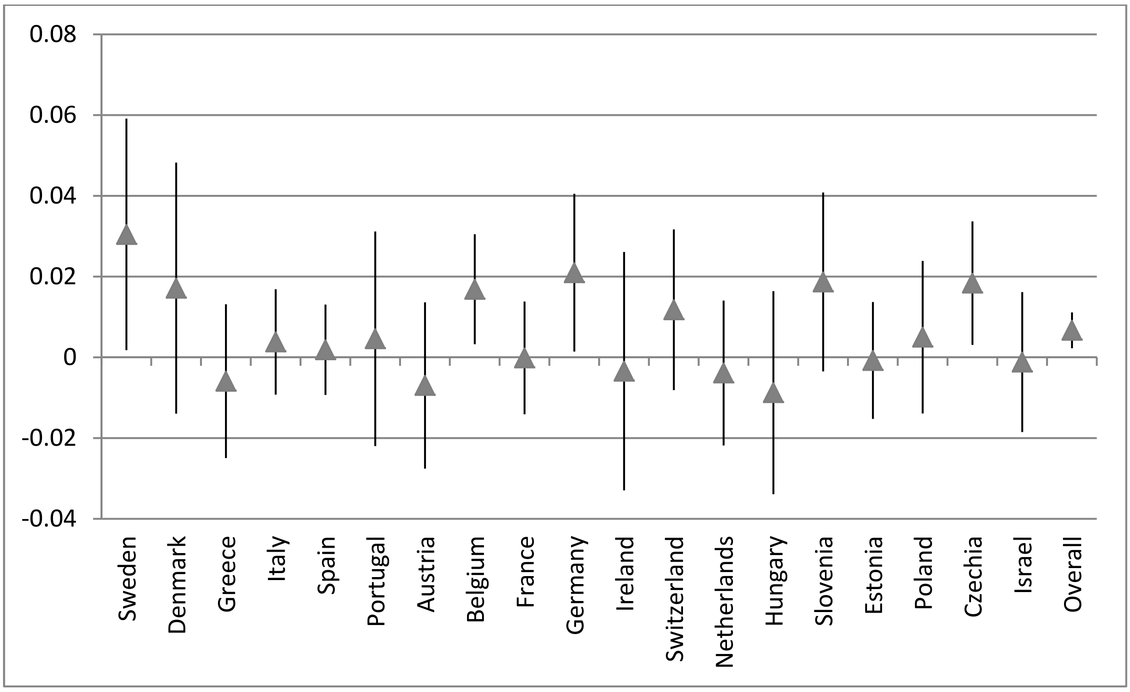

Table A.1 Fixed effects estimation

	SHARE			GAS		
VARIABLES	Employment	Working hours	Early retirement	Employment	Working hours	Early retirement
Grandchild care	0.00363	0.0452	-0.00257	-0.134***	-3.490**	-0.0268
	(0.00721)	(0.257)	(0.00644)	(0.0412)	(1.609)	(0.0315)
Married	-0.144	0.139	-0.0960	0.113	-12.39	-0.00116
	(0.148)	(5.269)	(0.132)	(0.262)	(10.22)	(0.200)
Widowed	-0.0536	3.135	-0.210	0.0542	-21.14*	0.354
	(0.163)	(5.817)	(0.146)	(0.293)	(11.43)	(0.224)
Observations	4,731	4,731	4,731	312	312	312
R-squared	0.070	0.068	0.092	0.225	0.202	0.273
Number of individuals	1,577	1,577	1,577	104	104	104

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for year fixed effects, marital status with divorced and singles as reference group, and a constant.

Chapter 2
Should We Care that They Care?
Grandchild Care and Its Impact on Grandparent Health[1]

2.1 Introduction

Increasing life expectancy and declining fertility rates are dominant demographic characteristics of most Western economies. Europe, in particular, is an ageing continent. According to mainstream projections, by 2025 more than one-fifth of the European population will be age 65 or older, with the number of persons more than 80 years old growing especially rapidly. This trend will put a great deal of pressure on most societal systems, including social insurance and healthcare. For example, the total spending for age-related health care is expected to sharply increase. In most European countries, public health expenditures have already doubled their share of GDP since the 1970s. Currently, these expenditures are as much as 11% of the national GDP in some European countries (Przywara 2010).

At the same time, female labour supply has increased considerably, supported by an increase in public child-care provision. Appropriate public solutions for childcare have become a significant aspect of family and labour market policy. However, publicly-financed childcare is not the only option parents might have. For many, informal childcare by friends, neighbours, and, most importantly, grandparents is an attractive alternative. Potential advantages of informal childcare include its flexibility, a better fit to personal needs, and accessibility at short notice as well as during nonbusiness hours. What makes informal childcare a particular relevant object of study is that it not only helps women combine labour force participation and family life, but it may also affect those providing it. Qualitative studies of this issue in Britain show that most of the informal care is provided by grandparents (Wheelock and Jones 2002).

Thus, in light of an increasing number of grandparents available for grandchild care due to their increasing life expectancy combined with working parents relying on grandparents for childcare, this paper investigates how grandchild care affects the older generation.

Scholars identify two potential ways grandchild care could affect grandparent health. On the one hand, grandchild care can be rewarding and thus allow the grandparent to derive more satisfaction from the role of being a grandparent (Pruchno 1999), leading to a positive effect

[1] This paper uses data from SHARE wave 4 release 1, as of November 30th 2012 or SHARE wave 1 and 2 release 2.5.0, as of May 24th 2011 or SHARELIFE release 1, as of November 24th 2010. The SHARE data collection has been primarily funded by the European Commission through the 5th Framework Programme (project QLK6-CT-2001-00360 in the thematic programme Quality of Life), through the 6th Framework Programme (projects SHARE-I3, RII-CT-2006-062193, COMPARE, CIT5- CT-2005-028857, and SHARELIFE, CIT4-CT-2006-028812) and through the 7th Framework Programme (SHARE-PREP, N° 211909, SHARE-LEAP, N° 227822 and SHARE M4, N° 261982). Additional funding from the U.S. National Institute on Aging (U01 AG09740-13S2, P01 AG005842, P01 AG08291, P30 AG12815, R21 AG025169, Y1-AG-4553-01, IAG BSR06-11 and OGHA 04-064) and the German Ministry of Education and Research as well as from various national sources is gratefully acknowledged (see www.share-project.org for a full list of funding institutions).

on the grandparent's health. Being a grandparent has a positive impact on the life satisfaction of the elderly (Powdthavee 2011) and grandchild care strengthens intergeneration relations (Pruchno 1999). Occasional grandchild care (200 to 500 hours per year) increases the likelihood of exercising and of reporting fewer functional limitations. Moreover, those who continue to provide this level of care show fewer depressive symptoms (Hughes et al. 2007). On the other hand, the responsibility and the associated physical and mental stress of providing such care may harm the health of the elderly (Hughes et al. 2007). Indeed, some empirical literature finds that custodial grandchild care (National Family Health Survey, NFHS) and grandchildren joining the grandparent household (Health and Retirement Survey, HRS) have a detrimental effect on grandparent health (Blustein et al. 2004; Szinovacz and Davey 2006; Fuller-Thomson et al. 1997; Szinovacz et al. 1999). However, grandparents in this situation might also be experiencing harmful effects from the circumstances resulting in the need for them to care for their grandchildren and thus one must be careful in interpreting the negative health outcome as purely a consequence of grandchild care. Grandchild care shows a negative effect on health only in cases of long hours or full-time care and low income (Hughes et al. 2007), which suggests that it may be the intensity of grandchild care that is an important determinant of its effect on grandparent health.

This study looks at the effect of occasional grandchild care on physical health, cognitive functioning and mental health of grandmothers in Europe. Using a representative European dataset on the elderly (SHARE), we find that the positive correlation between grandchild care and grandparent health persists when controlling for several possible channels that might induce the correlation. We employ semi-parametric propensity-score-based matching, as an alternative to OLS, to check the robustness of the results to underlying functional form of the estimation approach. To see whether this relation can be interpreted as causal, we exploit the panel character of the data using lagged dependent variable and fixed effects estimation, and adopt an instrumental variable approach; these causal effects are less clear-cut.

The remainder of this paper is organized as follows. Section 2.2 discusses the underlying theoretically expected link between childcare and health status and provides some examples of the motivations and circumstances under which grandchild care takes place. Section 2.3 reviews the empirical literature on the topic. Section 2.4 presents the data and Section 2.5 discusses the empirical results. Section 2.6 concludes.

2.2 Why Do Grandparents Offer Care, and Why Do Their Children Request It?

Grandparents and parents agree on grandchild care for various reasons, and the motivation for and the circumstances of grandchild care may have much to do with how providing it affects grandparent health.

First, grandparents may want to spend time with their grandchildren. Powdthavee (2011) shows a positive impact of being a grandparent on the life satisfaction of the elderly, and this effect might coincide with grandchild care. As grandparents usually do not have primary responsibility for the child, but may receive a great deal of unconditional affection, grandchild care can be very rewarding. Providing care also gives grandparents the opportunity of handing down knowledge from their own life experience.

Second, grandparents may wish to provide grandchild care in order to help their children. Raising children and assuring the economic welfare of a family at the same time can be demanding and parents with young children may feel relieved if they can rely on their parents for help with childcare.

Third, grandparents might also take into account intertemporal reciprocity. One day, they themselves will need help. Grandparents may provide grandchild care to their children today in the expectation of receiving care in return when they need it. This would be consistent with findings by Cox and Rank (1992), who find inter-vivos (between living) transfers to be more based on exchange than on altruism.

When looking at the "demand side" explanation for grandchild care, that is, children asking their parents to provide grandchild care, three examples help illustrate how the nature of care can depend on family structure and labour market behaviour.

First, take the case of a family in which one parent works and one parent looks after the children. In this case, grandparental care is not needed in a strict sense, and thus may be of an optional and irregular character. The core family is relatively flexible concerning its demand for grandchild care. The task thus can be adapted to personal preferences of the grandparent.

The second example involves two types of families: single parents and intact families with a double income, that is, both parents are working. In both types of family, parents are responsible for childcare and for the financial situation of the family. In this situation, the care-providing grandparent will need to adapt his or her personal life to the schedule of the core family. Even if the family has access to public childcare, due to restrictive open hours, high cost, and long working hours, demand for care is less flexible. The family relies on the grandparent to take on a certain amount of responsibility, maybe provide spontaneous care if needed, and spend more hours providing care.

A third example is highly intensive grandchild care, for example, custodial care or cases where the grandchildren live in the same household as the grandparents. In these situations, the grandparents have primary responsibility for their grandchildren. This can occur when the grandchildren's core family falls apart due to drug abuse, incarceration, or the death of a parent. As the literature review will show, these types of grandchild care are likely to result in poor grandparent health. However, it must be remembered that it could be the circumstances leading to the need for intensive grandchild care that are causing the poor health outcome, not necessarily the provision of care itself.

2.3 Previous Literature

There are two strands in the literature on grandparent childcare. The larger body of sociological, gerontological, and health-related literature focuses on highly intensive and custodial grandchild care, which often leads to a negative effect on grandparent health. Only a handful of studies looks at "occasional" childcare, and this work finds that providing this type of childcare is beneficial for the health of grandparents.

However, it could be the initial health endowment and socio-demographic characteristics that lead to these diverging effects if grandparents self-select into the different types of care. Fuller-Thomson and Minkler (2001) look at the characteristics of grandparents and the sort of care they provide (occasional, extensive, or custodial grandchild care). They find that the population of occasional care providers is less likely to be poor and more likely to have completed high school. Extensive and custodial caretakers are similar in their characteristics; however, extensive care is more likely to be provided by younger and married grandmothers who are living in close proximity to an adult child. The probability of providing custodial grandchild care is strongly influenced by co-residing children and the loss of a child (Fuller-Thomson et al. 1997).

In the US, compared to non-care-providing grandparents, care-providing ones are at an initial health disadvantage, but the activity itself does not make their health worse (Hughes et al. 2007; Musil et al. 2011). Grandmothers who start or continue to provide occasional care report better self-rated health than non-care-providing grandmothers. Those grandmothers who start providing 200 to 500 hours of care per year are more likely to exercise, to report fewer functional limitations, and those continuing this level of care show fewer depressive symptoms. Grandparents who continue to provide 200 hours or increase their hours of care also increase their probability of exercising. Only long hours or full-time care and low income providers of grandchild care seem to suffer a negative effect on health (Hughes et al. 2007). Two recent papers use instrumental variable approaches to overcome the endogeneity of grandchild care. The instruments they use are grandparenthood (Arpino and Bordone 2012), the number of grandchildren and marital status of adult children (Ku et al., 2012). Both studies find a positive effect, on cognitive functioning (Arpino and Bordone 2012) as well as a reduction of mobility limitations (Ku et al., 2012). These instruments base on the assumption, that children do not take the provision of grandchild care by their parents into account, when deciding on their fertility. Gete and Porchia (2010) and Garcia-Moran and Kuehn (2012), however, show that children do take the availability and the current provision of grandchild care to the offspring of their siblings into account.

The larger part of the literature focuses on primary and custodial grandchild care, and much of this work relies on very small, and often unrepresentative, datasets. Burton (1992) uses a sample of grandparents that took care of their grandchildren because the grandchildren's parents were absent due to drug abuse. Based on in-depth interviews, Jendrek (1994) reports that grandparents engaged in primary care giving mainly to avoid their grandchildren being placed in foster care, and that they started to provide care long before a custody relationship had been established. The problems these grandparents face are manifold and range from financial difficulties to stress-related illnesses and social isolation (Roe and Minkler 1996). Miller (1991) reports an increased incidence of depression, insomnia, hypertension, back and stomach problems, and so forth due to the physical or emotional demands of taking on the role of grandparent caretaker. Deterioration in self-rated health is most likely for working grandchild care providers, great-grandmothers, and those caring for several grandchildren (Roe et al. 1996). Care-providing grandparents also report that the high demands of care provision lead to cancelling a medical appointment within the past year.

The research using large datasets also tends to concentrate on highly intensive care. The National Survey of Families and Households (NSHF), focuses on custodial or primary care, and the Health and Retirement Survey (HRS), asks about grandchildren living in the same household as the responding grandparent. Still, many of the health deficits among these grandparents are not caused by grandchild care provision, but are due to their socioeconomic characteristics and to prior health status (Hughes et al. 2007). Compared to non-care-providing grandparents, custodial-care-providing grandparents show significantly higher functional health limitations (Minkler and Fuller-Thomson 1999), they are more likely to be poor, to have a low level of education, and to be socially isolated and depressed. Minkler et al. (1997) look at the impact of custodial grandchild care and add lagged depressive symptoms as well as self-rated health status and social integration to the general socio-demographic characteristics. They find the effect of grandchildren moving into the grandparent's household to have an ambiguous impact on health. Bulstein et al. (2004) find no detrimental effect of grandchildren living in the same household if a partner or an adult child co-resides. For grandmothers who live alone, however, grandchild care is found to increase the probability of reporting depressive symptoms. Szinovacz et al. (1999) look at the general well-being of caring grandparents and control for changes in marital status, care giving to other family members, and spouse's health as potential risk factors influencing grandparent health. They find a significant negative impact of starting care on the grandmother's health, as well as reduced church attendance and a lower frequency of socializing. At the same time, however, the support grandparents receive from friends and relatives increases.

Grandfathers are mostly involved in grandchild care if they co-reside with a care-providing grandmother, and the literature does not find significant benefits to these men from a co-residing grandchild, but finds detrimental effects of grandchildren moving out of the household (Szinovacz et al.1999).[2]

Thus, it appears that custodial grandchild care is likely to coincide with a disadvantageous social background; however, the more common type of care is occasional grandchild care, and grandparents are likely to benefit from it.

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[2] Other consequences of grandchild care, such as child outcomes and the mid generation's labor supply, are also covered in the literature. Child outcomes of children raised by their grandparents are better than those of children raised by a single parent and not significantly different from those raised in intact families when it comes to behavioral and health aspects. However, they do differ in their academic performance (Solomon and Marx 1995). Grandchild care highly correlates with geographical proximity to the grandmother and has a strong positive impact on the female labor supply of the mid generation (Compton and Pollak 2011; Dimova and Wolff 2008, 2011).

2.4 Data and Estimation Method

2.4.1 Survey of Health, Ageing and Retirement in Europe (SHARE)

We use the Survey of Health, Ageing and Retirement in Europe (SHARE). Participating countries are: Austria, Belgium, Czechia, Denmark, Estonia, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Netherlands, Poland, Portugal, Slovenia, Spain, Sweden and Switzerland. The dataset covers the non-institutionalized (i.e., not living in nursing homes, etc.) population aged 50 and older and their spouses (who are interviewed even if they are younger than 50). The multidisciplinary dataset consists of three panel waves from 2004/2005, 2006/2007 and 2011/2012. The 2008 questionnaire focuses on retrospective life history and does not cover grandchild care information.

The panel questionnaire covers socioeconomic status and social and family networks, and is comparable across countries. Detailed health information is available. To improve statistical power, we generate an index of physical health from a set of five indicators: the number of chronic condition (diabetes, high blood pressure, chronic lung disease etc.), the number of symptoms (back pain, heart trouble, swollen legs etc.), number of limitations concerning mobility, arm function and fine motor limitations (walking 100 meters, sitting for about two hours, climbing several flights of stairs without resting etc.), number of limitations with activities of daily living (adl, like dressing, walking, bathing etc.), number of limitations with instrumental activities of daily living (iadl, like using a map, preparing a hot meal or shopping groceries).

For chronic conditions and the number of symptoms, the waves provide varying numbers of categories; we use only those available in all waves and subsume all those not available in all waves into the category of other condition. Cognitive functioning measures memory, i.e. the immediate and the delayed recall of up to ten words.

The indices consist of the equally weighted average of the z-scores of their components. Components are recoded if necessary, so that the highest value is the most preferable. The z-scores are obtained by subtracting the mean in the estimation sample (after dropping all observations showing missing observations in any of the components) and dividing by the standard deviation. The standardized components, thus, have a mean of zero and a standard deviation of one. To generate the indices, we then sum the standardized components and divide this sum by the number of components.

Mental health is generated using the standardized Euro-D depression index, which sums the number of depressive symptoms a person reported to have experienced. Depressive symptoms include, for example, trouble sleeping, self-blame, guilt, suicidal feelings, and loss of interest or appetite (for descriptive analyses, see Table 2.1).

A mayor advantage of SHARE compared to HRS and NFHS is that it provides the age of the youngest grandchild for each respondent, (HRS data report only the age of co-residing grandchildren, and NFHS concentrates on primary or custodial care). In the SHARE questionnaire, all elderly who claim to have grandchildren are asked whether they provided grandchild care.

Table 2.1 Descriptives: Health outcomes, grandchild care and socio-demographics

Variable	Description	Obs	Mean	StdDev	Min	Max
#Chronic conditions	diabetes, high blood pressure, chronic lung disease etc.	29427	8.4533	1.3138	1	10
#Symptoms	back pain, heart trouble, swollen legs etc.	29427	10.0033	1.9580	0	12
Mobility	number of limitation concerning mobility, arm function and fine motor limitations (walking 100meters, sitting for about two hours, climbing several flights of stairs without resting etc.)	29427	8.2852	2.2298	0	10
#ADL	number of limitations with activities of daily living (dressing, walking, bathing etc.)	29427	5.8319	0.6611	0	6
#IADL	number of limitations with instrumental activities of daily living (using a map, preparing a hot meal or shopping groceries)	29427	6.7204	0.7946	0	7
Immediate recall	counts of recalled words out of ten words that were asked to remember	29427	5.2594	1.7480	0	10
Delayed recall	counts of recalled words out of ten words that were asked to remember	29427	3.8730	2.0724	0	10
Euro-D	number of depressive symptoms for example trouble sleeping, self-blame, guilt, suicidal feelings, and loss of interest or appetite.	29427	9.2655	2.3315	0	12
Grandchild care	average weekly hours of grandchild care	29427	8.8314	12.4413	0	38.7
Care frequency	Never cared in the last 12 months	29427	0.3552	0.4786	0	1
	less than montly	29427	0.1532	0.3602	0	1
	almost every month	29427	0.1309	0.3373	0	1
	almost every week	29427	0.2283	0.4197	0	1
	almost daily	29427	0.1324	0.3390	0	1
Age	age in years	29427	64.0242	8.0624	45	90
Education	low education (isced1/2)	29427	0.5059	0.5000	0	1
	medium education (isced3/4)	29427	0.3264	0.4689	0	1
	higher education (isced5/6)	29427	0.1677	0.3736	0	1
Married	1 if married	29427	0.7311	0.4434	0	1
Widowed	1 if widowed	29427	0.1601	0.3667	0	1
Retired	1 if retired	29427	0.4819	0.4997	0	1
Employed	1 if employed	29427	0.2265	0.4186	0	1
Unemployed	1 if unemployed	29427	0.0326	0.1777	0	1
Sick	1 if chronically ill	29427	0.0388	0.1931	0	1
Homemaker	1 if homemaker	29427	0.2201	0.4143	0	1
Homeowner	1 if owns real estate	29427	0.5167	0.4997	0	1
#Children	number of children	29427	2.6864	1.3134	1	17
#Grandchildren	number of grandchildren	29427	3.9315	3.0569	0	23
Retired b/o health	1 if retired early because of bad health	29427	0.0592	0.2360	0	1

Table 2.2 Descriptives: Health outcomes, grandchild care and socio-demographics (contd')

Variable	Definition	Obs	Mean	StdDev	Min	Max
Closest child	same house/household	25618	0.2771	0.4476	0	1
	within a 5-km radius	25618	0.3845	0.4865	0	1
	5km to 25km	25618	0.1807	0.3848	0	1
	25km to 100 km	25618	0.0863	0.2809	0	1
	over 100km	25618	0.0714	0.2575	0	1
Contact frequency	no contact	25618	0.1954	0.3965	0	1
	contact less than monthly	25618	0.2869	0.4523	0	1
	contact almost every month	25618	0.3432	0.4748	0	1
	contact almost every week	25618	0.1436	0.3507	0	1
	contact almost daily	25618	0.0308	0.1729	0	1
Received help	1 if received any help from a child	25618	0.1958	0.3968	0	1
Given help	1 if given any help to a child	25618	0.3200	0.4665	0	1
Charity	1 if done voluntary/charity work weekly	25618	0.0805	0.2721	0	1
Attend training	1 if attended educational or training course weekly	25618	0.0403	0.1967	0	1
Sport	1 if gone to a sport, social, or other club weekly	25618	0.1585	0.3652	0	1
Church	1 if taken part in activities of a religious organization weekly	25618	0.0934	0.2910	0	1
Politics	1 if taken part in a political or community-related organization weekly	25618	0.0107	0.1031	0	1

Those who answer "yes" are then asked for the frequency of care (less than monthly, almost every month, almost every week, almost daily), and, based on that frequency, they are also asked for the number of hours of care in wave 1 and 2 (the third wave provides the care frequency, but not the hours of care). From this information we calculate the weekly caring hours in the first two waves.

To optimize interpretability of the care frequency, we replace the standard values of the categorical variable by the mean weekly hours of grandchild care these categories had in the first two waves (0 for no care, 38.7 hours per week for almost daily, 11.3 hours per week for almost every week, 5.8 hours per week for almost monthly and 2.4 hours per week for less than monthly care). This adjustment means we do not have to assume that the categories have linear effects; it also aids interpretation of the coefficients.

We restrict the sample to 45- to 90-year-old females who report having at least one grandchild aged 16 or younger and have complete survey records. The final sample consists of about 29,461 grandmothers. Table 2.1 sets out variable definitions and descriptives of the measures for health and the explanatory variables.

2.4.2 Variable Selection

As a first step, we employ pooled OLS estimation to measure the partial correlation between grandchild care and grandparent health. However, a simple bivariate correlation might be misleading as healthy grandparents are more likely to be asked, and more likely to feel able, to look after their grandchildren. This would induce causality from the health status to grandchild care, that is, reversed causality. The literature on custodial care does not face this problem as grandparents providing custodial care are not able to make the decision about care provision depending on their health status; instead, due to the circumstances, they feel as though they have no choice but to take in their grandchildren. Occasional care, on the other hand, is likely to be provided voluntarily. The healthier grandmothers thus self-select into grandchild care, which leads to an upward bias of our results.

We control for age and education (dummies for medium and high education, with low education as the reference group), marital status (dummies indicating whether a person is currently married or is widowed; the reference group consists of singles and the divorced as both show similar patterns), current employment status, (dummies for homemaking, employment, unemployment, and chronically ill, with retired as the reference group), and wealth (a dummy variable for owning residence, being member of a cooperative, or owning a secondary home, holiday home, or other real estate or land). We also include the number of children and grandchildren as explanatory variables.

SHARE contains a great deal of information on the life of elderly people, most of which is only partially covered in the literature on custodial care. This allows us to separate the variation caused by confounding factors from the correlation of interest. Potentially distorting factors include support from their children and social engagement. By controlling for these factors, we can discover whether, for a given frequency of contact to one’s children, a given amount of social engagement etc., grandchild care still has an effect on grandparent health.

A grandmother providing grandchild care might be healthier because of her care provision; however, it might also be the contact with the children and the support she receives along with grandchild care that leads to better health. For example, contact with the children can lead to health-relevant information exchange; children can give their parents advice on whether to visit a doctor. On the other hand, frequent contact and the receipt of support could also indicate that the grandmother suffers some physical constraints. The frequency of contact is coded here the same way the care frequency is, with dummies for “no contact”, “less than monthly”, “almost every month”, “almost every week” and for “almost daily.” And we include a dummy indicating the receipt of any help.

Geographic distance to one’s children is likely to determine the frequency of contact to a large extent and to impact the likelihood of a grandparent to provide grandchild care. However, the child’s choice of where to live could be endogenous: grandparents in poor health may have to give up their own household and move in with their children, and children who anticipate that their parents may need help in the future may factor that into their residence location choice (Rainer and Siedler 2009).

Similarly, providing grandchild care is much more likely for grandmothers who have their children nearby, but the expectation of receiving grandchild care might induce children to live close to their parents.[3] Controlling for geographic distance allows us to compare the health of grandmothers living at the same distance from their closest child but who differ in the amount of grandchild care provided.

Also, grandmothers who provide care to their grandchildren might be active in more than one aspect of life. By including various aspects of social engagement, we ensure that we are comparing grandparents who have an equal level of engagement and are thus discovering variation in health caused solely by grandchild care. Social engagement can range from charity work to caring for a sick person to taking part in a religious or political organization. We control for at least weekly engagement in charity or voluntary work, care for a sick or disabled adult, provision of help to a friend, educational training, and participation in a sport, social, or other club or in a religious organization.

2.4.3 Estimation Design

We start with OLS estimates. As an alternative, we use a semi-parametric propensity score method. This method does not rely on a particular functional form of the regression equation; the approach is to compare the sample average of the outcome variable of caring grandmothers to grandmothers who have similar characteristics but do not provide grandchild care. The mean difference between the two groups can be interpreted as the average treatment effect, if two assumptions are fulfilled. The first assumption is the conditional independence or unconfoundedness assumption. It implies that systematic differences in the outcome between individuals with the same values of covariates, that is, the same propensity score value in the treatment and the comparison group, are fully attributable to the treatment variable. The assumption is not testable, but it is expected to be fulfilled if all relevant variables are observable. We do not claim to have access to all variables influencing the outcome; however, we have at our disposal a set of care- and health-relevant variables not used in the literature to date, and thus we do make a relevant contribution to this scholarship. The second assumption is the overlap or common support assumption, which postulates that individuals with the same characteristics have a positive probability of both providing and not providing grandchild care.

The estimation strategy consists of two steps. In the first step, the predicted probability of treatment (propensity score) is estimated using a probit model. This propensity score is then used to match observations.

The effect of grandchild care $\widehat{\theta_{ATT}}$ using the outcome difference between treated (T) and comparison grandmothers (C) can be estimated empirically as:

[3] As an example of how to cope with the endogeneity of location choice, Compton and Pollak (2011) look at a sample of mothers with young children whose husbands are serving in the U.S. military: the location of these families is determined by military needs, and is thus exogenous to the grandparents' location. They find that the labour supply of women living in close proximity to their mothers or mothers-in-law is greater than that of those living distant from parents.

(2.1) $\widehat{\theta_{ATT}} = \frac{1}{N}\sum_{i\epsilon T}\left[health_{care,i} - \sum_{j\epsilon C} w(i,j)health_{no\ care,j}\right]$

where N is the total number of treated grandmothers i, $health_{care}$ and $health_{no\ care}$ denote outcome values for treated and comparison observations j, respectively. The match of each treated grandmother is constructed as a weighted average over the outcomes of non-treated, where the weights $w(i,j)\ \epsilon\ [0,1]$ depend on the 'distance' between i and j.

The most popular matching method is nearest neighbour matching. However, the mean comparison for Kernel Epanechnikov matching with a bandwidth of 0.06 has the best fit with regard to the mean comparison after matching, see Appendix. Also, Kernel matching has better finite sample properties than k-nearest neighbour matching functions (Frölich 2004).

OLS and propensity score matching both build on the assumption, that all characteristics influencing grandparental health and grandchild care provision can be observed in practice. However, there may exist differences that cannot be observed.

Making use of the panel structure of our dataset, we can control for time invariant individual fixed characteristics. Still, we might be facing time-varying unobservable correlation with the variables of interest. To cope with that, we are looking for exogenous variation in the amount of grandchild care using an instrumental variable approach. The estimation methods applied here are similar to the ones used in Chapter 1. A detailed description can be found in 1.3.1 Estimation Designs.

2.5 Empirical Results

In this section, we show empirical results, starting with a description of the characteristics of caring grandmothers. In a first step we then show pooled OLS estimates, control for further possible channels that might induce the correlation we are interested in, and look at the patterns across Europe. We then move on to a propensity-score matching approach to check the robustness of the findings to the assumed underlying functional form. As to this point, estimated coefficients can only be interpreted as causal if we assume that all relevant factors influencing grandchild care and grandparent health have been included.

Thus in a next step we make use of the time dimension of our data by applying fixed effects and lagged dependent variable estimation, and use an instrumental variable: the gender of the firstborn child.

2.5.1 Which Grandmothers are Taking Care of Their Grand-children?

Table 2.1 shows that 35.6% of all grandmothers in this sample do not provide care to any of their grandchildren and 64.4% do (for a more detailed descriptive analysis of the care-relevant variables in SHARE, see Hank and Buber, 2009). Descriptive analysis (available on request) tell us that the amount of grandchild care is at about 9.7 hours per week for grandmothers aged between 45 and 69, at about 6.5 hour per week for grandmothers in their seventies, and at 3.0 hours for grandmothers in their eighties. Across education levels, grandmothers with a low level of education care for the longest hours (9.3 hours per week compared to 7.4 hours per week provided by grandmothers with a high level of education).

2.5.2 OLS Estimates of the Impact of Grandchild Care on Grand-parent Health

The pooled OLS results for the regression approach are shown in Table 2.3. Grandchild care has a persistent positive and statistically significant effect on grandmothers' health. The full regression output based on this step-wise modelling approach is given in Table B.1 in the Appendix and shows the coefficients for all control variables. Grandmothers providing ten more hours of grandchild care show a 2.3 percent of a standard deviation better physical health, when controlling for the grandmother's age and education. Adding further socio-demographic controls leads to only a minor reduction in the care coefficient. Even though we cannot infer causality from this, including the variable allows us to state that grandparents living at the same distance from their grandchildren have a significantly higher physical health if they provide grandchild care. Grandparents living at long distances from their children are healthier, but we strongly suspect distance to be an endogenous variable: they are able to live at a long distance from their children because they are healthier. Compared to grandparents who have no contact with their children, the ones who are in contact, but less than monthly, show significantly better physical health. No contact at all with one's children may be indicative of a family conflict.

Table 2.2 OLS regressions of health outcomes on grandchild care

Physical health				
Grandchild care	0.00233***	0.00179***	0.00162***	0.00188***
	(0.000329)	(0.000312)	(0.000328)	(0.000332)
Cognitive functioning				
Grandchild care	0.00238***	0.00193***	0.00204***	0.00222***
	(0.000385)	(0.000384)	(0.000409)	(0.000419)
Mental health				
Grandchild care	0.00166***	0.00102*	0.000483	0.000798
	(0.000528)	(0.000520)	(0.000553)	(0.000567)
Age	yes	yes	yes	yes
Education	yes	yes	yes	yes
Further socio-demographics		yes	yes	yes
Social interaction				yes
Observations	29,427	29,427	25,619	25,618

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for further socio-demographics: year dummies, education: high and medium with low education as the reference group, marital status: married, widowed, with divorced and singles as reference group, employment status: employed, retired, chronically ill, homemaker, with retired as reference group, possession of any real estate, number of children, number of grandchildren and retirement because of bad health.

The grandparents with almost daily contact with their children however, are less healthy compared to those with no contact. High frequency of contact with one's children thus does not seem to be an indicator for the frequency of grandchild care or for the exchange of health-relevant information but, instead, for a need for companionship and help. Just like close contact with a child, receiving help indicates a significant negative effect on the health status, while giving help to family members, friends, and neighbours, as well as all sorts of social engagement, show significant positive coefficients.

Table 2.2 provides the coefficients from a regression of physical, cognitive and mental health on grandchild care. For the baseline sample, the first two Columns show the coefficients of grandchild care when controlling for age and education as well as a set of country and year dummies (Column 1) and further socio-demographic characteristics like marital status, employment status, number of children and grandchildren (Column 2). Columns 3 and 4 show the change in the coefficient for the sample of observations that report all variables of social interaction. Column 3 thus corresponds to Column 2 run on the smaller sample. From here on we use the specification controlling for all socio-demographic factors as our baseline specification. In this specification, the effect of grandchild care on all outcomes is positive and statistically significant. Grandmothers providing ten more hours of grandchild care per week show 1.79 percent of a standard deviation higher physical health (significant at the 1 percent level), 1.93 percent higher cognitive functioning and 1.02 percent of a standard deviation higher mental health. Controlling for indicators of social interaction hardly changes the size of the coefficients for physical health and cognitive functioning. However, with the baseline identification run on the smaller sample of observations reporting social interaction, we see that the correlation between grandchild care and mental health decreases to about half the size and turns insignificant. Controlling for social interaction slightly increases the size of the insignificant coefficient.

2.5.3 Region Specific Estimation

Across European regions, there are large variations in cultural and demographic characteristics. Northern European countries are known to show high shares of public care provision for children as well as for the elderly, while in Southern Europe family ties are stronger (Bolin et al, 2008) and co-residence is described as the way that Southern Europeans make intergeneration transfers (Albertini et al. 2007).

Albertini et al. (2007) also point out that outside a shared household, the intergeneration exchange of help is rare in Southern Europe, while in Scandinavian countries there is a high share of grandparents looking after their grandchildren but for a relatively low number of hours. Western European countries show a higher variation in their patterns, lying somewhere in between these two extremes (Dimova and Wolff, 2011).

As the samples for individual countries vary strongly in size, and some are rather small, four groups of regions are generated: Northern Europe (Denmark, Sweden), Southern Europe (Greece, Italy, Spain, Portugal), Western Europe (Austria, Belgium, France, Germany, Ireland, Switzerland, Netherlands) and Post-Communist Countries (Hungary, Slovenia, Estonia, Poland, Czech Republic) (as Israel cannot be subsumed into either of those groups, we do not include it in this specification).

Table 2.3 OLS with region specific care coefficients

Dependent	Physical health	Cognitive functioning	Mental health
Grandchild care	0.000814*	0.00193***	0.000301
	(0.000493)	(0.000718)	(0.000845)
Grandchild care*Northern Europe	0.00150	-0.000882	4.02e-06
	(0.00165)	(0.00204)	(0.00269)
Grandchild care* Post-Communist	0.000844	-0.00144	0.000519
	(0.000776)	(0.00100)	(0.00127)
Grandchild care*Southern Europe	0.00140*	0.000781	0.00123
	(0.000775)	(0.000967)	(0.00131)
Northern Europe	0.0590***	0.217***	0.201***
	(0.0155)	(0.0208)	(0.0239)
Post-Communist Countries	-0.192***	-0.269***	-0.195***
	(0.0139)	(0.0163)	(0.0212)
Southern Europe	-0.194***	-0.472***	-0.300***
	(0.0170)	(0.0181)	(0.0257)
Socio-demographics	yes	yes	yes
Observations	28,618	28,618	28,618
R-squared	0.198	0.253	0.084

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Controlling for further socio-demographics: year dummies, education: high and medium with low education as the reference group, marital status: married, widowed, with divorced and singles as reference group, employment status: employed, retired, chronically ill, homemaker, with retired as reference group, possession of any real estate, number of children, number of grandchildren and retirement because of bad health.

Table 2.3 shows the results from a regression that controls for grandchild care, region dummies and the interaction of the two. In general, compared to Western European grandmothers, Post-Communist or Southern European grandmothers are on average less healthy, while Northern European ones are significantly healthier. Grandchild care providing Western European grandmothers, show .81 percent of a standard deviation better physical health when increasing their weekly time of care by 10 hours, Northern European and grandmothers in Post-Communist Countries do not differ significantly from the Western European pattern, and Southern European grandmothers show an additional positive coefficient of 1.40 percent which sums to give 2.21 percent of a standard deviation (.81+1.40). For cognitive functioning we do not find significant differences in the region specific care effects, while, due to the small point estimate and the large standard errors, for mental health we do not find a significant correlation at all. Southern European grandmothers' physical health thus seems to profit more from their grandchild care than grandmothers in the rest of Europe.

After controlling for social interaction and looking at regional variation, grandchild care is significantly positively correlated with physical health and cognitive functioning. For mental health also, we find positive correlations, even though they turn insignificant when controlling for social interactions.

2.5.4 Propensity Score Matching Estimation

As OLS makes an assumption about functional form, we alternatively apply a semi-parametric matching method to estimate the effect of grandchild care on grandparent health. Matching does not rely on a particular functional form of the regression equation; its approach is to compare the sample average of the outcome variable of caring grandmothers to grandmothers with similar likelihood of caring but who do not care. The latter thus serve as a comparison group for the caring grandmothers. Conditional on the two assumptions – conditional independence or unconfoundedness assumption – discussed in the method section, the mean difference between the two groups can be interpreted as the average treatment effect or, in other words, as the effect grandchild care has on grandmother health.

Table 2.4 Average treatment effect on the treated for different health variables

Matching method	Physical health		Cognitive functioning		Mental health	
Kernel Epan. bw(.06)	0.0648***	.0567***	0.0941***	.0768***	0.0725***	.0502***
	(.0100)	(.0117)	(0.0121)	(.0141)	(0.0143)	(0.0166)
Kernel Epan. bw(.02)	.0622***	.0543***	.0885***	.0707***	.0705***	.0473***
	(.0101)	(.0118)	(0.0122)	(.0143)	(.0144)	(.0168)
Nearest neighbour	.0540***	.0505***	.0958***	.0594***	.0658***	.0395***
	(.0125)	(.0145)	(.0156)	(.0179)	(.0184)	(.0211)
5 Nearest neighbour	.0616***	.0579***	.0962***	.0718***	.0711***	.0422***
	(.0106)	(.0125)	(.0130)	(.0151)	(.0154)	(.0179)
N neighbour caliper(.0005)	.0549***	.0513***	.0949***	.0588***	.0669***	.0417***
	(.0125)	(.0143)	(.0156)	(.0177)	(.0184)	(.0208)
Radius caliper (.05)	.0652***	.0572***	.0951***	.0779***	.0727***	.0507***
	(.0099)	(.0117)	(.0121)	(.0141)	(.0143)	(.0766)
OLS	0.0840***	0.0753***	0.111***	0.100***	0.0764***	0.058***
	(0.00823)	(0.0086)	(0.0102)	(0.0109)	(0.0130)	(0.0139)
Socio-demographics	yes	yes	yes	yes	yes	yes
Social interaction		yes		yes		yes
Observations	29416 (11)	25611 (6)	29417 (11)	25612 (6)	29417 (11)	25612 (6)

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for Socio-demographics: country and year dummies, education with low education as the reference group, marital status with divorced and singles as reference group, employment status with retired as reference group, possession of any real estate, number of children, number of grandchildren, retired early because of bad health and for Social interaction: most frequently contacted child with no contact as reference group, distance to closest child with living in the same house or household as reference group, a dummy for any help received, a dummy for any help given, a dummy for done voluntary/charity work, attended educational or training course, gone to a sport, social, or other club, taken part in activities of a religions organization, at least once a week. Nearest neighbour matching with Abadie and Imbens (2006) standard errors.

Figure B.1 and Figure B.2 in the Appendix show the distribution of propensity score values in the treatment and comparison group. When matching on the socio-demographic controls (Figure B.1), we see a close to normal distribution for the untreated, while the distribution of the treated is left-skewed. If we add social interaction variables (Figure B.2), we find flatter distributions for both groups. This means more dispersed propensities for the treatment group and a broader distribution of the untreated at both ends of the distribution. Very few (11 and 6) observations are dropped when imposing the common support. Table B.2 in the Appendix shows that the comparison group matches the treatment group quite well, except for a few significant but numerically minor differences in age, homeownership and the number of grandchildren. Adding social interaction variables to the matching criteria, treatment and comparison groups differ because treated grandmothers have their children living close by more often and more of them are receiving help (Table B.3). Numerically the differences, however, remain small.

Table 2.4 shows the results for several matching procedures on the control variables that are also used in the OLS estimations above. Based on the propensity score estimation, observations are matched with Kernel Epanechnikov matching with a bandwidth of 0.06 and 0.02. We also perform one- and five-nearest neighbour matching as well as one-nearest neighbour within a caliper of (.005), that is, we allow for matching within a 0.05% difference in the propensity score and all observations without any match are dropped. This relatively small caliper is chosen because the results of nearest-neighbour matching with larger calipers are identical to the default nearest-neighbor matching. We also use a radius matching with a caliper of 0.005 and 0.05 and match a treated observation to all observations within a .5% and 5% difference in the propensity score.

The average treatment effect of grandchild care on physical health, when matched by socio-demographic characteristics, amounts to 6.48 percent of the standard deviation for Kernel matching; the effect is significant at the 1% level and varies between 5.40 and 6.52 across matching procedures. These average treatment effects are all smaller than the OLS coefficient obtained from regressing the outcome variables on a dummy for grandchild care. The effect decreases further to 5.67 percent when additionally including social interaction in the propensity score estimation. The other outcomes show similar patterns. The average treatment effect of grandchild care increases the cognitive functioning by 9.41 percent and mental health by 7.25 percent of a standard deviation when Kernel matching on socio-demographic characteristics. The effects persist even though they decrease when we include social interaction controls.

2.5.5 Panel Estimation

The correlations shown up to now can not necessarily be interpreted as causal, grandchild care providing grandmothers might still differ from non-caring ones in ways we cannot observe. Thus, in order to get closer to a causal interpretation of our results, we make use of the panel dimension of our data and looking at an instrumental variable, the gender of the firstborn child.

Fixed effect and lagged dependent estimation make both use of the time dimension of the data. Fixed effect estimations use the variation within one individual over time in order to get rid of unobserved time invariant heterogeneity, and lagged dependent estimations assume that all unobserved individual fixed characteristics can be approximated by controlling for the outcome variable in the earlier period.

Table 2.5 Fixed effect estimation

Physical health	
Grandchild care	0.000982
	(0.000623)
Cognitive functioning	
Grandchild care	0.000949
	(0.00109)
Mental health	
Grandchild care	-0.00180
	(0.00125)
Socio-demographics	yes
Observations	5,535
Number of individuals	1,845

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for year fixed effects, education: high and medium with low education as the reference group, marital status: married, widowed, with divorced and singles as reference group, employment status: employed, retired, chronically ill, homemaker, with retired as reference group, possession of any real estate, number of grandchildren, retirement because of bad health.

Table 2.5 shows the fixed effect estimates, which suggest that grandchild care has no significant effect on any of the health outcomes. The point estimates of the coefficients on physical health and cognitive functioning are about half the size of the pooled OLS estimates. Ten more hours of weekly grandchild care increase physical health by .98 and cognitive functioning by .95 percent of a standard deviation. For mental health, we see the fixed effect coefficient change the sign to -1.80 percent of a standard deviation.

As only three periods of data are available, and fixed effects estimation is based on the variation within an observed individual, we also look at lagged dependent variable estimation, which allows us to compare grandmothers that showed a similar health status in the previous period; the grandchild care coefficient can then be interpreted as the short term effect of grandchild care provided in this period. To make fixed effects and lagged dependent estimations comparable, both regression results are shown for the balanced sample.

Table 2.6 Column 1 shows the pooled OLS estimates for the balanced sample, and Column 2 shows the results when adding the lagged dependent variable. Controlling for the past period's physical health reduces the apparent impact of grandchild care, but it remains significant at the ten percent level, i.e. ten more hours of grandchild care leading to an increase in physical health of 1.25 percent of a standard deviation. The effect on cognitive functioning decreases slightly to 2.19 percent of a standard deviation (significant at the ten percent level); for mental health, as in the fixed effect estimation, we find an insignificant negative, but much smaller, effect of 0.42 percent of a standard deviation. For all three health outcomes, the causal effect of grandchild care seems to be smaller that estimated from the OLS.

Both approaches allow us to control for time invariant personal characteristics influencing both grandchild care and health outcomes. If, however, there are time-varying unobservables correlated with the variables of interest, the results would still be biased. In the next section, we thus use exogenous variation in the amount of grandchild care.

Table 2.6 Lagged regressions on grandchild care

Physical health		
Grandchild care	0.00332***	0.00125**
	(0.000985)	(0.000617)
Cognitive functioning		
Grandchild care	0.00265**	0.00219**
	(0.00117)	(0.000991)
Mental health		
Grandchild care	0.00127	-0.000422
	(0.00159)	(0.00127)
Socio-demographics	yes	yes
Lagged dependent variables		yes
Observations	3,690	3,690

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for further socio-demographics: country and year dummies, education: high and medium with low education as the reference group, marital status: married, widowed, with divorced and singles as reference group, employment status: employed, retired, chronically ill, homemaker, with retired as reference group, possession of any real estate, number of children, number of grandchildren and retirement because of bad health.

2.5.6 Instrumental Variable Estimation

Finally, we use an instrumental variable that leads to a change in the provision of grandchild care but which is arguably otherwise unrelated to the health of a grandmother: the gender of the firstborn child. This instrument relies on the random distribution of a child's gender. Its influence on grandchild care has been shown in previous literature (see Rupert and Zanella, 2011).

When we look at the 2SLS estimation in Table 2.7, we make use of the fact that women on average become parents at an earlier age than men, due to the average age difference of about two years between the male and the female partner. If the firstborn is a daughter, her mother is likely to become a grandmother earlier in life than if the firstborn is a son. When controlling for the number of children and the number of further daughters a grandmother has, we can thus distinguish the effect of becoming a grandmother and providing grandchild care earlier in life, from the one of having more daughters.

The first stage estimate in Table 2.7 shows that when controlling for the number of further daughters, a grandmother who has a daughter as her firstborn, provides on average 1.02 hours of grandchild care more per week, with an F-value of 42.36 this is a relatively strong instrument (as not all observations in our sample provide the gender and the birth year for all of their children, we are left with the 29.069 observations that do).

Table 2.7 IV estimation, firstborn a daughter

Physical health	OLS	2SLS
Grandchild care	0.00164***	-0.00322
	(0.000314)	(0.00794)
Cognitive functioning		
Grandchild care	0.00182***	-0.00622
	(0.000386)	(0.00980)
Mental health		
Grandchild care	0.000853	-0.00633
	(0.000523)	(0.0124)
Socio-demographics	yes	yes
Number of further daughters	yes	yes
Observations	29,036	29,036
First stage		
Firstborn a daughter	1.021***	
	(0.156)	
F-value	42.63	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for further socio-demographics: country and year dummies, education: high and medium with low education as the reference group, marital status: married, widowed, with divorced and singles as reference group, employment status: employed, retired, chronically ill, homemaker, with retired as reference group, possession of any real estate, number of children, number of grandchildren and retirement because of bad health.

The 2SLS estimates of the grandchild care effect are insignificant. The point estimates are all larger in magnitude than for OLS, and the signs for all three health outcomes are negative. Ten more hours of grandchild care would then lead to a 3.22 percent of standard deviation deterioration in physical health, a 6.22 percent reduction in cognitive functioning and a 6.33 percent reduction in mental health. For physical health, the IV estimate is smaller than the OLS coefficients. In contrast to Arpino and Bordone (2012), cognitive functioning of grandmothers does not seem to profit from grandchild care; the point estimate has a negative sign, just like mental health.

Are there other ways than grandchild care for the gender of the firstborn to influence the health of a grandmother? Ejrnaes and Pörtner (2004) find that educational attainment is higher for children with higher birth order. As higher education increases the probability of employment, a better educated and thus working daughter is more likely to rely on her mother's grandchild care than a son. This is part of the grandchild care channel we are investigating.

The gender of the firstborn has also been used as an instrument for marital instability by Bedard and Deschenes (2005). If, however, a marriage is more likely to result in divorce if the firstborn was a girl, and marriage is positively correlated with health, having a daughter, and being more likely to divorce should have a negative effect on health. This, however, leads only to an underestimation of our 2SLS results. Thus we want to emphasize again, that these insignificant negative estimates are the lower bound of the true care effect only.

2.6 Conclusion

Health-care costs for the elderly are increasing in today's ageing societies, and the rise in female labour force participation means that parents rely more and more on grandparents to provide informal care. We investigate the correlation between occasional grandchild care and the health of grandparents. To date, there is very little research on occasional childcare as representative datasets such as HRS and NFHS focus on custodial care. SHARE provides us with a representative sample of grandparents from several European countries and detailed information about care intensity.

In contrast to the literature on custodial care, the analysis of occasional care faces the problem of self-selection. Also, grandparents who provide grandchild care might differ from the non-care-providing grandparents in their characteristics. Both situations could lead to an upward bias in our results. We control for several channels that might be driving the correlation. Potential channels include contact with the children, help provided to family members, friends, and neighbours and social engagement. The correlation between grandchild care and grandparent health, however, remains positive when controlling for all these channels. Across cultural regions in Europe the effect of grandchild care is very similar, only Southern European grandmothers tend to profit significantly more from their care provision than Western European grandmothers. Also, using semi-parametric propensity score matching, we see that the relation is robust to the assumed underlying functional form. We use panel analyses and instrumental variable estimation to get a sense as to whether these relations can be interpreted as causal. These methods impose higher requirements on the data and we hardly find any significant causal effects. All the estimates, however, point into the direction of the causal effect of grandchild care being smaller than the OLS correlations suggested.

The effect of occasional grandparent childcare on grandparent health is of current relevance in Europe. Policies encouraging grandchild care are being discussed and implemented, for example in the Netherlands, since the Childcare Act from 2005 grandparents can be considered as self-employed child-minders. In Germany the implementation of a grandparental leave as a supplement for parental leave has been discussed.

Future research could take a closer look at the interaction between public childcare and grandparent care. As female labour force participation increases in Western countries, these two major sources of childcare might either begin competing with each other or perhaps become combined in a "care-mix."

Appendix B Supplementary Figures and Tables

Figure B.1 Propensity score distribution for treated and comparison group (baseline model)

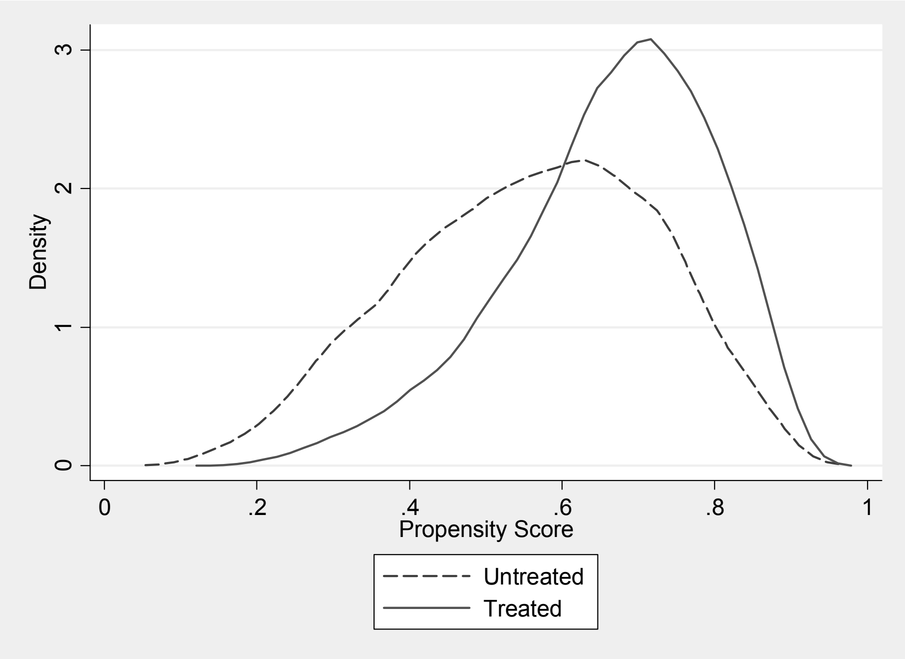

Figure B.2 Propensity score distribution for treated and comparison group (socio-demographic and social interaction controls)

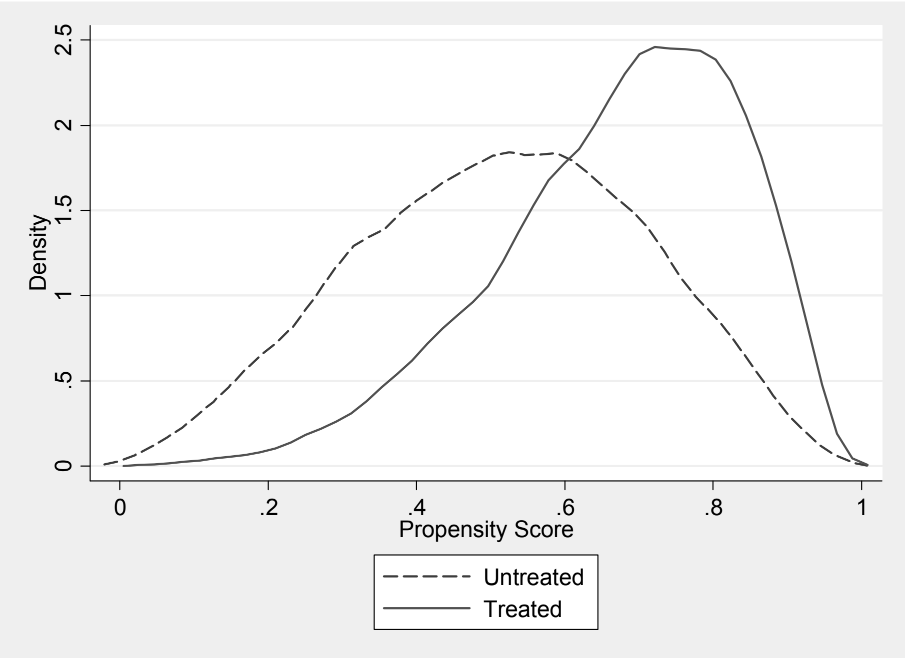

Table B.1 Step-wise model construction

Dependent	Physical health			
Grandchild care	0.00233***	0.00179***	0.00162***	0.00188***
	(0.000329)	(0.000312)	(0.000328)	(0.000332)
Age	-0.0193***	-0.0189***	-0.0190***	-0.0174***
	(0.000603)	(0.000826)	(0.000841)	(0.000820)
Medium education	0.156***	0.114***	0.119***	0.0994***
	(0.0101)	(0.00949)	(0.00967)	(0.00945)
High education	0.254***	0.183***	0.188***	0.158***
	(0.0120)	(0.0114)	(0.0118)	(0.0118)
Married		0.0785***	0.0671***	0.0305**
		(0.0134)	(0.0135)	(0.0131)
Widowed		0.0122	0.00507	0.0126
		(0.0176)	(0.0176)	(0.0170)
Employed		0.0178	0.0192	0.0320***
		(0.0114)	(0.0118)	(0.0116)
Unemployed		-0.0970***	-0.102***	-0.0856***
		(0.0212)	(0.0225)	(0.0217)
Chronically ill		-0.870***	-0.873***	-0.806***
		(0.0308)	(0.0316)	(0.0306)
Homemaker		-0.0378***	-0.0390***	-0.0296**
		(0.0120)	(0.0126)	(0.0123)
Homeowner		0.0322***	0.0282***	0.0297***
		(0.00781)	(0.00812)	(0.00793)
#Children		-0.0214***	-0.0181***	-0.00489
		(0.00445)	(0.00452)	(0.00480)
#Grandchildren		-0.0101***	-0.0103***	-0.00945***
		(0.00209)	(0.00213)	(0.00208)
Retired b/o health		-0.444***	-0.469***	-0.446***
		(0.0197)	(0.0206)	(0.0200)
Contact frequency				
less than monthly				0.0252**
				(0.0116)
almost every month				0.0153
				(0.0123)
almost every week				-0.0364**
				(0.0161)
almost daily				-0.155***
				(0.0299)
Closest child				
within a 5km-radius				0.0220**
				(0.0110)
5km to 25km				0.0619***
				(0.0127)
25km to 100km				0.0754***
				(0.0158)
over 100km				0.0769***
				(0.0171)

Table B.1 Step-wise model construction (cont'd):

Received help				-0.307***
				(0.0119)
Given help				0.0375***
				(0.00766)
Charity				0.0367***
				(0.0128)
Attend training				0.0234
				(0.0154)
Sport				0.105***
				(0.00866)
Church				0.0339***
				(0.0131)
Politics				0.00196
				(0.0262)
Observations	29,427	29,427	25,619	25,618
R-squared	0.125	0.215	0.222	0.260

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Controlling for country and year dummies, education with low education as the reference group, marital status with divorced and singles as reference group, employment status with retired as reference group, possession of any real estate, number of children, number of grandchildren and retirement because of bad health, most frequently contacted child with no contact as reference group, distance to closest child with living in the same house or household as reference group, a dummy for any help received, a dummy for any help given, a dummy for done voluntary/charity work, attended educational or training course, gone to a sport, social, or other club, taken part in activities of a religions organization, at least once a week.

Table B.2 Mean comparison before and after matching (baseline model)

Variable	Treated	Comparison (unmatched)	Comparison (matched)
Physical health	0.073	-.1336***	.0083***
Cognitive functioning	0.2347	-.0742***	.1406***
Mental health	-0.0717	-.2394***	-.1442***
Age	62.83	66.2110***	62.5630***
Medium education	0.3474	.2877***	.3466
High education	0.1802	.1450***	.1806
Married	0.756	.6856***	.7559
Widowed	0.1363	.2034***	.1297*
Employed	0.2515	.1810***	.2539
Unemployed	0.0346	.0291***	.0361
Permanently sick	0.0367	.0427***	.0378
Homemaker	0.2148	.2291***	.2116
Homeowner	0.5357	.4818***	.5249**
#Children	2.602	2.8403***	2.5916
#Grandchildren	3.7383	4.2835***	3.6079***
Retired b/o health	0.05465	.0665***	.0567
Observations	18992 (+11)[1)]	10424	10424

*** p<0.01, ** p<0.05, * p<0.1.
Kernel Epanechnikov matching with a bandwidth of 0.06. Controlling for country fixed effects, marital status with divorced and singles as reference group, employment status with retired as reference group, distance to closest child with living in the same house or household as reference group, contacted child with no contact as reference group. 1NN: Nearest neighbour matching one-on-one, Radius: Radius matching with a caliper of 0.05, Kernel: Kernel matching. 1)off support.

Table B.3 Mean comparison before and after matching (socio-demographic and social interaction controls)

Variable	Treated	Comparison group (unmatched)	Comparison group (matched)
Physical health	0.0737	-0.1276***	0.0167***
Cognitive functioning	0.2307	-0.0709***	0.1540***
Mental health	-0.0763	-0.2314***	-0.1265***
Age	62.4580	65.7660***	62.1830***
Medium education	0.3498	0.2892***	0.3452
High education	0.1790	0.1470***	0.1837
Married	0.7526	0.6779***	0.7561
Widowed	0.1390	0.2071***	0.1316**
Employed	0.2620	0.1909***	0.2650
Unemployed	0.0364	0.0312**	0.0363
Chronically ill	0.0368	0.0445***	0.0362
Homemaker	0.2190	0.2284*	0.2182
Homeowner	0.5381	0.4775	0.5374
#Children	2.6293	2.8543***	2.6304
#Grandchildren	3.7219	4.2698***	3.5795***
Retired b/o health	0.0570	0.0704***	0.0607
Contact frequency			
less than monthly	0.3106	0.2439***	0.3079
almost every month	0.3380	0.3527**	0.3422
almost every week	0.1097	0.2057***	0.1136
almost daily	0.0227	0.0458***	0.0252
Closest child			
within a 5km-radius	0.4008	0.3546***	0.3891**
5km to 25km	0.1842	0.1743**	0.1775
25km to 100km	0.0784	0.1010	0.0806
over 100km	0.0548	0.1017***	0.0559
Received help	0.1919	0.2029**	0.1834**
Given help	0.3831	0.2041***	0.3773
Charity	0.0909	0.0612***	0.0901
Attend training	0.0464	0.0292***	0.0455
Sport	0.1815	0.1159***	0.1767
Church	0.0963	0.0879**	0.0971
Politics	0.0126	0.0073***	0.0125
Observations	16550 (+6)	9062	9062

*** p<0.01, ** p<0.05, * p<0.1.

Kernel Epanechnikov matching with a bandwidth of 0.06. Controlling for country dummies with divorced and singles as reference group, retired as reference group, living in the same house or household as reference group, contact frequency with no contact as reference group. 1)off support.

Chapter 3
Does the Divorce of a Child Affect the Parents?[1]

3.1 Introduction

Divorce is one of the most dramatic events in life, it is known to have manifold repercussions for the divorcees and their families. Female labour supply has been found to increase significantly (Bargain et al., 2012). Nevertheless, disposable income drops for women, putting them and their children at poverty risk (Dew, 2009), while for men the disposable income increases after accounting for household members.

But it is not only the two divorcing adults that are affected by their decision. Having parents who divorce is found to have detrimental effects on children's school performance and educational attainments (Case et al., 2001; Ermisch et al., 2004; Gruber, 2004). Children of divorced parents leave home at an earlier age, and to become sexually active sooner (McLanahan and Sandefur, 1994); they are also more likely to exhibit risky health behaviour and are more likely to smoke (Francesconi et al., 2010).

Very little, however, is known about the effect of divorce of adult children on their parents. The breakdown of one's child's marriage may cause a certain discontent. This may be especially true, as the generation we are talking about was brought up with more conservative moral norms and may perceive divorce as a social stigma. Further, while the divorce of a child might cause a certain distress to the parents, seeing a third generation, i.e. grandchildren, touched by the divorce might strengthen the detrimental effect of a child's divorce.

This paper looks at the effect of divorcing children on the parents. We look at parents' labour supply, measured as employment and weekly working hours, and on health, using indices for physical health, cognitive functioning and mental health. To get a better idea of the channels through which the divorce of a child affects the parents, we also look at several aspects of intergeneration interaction.

One problem with any analysis of the impact of divorce is endogeneity: in this case, people whose children decide to divorce might show unfavorable outcomes because of the divorce, but there may also have been underlying disadvantageous characteristics that both led to the divorce and caused the outcome. When looking at the impact of divorce of children on

[1] This paper uses data from SHARE wave 4 release 1, as of November 30th 2012 or SHARE wave 1 and 2 release 2.5.0, as of May 24th 2011 or SHARELIFE release 1, as of November 24th 2010. The SHARE data collection has been primarily funded by the European Commission through the 5th Framework Programme (project QLK6-CT-2001-00360 in the thematic programme Quality of Life), through the 6th Framework Programme (projects SHARE-I3, RII-CT-2006-062193, COMPARE, CIT5- CT-2005-028857, and SHARELIFE, CIT4-CT-2006-028812) and through the 7th Framework Programme (SHARE-PREP, N° 211909, SHARE-LEAP, N° 227822 and SHARE M4, N° 261982). Additional funding from the U.S. National Institute on Aging (U01 AG09740-13S2, P01 AG005842, P01 AG08291, P30 AG12815, R21 AG025169, Y1-AG-4553-01, IAG BSR06-11 and OGHA 04-064) and the German Ministry of Education and Research as well as from various national sources is gratefully acknowledged (see www.share-project.org for a full list of funding institutions).

parents, it is highly likely that the parents have little direct control over their children's decision to divorce. However, the children might have inherited characteristics from their parents, or they might take the presence and the expected support of their parents – such as the provision of grandchild care – into account when deciding whether to divorce.

To solve these issues, we not only use ordinary least squares (OLS), but also make use of the panel structure of our dataset, the Survey on Health Ageing and Retirement in Europe. This allows us to disentangle the effect of a child's divorce from the time invariant individual fixed characteristics.

To summarise our results: although the OLS estimates show significant negative correlations between the divorce of a child and the parents' outcomes, we find no significant impact of divorce when using fixed effect or lagged dependent estimates. The insignificant estimates point towards positive impacts on physical health, cognitive functioning and working hours. Mental health is negatively influenced (although statistically insignificantly) by the divorce of a child. When we study the interaction between the generations, OLS estimates suggest negative correlations of the divorce of a child with the frequency of contact and the help provided to the child, and a positive correlation with grandchild care. Fixed effects estimators, though, suggest that the frequency of contact and the support from the parent increase after a divorce, and that the share of the total grandchild care provided increases (but insignificantly).

3.2 Literature Review

We are not aware of other papers that use quantitative techniques to estimate the impact of the divorce of a child on the parents. Related qualitative literature covers the changes in intergeneration relationships and grandparents' provision of grandchild care that occur when a child divorces. Most of this research is based on interviews with small numbers of families. For example, Matthews and Sprey (1984) investigate the relationship of parents with their divorced children, children in-law and grandchildren. They interview 37 parent couples, about half of whom experienced the divorce of one or more children. While parents without divorced children thought that a divorce was very unlikely and that they would be informed before the event, only a small number of parents who had experienced the divorce of a child had actually heard about before it occurred. The emotional reaction to the divorce of a child is most often described as a feeling of sadness and disappointment rather than relief or anger. Grandchild care in co-located or close-living families seems to be most intense for divorced children (Dench and Ogg, 2002). Usually it is the mother who is awarded custody of minor children (Matthews and Sprey, 1984). Thus it is not surprising that maternal (grand-) mothers are playing an important role in the grandchildren's lives, both, before and after divorce (Douglas and Ferguson 2006). Matthews and Sprey (1984) find that most of the grandparents with a divorced child agree with the statement, that the custody decision had an impact on their relationship with their grandchildren. The majority of (grand-) parents with a divorced daughter holding custody report to see the grandchildren more frequently than before the divorce. The evidence for parents whose daughter in law held custody is less clear, but points towards lower frequency of contact after divorce.

3.3 Data

Our analysis is based on the multidisciplinary Survey of Health, Ageing and Retirement in Europe (SHARE). SHARE is a longitudinal study, and we use three waves from 2004/2005, 2006/2007 and 2011/2012. Participating countries are Austria, Belgium, Czechia, Denmark, Estonia, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Netherlands, Poland, Portugal, Slovenia, Spain, Sweden and Switzerland. The sampling frame was the non-institutionalized population aged 50 and older and their spouses.

As health outcomes, we use indices of indicators for physical health, cognitive functioning and mental health. As labour outcomes, we use a dummy for employment and weekly working hours. These variables have been used in the two earlier chapters, where more detailed descriptions can be found.

We are interested in how the divorce of a child changes the interaction between the child and the parent. For this part of our analyses we use the child generation as the unit of observation. The questionnaire asks detailed information about these interactions for up to four children in the first two waves and up to twenty children in the third wave. For consistency, we restrict the sample to observations with four or fewer children in all three waves. For each of these children, the parent is asked in detail about aspects of intergeneration interaction, including the frequency of contact, the distance at which each child is living, help provided to and received from each child, and any grandchild care that this child has been receiving for one or more of his or her children. Further, for each child, the grandparent is asked to indicate the year of birth of this child's youngest child.

The frequency of contact and the distance to the location of the child are indicated in categories. While we use contact frequency with its abstract values of (1 never to 7 daily), we make the distance to the child more interpretable by replacing the nine distance categories with the average distance of the category (0 if in the same household or in the same building, .5 if less than 1 kilometer away, 3.5 if between 1 and 5 kilometers away, and so on and, 500 if more than 500 kilometres away in another country). Information about help provided to and received from each child is available in wave 1 and 2, but in wave 3 the information on help exchanged between the generations cannot be assigned to a particular child, when examining this outcome, we thus use the first two waves only. The frequency of grandchild care can be attributed to the particular child in wave 3. However, as only the first two waves provide information on the hours of care provided, we optimize interpretability of the frequency information by replacing the standard values of the categorical variables by the mean weekly hours these categories had in the first two waves (0 for no care, 2.07 hours for less than monthly, 5.39 for almost every month, 10.63 for almost every week, 32.78 for almost daily).

Table 3.1 Descriptives of the grandparent sample

Variable		Obs	Mean	Std. Dev.	Min	Max
Physical health	index of physical health variables	46489	-0.0361	0.7345	-5.3269	0.6780
Cognitive functioning	index of cognitive functioning variables	46489	0.0938	0.9269	-2.2013	2.8458
Mental health	index of mental health indicators	46489	-0.1404	1.0276	-4.1826	1.0648
Employed	1 if employed	46489	0.2509	0.4335	0	1
Working hours	working hours per week	46489	8.9680	16.3094	0	168
Retired	1 if retired before official retirement age	46489	0.4854	0.4998	0	1
#Children	number of children	46489	2.2436	0.8708	1	4
#Divorced children	number of divorced children	46489	0.1626	0.4207	0	4
#Children with (minor) grandchildren	number of children with (grand-)children aged 16 or younger	46489	0.3467	0.4759	0	1
#Divorced children with grandchildren	number of divorced children with (grand-) children aged 16 or younger	46489	0.0442	0.2055	0	1
Age	age in years	46489	64.9709	10.0390	45	94
Education						
low education	1 if isced1/2	46489	0.4874	0.4998	0	1
medium educ.	1 if isced3/4	46489	0.3315	0.4707	0	1
high educ.	1 if isced5/6	46489	0.1812	0.3852	0	1
Married	1 if married	46489	0.6781	0.4672	0	1
Widowed	1 if widowed	46489	0.2053	0.4040	0	1
Employed	1 if employed	46489	0.2509	0.4335	0	1
Unemployed	1 if unemployed	46489	0.0286	0.1668	0	1
Sick	1 if chronically ill	46489	0.0325	0.1772	0	1
Homemaker	1 if homemaker	46489	0.2026	0.4020	0	1
Retired b/c bad health	1 if retired early because of bad health	46489	0.0629	0.2427	0	1

We include a set of parent and child related socio-demographic controls. For the parent, we can control for age, education, marital status, employment status and a dummy indicating early retirement because of bad health. For the child, we observe gender, marital status, number of children and education.

From Douglas and Ferguson (2003), we know that the tie between a mother and her children is stronger than other family ties. Also, women are more likely to adapt their lives, for example their labour supply to family needs. We thus concentrate on mothers in the following empirical analyses.

The parent sample is limited to women who are aged 45 to 94 years old who report having at least one child and have complete survey records. The child sample is limited to the children of those in the parent sample. When we study the impact on labour supply outcomes, we further restrict the sample to parents below the official national retirement age. The final samples consist of 46489 observations on the parent level for health related outcomes and 21811 for labour outcomes, and of 86749 child level observations. When we look at grandchild care, we restrict the sample to children of the SHARE sample members who themselves have children aged 16 or younger. Table 3.1 and Table 3.2 show variable definitions and descriptives for the outcomes and explanatory variables on the child and on the parent level.

Table 3.2 Descriptives of the child related sample

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
Contact frequency	Contact frequency	86749	5.6439	1.4093	1	7
Distance to parent	Distance to parent	86749	77.0327	135.803	0	500
Help CtoP	Weekly hours of help provided by child	86749	2.7985	7.8522	0	38.3
Share help CtoP	Share of overall help	86749	0.1852	0.3591	0	1
Help PtoC	Weekly hours of help provided by (grand-) parent	41167	0.2164	2.6756	0	168
Share help PtoC	Share of overall help provided by (grand-) parent	41167	0.0339	0.1727	0	1
Grandchild care	Weekly hours of grandchild care	41167	0.2600	3.0897	0	168
Share care	Share of overall grandchild care	41167	0.0373	0.1805	0	1
Child characteristics						
Gender	1 male, 2 female	86749	1.4927	0.4999	1	2
Divorced	1 if child is divorced	86749	0.0791	0.2699	0	1
#(Grand-) children	Number of (grand-) children	86749	1.2683	1.2224	0	23
Child education						
low education	1 if low education	86749	0.1869	0.3898	0	1
medium education	1 if medium education	86749	0.4759	0.4994	0	1
high education	1 if high education	86749	0.3372	0.4728	0	1
Parent characteristics						
Age	Age of the parent	86749	65.5042	9.7895	45	94
Education						
low education	1 if isced1/2	86749	0.5037	0.5000	0	1
medium education	1 if isced3/4	86749	0.3217	0.4671	0	1
high education	1 if isced5/6	86749	0.1746	0.3796	0	1
Married	1 if married	86749	0.6835	0.4651	0	1
Widowed	1 if widowed	86749	0.2084	0.4062	0	1
Employed	1 if employed	86749	0.2337	0.4232	0	1
Unemployed	1 if unemployed	86749	0.0264	0.1602	0	1
Permanently sick	1 if permanently sick	86749	0.0321	0.1763	0	1
Homemaker	1 if homemaker	86749	0.2087	0.4064	0	1
Retired b/c bad health	1 if retired because of bad health	86749	0.0654	0.2472	0	1

3.4 Methods

For our analyses, we first show pooled OLS estimates. These correlations can be interpreted as causal only if we assume that we are controlling for all factors influencing the divorce of a child and the dependent variable.

However, we are concerned about endogeneity. Even though it is highly unlikely that parents actively decide to become the parent of a divorced child, children might take the presence and the likely support they would receive from their parents into account when they consider whether to divorce. Also, it might be the case that unobservable characteristics common to the parent and the child cause both the divorce of the child and the negative outcomes of the parent.

We therefore use panel analysis methods like fixed effects (FE) and lagged dependent variable analyses (LDV). Fixed effect estimation gets rid of all individual fixed time invariant unobserved heterogeneity by using only the deviation from the individual mean, and lagged dependent variable estimation uses the past outcome as a proxy containing these time invariant characteristics. Both methods allow us only to determine how the divorce of a child affects those people whose children actually divorce; we are thus not able to get rid of the selection into having a divorced child.

3.5 Results

In the first two subsections, we are going to look at how the divorce of a child affects parental health and labour outcomes. In the third and fourth, we look at changes in intergeneration interaction patterns and the exchange of grandchild care when a child divorces.

3.5.1 What Happens to Parental Health Outcomes?

When we look at the effect of a child's divorce on the parent, the OLS results point towards a significant negative correlation with physical health and with mental health, and a smaller and insignificant negative correlation with cognitive functioning (Table 3.3). On average, having one more child comes along with 1.04 percent of a standard deviation worse physical health, and one more divorced child is correlated with 2.92 percent of a standard deviation lower physical health. For cognitive functioning we also find a significantly negative correlation with the number of children, but only a very small and insignificantly negative correlation with the number of divorced children. Mental health shows an insignificant positive correlation of the number of children, but a significant negative correlation with the number of divorced children: one more divorced child is linked with 8.24 percent of a standard deviation lower mental health.

Moving to estimation strategies that take the panel character of the data into account (Table 3.4), we generally find insignificant effects. When we look at the point estimates, we can see that the divorce of a child – depending on the estimation method - seems to have an ambiguous impact on the physical health of a parent. While the fixed effect estimate indicates a 3.23 percent of a standard deviation lower physical health, the lagged dependent estimate indicates slightly lower physical health, by .37 percent of a standard deviation.

Table 3.3 Pooled OLS, health outcomes

Dependent	Physical health	Cognitive functioning	Mental health
#Children	-0.0104**	-0.0101**	0.00706
	(0.00416)	(0.00477)	(0.00612)
#Divorced children	-0.0292***	-0.00179	-0.0824***
	(0.00864)	(0.00966)	(0.0128)
Socio-demographics	yes	yes	yes
Observations	46,489	46,489	46,489
R-squared	0.290	0.330	0.124

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for socio-demographics: year dummies, education: high and medium with low education as the reference group, marital status: married, widowed, with divorced and singles as reference group, employment status: employed, retired, chronically ill, homemaker, with retired as reference group and retirement because of bad health.

For cognitive functioning, also, we find (insignificant) 1.19 and .69 percent of a standard deviation reductions caused by divorce. For both physical health and cognitive functioning, we thus have to call the significant and larger negative correlation of the OLS into question. Comparing these estimates with the OLS, we can assume that a large share of the negative correlation between the divorce of a child and the physical health of a parent rears from unobservable characteristics and that the event of the divorce of a child leads to a much smaller insignificant and even positive deviation from the individual mean. Only mental health still shows negative signs, with coefficients that are, at 4.42 and 3.82 percent of a standard deviation, about half the size of the OLS correlation.

Table 3.4 Fixed effects and lagged dependent variable estimates, health outcomes

Dependent	Physical health		Cognitive functioning		Mental health	
	FE	LDV	FE	LDV	FE	LDV
#Divorced children	0.0323	-0.00373	0.0119	0.00693	-0.0442	-0.0382
	(0.0205)	(0.0136)	(0.0352)	(0.0193)	(0.0431)	(0.0258)
Socio-demographics	yes	yes	yes	yes	yes	yes
Lagged dependent		yes		yes		yes
Observations	10,056	6,704	10,056	6,704	10,056	6,704
R-squared	0.072	0.554	0.007	0.439	0.011	0.298
Number of individuals	3,352		3,352		3,352	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In fixed effects model: controlling for year fixed effects, marital status: married, widowed, with divorced and singles as reference group. In OLS and LDV further controlling for country and age dummies, and education: high and medium with low education as the reference group.

3.5.2 Do Parents' Labour Outcomes Change?

Table 3.5 shows that having one more child is correlated with a 1.9 percentage points reduction in the likelihood of employment and with a reduction of .77 weekly working hours.

Table 3.5 Pooled OLS, labour outcomes

Dependent	Employed	Working hours
#Children	-0.0190***	-0.768***
	(0.00421)	(0.163)
#Divorced children	-0.0188*	-0.851**
	(0.0103)	(0.395)
Socio-demographics	yes	yes
Observations	21,811	21,811
R-squared	0.249	0.235

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for socio-demographics: year dummies, education: high and medium with low education as the reference group, marital status: married, widowed, with divorced and singles as reference group, number of children.

This is unsurprising: women of the generation we are looking at are likely to have dropped out of the labour force for quite a while after the birth of each child, and, with a higher number of children comes a greater chance of being a grandparent and thus the opportunity to provide grandchild care. One more divorced child is correlated with 1.88 percentage points lower propensity of employment and .85 lower weekly working hours. As we show later on, two potential mechanisms are that the divorce of a child leads to a deterioration of mental health, and increases the amount of grandchild care.

Table 3.6 Fixed effects and lagged dependent variable estimates, labour outcomes

Dependent	Employment		Working hours	
	FE	LDV	FE	LDV
#Divorced children	0.0208	-0.00834	1.518	0.263
	(0.0452)	(0.0250)	(1.497)	(0.923)
Socio-demographics	yes	yes	yes	yes
Lagged dependent variable		yes		yes
Observations	3,120	2,080	3,120	2,080
R-squared	0.075	0.542	0.078	0.563
Number of individuals	1,040		1,040	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In fixed effects model: controlling for year dummies, marital status: married, widowed, with divorced and singles as reference group. In LDV further controlling for country and age dummies, and education: high and medium with low education as the reference group.

The estimates in Table 3.6 , which take into account time invariant (FE) and short term fixed effects (LDV), show insignificant effects of divorce on employment and working hours. The point estimates, however, again point towards omitted variables leading to a negative correlation in the OLS results, while the event of a child's divorce seems to increase the working hours by 1.51 (FE) or .26 (LDV) weekly working hours and to lower the likelihood of employment to a smaller extent by .83 percentage points (LDV) or even increase it by 2.08 percentage points (FE).

These results all point towards unfavourable general circumstances in the parent generation affected by the divorce of a child. Much less, however, do they point towards a negative causal effect of divorce. Only mental health of a parent seems to suffer (albeit statistically insignificantly) in case of the divorce of a child.

3.5.3 How Does Divorce Impact Intergeneration Interaction?

To estimate how divorce affects intergeneration interactions, we use the child as the unit of observation and control for child and parent characteristics. Following Pepper (2002), we cluster on the parent, the highest level of aggregation.[1]

Table 3.7 OLS of intergeneration interaction variables on divorce and gender of a child

Dependent	Frequency of contact	Distance to parent	Help CtoP	Help PtoC
Daughter	0.289***	1.773	0.160***	0.165***
	(0.0107)	(1.117)	(0.0274)	(0.0338)
Divorced	-0.109***	4.907**	0.0497	0.0961
	(0.0220)	(1.964)	(0.0584)	(0.0601)
Socio-demographics	yes	yes	yes	yes
Wave	1, 2, 3	1, 2, 3	1, 2	1, 2
Observations	86,645	86,645	41,117	41,117
R-squared	0.094	0.078	0.020	0.005

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for socio-demographics: year dummies, Parent characteristics are education: high and medium with low education as the reference group, marital status: married, widowed, with divorced and singles as reference group, employment status: employed, retired, chronically ill, homemaker, with retired as reference group, number of children and retirement because of bad health. Child characteristics are education: high and medium with low education as the reference group and number of children.

Table 3.7 shows the correlation between the divorce of a child and a set of variables describing intergeneration relationships including frequency of contact, distance to the parent, help provided to the parent and help received from the parent. The divorce of a child is significantly negatively correlated with the frequency of contact, with divorced children having on average .11 categories lower frequency of contact; to put this into context, daughters have about .29 categories more contact. Daughters live about 1.8 km further from their parents than sons, and divorced children live 4.9 km further away. Daughters provide and receive .16 and .17 hours (about 10 minutes) more support per week, and divorced children provide and receive slightly more (but insignificantly so). For all variables shown here, the gender of the divorced child does not correlate significantly with divorce; these results can be provided on request.

[1] Usually standard errors are clustered on the individual level to account for correlation within one individual over time. By clustering at the parent level, we do, what Pepper calls “treating the cluster rather than the individual as the unit of observation”. Alternatively one can use multi-level modeling to account for variation on the parent and the child level. The results, however, are similar to the OLS results shown here.

Table 3.8 reports results of panel estimation models and shows that we find significant effects of divorce only on the frequency of contact, and the help that children receive from their parents. Compared to the individual mean, the frequency of contact to the parent increased after the divorce of a child (FE). The same can be found, when controlling for the frequency of contact in the past, being divorced is still positively correlated (LDV).

Table 3.8 FE and LDV of intergeneration interaction variables on divorce

Dependent	Frequency of contact		Distance to parent		Help CtoP		Help PtoC	
	FE	LDV	FE	LDV	FE	LDV	FE	LDV
Divorced	0.118*	0.0878**	3.504	0.0739	-0.0141	-0.0747	0.156*	0.125
	(0.0681)	(0.0390)	(4.888)	(2.223)	(0.0547)	(0.0695)	(0.0947)	(0.115)
Socio-demographics	yes	yes	yes	yes	yes	yes	yes	yes
Lagged dep.		yes		yes		yes		yes
Observations	15,375	10,250	15,375	10,250	10,250	5,125	10,250	5,125
R-squared	0.018	0.412	0.002	0.821	0.001	0.119	0.004	0.052
Number of individual	5,125		5,125		5,125		5,125	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In fixed effects model: controlling for year fixed effects, marital status: married, widowed, with divorced and singles as reference group. In LDV further controlling for socio-demographics: year dummies, Parent characteristics are education: high and medium with low education as the reference group, marital status: married, widowed, with divorced and singles as reference group, employment status: employed, retired, chronically ill, homemaker, with retired as reference group, number of children and retirement because of bad health. Child characteristics are education: high and medium with low education as the reference group.

For the distance to the parents, the panel estimates do not differ so much from the OLS results. Both fixed effects and lagged dependent variable estimates find - insignificant - positive coefficients and thus an increased distance to the parents after a divorce. The help children provide to their parents seems to decrease after a divorce of a child. While the help parents provide to their divorced children increases significantly by .16 weekly hours (FE), the lagged dependent variable estimate is about the same size, but insignificant.

3.5.4 How Does the Provision of Grandchild Care Change after Divorce?

The literature tells us that the gender of the child plays a major role in determining how the divorce of a child affects the provision of grandchild care: as daughters usually hold custody, it is the daughter's parents who are more involved in grandchild care after divorce.

Table 3.9 investigates this for child observations that have children aged 16 or younger, and we additionally control for child age dummies. Consistent with the literature, we find that grandchild care is .84 hours per week higher for divorced children than non-divorced ones, and that daughters receive about 1.7 hours more grandchild care than sons. When we differentiate by the gender of the divorced child, we find that divorced daughters receive 1.1 hours per week more care than divorced sons.

Table 3.9 OLS for grandchild care

Dependent	Grandchild care		Share of total care	
Daughter	1.720***	1.634***	0.0746***	0.0695***
	(0.101)	(0.105)	(0.00492)	(0.00511)
Divorced	0.835***	0.273	0.0268***	-0.00413
	(0.177)	(0.216)	(0.00846)	(0.0116)
Divorced daughter		1.091***		0.0614***
		(0.345)		(0.0169)
Socio-demographics	yes	yes	yes	yes
Observations	38,887	38,887	27,669	27,669
R-squared	0.097	0.097	0.095	0.096

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Controlling for socio-demographics: year dummies, Parent characteristics are education: high and medium with low education as the reference group, marital status: married, widowed, with divorced and singles as reference group, employment status: employed, retired, chronically ill, homemaker, with retired as reference group, number of children and retirement because of bad health. Child characteristics are grandchild age dummies and education: high and medium with low education as the reference group.

This analysis does not, however, tell us whether parents of divorced children provide more care overall, or whether they shift their attention towards their divorced children. Thus, we also look at the share of the total amount of care a grandparent is providing, received by each child. We do this in a sample of SHARE sample members who have more than one child with own children aged 16 or younger. For these 27,669 observations, we see that the share of total grandchild care is 2.7 percentage points higher for divorced children. When we distinguish between divorced sons and divorced daughters, we see that the effect is concentrated amongst divorced daughters: divorced sons receive an insignificantly smaller share of grandchild care compared to non-divorced children, but divorced daughters receive 6.1 percentage points more.

Table 3.10 FE and LDV for grandchild care

Dependent	Grandchild care		Share of total care	
	FE	LDV	FE	LDV
Divorced	-0.399	0.0267	0.0292	0.0163
	(0.480)	(0.249)	(0.0230)	(0.0125)
Socio-demographics	yes	yes	yes	yes
Lagged dep.		yes		yes
Observations	9,750	6,500	7,092	4,728
R-squared	0.025	0.334	0.032	0.313
Number of individual	3,250		2,364	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In fixed effects model: controlling for year fixed effects, the child's marital status: married, widowed, with divorced and singles as reference group and the number of (grand-)children a child has. In LDV further controlling for socio-demographics: year dummies, Parent characteristics are education: high and medium with low education as the reference group, marital status: married, widowed, with divorced and singles as reference group, employment status: employed, retired, chronically ill, homemaker, with retired as reference group, number of children and retirement because of bad health. Child characteristics are education: high and medium with low education as the reference group.

When we turn to panel analyses, in Table 3.10 we find that the divorce of a child leads to ambiguous effects on grandchild care depending on the method. Compared to the individual mean, a child receives insignificantly less support after a divorce, while when controlling for the amount of care received in the past, divorced children still receive more care. One reason for the negative effect in the FE might be that children who decide to divorce are more likely to receive grandchild care before and after divorce. The share of the total amount of care increases insignificantly after a divorce. The amount of the increase is similar to the one we found in the OLS, but insignificant.

3.6 Conclusion

In this chapter, we have estimated the impact of a child's divorce on its parents, an issue that we do not think has been previously addressed using quantitative methods.

For our empirical analyses we use SHARE data. We find that there is a significant negative correlation between the number of divorced children and a variety of health and labour outcomes. This correlation, however, seems to be driven by unfavorable underlying circumstances in the parent generation affected by the divorce of a child, rather than being a negative causal effect of divorce; when we apply panel analyses, we find only mental health of a parent to suffer in case of the divorce of a child.

To investigate potential channels by which the divorce of a child might affect the parents, we look at how the interaction between parents and their children changes after divorce. OLS estimates show a negative correlation between the frequency of contact and a divorce, and a positive correlation between help provided to the children and grandchildren, but fixed effects show the contact and the help provided to a child increase after a divorce.

Overall, the divorce of a child does significantly increase the frequency of contact between the child and the parent and children receive significantly more support. And while we find an insignificant positive impact on most parent outcomes, the mental health deteriorates insignificantly.

Chapter 4
Does Cluster Policy Trigger R&D Activity? Evidence from German Biotech Contests

This article is co-authored by Dirk Engel, Timo Mitze and Roberto Patuelli, it has been accepted for publication in European Planning Studies.

4.1 Introduction

Throughout the 1990s, the design of the German national research and development (R&D) policy experienced a paradigmatic shift from standard grant schemes to a competition-based and regionally focused R&D policy, which provided public funding mainly to regions with a high expected social return on public funding. Among the first programmes implementing a competitive spirit in German R&D policy were the BioRegio and BioProfile contests starting in 1997 and 1999, respectively. Both programmes aimed at fostering the commercialization in biotechnology and at pushing Germany towards the international technological frontier. Since the programmes operated on a competitive basis, they were also labelled as "contests of cooperation" (see Eickelpasch and Fritsch 2005).

Although there exists a huge stock of theoretical and empirical contributions on the effects of geographical concentration among its main actors in regional and/or sectoral innovation systems (e.g., Marshall 1890, Jaffe et al. 1993, Porter 2003), hardly anything is known about the effects of policies aiming at the stimulation of R&D activity in selected regions through such contests for cooperation. Thus, in this paper we evaluate the research performance of winners compared to participating (but non-winning) and non-participating regions in the BioRegio and BioProfile contests, both for the periods during (treatment) and after funding (post-treatment). As outcome variables, we use the regions' patenting activity and their ability to raise public R&D funds due to the status of being a winner in the respective contest.[1] Our database covers 426 German NUTS-3 districts (Kreise) for the period 1991 to 2007.

From a methodological point of view, we use a Difference-in-Differences (DiD) estimation framework based on (zero inflated) Poisson regressions, where the latter account for excessive zeros in the outcome variables: the number of biotech research projects raised through public funding, as well as the number of biotech patent applications for all German NUTS-3 districts. The remainder of the paper is structured as follows. In Section 4.2, we briefly discuss the theoretical background of cluster-oriented R&D policy. Section 4.3 presents the data and several descriptive findings, followed by a brief summary of the estimation strategy in Section 4.4. In this section we also discuss our estimation results. Section 4.5 concludes the paper.

[1] Using data on patenting activity, we explicitly account for the fact that patent applications are typically made with a time lag relative to the received funding.

4.2 The Regionalization of R&D Policy

4.2.1 Rationales

The competition- and contest-based regionalization of R&D policy described above fits quite closely to the theoretical expectation that the extent of externalities, technological change and commercialization of innovative ideas are all positively affected by the geographical concentration of public and private research actors who share interests in similar fields of technology. The idea of positive effects of local agglomeration has its roots in Marshall's (1890) externalities based on specialized labour pools, input sharing and knowledge spillover as well as Porter's (2003) view of an enhanced competition in clusters.[2] While the positive effects of local agglomeration on knowledge intensive industries might be clear from a theoretical point of view, it is not easy to identify empirically the causal effect of geographical proximity on R&D activity. Starting from the influential work of Acs et al. (1993), Jaffe et al. (1993), Audretsch and Feldman (1996) and Anselin et al. (1997), there is a growing literature identifying the transmission channels from clustered firms to enhanced R&D, innovation activity and finally productivity growth. Acs et al. (1993), for instance, estimate production functions for US data and find that, beside standard input factors, the geographical position in a cluster matters strongly.

Jaffe et al. (1993) find that the probability of an inventor to be cited in a patent application is larger if the actors are located in geographical proximity. Likewise, Baptista and Swann (1998), based on UK micro data, show that firms in sectors that show a geographical concentration indeed exhibit, on average, more intensive research activities. In a further study, Baptista (2000) shows that firms adopt technical innovations particularly in those regions which are characterized by a high share of firms having implemented the same innovations already. With respect to Germany, Dauth (2010) reports evidence that compared to regions without industrial agglomeration, the existence of industrial agglomeration is significantly correlated with higher regional employment growth rates. Finally, Grimpe and Patuelli (2011) show the importance of co-location among firms (private R&D) and public research institutes (public R&D) for the case of nanomaterials innovation in German regions.

The main question remains how to interpret such findings. For example, Baptista (2000, p. 529) states: "...[o]ne can, therefore, claim that there are significant learning effects arising from the geographical proximity to previous adopters". In fact, it is quite likely that learning effects are higher in local agglomerations due to the existence of firms with higher knowledge competencies and absorptive capacities. One may then assume that local agglomerations are characterized by a "selection of the fittest", that is, actors with research activities and knowledge competencies above average prefer geographical proximity to actors with similar skills. Studies by Zucker et al. (2006) and Klepper (2007) clearly support this view. Klepper (2007), for instance, argues that better-performing firms will have more and better spinoffs,

[2] However, Dohse (2000, p. 1111) points out that the implementation of regionalized technology policy in Germany was not purely intended to be a "...carbon-copy of the ideas proposed in the theoretical literature".

and these spinoffs will generally locate close to their parents. Zucker et al. (2006) show that scientific stars become more geographically concentrated over time because of relocations from areas with relatively few peers to those with many actors in their field of expertise.

These insights are essential for understanding any potential effect stemming from a regionalized, cluster-oriented R&D policy. The funding of projects in such leading-edge local agglomerations might have larger effects due to the additional acquisition of outside money, and higher effectiveness based on the selection of the fittest and the geographical proximity between well-performing actors.

4.2.2 Cluster-oriented R&D Policy and Its Evaluation

The BioRegio contest (BRC) marks a major milestone of the German Federal Government's policy to stimulate the transfer of new knowledge into new products, and thereby narrows the gap between Germany and those countries leading in the application of biotechnological knowledge, i.e. the USA and Great Britain. The BRC was initiated by the Federal Ministry of Education and Research (BMBF) in 1995, and encouraged regions to apply for subsidies to be used for the establishment of biotech industry in the region (Dohse 2000). The funding concept aimed at developing a new holistic approach for R&D and innovation policy, and was planned to integrate biotechnological capacities and scientific, economic and administrative activities. The main governmental purpose of funding biotechnology was to catch up with the high international standard of performance. From the political perspective, R&D funding via contests should ideally lead to two effects: First, a direct output and reputation effect for winners, as well as, second, an indirect mobilization effect of the contest. The latter is expected to arise if regions, which have organized themselves and formulated a common strategy, can use these efforts as future assets even without the receipt of direct financial benefits.

In sum, 17 BioRegions were formed and participated in the BRC. An independent jury selected four winning regions (Rhineland, Rhine-Neckar, Munich, and Jena with a special vote) out of a total of 17 participant “meso”-regions (exceeding the size of NUTS-3 districts). Major criteria were based on “hard” facts like the existence of a critical mass of biotech firms and research facilities within the region, regarding the absolute number of firms, the average firm size, and the firms’ R&D and economic performance (for details, see Dohse, 2000). Each winning region received a total amount of public grants of about €25 Mio. (exception Jena: €15 Mio.) to run R&D-projects. Additionally, winning regions were favored in terms of getting access to the standard R&D-grant schemes of the BMBF. The total amount of these grants was about €750 Mio. for the time span 1997–2001.

The follow-up BioProfile contest (BPC) started in 1999, and a total of 30 regions participated in this contest. Three winning BPC “clusters” (Potsdam-Berlin; Braunschweig-Göttingen-Hannover; Stuttgart-Tübingen-Esslingen-Reutlingen-Neckar-Alb) were awarded funding by the jury in May 2001. Public subsidies with a maximum of €50 Mio. have been provided by the Federal Government for each of the three clusters between 2001 and 2007.

Participation in the BRC and BPC was thus generally attractive in order to receive additional subsidies and to attract actors within and outside the region for participation in biotech-related research projects. It also offered access to different valuable resources increasing knowledge competencies and accelerating the commercialization of biotechnology-related products.

Despite its growing political importance, only very few quantitative studies measure the success of cluster-oriented R&D policies. Only recently, Martin et al. (2011) were among the first scholars to apply a quantitative (DiD) approach to the evaluation of economic effects of the French "Local Productivity System" (LPS) cluster programme. A further analysis for the subsequent French Policy of "Competitiveness Clusters" has been conducted by Fontagne et al. (2010), mainly finding that the policy was effective in picking the winners. With respect to German data, Falck et al. (2010) use a similar estimation strategy in order to analyse a regional innovative cluster policy for Bavaria. While Martin et al. (2010) do not find evidence of productivity advantages of the specific cluster policy, Falck et al. (2010) conclude that the Bavarian state-wide cluster policy led to a significant increase in the probability of being innovative for Bavarian targeted sectors relative to non-Bavarian targeted sectors and Bavarian non-targeted sectors (two comparison groups).[3]

With respect to the biotechnology sector, different studies have analysed both the general role of clustering and the impact of public funding. Using a global dataset for 59 consolidated biotechnological firms, Lecocq et al. (2011) report evidence for a positive relationship between the number of technology clusters in which a firm is present, and its overall measured patent performance. Similar results are also reported in Fornahl et al. (2009) for a sample of German biotech firms in the period 1997–2004. Wolf et al. (2010) analyse the determinants of transition from nascent into real entrepreneurship for German biotechnology firms. The authors confirm the role of regional factors and the entrepreneurial environment, which are both typical for clusters and relevant for the success in the start-up activity of biotechnology firms.

Focusing on policy effects, Cooke et al. (2007) compared several measures as indicators for the success of policy support in the biotechnology sector (e.g., number of biotech firms, products in pipeline, etc.). The authors find that BRC and BPC winners perform better than non-funded biotech regions. However, the authors do not differentiate between non-winning participants and non-participants within the group of non-funded biotech regions. In doing so, Engel and Heneric (2008) find that non-winning participants of BRC outperform winning and non-participants regions of BRC with respect to the change in the number of newly founded biotech-firms between 1995–98 and 1999–2003. Thus, the authors conclude that the certification as a winner and exclusive financial support do not matter in attracting new biotech firms, compared to other participants.

A shortcoming of both studies is that the authors do not address the evolution of BRC winning regions after the funding period. Using actual data for the total amount of public R&D funds raised, we take up this research question explicitly. While many studies point out

[3] In fact, the Bavarian State Government provided an amount of €1.45 billion for R&D projects to Bavarian firms and research institutes, which comes close to typical funding schemes at the Federal government level.

that a firm's public funding implies higher R&D activity, we are explicitly interested to know whether path dependence matters for the acquisition of public R&D funding. Furthermore, we will provide empirical evidence on whether BRC and BPC winning regions were more successful in terms of patent applications during the funding period.

4.3 Data and Stylized Facts

In the following, we give a short description of the variables used to analyse the effects of the BRC and BPC at the level of 426 German NUTS-3 districts. Several databases are needed to analyse the regional structure of Federal support for biotechnology projects and its determinants. In detail, we link the following data sources:

- Federal Government Project Funding Information Database (PROFI),
- Patent data from the European Patent Office (EPO), namely "ESPACE" Bulletin,
- Socio-Economic data from various sources including Federal Agency for Labour, ZEW Foundation Panel, as well as the Federal Statistical Office.

The PROFI database covers the civilian R&D funding of the German Federal Government. For the purpose of this paper, we focus on direct funding of biotechnology-related projects. The database contains information on the number of projects, expenditures, name and address of recipients, type of project (individual versus collaborative projects), and so on.[4] Based on the "ESPACE" Bulletin, we extract information regarding patenting behaviour. Patent applications are the most important measure of innovative capacity (for comprehensive discussions on the informative value of patents, see, e.g., Griliches, 1990). We measure patent applications in the technology field "biotechnology" (see Table D.2 in Appendix) at the location of inventors, and sum up the number of patent application per county when at least one inventor comes from this county.

Acquisition of public funding and patent applications as outcome variables are determined by the innovative capacity in the region. In order to minimize any bias stemming from time-varying omitted variables, our set of explanatory variables considers several aspects of the districts' innovative capacity, which are extracted from several databases. Among others, R&D employment data, defined as the share of employees trained in mathematics, engineering and natural sciences relative to total employment, and obtained from the Federal Employment Agency, are used to extract measures regarding the innovative capacity of counties.

[4] We thank Mr. Günter Krauss from the Federal Ministry of Education and Research – Department Z 22 'Information technology' – for his effort in extracting related information from the PROFI database. In order to minimize the potential endogeneity problem stemming from the fact that winning the contests is directly associated with financial benefits for the respective regions, we use the number of raised research projects rather than the financial volume. The correlation of both indicators is reasonably high (Pearson's correlation coefficient is 0.87 for all projects and 0.91 for cooperative R&D projects), so that the number of projects serve as a good substitute for the financial volume. This strategy also avoids putting strong assumptions on the annual streams of funding over the project period.

Table 4.1 Variable description and data source

Variable	Source	Description
Government funding	PROFI database	Direct funding of biotechnology-related R&D projects by Federal government (number of projects and volume of expenditures)
Patents	European Patent Office (EPO)	Non-weighted number of patent applications in biotechnology (for a definition of the Biotech sector based on IPC classes, see Appendix)
Number of Firms	German Statistical Office	Number of firms in manufacturing sector
Average Firm size	German Statistical Office	Average number of employees per firm in manufacturing sector
Export share	German Statistical Office	Share of foreign turnover in manufacturing sector relative to total turnover in manufacturing sector
MINT Employment	Bundesagentur für Arbeit (Federal Employment Agency)	Share of employees trained in mathematics, informatics, natural sciences and technology relative to total employment
Start-up	ZEW Foundation Panel	Number of overall start-ups relative to total employment
Start-up (High-Tech)	ZEW Foundation Panel	Number of start-ups in high-tech industries relative to MINT employees
Population Density	German Statistical Office	Number of inhabitants per area
Sectoral Specialization	Alecke et al. (2006)	Sum of squared deviations of regional average employment shares for NACE3 sectors from national average
Ellison-Glaeser Index	Alecke et al. (2006)	Employment in sectors with high Ellison-Glaeser Index (>0.005) relative to total employment in the region
Dummy BioRegio Winner	Dohse (2000)	Binary dummy for winner districts in the BioRegio contest (for complete list, see Appendix)
Dummy BioRegio Participant	Dohse (2000)	Binary dummy for non-winning districts in the BioRegio contest (for complete list, see Appendix)
Dummy BioProfile	Cooke et al. (2007)	Binary dummy for winner districts in the BioProfile contest (for complete list, see Appendix)

For our empirical analysis, we collapse the yearly observations from our sample data into three periods: 1.) pre-treatment period, 2.) treatment period and 3.) post-treatment period. The time span of each period differs for BRC and BPC due to the fact that BPC ran two years after BRC (see Table 4.2). Therefore, we prepare two samples, one for the evaluation of BRC and the other one for the evaluation of BPC. The first BRC sample contains BRC winners, non-winning participants and non-participants.[5] While non-winning participants are needed as a comparison group to assess the expected direct effects of funding, non-participating regions serve as second comparison group (both relative to winners and non-winners) in order to give

[5] A total of 55 NUTS3 regions participated in the BRC (see Table A.1 in the appendix for details). Although the BioRegio contest was officially set up on a five-year basis, between 1997 and 2001, we include an additional year as treatment period in order to account for the usual funding practice according to an *N+1* period, where *N* stands for the nominal time span of a specific project.

a first quantification of the possible indirect effects of funding as outlined above. We exclude BPC winners from the group of non-winning participants in this sample in order to avoid the problem that BPC winners – due to the overlap of both contests – also received funding during the BRC.

We add further measures for research activity, such as firm-specific information in the manufacturing sector (export share, firm size, etc.) and start-up activity in high-tech industries. The latter variable measures the entrepreneurial climate, and thus the potential to commercialize innovative ideas via the channel of business creation.

Finally, we also include proxies for the regional patterns in sectoral specialization and agglomeration in general. The latter variable is measured in terms of employment in sectors with a high Ellison-Glaeser-Index (>0.005) relative to total employment in the region.[6] This measure, in turn, may provide general information about the Marshallian forces at work at the NUTS-3 level (i.e., forward-backward linkages, labour market pooling and knowledge spillovers). A detailed description of the data definitions is given in Table 4.1.

This sample reduction, however, might be critical given that the BPC winners can be seen as an ideal comparison group for BRC winners since the problem of selection into the treatment given unobserved regional characteristics should be less prevailing. In other words: Both groups should only differ with respect to the timing of exclusive funding. Therefore, we use a second shorter BRC sample (labelled BRC2) that – as comparison unit – also contains BPC winner regions prior to the BPC contest. To guarantee the comparability between the analysed groups the period of observation ends as the BPC starts. This approach thus has the advantage of an appropriate comparison group on the one hand, while it faces the disadvantage of shortening the investigation period on the other hand. However, while many R&D projects started immediately after the announcement of "BRC winner", we believe that losing two years does not fundamentally affect the precision of our estimates in the BRC2 sample. Descriptive statistics of the samples according to Table 4.2 are given in the Appendix.

Table 4.2 Sample periods under investigation

	Outcome variable	Pre-treatment period (before funding)	Treatment period (exclusive funding)	Post-treatment period (after funding)
BRC1[a]	Funding	1991–996	1997–2002	2003–2007
	Patents	1991–1997	1998–2006	n.a.
BRC2[b]	Funding	1991–1996	1997–2000	n.a.
	Patents	1991–1997	1998–2002	n.a.
BPC[c]	Funding	1991–2000	2001–2007	n.a.
	Patents	1991–2000	2002–2006[d]	n.a.

Notes: We assume that patent applications based on funding are earliest declared one year after the beginning of exclusive funding and latest one year after the exclusive funding is closed. a The sample BRC1 contains BRC winners, non-winning BRC participants (without BPC winners) and non-participants. b In addition to sample BRC1, the sample BRC2 contains BPC winners. c The sample BPC contains BPC winners, non-winning BRC participants and non-participants of BRC. d Due to limitations in patent data, we can only consider five years instead of seven years in the ideal case.

[6] The threshold level of 0.005 was chosen in line with the empirical literature (see, e.g., Alecke et al. 2006).

Although collapsing the annual observations into three time periods results in a loss of information, there are statistical reasons that advocate carrying out the DiD-estimation strategy this way. Bertrand et al. (2004), for instance, propose to collapse data with a long sample range into just two periods (one before and one after the policy intervention) in order to minimize the risk of obtaining underestimated standard errors due to serially correlated errors when unobservable factors are present over time. In doing so, we also circumvent the problem that certain variables such as start-up activity are only available at longer time intervals. For the outcome variables, we sum up the number of patents and publicly funded projects observed for each region for the time intervals defined in Table 4.2. For the set of explanatory variables, we use sample averages for each respective time period.

Table 4.3 shows that both the number of directly funded projects and the sum of allocated grants in the field of biotechnology increased significantly between 1991 and 2007. In particular, we observe a take-off between the periods 1991–96 and 1997–2002, which may give a first indication of the boost in Biotech funds throughout the BRC competition. Compared to this, for the period 2003–07 we observe a consolidation phase of public R&D spending in biotechnology. The apparent time trend faced by the whole industry makes it thus important to compare the performance of winning regions not only over time, but also relative to the other actors, in order not to erroneously allot the positive industry trend to the causal impact of BRC (and BPC) funding.

Table 4.3 Directly funded biotechnology related R&D projects

	Pre-treatment 1991–96	Treatment 1997–02	Post-treatment 2003–07
Number of directly funded projects	3,692	4,482	4,603
Total amounts of directly funded projects (in €1000)	723,995	1,055,159	1,331,133

Source: PROFI, own calculation.

Table 4.4 and Table 4.5 show the allocation of federal funds with respect to the different regions and the share of cooperative R&D projects, respectively. Table 4.4 points out that BRC winners could further increase their relative share of the total funding during the treatment period from 1997 to 2002. However, for the post-treatment period we see a significant decline in the regional share of total direct project funds. By contrast, especially BPC winners and non-winning BRC participants were able to increase their share in this latter period. Regarding the distribution of funds among the four groups, the table shows that all parties have received a fairly similar share of funding, indicating that they may serve as homogeneous comparison groups with respect to the outcome variable of publicly funded R&D projects.

Table 4.4 Allocation of direct project funding to biotechnology programs (percentage)

Participation State	Pre-treatment 1991–96	Treatment 1997–2002	Post-treatment 2003–07
BRC winner	32.1	33.8	27.3
Non winning BRC participants	17.1	15.0	18.6
BPC winner	24.1	24.5	26.6
Other NUTS-3 districts	26.6	26.7	27.5
Sum (Germany)	100.0	100.0	100.0

Source: PROFI, own calculation.

Table 4.5 further highlights that, for all regions, the share of cooperative R&D projects increased over time. It seems that exclusive funding for "winners" correlates with the extension of collaborative projects. BRC and BPC winners show a significant increase in the share of collaborative projects during the treatment period (1997–2002 for BRC and 2001–07 for BPC). Most interestingly, the importance of collaborative projects (as share of overall projects) reduces for BRC winners in the post-treatment period. In the result, the change in the collaborative share for the winning and non-winning regions of BRC is very similar over the periods.

Table 4.5 Percentage of cooperative R&D projects relative to overall funding per group

Participation State	Pre-treatment 1991–96	Treatment 1997–2002	Post-treatment 2003–07
BRC winner	20.4	36.9	29.0
BPC winner	32.3	42.9	49.6
Non winning BRC participants	31.6	39.0	40.3
Other NUTS-3 districts	26.4	42.9	42.9

Source: PROFI, own calculation.

Given the fact that patenting activity inherently exhibits a time lag in the transmission process from R&D funds to R&D activity and finally to R&D outcome, we are only able, at this point, to compare the treatment effect relative to the pre-treatment period for winning regions of the BRC/BPC with the specific comparison groups. Due to restrictions in patent data publication, as well as to time lags in the transmission from R&D inputs to outputs, we cannot construct a sufficiently long post-treatment period. Thus, for patent applications, we set the treatment and pre-treatment periods as follows: from 1991 to 1997, we assume that there is – by definition – no significant patent application activity as a result of the BRC. Instead, for the period 1998 to 2006, we assume that patent applications are directly influenced by the BRC (2002–06 for the BPC).

As Table 4.6 shows, BRC winning regions significantly increased their number of patents in the treatment period. The growth rate was about +183 per cent. However, BPC winners showed a significant boost in their patenting activity as well (+281 per cent), showing the strongest growth performance among all four groups. Table 4.6 shows that, compared to BRC winners, BPC winners were initially smaller in absolute size, but showed a convergence to the

BRC level throughout the sample period. For the non-winning participants and all remaining NUTS-3 districts, the number of patent applications showed a smaller increase (+93 per cent and +168 per cent, respectively). Finally, compared to public R&D spending from Table 4.6, we also see that here the inter-group heterogeneity is much higher, indicating that in particular the comparison between winning and participant regions is expected to yield the utmost reliable results in the estimation approach, trying to minimizing any possible self-selection bias. We turn to the model set-up in the following.

Table 4.6 Total number of biotech patent applications (Average per NUTS-3 district for each category)

	Pre-treatment 1991–97	Treatment 1998–06	Growth rate
BRC winner	83.6	236.6	+183.0%
Non winning BRC participants (excluding BPC winner)	49.2	95.1	+93.3%
BPC winner	55.7	212.3	+281.1%
Other NUTS-3 districts	9.2	24.7	+168.4%

Source: EPO, own calculation

4.4 Econometric Approach and Estimation Results

4.4.1 Model Set-Up

In order to analyse the effects of funding on private R&D activity, we have to estimate a set of models which differ by the design of the treatment versus the comparison group and the time period employed, as shown in Table 4.2. The econometric literature offers different approaches to estimate treatment effects. Here we apply a Difference-in-Differences (DiD) technique, which aims at isolating the policy effect related to changes in the outcome variable $Y_{i,t}$ for a group of treated individuals (i, in our case: NUTS-3 regions) over time (t, in our case: limited to two consecutive periods) relative to a comparison group. The underlying identification assumption of this approach is that the difference between treatment and comparison groups would have been constant over time if the treatment group had not received the subsidy. Since we are dealing with three groups (winners, participants and non-participants), our model specification has the following general form

$$(4.1)\quad Y_{it} = \alpha + \beta_1 D_i^1 + \beta_2 D_i^2 + \gamma T_t + \delta_1 (D_i^1 \times T_t) + \delta_2 (D_i^2 \times T_t) + \omega' X_{it} + u_{it}$$

where D_i^1 and D_i^2 are defined as binary variables with values

$$D_i^1 = \begin{cases} 1 & \text{if region } i \text{ belongs to the group of contest winners,} \\ 0 & \text{otherwise.} \end{cases}$$

$$D_i^2 = \begin{cases} 1 & \text{if region } i \text{ belongs to the group of non-winning participants,} \\ 0 & \text{otherwise.} \end{cases}$$

The third group of non-participating regions serves as reference group. Statistically significant positive parameters for D_i^1 and D_i^2 indicate level differences among the groups for the outcome variable. In addition to these dummy variables, we include a common time period indicator *T*, which takes either a value of zero (pre-treatment period) or one (treatment or post-treatment period respectively). The crucial parameters of interest are the two DiD-terms, which are calculated as interaction effects between the common time trend and the individual group dummies as $(D_i^1 \times T_t)$ and $(D_i^2 \times T_t)$. Both terms measure the difference between the expected outcome for treated regions before and after treatment, net of the outcome difference of the comparison or reference group during the treatment.

Statistically significant parameters δ_1 and δ_2 indicate a treatment effect for each subgroup relative to the benchmark case of non-participant regions. Specifically, δ_i measures the change in expected outcome variable $E[Y]$ for treated ($D=1$) and non-treated individuals ($D=0$) between the treatment ($t=1$) and pre-treatment ($t=0$) periods as

$$\text{(4.2)} \qquad \delta_i = (E[Y|D=1, t=1] - E[Y|D=1, t=0]) \\ -(E[Y|D=0, t=1] - E[Y|D=0, t=0]).$$

They can be interpreted as the combined direct and indirect effects of funding, respectively. By testing for parameter restrictions in terms of $\delta_3 = (\delta_1 - \delta_2)$, we are finally able to identify the treatment effect of winners versus non-winners within a common regression exercise, which allows us to isolate the direct treatment effect of funding "on the fly". In other words, the latter effect can be defined as a further Difference in the Difference-in-Differences parameters (DiDiD).

By the inclusion of the group-specific binary variables we are able to control for time-invariant omitted variables, however, the model may still be sensitive to temporary fluctuations that influence the performance of the treatment and control groups differently. The latter problem can be handled by including a set of time-varying control variables (**X**) for further regional characteristics, like the number of firms, new firm formations, international competiveness, share of MINT employees, sectoral specialization and agglomeration. Finally, $u_{i,t}$ is the error term of the model, and α, β_1, β_2, γ and ω are further regression coefficients.

Since patent applications and R&D grants are count data that exhibit a high share of zeros, the underlying distribution of the outcome variables may be neither normal-distributed nor conforming to a regular or over dispersed Poisson. A common solution to this problem is to rely on a so-called zero-inflated Poisson (ZIP) model.[7] Another crucial point for our empirical policy analysis is whether the estimated DiD-parameters in the (non-linear) ZIP model can be interpreted in the usual (linear) fashion. For the case of the Poisson model, the answer is straightforward, since the latter is just a flexible generalization of the ordinary least squares

[7] For our estimation approach, we explicitly test for the appropriateness of the ZIP specification versus the standard Poisson model by means of standard post-estimation tests.

regression. In other words, we are still in the linear case and the usual assumptions hold. Since the Poisson model uses the logarithm as the link function, we can obtain the marginal effect for the DiD-parameter as $[exp(\delta_i) - 1]$.[8]

4.5 Results

In this section, we estimate different ZIP models for the samples designed according to Table 4.2. Statistical inference for the two DiD-terms is made directly from the regression output, and significance of the DiDiD term is tested ex-post based on the so-called delta method (for details, see Greene 2003). The main empirical results regarding the parameter of the DiD term for different sample designs are given in Table 4.7. Full regression outputs are reported in Table 4.8–11.

As Panel A.1 in Table 4.7 (for the BRC) shows, we detect a positive and statistically significant higher number of patent application and raised R&D projects for BRC winners compared to non-participants, throughout the treatment period. Likewise, the result holds for all R&D projects, as well as for the subgroup of collaborative R&D projects. These findings clearly support the existence of direct treatment effects of funding, and suggest that the label "winner" signals an above-average R&D performance and it may contribute positively to a better innovative performance in biotechnology. However, we do not find evidence of indirect effects of funding when comparing non-winning participants with non-participants (others).

One drawback for the approach in Panel A.1 is that one may still argue that BRC winners differ from remaining regions with respect to adjustments due to environmental changes.[9] For instance, the implementation of the "Neuer Markt" in April 1997, Germany's equivalent to the United States' NASDAQ, and its rapid growth measured by the number of listed companies and market capitalization, marks a remarkable change and may be an alternative source for increased patent activity.[10] However, comparing BRC winners with BPC winners (as a comparison group in BRC2) may be seen as an effective strategy to eliminate some of above-mentioned unobservable differences. In fact, the share of venture capital-financed firms does not differ remarkably between BRC and BPC winners (see Engel and Heneric 2005).

In Panel A.2, we report the estimation results of the BRC2 sample, where we compare the relative performance of BRC winners against the one of non-winning participants, including BPC winners, prior to the starting date of the BPC competition. The results for patent applications show that BRC winners again show a better track record compared to the

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[8] We do not include the DiD terms in the non-linear Probit part of the model since both the BRC and BPC aim to improve the track record of promising biotech regions rather than initiating a regime switch from non-innovators to innovators.

[9] Additionally, we have to keep in mind that the group of non-winning participants is defined as net of the winning regions from the BPC contest, and thus has been subject to a dual selection mechanism, leaving only poor candidates within this group.

[10] While highly profitable exit opportunities are offered to investors in non-listed firms, venture capital investments in biotechnology went up by a factor of six between 1997 and 2001 (see OECD 2006: 119). According to the "selection of the fittest" hypothesis, firms and scientists in BRC winning regions are more stimulated by the rapid growth of the venture capital market. As a result, inventions could be better protected by patent applications to secure a unique selling proposition in the commercialization process of innovative ideas.

remaining full candidate set for the treatment period (1998–2002), both in terms of patent applications and of the number of raised R&D projects. However, if we split the latter candidate set into BPC winners and remaining participants, we see that the obtained positive direct treatment effect of BRC winners for patent applications stems mainly for the relative superiority of winners relative to non-winners (net of BPC winners). Compared to them, BPC winners show a better patent performance, while they clearly fall behind in terms of raising R&D funds relative to BRC regions.

Table 4.7 Estimated elasticity for the DiD-interaction term for different subsamples

Elasticity of DiD term	Patents	R&D Projects (total)	R&D Projects (collaborative)
Panel A.1. Treatment Period for BRC1: Period 2 versus Period 1			
Winner / Non-Winner	0.72***	0.37***	0.41***
Winner / Others	0.59***	0.43***	0.49***
Non-Winner / Others	–0.07**	0.04	0.06
Panel A.2. Treatment Period for BRC2: Period 2 versus Period 1			
Winner / Non-Winner (All)	0.15***	0.46***	0.55***
Winner / Non-Winner (Only BPC)	–0.28***	0.52***	0.61***
Winner / Non-Winner (Rest)	0.61***	0.41***	0.49***
Panel B. Post Treatment Period for BRC1: Period 3 versus Period 1			
Winner / Non-Winner	n.a.	0.24***	0.09
Winner / Others	n.a.	0.09	0.25**
Non-Winner / Others	n.a.	–0.11*	0.14
Panel C. Treatment Period for BPC: Period 2 versus Period 1			
Winner / Non-Winner	0.42***	0.32***	0.36***
Winner / Others	–0.04	0.07*	0.38***
Non-Winner / Others	–0.33***	–0.18***	0.02

***,**,* indicate statistical significance at the 1, 5 and 10 per cent level.

The reported elasticities are calculated as [exp(δ_i) – 1], where δ_i is based on the DiD- and DiDiD-parameters of the full regression outputs given in Table 4.8 to 11.

Given the absence of direct effects (or even negative ones) for patent activity between BRC and BPC winners, one may thus ask whether the selection mechanism in the BRC competition was operating poorly. In order to answer such a question, one has to recall that the goal of the programme was to push the technological competitiveness of German biotechnology towards an international dimension. As the regression parameters for the treatment variables (Di) in Table 4.8 (Column BRC2) show, the (initial) level of patent applications of BRC winners was more than twice as large as the one of the reference group (calculated as exp[0.745] – 1 = +1.1), while BPC winners were only 1.3 times larger (as exp[0.261] – 1 = +0.3) in terms of patent applications. Thus, among the positively performing candidates, the jury in the BRC picked the heavyweights, and put a focus on dynamically growing – but smaller – "rising stars" in the BPC. This finding provides further empirical evidence that both the BRC and BPC are a sequential result of "picking the winners", as argued, for example, by Dohse (2000).

When it comes to the long-term effects of BRC participation and exclusive funding, Panel B of Table 4.7 shows the findings for the R&D performance of BRC winners and both comparison groups in the post-treatment period. This may give an indication of which new equilibrium levels will be reached after the extensive funding by the BRC. On the one hand, we may expect that the receipt of additional public funding leads firms to acquire competences, and thus, positive path dependence should matter. On the other hand, the number of raised public R&D grants may actually follow different motives than allocating R&D sources to the most successful region (e.g., distributive rather than allocative arguments from a policy perspective). As the results in Table 4.7 show that, in comparison with the short-term effects in the treatment period, statistical evidence for long-term effects of funding is indeed much weaker. Although BRC winners still tend to outperform non-winners with respect to raised public R&D funds, there is no evidence of an overall better performance compared to non-participating regions, and non-winners even appear to fall behind the reference group of non-participating regions.

Compared to non-participating regions, the only significant difference of BRC winners is their ability to raise more collaborative projects. This result hints at the successful ability to create networks. We do not find statistically significant long-term effects when comparing non-winning participants and other regions. This latter result may point to the fact that the number of biotech regions and, subsequently, their ability and success in acquiring R&D grants have grown over time. BRC non-winners and non-participants have significantly improved their position relative to BRC winners. As a matter of fact, ten more biotech-regions were formed by 2005 (for details, see Engel and Heneric 2005).

In addition to the efforts of the Federal Government, many Federal States governments promote these biotech-regions within state programmes. At this stage, we cannot conclude that regionalized technological policy lacks efficiency in the long term. We believe that improvements in non-participant regions are the key explanation for the absence of long-term effects of BRC.

Finally, with regard to the evaluation of the BPC, Panel C of Table 4.7 shows the findings for BPC winners and the two comparison groups. Consistently with the findings discussed above, here we obtain fairly small effects when comparing winning regions and the others, as the winners only appear to perform better in terms of raising collaborative R&D projects. Nevertheless, the “selection of the fittest” also seems to works in both stages of the competitions, since the BPC winners also perform significantly better than non-winning participants (during the treatment period) for the latter contest. The estimated elasticity of the DiD-term is about the same size as the effect identified for the BRC. This is an important finding, since one might expect the performance of the winners at the second stage to be characterized by lower differences with the non-winners.

Table 4.8 Estimation Results for Patent Applications (Treatment Period)

Sample	BRC1		BRC2		BPC	
D^1	0.682***	(0.0375)	0.745***	(0.0376)	0.879***	(0.0315)
D^2	0.521***	(0.3577)	0.542***	(0.0358)	0.580***	(0.0267)
D^3			0.261***	(0.0486)		
T	0.727***	(0.0207)	0.520***	(0.0211)	–0.733***	(0.0197)
(D^1xT)	0.465***	(0.0383)	0.378***	(0.0400)	–0.046	(0.0420)
(D^2xT)	–0.079**	(0.0398)	–0.099**	(0.0419)	–0.401***	(0.0421)
(D^3xT)			0.706***	(0.0502)		
Number of Firms	0.002***	(0.0001)	0.003***	(0.0001)	0.002***	(0.0001)
Average Firm size	0.001***	(0.0001)	0.001***	(0.0002)	–0.001***	(0.0002)
Export Share	0.008***	(0.0008)	0.007***	(0.0006)	0.011***	(0.0007)
MINT Employment	0.064***	(0.0061)	0.018***	(0.0063)	0.006	(0.0074)
Population Density	0.072***	(0.0113)	0.041***	(0.0118)	0.167***	(0.0116)
Sectoral Specialization Manu	0.191	(0.1683)	–0.434**	(0.1781)	–0.569***	(0.1898)
Sectoral Specialization Serv1	–1.222***	(0.1432)	–0.386**	(0.1643)	–0.585***	(0.1520)
Sectoral Specialization Serv2	0.166	(0.1024)	–0.183*	(0.1054)	0.066	(0.1103)
$(\text{Sectoral Specialization Manu})^2$	–0.032**	(0.0133)	0.019	(0.0141)	0.028*	(0.0150)
$(\text{Sectoral Specialization Serv1})^2$	0.128***	(0.0133)	0.055***	(0.0152)	0.068***	(0.0143)
$(\text{Sectoral Specialization Serv2})^2$	–0.012	(0.0109)	0.033***	(0.0111)	–0.001	(0.0118)
Ellison-Glaeser Manu	0.059***	(0.0034)	0.049***	(0.0035)	0.078***	(0.0042)
Ellison-Glaeser Serv1	0.151***	(0.0097)	0.100***	(0.0105)	0.093***	(0.0104)
Ellison-Glaeser Serv2	0.019	(0.0123)	0.101***	(0.0131)	0.071***	(0.0128)
$(\text{Ellison-Glaeser Manu})^2$	–0.001***	(0.0001)	–0.001***	(0.0001)	–0.002***	(0.0001)
$(\text{Ellison-Glaeser Serv1})^2$	–0.003***	(0.0003)	–0.002***	(0.0003)	–0.001***	(0.0003)
$(\text{Ellison-Glaeser Serv2})^2$	–0.001**	(0.0006)	–0.004***	(0.0007)	–0.002***	(0.0007)
Probit (ZIP)						
Start-up (High-Tech)	0.569**	(0.2225)	1.078***	(0.3473)	0.989**	(0.3929)
Start-up (all)	–0.045**	(0.0164)	–0.095***	(0.0274)	–0.125***	(0.0346)
$DiDiD_1 = (D^1xT) – (D^2xT)$	0.545***	(0.0047)	0.478***	(0.0498)	0.355***	(0.0531)
$DiDiD_2 = (D^1xT) – (D^3xT)$			–0.327***	(0.0570)		
diff(BIC)	3768.5	(ZIP)	4062.0	(ZIP)	3741.1	(ZIP)
diff(AIC)	4.62	(ZIP)	4.87	(ZIP)	4.62	(ZIP)
Vuong test (p-value)	5.87	(0.00)	7.26	(0.00)	6.44	(0.00)
No. of obs.	818 [a]		836		812 [a]	

***,**,* indicate statistical significance at the 1, 5 and 10% level. Standard errors in brackets. Specialization and Ellison-Glaeser indices: Manu = manufacturing, Serv1 = business-related services, Serv2 = household-related services. Dummy variables: D^1 = winners, D^2 = participants (in the BRC2 sample: D^2 = participants net of BPC winner, D^3 = BPC winner). (D^1xT) to (D^3xT) indicate the DiD-interaction terms calculated as the product of the level dummies and the common time period indicator T. [a] BPC winners dropped in sample BRC1, BRC winners dropped in sample BPC. For diff(BIC) and diff(AIC), the expression in brackets indicates the preferred model as either ZIP or PRM.

Table 4.9 Estimation Results for all R&D Projects (Treatment Period)

Sample	BRC1		BRC2		BPC	
D^1	1.099***	(0.0617)	1.186***	(0.0598)	1.650***	(0.0441)
D^2	0.656***	(0.0543)	0.677***	(0.0538)	0.779***	(0.0420)
D^3			1.526***	(0.0542)		
T	0.228***	(0.0407)	–0.121**	(0.0493)	0.127***	(0.0331)
(D^1xT)	0.357***	(0.0615)	0.173**	(0.0718)	0.076	(0.473)
(D^2xT)	0.041	(0.0624)	–0.176**	(0.0740)	–0.204***	(0.0510)
(D^3xT)			–0.245***	(0.0706)		
Number of Firms	0.002***	(0.0001)	0.002***	(0.0001)	0.002***	(0.0001)
Average Firm size	–0.002***	(0.0003)	–0.001***	(0.0003)	–0.003***	(0.0004)
Export Share	0.018***	(0.0017)	0.007***	(0.0008)	0.010***	(0.0008)
MINT Employment	0.086***	(0.0111)	0.089***	(0.0114)	0.108***	(0.0100)
Population Density	0.237***	(0.0244)	0.293***	(0.0237)	0.246***	(0.0186)
Sectoral Specialization Manu	–1.038**	(0.3965)	–2.427***	(0.4196)	–4.258***	(0.3185)
Sectoral Specialization Serv1	–2.379***	(0.2771)	–1.947***	(0.3227)	–1.958***	(0.2767)
Sectoral Specialization Serv2	1.099***	(0.2137)	0.920***	(0.2296)	1.022***	(0.1875)
(Sectoral Specialization Manu)^2	0.072**	(0.0311)	0.177***	(0.0332)	0.318***	(0.0254)
(Sectoral Specialization Serv1)^2	0.219***	(0.0265)	0.181***	(0.0308)	0.148***	(0.0274)
(Sectoral Specialization Serv2)^2	–0.058***	(0.0218)	–0.052**	(0.0233)	–0.071***	(0.0195)
Ellison-Glaeser Manu	–0.065***	(0.0066)	–0.019***	(0.0062)	0.036***	(0.0065)
Ellison-Glaeser Serv1	–0.202***	(0.0203)	–0.236***	(0.0231)	–0.231***	(0.0198)
Ellison-Glaeser Serv2	0.225***	(0.0264)	0.289***	(0.0273)	0.318***	(0.0224)
(Ellison-Glaeser Manu)^2	0.001***	(0.0001)	–0.0002	(0.0001)	–0.001***	(0.0001)
(Ellison-Glaeser Serv1)^2	0.005***	(0.0006)	0.005***	(0.0007)	0.006***	(0.0006)
(Ellison-Glaeser Serv2)^2	–0.005***	(0.0011)	–0.007***	(0.0012)	–0.008***	(0.0011)
Probit (ZIP)						
Start-up (High-Tech)	1.104***	(0.2107)	1.025***	(0.2076)	1.113***	(0.2242)
Start-up (all)	–0.051***	(0.0153)	–0.053***	(0.0150)	–0.084***	(0.0182)
$DiDiD_1$ = (D^1xT) – (D^2xT)	0.316***	(0.0676)	0.349***	(0.0772)	0.280***	(0.0524)
$DiDiD_2$ = (D^1xT) – (D^3xT)			0.419***	(0.0745)		
diff(BIC)	2677.1	(ZIP)	2212.1	(ZIP)	3173.9	(ZIP)
diff(AIC)	3.31	(ZIP)	2.67	(ZIP)	3.92	(ZIP)
Vuong test (p-value)	8.41	(0.00)	8.27	(0.00)	8.16	(0.00)
No. of obs.	812 [a]		834		812 [a]	

***,**,* indicate statistical significance at the 1, 5 and 10% level.

Standard errors in brackets. Specialization and Ellison-Glaeser indices: Manu = manufacturing, Serv1 = business-related services, Serv2 = household-related services. Dummy variables: D^1 = winners, D^2 = participants (in the BRC2 sample: D^2 = participants net of BPC winner, D^3 = BPC winner). (D^1xT) to (D^3xT) indicate the DiD-interaction terms calculated as the product of the level dummies and the common time period indicator T. [a] BPC winners dropped in sample BRC1, BRC winners dropped in sample BPC. For diff(BIC) and diff(AIC), the expression in brackets indicates the preferred model as either ZIP or PRM.

Table 4.10 Estimation Results for collaborative R&D Projects (Treatment Period)

Sample	BRC1		BRC2		BPC	
D^1	0.731***	(0.0962)	0.897***	(0.0950)	1.173***	(0.0644)
D^2	0.318***	(0.0872)	0.352***	(0.0866)	0.431***	(0.0605)
D^3			1.128***	(0.0879)		
T	0.554***	(0.0647)	0.114*	(0.0708)	0.257***	(0.0450)
(D^1xT)	0.399***	(0.0929)	0.360***	(0.0865)	0.328***	(0.0654)
(D^2xT)	0.054	(0.0962)	–0.043	(0.1085)	0.022	(0.0699)
(D^3xT)			–0.116	(0.1036)		
Number of Firms	0.003***	(0.0002)	0.003***	(0.0002)	0.002***	(0.0001)
Average Firm size	0.0006	(0.0004)	0.001*	(0.0005)	–0.002***	(0.0005)
Export Share	0.019***	(0.0025)	0.002*	(0.0012)	0.009***	(0.0012)
MINT Employment	0.041***	(0.0153)	0.036**	(0.0163)	0.082***	(0.0130)
Population Density	0.022	(0.0354)	0.068**	(0.0349)	0.101***	(0.0254)
Sectoral Specialization Manu	0.796	(0.5570)	–0.485	(0.620)	–4.111***	(0.4407)
Sectoral Specialization Serv1	–1.818***	(0.3806)	–1.294***	(0.4367)	–0.750*	(0.3826)
Sectoral Specialization Serv2	0.854***	(0.3148)	0.469	(0.3517)	0.095***	(0.2632)
$(\text{Sectoral Specialization Manu})^2$	–0.074*	(0.0436)	0.027	(0.0491)	0.031***	(0.0354)
$(\text{Sectoral Specialization Serv1})^2$	0.154***	(0.0371)	0.114**	(0.0448)	0.020	(0.0383)
$(\text{Sectoral Specialization Serv2})^2$	–0.028	(0.0323)	–0.001	(0.0357)	0.060*	(0.0275)
Ellison-Glaeser Manu	–0.055***	(0.0094)	–0.006	(0.0094)	0.056***	(0.0092)
Ellison-Glaeser Serv1	–0.221***	(0.0281)	–0.265***	(0.0329)	–0.165***	(0.0261)
Ellison-Glaeser Serv2	0.311***	(0.0364)	0.334***	(0.0388)	0.259***	(0.0288)
$(\text{Ellison-Glaeser Manu})^2$	0.001**	(0.0002)	–0.0005**	(0.0003)	–0.002***	(0.0002)
$(\text{Ellison-Glaeser Serv1})^2$	0.004***	(0.0008)	0.005***	(0.0010)	0.004***	(0.0008)
$(\text{Ellison-Glaeser Serv2})^2$	–0.007***	(0.0016)	–0.007***	(0.0017)	–0.003**	(0.001)
Probit (ZIP)						
Start-up (High-Tech)	1.194***	(0.2430)	1.249***	(0.2399)	1.131***	(0.2370)
Start-up (all)	–0.033**	(0.0166)	–0.033**	(0.0161)	–0.062***	(0.0186)
$DiDiD_1 = (D^1xT) – (D^2xT)$	0.345***	(0.0995)	0.403***	(0.1109)	0.307***	(0.0722)
$DiDiD_2 = (D^1xT) – (D^3xT)$			0.475***	(0.1068)		
diff(BIC)	2017.8	(ZIP)	1472.3	(ZIP)	2551.7	(ZIP)
diff(AIC)	2.50	(ZIP)	1.78	(ZIP)	3.16	(ZIP)
Vuong test (p-value)	7.80	(0.00)	7.19	(0.00)	7.98	(0.00)
No. of obs.	812 [a]		834		812 [a]	

***,**,* indicate statistical significance at the 1, 5 and 10% level.

Standard errors in brackets. Specialization and Ellison-Glaeser indices: Manu = manufacturing, Serv1 = business-related services, Serv2 = household-related services. Dummy variables: D1 = winners, D2 = participants (in the BRC2 sample: D2 = participants net of BPC winner, D3 = BPC winner). (D1xT) to (D3xT) indicate the DiD-interaction terms calculated as the product of the level dummies and the common time period indicator T. a BPC winners dropped in sample BRC1, BRC winners dropped in sample BPC. For diff(BIC) and diff(AIC), the expression in brackets indicates the preferred model as either ZIP or PRM.

Table 4.11 BRC1-Estimation Results for R&D Projects (Post-Treatment Period)

Sample: BRC1	All Projects		Collaborative	
D^1	1.037***	(0.0618)	0.644***	(0.0962)
D^2	0.607***	(0.0543)	0.223**	(0.0881)
T	0.244***	(0.0443)	0.504***	(0.0688)
(D^1xT)	0.094	(0.0638)	0.224**	(0.0959)
(D^2xT)	–0.117*	(0.0638)	0.134	(0.0969)
Number of Firms	0.003***	(0.0001)	0.003***	(0.0002)
Average Firm size	0.0001	(0.0002)	0.002***	(0.0004)
Export Share	0.013***	(0.0016)	0.015***	(0.0022)
MINT Employment	0.087***	(0.0115)	0.035**	(0.0159)
Population Density	0.232***	(0.0245)	0.082**	(0.0366)
Sectoral Specialization Manu	–1.616***	(0.4112)	–1.177**	(0.5699)
Sectoral Specialization Serv1	–1.7199***	(0.2883)	–1.885***	(0.4011)
Sectoral Specialization Serv2	1.094***	(0.2239)	0.0033	(0.3227)
$(\text{Sectoral Specialization Manu})^2$	0.0995***	(0.0322)	0.065***	(0.0446)
$(\text{Sectoral Specialization Serv1})^2$	0.152***	(0.0277)	0.160***	(0.0393)
$(\text{Sectoral Specialization Serv2})^2$	–0.051**	(0.0229)	0.068**	(0.0329)
Ellison-Glaeser Manu	–0.047***	(0.0065)	–0.027***	(0.0093)
Ellison-Glaeser Serv1	–0.262***	(0.0225)	–0.223***	(0.0304)
Ellison-Glaeser Serv2	0.358***	(0.0287)	0.347***	(0.0385)
$(\text{Ellison-Glaeser Manu})^2$	0.001	(0.0013)	–0.0003*	(0.0001)
$(\text{Ellison-Glaeser Serv1})^2$	0.005***	(0.0007)	0.004***	(0.0009)
$(\text{Ellison-Glaeser Serv2})^2$	–0.010***	(0.0013)	–0.008***	(0.0017)
Probit (ZIP)				
Start-up (High-Tech)	1.099***	(0.2165)	1.557***	(0.2655)
Start-up (all)	–0.057***	(0.0151)	–0.040**	(0.0167)
DiDiD = (D^1xT) – (D^2xT)	0.212***	(0.0707)	0.091	(0.1015)
diff(BIC)	2708.9	(ZIP)	1821.4	(ZIP)
diff(AIC)	3.379	(ZIP)	2.27	(ZIP)
Vuong test (p-value)	8.17	(0.00)	7.64	(0.00)
No. of obs.	806 [a]		806 [a]	

***,**,* indicate statistical significance at the 1, 5 and 10% level.

Standard errors in brackets. Specialization and Ellison-Glaeser indices: Manu = manufacturing, Serv1 = business-related services, Serv2 = household-related services. Dummy variables: D^1 = winners, D^2 = participants. (D^1xT) to (D^2xT) indicate the DiD-interaction terms calculated as the product of the level dummies and the common time trend T. [a] BPC winners dropped. For diff(BIC) and diff(AIC) the expression in brackets indicates the preferred model as either ZIP or PRM.

The smaller treatment effects found for BPC winners relative to non-participants may be partly due the consolidation phase going on in the industry throughout the second half of the last decade. Although we control for a common time trend among all groups, which turns out to be significantly negative according to Table 4.7, throughout this consolidation period the chances to realize excess returns may have been limited for funded regions as well.

We finally report some details of the full regression outputs shown in Table 4.8 to Table 4.11. Regarding the appropriate functional form, in most specifications the ZIP model is favoured over the Poisson model based on model information criteria (AIC, BIC) as well as on the Vuong (1989) non-nested test between the Poisson and ZIP models. As a key explanatory variable in the Probit specification, we use the share of regional high-tech startups indicating an innovative climate for a region that either supports R&D or not. In all specifications, this variable turns out to be statistically significant and of the expected sign.

Also, the remaining variables in the Poisson part of the model mostly reflect our ex-ante expectations, that is, both the share of MINT employees and the export share have a positive impact on R&D activity. Moreover, the total number of firms, the variables measuring general agglomeration (e.g., population density), and sectoral concentration indices (and their squared values) are statistically significant. As a robustness check, we also controlled for the likely role of spatial dependence in the variables. Though positive spatial autocorrelation was found to be present for patent applications (no statistically significant spatial autocorrelation in the case of public R&D funding), the inclusion of spatial filters to control for unobserved spatial heterogeneity did not alter the key conclusions from the DiD-estimation approach.[11]

4.6 Conclusion

In this paper, we have analysed the performance of winning regions for Germany's well-known BioRegio and BioProfile contests. These contests marked a milestone in the attempt to allocate public R&D funds in a competitive way, which strongly emphasizes the role of geographic proximity in knowledge creation, and to push collaborative R&D projects in leading biotechnology clusters. Although the BioRegio contest was one of the major attempts of the German Federal Government to narrow the gap between Germany and those countries leading in the application of biotechnological knowledge, little is known so far about its innovation and economic impact during the treatment period and in the post-treatment period. We tackled this issue by analysing two measures of R&D performance, namely the number of biotech patent applications and the number of raised public R&D projects. Using a Difference-in-Differences estimation strategy with data for 426 German NUTS-3 districts, our estimation strategy controls for observable and time-invariant unobservable differences in the pre-funding period, which also drive R&D performance in the treatment and post-treatment periods.

In first place, we compare the research outcomes of winning regions against non-winning participants. The choice of this comparison is motivated by the need to reduce any potential self-selection bias stemming from a non-random selection into treatment. Our results show that BRC winners and (to a lesser extent) BPC winners outperform non-winning participants during the treatment period. Exclusive funding, as well as stimulating effects of the “winner” label, seem to work for them in the short run. Given the sequential starting dates of the BioRegio and BioProfile contests, we are also able to compare the performance of BRC and BPC winners during a common (but temporally truncated) treatment period. In this case, the results highlight two facts: on the one hand, after being selected, the BRC winners

[11] Detailed results can be obtained from the authors upon request and are reported in an earlier version of this paper (“Does the Support of Innovative Clusters Sustainably Foster R&D Activity? Evidence from the German BioRegio and BioProfile Contests”, Quaderni della facoltà di Scienze economiche dell'Università di Lugano, No. 1105-2010).

significantly increased their relative performance in raising public R&D projects; on the other hand, they did not outperform BPC winners in terms of patent applications during the treatment period, although both groups show a significant positive effect compared to non-winning participants. The catching up of BPC winners to BRC winners can be explained by their smaller absolute size in terms of the number of patent applications prior to treatment. Thus, among the candidates in the BRC, the jury clearly selected heavyweights, rather than dynamically growing, but smaller “rising stars”. The latter were selected in the second competition, the BPC. This finding provides further empirical evidence that the outcome of both the BRC and BPC are the result of “picking the winners”, as argued, for example, by Dohse (2000).

In contrast with these positive effects during the treatment period, we do not find significant outcome effects of public R&D grants for BRC winners in the post-treatment period. This result is striking, and may indicate that the success of the BRC seems to be only of a temporary manner. Still, there is some evidence of positive long-term effects for collaborative R&D projects. It should be pointed out that our findings may be limited by the quality of the indicator used: in fact, we are only able to compare the number of raised public R&D grants, which may actually follow different allocation guidelines than the one of serving the most successful regions (e.g., distributive arguments). Finally, the absence of long-term effects of BRC may also driven by the fact that non-winning regions have increased their efforts to establish networks between biotech-related firms and research units, that is, ten more biotech-regions were formed by 2005 after the BioRegio contest, and several Federal States have promoted strongly the emergence of BioRegions locally. However, it is very difficult to quantify these indirect effects. Future analyses will thus be needed to consider additional measures for the assessment of R&D performance (e.g., the share of turnover with new biotech products, or employment in biotechnology-related firms).

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Appendix D Supporting Material

Table D.1 List of regions in the BioRegio and BioProfile contests

ID	Name	BioRegio Winner	BioRegio Non-Winner	BioProfile Winner
1002	Kiel (KS)	0	1	0
1003	Lübeck (KS)	0	1	0
2000	Hamburg (KS)	0	1	0
13003	Rostock (KS)	0	1	0
13001	Greifswald (KS)	0	1	0
3405	Wilhelmshaven (KS)	0	1	0
3403	Oldenburg (KS)	0	1	0
4011	Bremen (KS)	0	1	0
4012	Bremerhaven	0	1	0
3241	Region Hannover	0	1	1
3201	Hannover (KS)	0	1	1
3101	Braunschweig (KS)	0	1	1
3152	Göttingen	0	1	1
5124	Wuppertal (KS)	1	0	0
5111	Düsseldorf (KS)	1	0	0
5315	Köln (KS)	1	0	0
5313	Aachen (KS)	1	0	0
5316	Leverkusen (KS)	1	0	0
5354	Aachen	1	0	0
5358	Düren	1	0	0
5314	Bonn (KS)	1	0	0
6534	Marburg-Biedenkopf	0	1	0
6531	Gießen	0	1	0
6414	Wiesbaden (KS)	0	1	0
6412	Frankfurt (KS)	0	1	0
7315	Mainz (KS)	0	1	0
6411	Darmstadt (KS)	0	1	0
6413	Offenbach (KS)	0	1	0
6436	Main-Taunus	0	1	0
6438	Offenbach	0	1	0
7314	Ludwigshafen (KS)	1	0	0
7316	Neustadt a. d. W. (KS)	1	0	0
8111	Stuttgart (KS)	0	1	1
8116	Esslingen	0	1	1
8221	Heidelberg (KS)	1	0	0
8222	Mannheim (KS)	1	0	0
8416	Tübingen	0	1	1
8415	Reutlingen	0	1	1
8417	Zollernalbkreis	0	1	1
8311	Freiburg (KS)	0	1	0
8421	Ulm (KS)	0	1	0
9162	München (KS)	1	0	0
9188	Starnberg	1	0	0
9362	Regensburg (KS)	0	1	0
16053	Jena (KS)	1	0	0
15202	Halle (KS)	0	1	0
14365	Leipzig (KS)	0	1	0
15261	Merseburg-Querfurt	0	1	0
15265	Saalkreis	0	1	0
15154	Bitterfeld	0	1	0
11000	Berlin (KS)	0	1	1
12065	Oberhavel	0	1	1
12069	Potsdam-Mittelmark	0	1	1
12072	Teltow-Fläming	0	1	1
12054	Potsdam (KS)	0	1	1

Table D.2 Definition of the Biotech sector based on IPC classes

Patent class	Title
A01H 1/00	Processes for modifying genotypes
A01H 4/00	Plant reproduction by tissue culture techniques
A61K 38/00	Medicinal preparations containing peptides
A61K 39/00	Medicinal preparations containing antigens or antibodies
A61K 48/00	Medicinal preparations containing genetic material which is inserted into cells of the living body to treat genetic diseases; Gene therapy
C02F 3/34	Biological treatment of water, waste water, or sewage: characterized by the micro-organisms used
C07G 11/00	Compounds of unknown constitution: antibiotics
C07G 13/00	Compounds of unknown constitution: vitamins
C07G 15/00	Compounds of unknown constitution: hormones
C07K 4/00	Peptides having up to 20 amino acids in an undefined or only partially defined sequence; Derivatives thereof
C07K 14/00	Peptides having more than 20 amino acids; Gastrins; Somatostatins; Melanotropins; Derivatives thereof
C07K 16/00	Immunoglobulins, e.g. monoclonal or polyclonal antibodies
C07K 17/00	Carrier-bound or immobilized peptides; Preparation thereof
C07K 19/00	Hybrid peptides
C12M	Apparatus for enzymology or microbiology
C12N	Micro-organisms or enzymes; compositions thereof
C12P	Fermentation or enzyme-using processes to synthesize a desired chemical compound or composition or to separate optical isomers from a racemic mixture
C12Q	Measuring or testing processes involving enzymes or micro-organisms; compositions or test papers therefore; processes of preparing such compositions; condition-responsive control in microbiological or enzymological processes
C12S	Processes using enzymes or micro-organisms to liberate, separate or purify a pre-existing compound or composition processes using enzymes or micro-organisms to treat textiles or to clean solid surfaces of materials
G01N 27/327	Investigating or analysing materials by the use of electric, electro-chemical, or magnetic means: biochemical electrodes
G01N 33/53*	Investigating or analysing materials by specific methods not covered by the preceding groups: immunoassay; biospecific binding assay; materials therefore
G01N 33/54*	Investigating or analysing materials by specific methods not covered by the preceding groups: double or second antibody: with steric inhibition or signal modification: with an insoluble carrier for immobilizing immunochemicals: the carrier being organic: synthetic resin: as water suspendable particles: with antigen or antibody attached to the carrier via a bridging agent: Carbohydrates: with antigen or antibody entrapped within the carrier
G01N 33/55*	Investigating or analysing materials by specific methods not covered by the preceding groups: the carrier being inorganic: Glass or silica: Metal or metal coated: the carrier being a biological cell or cell fragment: Red blood cell: Fixed or stabilized red blood cell: using kinetic measurement: using diffusion or migration of antigen or antibody: through a gel
G01N 33/57*	Investigating or analysing materials by specific methods not covered by the preceding groups: for venereal disease: for enzymes or isoenzymes: for cancer: for hepatitis: involving monoclonal antibodies: involving limulus lysate
G01N 33/68	Investigating or analysing materials by specific methods not covered by the preceding groups: involving proteins, peptides or amino acids
G01N 33/74	Investigating or analysing materials by specific methods not covered by the preceding groups: involving hormones
G01N 33/76	Investigating or analysing materials by specific methods not covered by the preceding groups: human chorionic gonadotropin
G01N 33/78	Investigating or analysing materials by specific methods not covered by the preceding groups: thyroid gland hormones
G01N 33/88	Investigating or analysing materials by specific methods not covered by the preceding groups: involving prostaglandins
G01N 33/92	Investigating or analysing materials by specific methods not covered by the preceding groups: involving lipids, e.g. cholesterol

Source: OECD (2005), p.32. Notes: * = Those IPC codes also include subgroups up to one digit (0 or 1 digit). For example, in addition to the code G01N 33/53, the codes G01N 33/531, GO1N 33/532, etc. are included.

Table D.3 Biotech categories in PROFI database

Code:	Technology field
K	Biotechnology
I19080	Molecular Bioinformatics

Own definition according to the technology field classification of the Leistungsplansystematik des Bundes. - The following activities have not been considered; “Projektstabskosten” (Code XX XX 90), “Projektbegleiter” (Code XX XX 91), “Beratungsgremien” (Code XX XX 92), “Programmevaluation” (Code XX XX 95).

Table D.4 Descriptive statistics for total sample (Pre-, Treatment, Post-Treatment period)

Variable	N	Mean	Std. Dev.	Min	Max
Patents	1317	20.722	63.124	0	1099
Projects (all)	1317	10.845	40.491	0	673
Projects (collaborative)	1317	6.008	22.881	0	445
Number of Firms	1317	109.369	95.156	12	1071.5
Average Firm Size	1317	131.899	112.608	37.47	1816.60
Export Share	1257	27.334	13.233	0.15	96.19
R&D Employment	1317	2.206	1.305	0.40	13.55
Population Density	1317	5.606	1.085	3.68	8.30
Sectoral Specialization Manu	1311	6.257	0.682	4.97	9.00
Sectoral Specialization Serv1	1311	5.375	0.549	3.67	7.98
Sectoral Specialization Serv2	1311	4.634	0.677	2.97	6.41
Ellison-Glaeser Manu	1311	21.301	10.671	2.075	68.631
Ellison-Glaeser Serv1	1311	6.362	3.847	1.205	2.933
Ellison-Glaeser Serv2	1311	3.231	2.703	0.273	21.630
Start-up (High-Tech)	1317	0.401	0.267	0.03	2.04
Start-up (all)	1317	9.974	3.597	2.36	35.44

For variable definition, see text. Population Density and Sectoral Specialization are in log-levels. Specialization and Ellison-Glaeser indices: Manu = manufacturing, Serv1 = business-related services, Serv2 = household-related services.

Chapter 5
Does Firm Size make a Difference? Analysing the Effectiveness of R&D Subsidies in East Germany

This article was coauthored by Björn Alecke, Timo Mitze and Gerhard Untiedt and was published in German Economic Review 13 (2), 2012, 174–195.

5.1 Introduction

We evaluate the impact of public subsidies on private sector research and development (R&D) activity in East Germany. Two decades after reunification, the East German states are still challenged when it comes to their convergence towards the Western economic structures. Particularly private sector R&D activity continues to show a distinct structural weakness. For instance, private R&D expenditures and patent applications per capita in East Germany clearly are below the West German average. Consequently, there have been several political attempts to foster economic growth and convergence especially through public R&D funding. As a result, about 60% of all innovating firms in East Germany have received public grants since the mid-1990s compared with only 10% in West Germany (Czarnitzki and Licht, 2006). Given that roughly €1.1 billion per year or 0.4% of the East German gross domestic product go into R&D subsidies, the effectiveness of these subsidies should be assessed carefully.

Financial support for R&D is by now a common practice at the national and regional levels in most industrialized countries. Market imperfections are typically used as the main argument to justify government interventions of this form. They may arise since firms are not able to control for all outcomes of their R&D activities and, because undertaking R&D is costly and involves high risks, their access to external funds may be limited. Furthermore, the knowledge gained from innovation activity may not be fully internalized so that non-innovating firms profit from these research activities via knowledge spillovers without paying for them. In consequence, this will result in an underinvestment in R&D activity from a social perspective and hence government intervention may be justified (Büttner, 2006; Helm and Schöttner, 2008).

Compared with the large number of international studies on R&D policy effects, where public subsidies are typically found to exert a positive effect on different private sector outcome variables (see, e.g., the literature survey by Garcia-Quevedo, 2004), rather few empirical references study the East German case. Almus and Czarnitzki (2003), Czarnitzki (2001), Czarnitzki and Licht (2006) report that public R&D support has a statistically significant positive effect on private sector R&D and innovation activity. Since all these results stem from one single data source, we test their validity based on a novel dataset.

What makes East Germany in particular an interesting case study, is that it is dominated by small- and medium-sized firms. Compared with West Germany, the share of small- and medium-sized enterprises (SMEs) engaged in continuous R&D activity is far higher (36% of all SMEs relative to 9%). As earlier work has shown, SME-based knowledge production functions may substantially differ from innovation systems driven by large firms (Conte and Vivarelli, 2005). This points to the question as to what extent the publicly financed R&D factor inputs can be absorbed by SMEs without inducing substantial crowding-out effects of private spendings. The latter cannot be clearly answered from a theoretical perspective.[1] Besides, no specific empirical evidence is given regarding the effectiveness of R&D policy for SMEs in East Germany so far.

In this article, we analyse the effect of R&D subsidies on private sector innovation with a special focus on small- and medium-sized firms. Using a sample of 1,267 firms in the East German federal state Thuringia, we apply propensity score matching to identify the causal impact of funding. Our empirical results indicate that, compared with non-subsidized ones, subsidized firms have a statistically significant higher R&D intensity (R&D expenditures relative to total turnover) and a higher probability of applying for patents. We find that, on average, the R&D intensity increases from 1.5% to 3.9%. The probability of patent application rises from 20% to 40%. Based on the increase in the R&D intensity of about 2.4%-points we estimate as leverage effect that a 1% change in public R&D grants induces 0.21% additional private R&D expenditures in relation to a firm's sales. This positive effect also holds for three subgroups of SMEs (micro firms with 1 up to 10 employees, small firms with 21 and up to 50 employees, as well as medium-sized firms with 51 and up to 250 employees). Regarding R&D intensity, the largest outcome difference is found for micro firms. For the other two subgroups the effect is also found to be positive but of smaller size. With respect to patent activity we find statistically significant policy effects except for micro firms.

The remainder of the article is organized as follows. In Section 5.2, we briefly outline the matching approach. Section 5.3 describes the dataset, Section 5.4 discusses the empirical results for the full sample and SME subsamples. In Section 5.5 we report the results of robustness checks for hidden biases, sensitivity to alternative matching algorithms and a sample restriction using only distinct comparison firms. Section 5.6 concludes the article.

5.2 Causal Impact Analysis Using Matching Estimation

Quantitative evaluation of a policy programme involves analysing its effectiveness at the micro and macro levels as well as an examination of programme efficiency, which is typically done by means of cost-benefit analysis. Each step involves a considerable amount of research

[1] One may argue that SMEs are highly affected by barriers to innovation such as financial bottlenecks, shortage and hindered access to qualified personnel as well as limited internal and missing market know-how, which negatively affects their innovative performance. In particular, this may be true for SMEs in peripherical regions such as East Germany. R&D grants may thus help to remove barriers to innovation for SME and induce additional private R&D efforts. However, on the other hand, the maximum level of R&D activity may be low for SME, which is likely to result in crowding-out effects.

effort. Here, we focus on the microeconometric evaluation. Analysing the effect at the level of the individual firm can be seen as a necessary condition for the overall success of a policy programme.[2]

A major methodological problem arising in this context is that empirical identification strategies may suffer from potential selection problems. That is, firms receiving a grant may have been chosen by the policy-maker because they are likely to carry out successful research projects and thus a selection procedure following a 'picking the winners' pattern may apply; or from the firms' perspective only those may apply for R&D grants, who are already successful in conducting R&D projects. Overlooking this self-selection mechanism can bias the empirical results and lead to unreliable policy recommendations. The crucial feature of investigations at the firm level is to identify industry and firm heterogeneity, since industries differ in technological opportunities and possibilities to internalize returns from innovation.[3] One can expect important differences in innovative activities depending on the company size, international orientation and general business strategy.

We chose the method of non-parametric matching to cope with these issues and analyse the causal impact of public subsidies on private sector R&D innovation. Since matching is now a standard approach in microeconometric evaluation, we will confine at this point to only a few central comments. For a more rigorous overview of the method the reader is referred to Caliendo and Kopeinig (2008). Matching estimation compares the sample average of an outcome variable for firms that exhibit a treatment with those firms that are similar in terms of a predefined set of characteristics, but are not subject to the treatment. The main parameter of interest in matching estimation is the 'average treatment effect on the treated' (ATT), which identifies the benefit of treatment for the treated group.[4] Identification of the ATT thereby faces the empirical problem that the counterfactual situation is not observable. That is, the question 'how would the outcome variable for treated firms look like for all things being equal except that no treatment would have occurred?' cannot be answered as we can only observe either of the states for one firm. Thus, one has to choose a proper substitute to estimate the ATT.

An obvious choice would be to take the observed expected outcome of untreated firms. However, it is likely that components which determine the treatment decision also determine the outcome variable of interest. This potential selection bias can only be avoided if

[2] We are aware that solely focusing on this point is not sufficient for an overall judgement of R&D policy. For instance, the first-round impacts on subsidized firms could be weakened by displacement effects on non-subsidized competing firms or could be amplified by positive knowledge spillovers accruing to other firms and institutions of the regional or even national innovation system. Finally, for a full assessment of the merits of R&D policy, one has to juxtapose the benefits in the form of additional R&D, innovations and jobs created with the budget costs of R&D subsidies. Thus, what matters from a policy point of view is not only an assessment of the effectiveness but also of the efficiency of R&D policy.

[3] Alternatively, country-level studies typically regress private on public R&D spendings controlling for common driving forces to avoid a spurious relationship between both variables; for an overview of macroeconomic studies, see Garcia-Quevedo (2004).

[4] Further parameters of interest for empirical work are the 'average treatment effect of the non-treated' (ATN) and the 'average treatment effect' (ATE) for the whole sample population.

assignment to the treatment is ensured to be random. While the latter is typically true for social experiments, in non-experimental studies one has to invoke some identifying assumptions to solve the selection problem.

A first assumption implies that systematic differences in the outcome between treated and comparison firms are fully attributable to the treatment variable if both firms have the same values of covariates. This so-called conditional independence assumption (CIA) is expected to be fulfilled if all variables influencing the outcome are at the researcher's disposal. Although the CIA cannot be tested, our sample contains various firm-level information which makes it likely to satisfy the CIA. In addition, test procedures have been developed which allow to quantify the distortive effects stemming from unobserved factors, which may both bias selection into treatment and outcome determination (Rosenbaum, 2002). A second assumption to be satisfied is the so-called stable unit treatment value assumption (SUTVA). It states that individual effects of a policy programme may not be influenced by the participation status of other firms. As for the CIA, the validity of the SUTVA cannot be tested empirically so that qualitative arguments have to be made. We support the argumentation outlined by Almus and Czarnitzki (2003) that the presence of distorting effects, altering the relative prices for R&D factor inputs, are not likely to be present in the case of the East German R&D funding scheme. The main reason is that pricing mechanisms for R&D factor inputs can be assumed to be merely driven by national and international rather than regional factors and associated policy distortions.[5]

Based on these assumptions the effect of the subsidy $\widehat{\theta_{ATT}}$ using the outcome difference between treated (T) and comparison firms (C) can be estimated empirically as:

$$(5.1)\quad \widehat{\theta_{ATT}} = \frac{1}{N}\sum_{i\epsilon T}\left[Y_{1,i} - \sum_{j\epsilon C} w(i,j)Y_{0,j}\right]$$

where N is the total number of treated firms i, Y_1 and Y_0 denote outcome values for treated and comparison firms j, respectively. The match of each treated firm is constructed as a weighted average over the outcomes of non-treated, where the weights $w(i,j)\ \epsilon\ [0,1]$ depend on the 'distance' between i and j.

There exists a wide range of matching algorithms either being exact on covariates or the so-called propensity scores. The latter approach rests on the idea to match not directly on the set of k covariates $\boldsymbol{X} = (X_1, \dots, X_2, \dots, X_k)$' but on a function of the former which describes the propensity to receive treatment as $P\,(D = 1|\boldsymbol{X}) = P(\boldsymbol{X})$. The predicted probability of group membership $(P(\boldsymbol{X}))$ is thereby typically estimated from a first-step probit model. A

[5] Another possibility why the SUTVA assumption might not hold in practice, this point was raised by a referee, are knowledge spillovers from R&D activity. As firms might find it easier to innovate in a region where there is a critical mass of other innovating firms, the participation status of other firms might become important. Thus, if there are knowledge spillovers the effect of the R&D subsidies would be underestimated. On the other hand, if the market performance of subsidized firms goes at the expense of non-subsidized firms the impact of R&D subsidies is overestimated. However, it is very difficult to judge the empirical content of these arguments. At this point we simply have to assume – in line with the rest of the microeconomic literature on R&D subsidies – that knowledge spillovers and displacement effects from additional R&D activities induced by public subsidies do not feed back into the decision processes of the individual firms and, at least empirically, do not play a substantial role.

major difference between these algorithms is the empirical operationalization of the elements w(i,j) of a weighting function W. Most criteria match treated firms only with a certain fraction of the comparison group, where selection is based on the propensity score. Prominent examples are nearest-, k-nearest neighbour and stratification matching. Other routines like Kernel matching use a weighted matching approach based on averaging procedures of the outcomes for all comparison units. One major advantage of these Kernel procedures is the lower variance, because more information is used (Caliendo and Kopeinig, 2008).

We use propensity score-based Kernel matching as default estimator as it has been shown to have good finite sample properties compared with the standard k-nearest neighbour matching function (Frölich, 2004). Since we are dealing with a small sample, we compute bootstrapped standard errors, which turned out to be more restrictive compared with the ones based on asymptotically normal statistical inference and may thus be seen as the more conservative benchmark in the evaluation exercise. We also apply a common support restriction to our Kernel matching routine to minimize the risk of bad matches. Finally, we use different robustness checks to validate the obtained policy outcome.[6]

5.3 Institutional Setup and Data Description

We assess the impact of direct R&D support measures using micro data based on the GEFRA Business survey (GEFRA et al., 2004a, 2005). This survey was conducted in the evaluation process of two direct enterprise support schemes, namely the 'Joint Task for the Promotion of Industry and Trade' and the 'Promotion of Joint Research Projects' on behalf of the Thuringian Ministry of Economics and the Thuringian Ministry of Science, Research and Arts. For the survey, a total of 6,861 firms in the manufacturing and service sector have been contacted. The response rate was about 21%, so the survey contains a total of 1,484 firms of which 284 firms received public R&D grants. The questionnaire refers to firm-specific data for the year 2003. Since earlier evidence on the effectiveness of R&D policies in East Germany was exclusively based on data from the Mannheimer Innovation Panel (MIP), our results may serve as a cross-check for the robustness of these results.[7]

Before turning to the details concerning the empirical operationalization of the treatment, outcome and control variables, we will give a short description of the institutional setup of support for R&D and innovation in Germany. In general, firms can rely on numerous forms of financial support for their R&D projects. There is a vast spectrum of programmes and measures for the direct support of R&D projects and start-up of young technology-oriented firms. With the exception of tax reductions, the full range of financial subsidy possibilities is used: direct grants for R&D and innovation expenses; loans with interest at reduced rates, as

[6] For estimation and sensitivity analysis we use software codes for Stata by Becker and Ichino (2002), Leuven and Sianesi (2003), DiPrete and Gangl (2004) and Becker and Caliendo (2007).

[7] Before applying the data for empirical analysis, we tested for sample representativeness. Using a standardized Z-statistic-based test we find that our survey data replicates the overall sectoral composition of the Thuringian economy quite well. Only the subsector WZ28 'Manufacture of fabricated metal products, except machinery and equipment' is tested to be overrepresented in the GEFRA Business survey. Test details are given in supporting information Table E.1.

well as extensions for repayments; national coventuring for subsidized credits and investments; funding of, generally, silent partnerships; and provision of free or low-priced information and mediation services.

Table 5.1 Variable definition

Variable	Description
R&D activity	
R&D intensity	R&D intensity defined as R&D expenditures relative to total turnover (net of intermediate inputs)
Patent activity	1 if firm has applied for patent registration
Treatment variable	
R&D subsidies	1 if firm received subsidies either from the federal state Thuringia, national or EU-wide programmes or combinations; 0 otherwise
Standard firm-specific control variables and skill structure	
Size	Firm size in terms of total employment
Age	Number of years since firm was created, relative to 2004
Capital	Capital intensity defined as total capital stock per employee
Investment	Investment intensity defined as total investment per sales
Human capital high	High-skilled employees as share of total employment
Human capital low	Low-skilled employees as share of total employment
Internationalization and regional input–output relations	
Regional sales	Sales within the core region (30 km) relative to total sales, in %
East German sales	Sales within East Germany relative to total sales, in %
West German sales	Sales within West Germany relative to total sales, in %
Exports	Total exports relative to sales, in %
Regional inputs	Input from suppliers within the core region (30 km) relative to total inputs, in %
East German inputs	Input from suppliers from East Germany relative to total inputs, in %
West German inputs	Input from suppliers from West Germany relative to total inputs, in %
Imports	Import share defined as imports relative to total production inputs, in %
Other variables	
Liability	1 if firm owner has full legal liability, 0 for limited liability
West German ownership	1 if firm belongs to a parent company in West Germany
East German ownership	1 if firm belongs to a parent company in East Germany
Foreign ownership	1 if firm belongs to a parent company abroad
R&D department	1 if firm has R&D employees within a fixed R&D department

Financing is provided by the German federal government, the individual German federal states and the European Union (EU). Taken together all R&D programmes in Germany addressed to the business sector until the year 2008, a total of 209 different programmes have been set up (Alecke et al., 2011). Of these, 82 programmes were funded by the federal government, 114 by the federal states and 13 by the EU. Unfortunately, detailed figures for the overall amount of R&D subsidies in Germany are not available. The yearly amount of

R&D subsidies for the business sector spent by the federal government could be estimated at around €1.5 billion. The East German states spent roughly €0.4–0.5 billion and the West German about €0.3 billion.

There are substantial differences between the R&D programmes with regard to the processes of application and approval and the selection criteria used by managing authorities. Usually firms must file an application in which they have to outline their R&D project and its innovative character and the technological risks involved in the realization of the project. Applications often have to set out a work and time schedule and a commercialization plan, describing how research results will be transformed into products, processes or services and be brought onto the market to ultimately generate additional sales and/or employment. Non-repayable project grants can reach up to 50% of eligible project costs. Higher incentive rates up to 75% are accessible for SMEs and firms settling in East Germany, or projects conducted in cooperation with other companies or research institutes. The amount of the subsidy also depends on the research category (fundamental research, industrial research and experimental development).[8] All in all, in Germany there is a rather complex collection of R&D programmes funded by different administrative bodies.

The questionnaire was designed to capture the afore described institutional settings of R&D subsidies and to obtain data on various factor inputs (labour, intermediate inputs, human and physical capital) as well as economic outcome variables such as sales, exports and labour productivity. With respect to variables representing R&D activity at the firm level the dataset includes the firm's R&D intensity as the ratio of R&D expenditure to sales and a binary dummy variable for general patenting activity. Firms were asked whether they received funding by any R&D support programme of the federal government, the federal states or the EU. Since all possible R&D programmes launched by public authorities are covered by the survey, this study is not restricted to a particular policy measure, but reflects the joint effect of the available set of public R&D policies as outlined before. This may be seen as a conceptual advantage, since many studies deal with only one specific public R&D programme and cannot control for possible effects of other sources of public R&D funding (for a discussion see, e.g. Almus and Czarnitzki, 2003). In contrast, our approach is able to construct a treatment group consisting of those firms which received subsidies at the regional, national or EU level.

However, there are two drawbacks. First, as we do not have information on the financial amount of R&D subsidies each firm received, we are only able to make a qualitative distinction between subsidized and non-subsidized firms. Second, whereas the questions with regard to the R&D activities refer to the year 2003, firms were asked if they received public

[8] However, whereas firms once selected into the R&D schemes are granted high subsidy rates, the selection rates differ quite substantially between programmes depending on the demanded degree of innovativeness of the R&D projects for the national or international markets. A description of the R&D incentive programmes offered in Germany and their technical regulations is given by the federal government agency Germany Trade & Invest, http://www.gtai.com.

subsidies in the three years 2001 up to 2003, but no further information is given on the receipt of subsidies before that period. Thus, our analysis is confined only to short-term effects of public funding.[9]

Since the main target of the R&D subsidies is on the expansion of the R&D activities of the subsidized firms we choose R&D expenditure scaled to total sales (R&D intensity) as our main outcome variable. As a result of its right-skewed distribution in the estimation we used the logarithm (log) of this outcome variable. In addition, we used a binary dummy variable for general patenting activity of the firm as a further outcome variable.

Table 5.2 Descriptive statistics

Variable	N	Mean	SD	Min	Max
R&D subsidies	1267	0.223	0.417	0	1
R&D intensity	1265	0.047	0.240	0	6.6
Patent activity	1412	0.141	0.348	0	1
Size	1431	56.67	148.03	1	2947
Age	1279	11.07	7.790	1	73
Capital	1238	70.97	178.26	0	3875
Investment	986	32.05	364.8	0	10831
Human capital high	1385	0.190	0.240	0	1
Human capital low	1431	0.070	0.390	0	1
Regional sales	1382	0.236	0.307	0	1
East German sales	1387	0.115	0.169	0	1
West Herman sales	1391	0.395	0.315	0	1
Exports	1365	0.127	0.222	0	1
Regional inputs	1261	0.234	0.288	0	1
East German inputs	1265	0.118	0.171	0	1
West German inputs	1269	0.398	0.297	0	1
Imports	1242	0.982	0.186	0	1
Liability	1426	0.275	0.447	0	1
West German ownership	1164	0.140	0.347	0	1
East German ownership	1164	0.043	0.203	0	1
Foreign ownership	1164	0.049	0.218	0	1
R&D department	1362	0.277	0.448	0	1

As we pointed out, firm-specific control characteristics are needed to ensure the identification of the causal effect of R&D subsidies. Basic variables are firm size in terms of total employment and firm age. Size can affect R&D decisions differently, for example, through better organization, easier use of the financial market and specialization of activities and routines. We further use capital intensity, defined as tangible assets per employee, to control for the technology used in the production process and also test for the effect of investment intensity in determining the propensity to participate in the policy programme (the

[9] However, as far as we know the only study for Germany which addresses the issues of a firm's history of R&D subsidies and long-term effects is Aschhoff (2009). She finds that for both first-time and frequent participants in the direct R&D project funding scheme of the Federal Ministry of Education and Research, full and partial substitution of privately financed R&D expenditures by the subsidy can be ruled out on average.

latter variable is defined as total investments divided by sales). As Carboni (2008) points out, capital and investment intensities are important variables since more capital-intensive firms may have higher commitments to innovate compared to labour-intensive ones. The skill structure of a firm's workforce is used as a determinant of research activity and the ability to attract public funding (Kaiser, 2006). We include the share of highly educated employees, i.e. those who hold a university degree (including universities of applied sciences). To account for the role of firm competitiveness we include the export ratio (besides other regional input and output linkages) in our model as a determinant for firm-specific heterogeneity. Recent research has hinted at the positive link between firms competing in foreign markets and their tendency to be more innovative than locally operating firms (Arnold and Hussinger, 2005).

In addition, we use binary dummy variables to indicate the firm's legal form and the affiliation to a parent company either in West or East Germany or abroad respectively. We also take into account whether a firm is performing research on a regular basis and is running its own R&D department. This latter variable should reflect the absorptive capacity and R&D experience for a specific firm. A detailed list of variables covered in this analysis together with their descriptive statistics is given in Table 5.1 and Table 5.2.

Finally, one should note that, according to Table 5.2, we have to deal with missing data for some variables. We discuss alternative ways of how to deal with this problem in the conduct of the matching estimation in the next section.

5.4 Empirical Results

We start estimating the propensity score for receiving R&D subsidies. Table 5.3 shows the results of the underlying probit regression. We report marginal effects of an independent variable evaluated at its mean value (and a discrete change for 0/1 dummy variables) for the different model specifications. We start with a fairly general specification in Column (I), which includes all available covariates in the dataset. Beside that only few variables turn out statistically significant, the full set of covariates leaves us with only 529 observations. This raises the problem that the bias induced from missing data in the estimation of the propensity score could be large (Qu and Lipkovich (2009) and may lead to a non-representative matched sample (Augurzky and Schmidt, 2001).

We present two potential solutions for this problem. One is to reduce the number of variables in a stepwise regression approach starting from a parsimonious model containing only two-digit industry dummies and subsequently only including variables that are found to be statistically significant at least at the 10% significance level. This leads to a much higher number of 1,023 observations in model II. We checked by means of 'leave-one-out' cross-validation whether dropping one of the statistically significant variables leads to a further substantial increase in sample size, which however was not the case. Although being the more parsimonious presentation in terms of covariates, the McFadden R for specification II is almost identical compared with the full model in Column (I).

Table 5.3 Probit estimation for receiving R&D subsidies (binary dummy)

Dependent Variable R&D subsidies)	(I) Full original	(II) Stepwise original	(III) Multiple imputation
log(Size)	0.024	.064***	.072***
	(.049)	(.024)	(.026)
log(1/Age)	-.295*	-.192**	-.131
	(.166)	(.085)	(.088)
log(1/Age)^2	-.052	-.035*	-.021
	(.037)	(.019)	(.023)
Capital	-.016		.0004
	(0.017)		(.001)
Investment	-.001		-.0001
	(.001)		(.001)
Human capital high	.562***	.356***	.348***
	(.125)	(.059)	(.059)
Human capital low	-.257		-.137
	(.176)		(.090)
Regional sales	-.287*	-.181***	-.183**
	(.122)	(.058)	(.082)
West German sales	-.083	-.078*	-.049
	(.089)	(.045)	(.069)
Exports	-.023		.005
	(.098)		(.079)
Regional inputs	.149**		.082
	(.106)		(.086)
West German inputs	-.037		.047
	(.088)		(.075)
Imports	.114		.058
	(.109)		(.087)
Liability	.064		-.024
	(.099)		(.034)
West German ownership	-.106**		-.102***
	(.039)		(.042)
East German ownership	-.038		-.010
	(.091)		(.051)
Foreign ownership	-.061		-.087
	(.061)		(.058)
R&D department	.337***	.345***	.259***
	(.053)	(.059)	(.028)
Observations	529	1023	1267
Industry dummies	yes	yes	yes
McFadden R^2	.35	.34	.35

***,**,*Significance levels at the 1%, 5% and 10% levels, respectively

For the input–output relationships, East German sales and inputs are taken as reference category. For the ownership dummy, the reference case is being an independent Thuringian firm. All report coefficients are marginal effects of an independent variable at its mean value (for dummy variable discrete change from 0 to 1). Sectoral dummies are based on NACE two-digit industries. For the multiple imputation approach, bootstrapped standard errors have been computed based on 500 replications.

Given the large increase in the numbers of observation versus the rather small loss in terms of model fit, the stepwise specification appears to be better suited as an empirical basis for our propensity score calculation as compared with the full model and serves as benchmark model for the remainder of the analysis.

An alternative approach is to use multiple imputation techniques proposed by Rubin (1987). The idea is to fill the missing values multiple times through sampling from the posterior predictive distribution of the missing values given the observed ones for the set of covariates. Then for each imputed sample the data can basically be analysed using 'standard methods'. However, one has to be aware that the procedure assumes missingness to be at random (which may not be the case, for instance, due to strategic answering behaviour in the questionnaire). Furthermore, in the case of propensity score estimation the usual multiple imputation variance estimator (Rubin's rule) may not work and the variance has to be evaluated by jackknife or bootstrap methods (Qu and Lipkovich, 2009).

Although the latter authors find in a Monte Carlo simulation study that the bias stemming from propensity score estimation with multiple imputated data is lower compared with the original estimator based on missings, we are cautious when relying solely on this approach and rather use model III as backup for the propensity score obtained from the stepwise original model [Column (II)]. In the multiple imputation approach missing data of the covariates is estimated based on their observed values so that the available number of observations of the treatment variable (R&D subsidies) is matched. We do not impute the latter and the two outcome variables. We use M=5 imputations and marginal effects are computed as weighted averages with bootstrapped standard errors. Further details are given in supporting information Appendix Table E.2.

Comparing our two alternative solutions for the missing data problem, namely the probit specifications in Columns (II) and (III) of Table 5.3, both approaches show almost identical results. That is, according to the stepwise original specification in Column (II) as well as the multiple imputation approach in Column (III), the probability of receiving R&D subsidies is mainly driven by the skill composition of the firm's employees and the presence of its own R&D department. For both variables we obtain statistically significant and positive coefficients. The same holds for the variable firm size. With respect to the set of regional input–output linkages, a high share of local sales is associated with a lower probability of obtaining R&D subsidies. Mixed results were found for inverted firm age (and its squared values), which turned out to be negative in both specifications (nevertheless statistically insignificant in the multiple imputation approach). On the contrary, the dummy for West German ownership was tested to have a statistically significant negative impact on receiving R&D subsidies in the latter approach.

Regarding the quantitative interpretation of the regression results, the reported coefficients in Table 5.3 are marginal effects computed as change in the probability of receiving R&D subsidies for an infinitesimal change in each independent continuous variable evaluated at its mean value and for a discrete change from 0 to 1 for each dummy variable. That is, for instance, based on the results from Column (III) firms with an endowment of high-skilled human capital above its sample mean of 19% relative to overall firm-level employment, have a roughly 35% higher probability of receiving R&D grants than firms with a high-skilled human capital endowment below the mean value. Likewise, for dummy variables, running an own R&D department increases the firm's probability of receiving R&D grants by 26%. On the contrary, being an affiliate of a West German company lowers the probability of the receipt of R&D subsidies by approximately 10%. Since both the computed marginal effects and the McFadden R as overall model evaluation criterion are about the same size in Columns (II) and (III), we have little empirical guidance to judge about their empirical superiority ex ante and thus use the propensity scores from both specifications for the matching approach in the remainder of this analysis.

Since the main concern in the propensity score estimation is to balance the set of covariates, model diagnostics have to be assessed carefully (Augurzky and Schmidt, 2001). When testing for differences among treated and comparison firms in the mean values of the covariates before and after matching, the resulting t-values indicate that the estimation approaches in models II and III are quite successful in balancing the latter set of covariates.[10] Whereas the null hypothesis of identical means for treated and non-treated firms is often rejected for the unmatched samples, after matching statistically significant differences vanish. As the McFadden R2 for both specifications is also statistically significantly reduced after reestimating the propensity score on the matched sample, we may conclude that the employed set of covariates explains the participation probability rather well (Sianesi, 2004).

Table 5.4 Outcome differences for treated and comparison firms (in % points)

	Stepwise original		Multiple imputation	
	R&D	Pat	R&D	Pat
All firms	2.36	19.95	2.44	20.09
Medium	1.26	24.87	1.29	33.01
Small	2.44	24.29	2.75	17.40
Micro	5.00	8.54	5.04	9.72

Variables are defined as: R&D = R&D intensity; Pat = patent activity.

Calculations are based on propensity score estimates according to Columns (II) and (III) in Table 5.3 Kernel matching algorithm with h = 0.06. For computational details, see Table E.4.

Using a Kernel-based matching algorithm we then compute the differences for the two outcome variables of interest, R&D intensity and patent activity, in Table 5.4.[11] We first look at the causal effect for the full sample of all firms. Table 5.4 reports the estimated ATT for both R&D intensity as well as patent activity measured in percentage points. Except for the

[10] Results for the mean comparison of the set of covariates for the treated and comparison groups before and after the matching are given in supporting information Table E.3 (see Appendix).

[11] Detailed results together with tests for statistical significance are reported in supporting information Table E.4. Here we have used the Epanechnikov kernel and a bandwidth parameter h according to h = 0.06. Since the choice of h may result in a tradeoff between efficiency and unbiasedness, we apply the method of cross-validation to estimate the ATT for a range of values for h. Generally, the qualitative interpretation of the results is not affected by the choice of h. The use of h = 0.06. turns out to be a conservative lower-bound estimate. Further results can be obtained on request.

patent activity of micro firms, the results for outcome differences between treated and comparison firms are at least statistically significant at the 5% critical levels (mostly at the 1% level).

Regarding the R&D intensity, the results show that the average intensity of treated firms is around 154% higher compared with the matched comparison group. This effect can be obtained from the semi-log parameter coefficients in Table E.4. Taking the estimated coefficient for the stepwise model of 0.933 for all firms as an example, then the relative outcome difference between treated and comparison firms can be calculated as $[(Y_1 - Y_0)/Y_0] = exp(0.933) - 1 = 154\%$. To arrive at a measure for the absolute difference in the R&D intensity for the two groups as shown in Table 5.4, we can then multiply the obtained 154% with the mean of the R&D intensity of (matched) non-subsidized firms which amounts to 1.5% [the latter can be recovered from Table E.4 as $Y_0 = exp(4.178) = 1.5\%$]. The R&D intensity of treated firms shows then to be around 2.4% points higher relative to the intensity of the matched comparison group. As an alternative outcome measure we also use the binary dummy for patent applications. The results in Table 5.4 show for the sample of all firms that for a treated firm the probability of applying for a patent is about 20% points higher relative to the comparison group. The two effects for R&D intensity and patent activity are estimated to be almost identical for the stepwise approach as well as based on multiply imputed data.

We then estimate the causal impact of funding for three different subgroups of SMEs. Starting with medium-sized firms, measured in terms of 51–250 employees, Table 5.4 shows that the effect on private R&D intensity is smaller compared with the average of all firms (though still highly statistically significant, see supporting information Table E.4 in the Appendix). We estimate a difference in the R&D intensity of about 1.3% points for both specifications (stepwise original and multiple imputation). Compared with the average of all firms the increase in the probability of a patent application is estimated to be higher (around 25–33% points). While the effect for small firms with 11 up to 50 employees is found to be in line with the average estimate for all firms (around 2.4–2.8% points for R&D intensity, between 17% and 24% points for patent activity), the results for the subgroup of micro firms with up to ten employees are rather interesting. We estimate a strong increase in the R&D intensity (5% points), while we do not find any statistically significant difference in the patent activity relative to the comparison group of non-subsidized micro firms.

The estimated similar performance concerning patent applications of subsidized and non-subsidized micro firms may in fact stem from a specific innovation strategy of small firms. Conte and Vivarelli (2005), for instance, find for Italian microdata between 1998 and 2000 that large firms rely heavily on own R&D innovative effort, while small firms more actively participate in cooperation agreements and business groups, including the acquisition of external technology, rather than choosing costly and time-consuming patent strategies. Ball and Kesan (2009) argue that due to high transaction costs of litigation, small firms may not be able to effectively monitor their patent rights and consequently choose not to apply for patents at all. Both observations give a qualitative argument, as to why input- and output-related

R&D activity measures cause different reactions depending on firm size. In addition, rather long time lags in the transmission from R&D inputs to R&D outputs have to be considered, which are not captured by the sample data. One should thus be careful using the latter result as an argument in favour of policy ineffectiveness of R&D subsidies. The strong increase in the R&D intensity for micro firms hints rather at a large leverage effect in terms of crowding-in private R&D inputs by the grant schemes. This latter high outcome difference in turn is likely to be driven by firms that start R&D activities induced by public fundings, which is likely to be associated with a certain threshold effect.

How do our results compare with the findings in the literature? The available evidence for East Germany points to a statistically positive effect of R&D subsidies on various outcome variables related to R&D, innovation or patent activity; however, this evidence rests exclusively on one database (the MIP). Our results show a statistically significant positive effect on R&D intensity and patent activity as well. Since our findings are based on a different dataset in which SMEs are much more represented they could be seen as an important, alternative indication that R&D subsidies do not fully lead to substitution effects, but instead increase the level of R&D intensity and probability of patent applications.

With regard to the magnitude of the impact, our estimated ATT is roughly in line with the results of Almus and Czarnitzki (2003), Czarnitzki (2001), and Czarnitzki and Licht (2006), both in terms of the resulting difference in percentage points between subsidized and non-subsidized firms and in terms of its relative size ($\widehat{\theta_{ATT}}$). Almus and Czarnitzki (2003) and Czarnitzki and Licht (2006), for instance, report for the R&D intensity of subsidized firms an ATE which is equal to 4% points; according to Czarnitzki (2001) the treatment effect amounts to a 5% points increase in the innovation intensity of supported firms. Compared with the R&D intensity of non-subsidized firms the estimated effect of Almus and Czarnitzki (2003) equals an increase of 184%, that of Czarnitzki and Licht (2006) of 150%. In Czarnitzki (2001), the innovation intensity of the (matched) non-subsidized firms would rise by 104%.

Using the estimated outcome effect we could calculate the leverage effect of the public R&D subsidies on private sector R&D expenditures if we assume by 'rule-of-thumb' that public spendings have to be cofinanced by private spending of 50% of the total R&D project volume. Then, we could proxy the additionally induced privately financed R&D intensity as 50% of the average of the R&D intensity for subsidized firms minus the average R&D intensity of the non-subsidized firms. The leverage effect is accordingly defined as additional private R&D expenditure in relation to the public R&D grants (see Table 4.5).[12]

The results show that for the sample of all firms the leverage effect amounts to 0.21, that is, public R&D spending which amounts on average to 1% of the sales of the supported firms

[12] The Update of the Mid Term Evaluation of the European Regional Development Fund in Thuringia (ERDF), by which the Thuringian R&D incentive programmes were cofinanced, shows that the subsidy rate for R&D projects amounted during the period 2000–4 on average to 50.7% (see GEFRA et al. (2004b, p. 41). According to the legal Community Framework for state aid for research and development (OJ C 45, 17.2.1996, pp. 5–16) the aid intensity for industrial research of firms was generally not allowed to exceed 50%. However, in cases where the subsidy was granted to SMEs, for R&D projects undertaken in cooperation between firms and public research bodies or carried out in an Article 92 region (to which Thuringia belongs) the aid intensity could rise to the maximum ceilings of 75% for industrial research and 50% for precompetitive development activities.

induces 0.21% of additional private R&D expenditures in relation to firm's sales (or as it is often stated in the evaluation literature, €1 of public money induces €0.21 of private money). This impact is the highest for micro firms, indicating that R&D subsidies of 1% of the sales of the supported micro firms lead to an additional R&D expenditure share of 0.63%. Measured as the percentage share of sales the leverage effect is smallest for the group of medium-sized firms.

Table 5.5 Additional private R&D expenditure relative to public R&D grants (leverage effect)

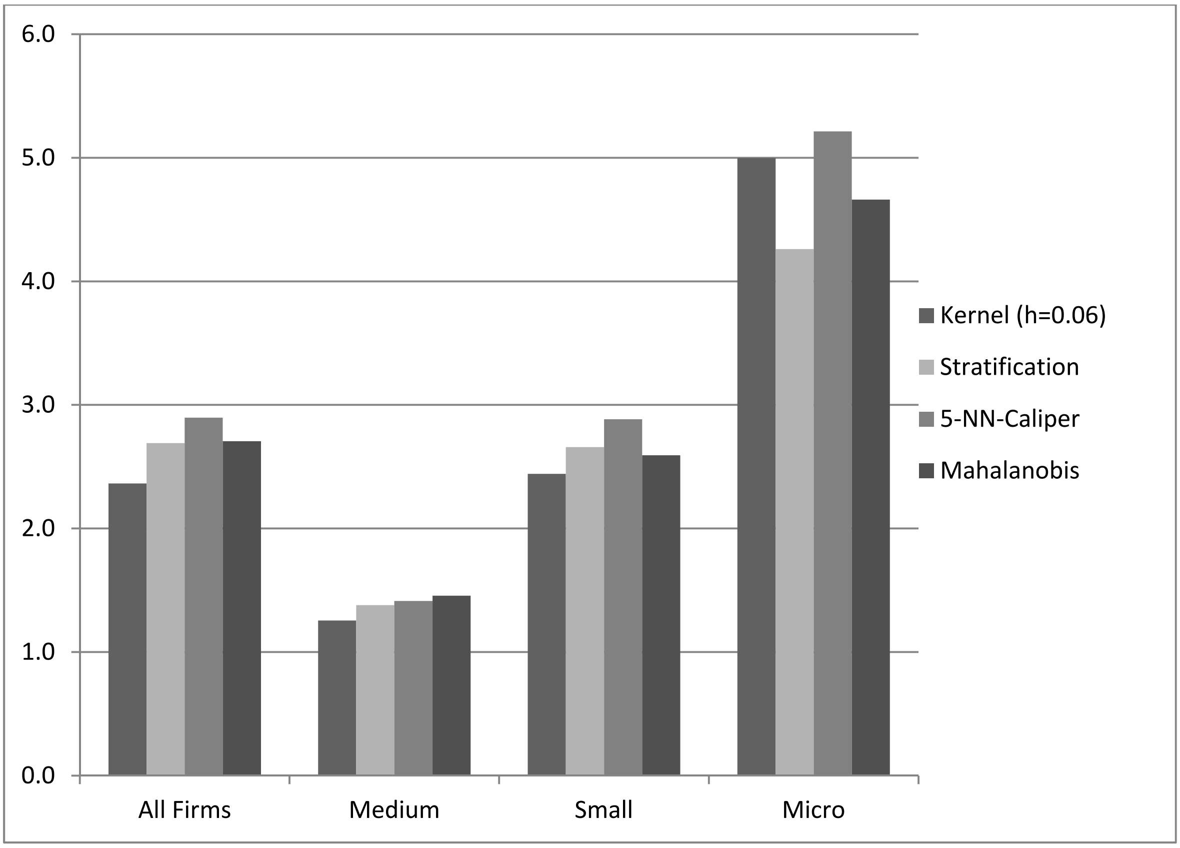
	R&D intensity of treated firms			R&D intensity comparison	Additional privately funded Column	
	All (% points)	50% publicly funded (% points)	50% privatly funded (%points)	100% privatly funded (%points)	V- IV (%points)	Leverage effect
All firms	3.9	1.95	1.95	1.53	0.42	0.21
Medium	2.34	1.17	1.17	1.08	0.09	0.07
Small	3.77	1.89	1.89	1.33	0.56	0.30
Micro	6.12	3.06	3.06	1.12	1.94	0.63

However, these calculations should be interpreted with some caution as we do not have accurate information about the actual level of support for each firm and accordingly not for the average subsidy rate in each firm size class. The assumption of an average subsidy rate of 50% is to be understood as a back to the envelope calculation. In particular, it appears likely that the subsidy rate for smaller firms has been higher. In this case, the leverage effect would be reduced. For instance, with a subsidy rate of 60% the leverage effect for the micro firms would be 0.36. If one assumes an average subsidy rate, which equals the maximum ceiling of 75% according to the Community Framework for state aid for research and development, the additional R&D expenditure of the supported micro firms would correspond almost exactly to the amount of the public R&D grants and, thus, the leverage effect would be reduced to zero. If one assumes this maximum subsidy rate for all firms the leverage effect would even turn negative (0.19), so that the supported firms would in part use the public R&D grants to substitute their private R&D expenditures (partial crowding out). However, against the background of the available evidence on R&D policy in East Germany this assumption does not seem to be very reasonable and could be more regarded as a worst case scenario.

5.5 Robustness Checks

Checking the sensitivity of the estimation results becomes increasingly important in applied work (Caliendo and Kopeinig, 2008). We account for this empirical prerequisite in various ways. In the first place, we analyse the potential role of hidden biases stemming from unobserved variables and consequently apply the Rosenbaum bounds approach both to our original data sample as well as to the multiply imputed data.

Figure 5.1 Outcome differences for R&D intensity (R&D expenditures relative to total turnover) by matching algorithms (in % points)



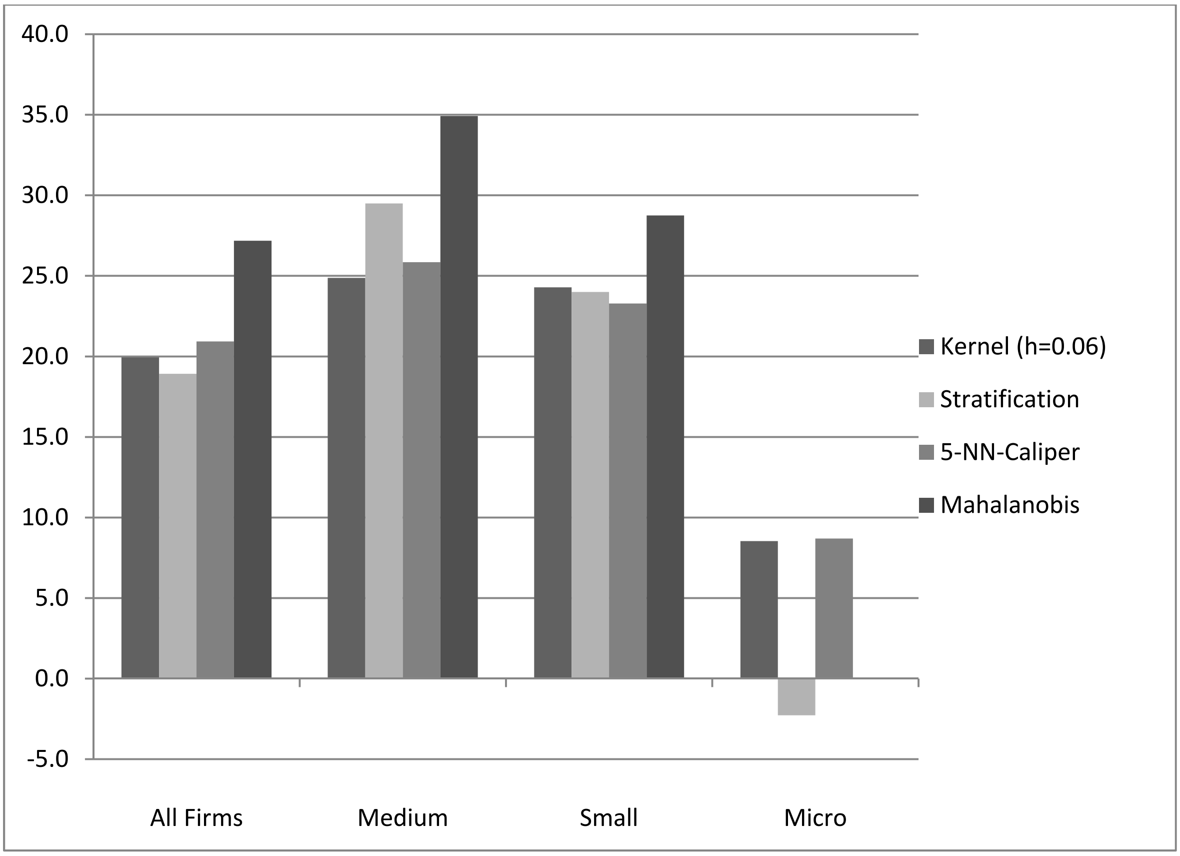
Notes: For estimation details, see Table E.6. Means of non-subsidized firms by size class: 1.53% (all firms), 1.08% (medium sized firms), 1.33% (small firms) and 1.12% (micro firms).

The approach aims at quantifying the likelihood that for two different firms with identical observed covariates their chances of receiving treatment actually differ. If the latter probability is not zero, both firms will differ in their odds of receiving treatment by a factor that involves a parameter Γ as the effect of an unobserved variable for firm $i(u_i)$ on the participation decision.

If there are no differences in unobserved variables between firms i and j (i.e. $u_i = u_j$) or if the unobserved variables have no influence on the probability of participating (Γ = 0), the odds ratio is equal to 1, implying the absence of hidden or unobserved bias (Becker and Caliendo, 2007). By means of sensitivity analysis now changing values of Γ and $(u_j - u_i)$ can be analysed. Rosenbaum (2002) defines a bounding approach for $e^{\Gamma} = B$ with $B > 1$, where individuals who appear to be similar (based on the observed set of covariates) could differ in their odds of receiving treatment by as much as a factor of B without changing the implications of our matching results. As DiPrete and Gangl (2004) point out, the Rosenbaum bounds approach can be interpreted as a worst case scenario to test for the stability of the outcome differences obtained, given unobserved influencing factors.[13]

[13] We follow DiPrete and Gangl (2004) and report the result of P-values from a Wilcoxon signedrank tests for the estimated ATT on R&D intensity as a continuous outcome variable and from the Mantel and Haenszel (1959) test statistic for the binary outcome variable of patent activity. The reported test statistics are constructed in such a way that at each level of Γ we are able to compute a hypothetical significance level 'p-critical', which

Figure 5.2 Outcome differences for patent activity (probability of applying for patents) by matching algorithms (in % points)



Notes: For estimation details see Table E.7. Means of non-subsidized firms by size class: 20.0% (all firms), 21.1% (medium-sized firms), 16.0% (small firms) and 9.4% (micro firms).

For R&D intensity in the full sample estimation, the results in Table E.5 show that an unobserved factor needs to cause the odds ratio to differ by at least a factor of 3 to result in statistically insignificant outcome differences.[14] The results for patent intensity even hold for this bound since implying that one firm in the matched pair may be three times more likely to receive subsidies as the other one due to different values on an unobserved covariate and the effect we observe would still be statistically significant. To illustrate the magnitude of this effect in terms of observed covariates (based on the propensity score), a critical level of $\Gamma = 3$ is attained at a difference in firm size by approximately 47 employees, which is almost the mean of the sample distribution (see Table 5.2) or a 34% difference in the share of highly skilled workers (sample mean equal to 19%).

Hence, we should only have doubts on our matching results if we have good reasons to believe that such an equally strong effect from an unobserved covariate is affecting treatment

represents the bound on the significance of the treatment effect in case of endogenous self-selection into treatment. As DiPrete and Gangl (2004) point out, by comparing the test results for different Γ, the researcher is able to assess the strength that unmeasured influences would require so that the estimated ATT would have risen purely through selection effects. For R&D intensity, we additionally compute Hodges–Lehmann point estimates measuring changes in the size of the estimated outcome differences for the alternative values of the unobserved influencing factors. Since the Hodges–Lehmann point estimates are based on the median difference between treated and comparison firms, the value obtained is slightly different compared with the ATT, even for the case of $\Gamma = 1$ (no hidden bias).

[14] See Table E.5 for estimation details. We do not find different results for the original and multiply imputed samples. In this exercise, we focus on the relevant case of an overestimation of the programme effect.

assignment. The Hodges–Lehmann point estimates show that with increasing Γ the outcome difference (in terms of the median) gradually decreases, nevertheless the general impression from the Rosenbaum bounds approach is that our estimates for convenient levels of Γ_i are rather robust with respect to any hidden bias. The results are broadly stable for the different subsamples. Only for small and micro firms do the reported 'p-critical' levels for the R&D intensity indicate that a change in odds ratio up to the factor $\Gamma = 2$ leaves the obtained treatment effects unaffected.

As a second test, we examine the sensitivity of the results with respect to the chosen matching estimator. Although the different algorithms yield asymptotically the same results since they compute only exact matches with growing sample size, their empirical results may differ in small samples. We thus use a set of alternative weighting schemes for the matching procedure. We apply stratification matching, $k = 5$ nearest-neighbour matching with an additional caliper restriction in terms of one fourth of the standard error of the propensity score (5-NN-Caliper), as well as Mahalanobis metric distance matching. The latter algorithm allows us to include additional matching information besides the propensity score (here two-digit industry classification and firm size categories). All the procedures are again subject to the common support restriction.

The estimated outcome differences for R&D intensity and patent applications are shown in Figure 5.1 and Figure 5.2.[15] Both figures show that the results are very stable for different weighting schemes. With respect to R&D subsidies we find a statistically significant result for all combinations of sample design and chosen matching routine. Depending on the weighting scheme, the overall effect for the sample of all firms varies from 2.4% to 2.9% points (with the highest effect found by the 5-nearest neighbour routine).

Moreover, as highlighted in Figure 5.1, all matching routines uniformly estimate the effect for micro firms to be higher compared with the samples of all, medium-sized and small firms. For patent activity, the estimated outcome difference for the overall sample including all firms varies between 20% and 27% points and is found to be statistically significant for all matching routines. In addition, all algorithms report much lower and statistically insignificant results for the sample of micro firms (see Figure 5.2). These results make us feel confident that our estimated results are not very sensitive regarding the chosen matching algorithms.

As a third and final robustness check for our estimates of the ATT, we restrict our sample only to those firms, which are permanently engaged in R&D activity (which was an explicit question in the survey). The motivation for this restriction is simply to 'raise the bar'. That is, since firms with permanent R&D activity should have an on average higher R&D intensity and probability of patent application, this will lead to a tighter selection of the comparison group and thus may shed additional light on the question of R&D policy effectiveness.

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[15] We report results for the stepwise original approach. Computational details are given in supporting information Table E.3. Findings for the multiply imputed dataset are very close to the stepwise approach and can be obtained from the authors upon request. Correction added after first publication online on 13 September 2011. Figure 5.1 legend has been changed from 'patent activity (probability of applying for patents)' to 'R&D intensity (R&D expenditures relative to total turnover)'.

As Czarnitzki and Licht (2006) argue, the latter setup is important since it compares treated and comparison firms that are similar in their structural characteristics, nevertheless it is also likely to underestimate the effect of R&D support, assuming that the subsidy alone cannot stir firms to start R&D activities. The results for both R&D intensity and patent activity remain statistically significantly positive, supporting the general effective ness of the R&D grant schemes (estimation details are given in Table E.8 in the Appendix). For the R&D intensity the calculated output effect now ranges from 2.7% to 4% points (depending on the matching algorithm) and is broadly in line with the results of the unrestricted sample. The same holds for the probability of applying for a patent, which increases by roughly 27% (uniformly predicted by all applied matching algorithms). Since both the treatment and comparison groups are rather small for permanently R&D active firms, a further disaggregation into SME subaggregates is not feasible at this point.

5.6 Conclusion

We have analysed the impact of public support schemes on private R&D activity for a cross-section of East German firms in the federal state of Thuringia in 2003. Using different matching routines to identify the causal effect of public funding, we estimate a statistically significant positive effect of public support on private R&D activity. On average we find an increase in the R&D intensity of about 2.4% points relative to non-subsidized firms. The probability of patent application rises by 20% points. Based on these findings, we were also able to estimate the share of additional private R&D expenditures relative to public R&D grants and the associated leverage effect. On average, we find that a 1% increase in public R&D grants induces 0.21% additional private R&D expenditures in relation to a firm's sales. That is, the R&D grants crowd-in additional private investments. While our overall results may thus be seen as a backup and robustness check for earlier empirical evidence on East Germany based on a different dataset (see Almus and Czarnitzki, 2003; Czarnitzki, 2001; Czarnitzki and Licht, 2006, for evidence based on the MIP), no specific empirical evidence has been reported so far with respect to the effectiveness of R&D subsidies for small- and medium-sized firms. Here our study fills an important gap in the empirical literature. The focus on SMEs is particularly relevant for East Germany, since its regional innovation system is largely driven by the latter group.

Our results show that the positive effects found for the total sample of firms also hold for three subgroups of SMEs (micro firms with 1–10 employees, small firms with 21–50 employees, as well as medium-sized firms with 51–250 employees). Regarding the R&D intensity as outcome variable, the biggest increase is found for micro firms. Here the policy schemes seem to be particularly successful in activating firms to start R&D activity.

For small- and medium-sized firms the effect is also found to be positive but of smaller size. With respect to patent activity, treated small- and medium-sized firms show a statistically significant increase in the probability of patent application, while we do not find any statistically significant effect for micro firms. The latter statistically insignificant result is likely to reflect differences in the innovation strategies between small and large firms, with very small firms choosing different innovation strategies rather than patenting.

We have also investigated whether subsidies add to private R&D inputs, when only those firms which regularly perform R&D activity are taken into account. The results confirm a statistically and economically significant difference in the R&D intensity and patent activity for subsidized and non-subsidized firms. Taken together, our results hint at the complementary nature of public subsidies to private sector R&D activity in the East German regional innovation system, which is to a large extent driven by innovative small- and medium-sized firms.

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Appendix E Supporting Information

Testing for Sample Representativeness

We test for sample deviations for each 2-digit industry from the underlying total population in terms of total employment using a standard Z-statistic based test, which compares the sample distribution relative to the overall distribution of 2-digit industries in the population. Since the total population of Thuringian Manufacturing Sector firms in 2003 is known the proportion based test is given $Z = \frac{\rho - P}{\sigma_\rho}$, where ρ is the sample population proportion, P is the population proportion and σ_ρ is the standard error of the proportion given by $\sigma_\rho = \sqrt{\frac{P(1-P)}{n}}$ n, where n is the number of observations in the respective (sub-) sample. Table E.1 plots the respective sector shares together with the standard error of the sample proportion and the corresponding Z-statistic.

Table E.1 Test for sample representativeness based on manufacturing sector data

WZ Code	Pop.	Share Pop.	Sample	Share Sample	σ_ρ	Z-Statistic
14	59	3.15%	10	0.76%	0.06	-0.43
15	213	11.38%	79	6.04%	0.04	-1.50
16	4	0.21%	2	0.15%	0.03	-0.02
17	51	2.73%	24	1.83%	0.03	-0.27
18	11	0.59%	6	0.46%	0.03	-0.04
19	14	0.75%	6	0.46%	0.04	-0.08
20	58	3.10%	65	4.97%	0.02	0.87
21	29	1.55%	22	1.68%	0.03	0.05
22	49	2.62%	60	4.58%	0.02	0.95
23	0	0.00%	0	0.00%	0.00	0.00
24	45	2.41%	38	2.90%	0.02	0.20
25	163	8.71%	123	9.40%	0.03	0.27
26	186	9.94%	111	8.48%	0.03	-0.51
27	28	1.50%	21	1.60%	0.03	0.04
28	314	16.78%	299	22.84%	0.02	2.80***
29	208	11.12%	128	9.78%	0.03	-0.48
30	11	0.59%	6	0.46%	0.03	-0.04
31	96	5.13%	65	4.97%	0.03	-0.06
32	46	2.46%	40	3.06%	0.02	0.24
33	97	5.18%	97	7.41%	0.02	0.99
34	66	3.53%	37	2.83%	0.03	-0.23
35	9	0.48%	1	0.08%	0.07	-0.06
36	104	5.56%	57	4.35%	0.03	-0.40
37	10	0.53%	12	0.92%	0.02	0.18

***, **, * = denote signicance levels at the 1%, 5% and 10% level.

As the results show, the Z-statistic generally reports statistically insignificant results except for the sub-sector, WZ28 “Manufacture of fabricated metal products, except machinery and equipment", which is overrepresented in the GEFRA Business survey.

Multiple Imputation for Propensity Score Estimation

This appendix introduces the estimation routine for propensity score matching with multiply imputed (MI) data. We basically follow the approach outlined in Qu and Lipkovich (2009) here. MI assumes that the set of k covariates $\boldsymbol{X} = (X_1, X_2, \dots, X_k)'$ to be imputed is distributed from a multivariate normal distribution $N(\mu, \Sigma)$. Then, for a subject i, the distribution of the unobserved values $\left(X_i^{(u)}\right)$ given the observed values $\left(X_i^{(o)}\right)$ is also normal. Compared to single imputation, which imputes the missing value with the conditional mean, MI imputes the missing value multiple times with values which are generated from the conditional distribution. Since the parameters μ and Σ are unknown in practical applications, Gibbs samples are required to generate multiply imputed samples from the posterior predictive distribution of $X_i^{(u)}$ given $X_i^{(o)}$. In the context of propensity score matching the estimation involves the following steps:

Impute the data multiple times using non-missing values of *X*. Let $X^{(1)}, X^{(2)} X^{(M)}$denote *M* imputed samples. For continuous variables standard OLS estimation is applied, for dummy variables we use binary choice estimators. We use logs for those variables which also appear transformed in the propensity score, in order to ensure normality of the variables. We also censor the variables to permitted intervals (e.g. to ensure that percentage shares do not exceed a lower bound of 0 and a upper bound of 100). Transformed variables such as squared values are imputed passively based on the values of the original variable. Regarding the number of imputations we choose $M = 5$ as proposed by Rubin (1987).

For each imputed sample $X^{(m)}$, the propensity scores $\hat{P}_1^{(m)}, \hat{P}_2^{(m)}, \dots, \hat{P}_n^{(m)}$ are estimated based on a probit model with independent variables $X^{(m)}$.

The treatment effect on the treated (ATT) from the *m*th imputed sample is then

$$\text{(E.1)} \quad \widehat{\theta_{ATT}^{(m)}} = \frac{1}{N} \sum_{i \epsilon T} \left[Y_{1,i} - \sum_{j \epsilon C} w^{(m)}(i,j) Y_{0,j} \right]$$

where *N* is the total number of treated firms i, Y_1 and Y_0 denote outcome values for treated and comparison firms *j*. The match of each treated firm is constructed as a weighted average over the outcomes of non-treated, with weights $w(i,j)$ defined as

$$\text{(E.2)} \quad w^{(m)}(i,j) = \frac{K[P_i^{(m)}(X) - P_j^{(m)}(X)/h]}{\sum_{j \epsilon C} K[(P_i^{(m)}(X) - P_j^{(m)}(X))/h]}$$

K is the Kernel function and h is the bandwidth parameter to obtain the Kernel matching estimator. As shown in the text, we chose $h = 0.06$ as default. Combining the estimates from multiply imputed data sets, the average ATT can be calculated as $\widehat{\theta_{ATT}} = M^{-1} \sum_{m=1}^{M} \widehat{\theta_{ATT}^{m}}$. We use bootstrapping methods in order to estimate the variance of the ATT as proposed by Qu and Lipkovich (2009).

For the case that Rosenbaum bounds have to be calculated as a robustness check, we use Fisher's combined probability test (Fisher 1932), which uses the P-values from M individual statistics to calculate a combined test as $\chi_F^2 = -2 \sum_{m=1}^{M} \ln(P_m)$, where Pm is the mth imputed critical P-value of the test statistic. If all the null hypothesis of the M individual statistics are true, then this χ_F^2 will follow a χ^2-distribution with 2M degrees of freedom. As explained in the main text, we use the P-values from the Wilcoxon sign rank tests for R&D intensity as a continuous outcome variable, for patent activity we use the Mantel and Haenszel (1959) test statistic.

Descriptive statistics for the multiply imputed set of covariate X are as follows:

Table E.2 Multiply imputed covariates for propensity score estimation

	Multiple Imputation				
Variable	N	Mean	S.D.	Variable	N
log(size)	1267	3.02	1.4	0.03	-0.01
log(1=age)	1267	-2.2	0.66	0.01	0
log(1=age)2	1267	5.3	2.71	-0.02	0.02
Capital	1267	3.49	1.25	0.01	0.01
Investment	1267	26.15	387.56	-5.9	22.75
Human capital high	1267	0.19	0.23	0	0
Human capital low	1267	0.06	0.16	-0.01	-0.24
Regional sales	1267	0.23	0.3	0	0
West German sales	1267	0.11	0.16	0	0
East German sales	1267	0.39	0.32	0	0
Exports	1267	0.13	0.23	0.01	0
Regional inputs	1267	0.24	0.28	0.01	-0.01
West German inputs	1267	0.12	0.17	0	0
East German inputs	1267	0.4	0.29	0	0
Imports	1267	0.1	0.18	0	-0.01
Liability	1267	0.27	0.44	-0.01	0
West German ownership	1267	0.12	0.33	-0.02	-0.02
East German ownership	1267	0.04	0.19	-0.01	-0.01
Foreign ownership	1267	0.05	0.21	0	-0.01
R&D department	1267	0.28	0.45	0.01	0

Both samples are restricted to non-missing data of the treatment variable (R&D subsidies), which is not filled by multiple imputation. Differences in mean and standard deviation relative to original sample statistics according to Table 2 are given in absolute terms.

Additional Estimation Tables

Table E.3 Mean comparison for treated and comparison group before and after matching

Specification	Stepwise original			Multiple Imputation		
Mean of:	Treated	Comparison unmatched	Comparison matched	Treated	Comparison unmatched	Comparison matched
log(size)	3.35	2.92***	3.29	3.35	2.92***	3.47
log(1=age)	-2.22	-2.19	-2.23	-2.22	-2.19	-2.23
log(1=age)2	5.24	5.32	5.23	5.22	5.32	5.28
Capital				3.31	3.55***	3.38
Investment				14.85	29.79	4.81
Human capital high	0.36	0.15***	0.36	0.36	0.14***	0.31
Human capital low				0.04	0.07***	0.04
Regional sales	0.131	0.264***	0.123	0.142	0.266***	0.115
West German sales	0.432	0.385**	0.408	0.431	0.389***	0.424
Exports				0.227	0.116***	0.242
Regional inputs				0.229	0.259***	0.197
West German inputs				0.421	0.403**	0.424
Imports				0.127	0.112***	0.126
Liability				0.11	0.31***	0.10
West German ownership				0.12	0.13	0.13
East German ownership				0.05	0.03***	0.04
Foreign ownership				0.05	0.04	0.05
R&D department	0.72	0.16***	0.73	0.71	0.16***	0.72
McFadden R2		0.34	0.01		0.35	0.02

***, **, * = denote significance levels at the 1%, 5% and 10% level respectively.

Statistical significance was tested in a two-tailed t-test between the supported firms and either firms from the total of controls or from the propensity score based selected comparison group (t-values in brackets). Since the exact design of the composition of the treated and comparison group changes slightly for different outcome variables and matching designs, we did run a specific test in each case. The reported results are for R&D intensity

Table E.4 Kernel matching results for R&D outcome variables

	R&D intensity			Patent activity		
	Treated (Mean/Obs.)	Comparison (Mean/Obs.)	$\widehat{\theta_{ATT}}$ (S.E.)	Treated (Mean/Obs.)	Comparison (Mean/Obs.)	$\widehat{\theta_{ATT}}$ (S.E.)
			Stepwise Original			
All firms	-3.245	-4.178	0.933***	0.4	0.201	0.199***
	207(10)	745(0)	-0.192	205(10)	740(0)	-0.042
Medium	-3.755	-4.525	0.770***	0.46	0.212	0.249***
(50<size≤250)	66(1)	160(0)	-0.293	64(1)	159(0)	-0.085
Small	-3.278	-4.321	1.043***	0.403	0.16	0.243***
(10<size≤50)	83(6)	308(0)	-0.332	83(6)	306(0)	-0.067
Mico	-2.794	-4.49	1.697***	0.179	0.094	0.085
(1≤size≤10)	50(11)	253(0)	-0.455	50(11)	252(0)	-0.071
			Multiple Imputation			
All firms	-3.266	-4.284	1.018***	0.402	0.201	0.201***
	250(18)	879(0)	-0.198	281(19)	975(0)	-0.044
Medium	-3.905	-4.928	1.023***	0.483	0.153	0.330***
(50<size≤250)	79(5)	186(0)	-0.277	80(5)	196(0)	-0.076
Small	-3.122	-4.102	0.980***	0.383	0.209	0.174**
(10<size≤50)	102(9)	362(0)	-0.331	119(9)	400(0)	-0.074
Micro	-2.687	-4.031	1.345**	0.231	0.134	0.097
(1≤=size≤10)	56(14)	300(0)	-0.565	68(13)	348(0)	-0.085

***, **, * = denote significance levels at the 1%, 5% and 10% level respectively.

Bootstrapped standard errors (in brackets) for the ATT are calculated based on 500 repetitions. Mean = average of outcome variable for the treated and comparison groups, Obs = number of treated and comparison firms used in the matching algorithm, the number in brackets denote those firms outside the common support. The number of treated and comparison firms is different for each outcome variable for the multiply imputed data, since these variables are not imputed.

Table E.5 Rosenbaum bounds for Kernel matching

	Stepwise original			Multiple imputation		
	R&D		Pat			R&D
	Hodges-Lehmann	Wilcoxon Rank	Mantel-Haenszel	Hodges-Lehmann	Wilcoxon Rank	Mantel-Haenszel
			All firms			
Γ_1	0.947	0.00	0.00	1.097	0.00	0.00
$\Gamma_{1.5}$	0.658	0.00	0.00	0.798	0.00	0.00
Γ_2	0.442	0.00	0.00	0.584	0.00	0.00
$\Gamma_{2.5}$	0.277	0.02	0.00	0.422	0.01	0.00
Γ_3	0.164	0.14	0.00	0.300	0.16	0.00
			Medium			
Γ_1	0.849	0.00	0.00	1.093	0.00	0.00
$\Gamma_{1.5}$	0.61	0.00	0.00	0.825	0.00	0.00
Γ_2	0.434	0.01	0.01	0.641	0.00	0.00
$\Gamma_{2.5}$	0.311	0.06	0.06	0.497	0.05	0.00
Γ_3	0.217	0.15	0.14	0.382	0.21	0.01
			Small			
Γ_1	1.115	0.00	0.00	0.984	0.00	0.00
$\Gamma_{1.5}$	0.725	0.00	0.00	0.649	0.00	0.00
Γ_2	0.485	0.04	0.00	0.418	0.08	0.00
$\Gamma_{2.5}$	0.31	0.16	0.00	0.247	0.48	0.00
Γ_3	0.133	0.34	0.00	0.109	0.85	0.00
			Micro			
Γ_1	1.631	0.00	0.00	1.321	0.00	0.00
$\Gamma_{1.5}$	1.176	0.01	0.00	0.904	0.05	0.00
Γ_2	0.944	0.05	0.01	0.603	0.29	0.00
$\Gamma_{2.5}$	0.679	0.13	0.04	0.376	0.61	0.00
Γ_3	0.492	0.24	0.08	0.215	0.82	0.01

Variables are defined as R&D = R&D intensity, Pat = Patent activity. We report Hogdes-Lehmann point estimates for additive treatment effects and P-values for the Wilcoxon sign-rank test and the Mantel-Haenszel (1959) statistic. The results of the Rosenbaum bounds for Γ_i are restricted to unweighted matched pairs.

Table E.6 Different matching algorithms for log(R&D intensity)

Dependent Variable	Stratification	5-NN Caliper	Mahalanobis
R&D intensity	*blocks=7*	$\eta = 0.25 * \rho_{PS}$	*PS, Ind, Size*
		All firms	
$\widehat{\theta_{ATT}}$	1.173***	1.360***	1.186***
	(0.215)	(0.198)	(0.218)
		Medium (50<size≤250)	
$\widehat{\theta_{ATT}}$	0.891***	0.927***	0.974**
	(0.294)	(0.266)	(0.392)
		Small (10<size≤50)	
$\widehat{\theta_{ATT}}$	1.220***	1.305***	1.064***
	(0.380)	(0.291)	(0.359)
		Micro (1≤=size≤10)	
$\widehat{\theta_{ATT}}$	1.192**	1.909***	1.435**
	(0.582)	(0.479)	(0.649)

***, **, * = denote significance levels at the 1%, 5% and 10% level respectively.

PS denotes Propensity Score, σ is the standard error. *Ind* denote 2-digit industry dummies, Size are size classes. Standard errors are given in brackets.

Table E.7 Different matching algorithms for Patent activity

Dependent Variable	Stratification	5-NN Caliper	Mahalanobis
Patent activity	*blocks=7*	$\eta = 0.25 * \rho_{PS}$	*PS, Ind, Size*
		All firms	
$\widehat{\theta_{ATT}}$	.189***	.209***	.272***
	(0.046)	(0.045)	(0.065)
		Medium (50<size≤250)	
$\widehat{\theta_{ATT}}$	0.295***	0.258***	0.349**
	(0.080)	(0.082)	(0.113)
		Small (10<size≤50)	
$\widehat{\theta_{ATT}}$	.240***	.233***	.287***
	(0.075)	(0.068)	(0.087)
		Micro (1≤=size≤10)	
$\widehat{\theta_{ATT}}$	.023	0.086	0.01
	(0.107)	(0.0083)	(0.111)

***, **, * = denote significance levels at the 1%, 5% and 10% level respectively.

PS denotes Propensity Score, σ is the standard error. *Ind* denote 2-digit industry dummies, Size are size classes. Standard errors are given in brackets.

Table E.8 Outcome differences for firms with permanent R&D activity

	R&D intensity			Patent activity		
	T=187(10)	C=150(0)		T=185(10)	C=149(0)	
Kernel	-2.831	-3.463	0.632***	0.434	0.238	0.196***
			(0.216)			(0.057)
Stratification	-2.831	-3.68	0.849***	0.434	0.244	0.190***
			(0.246)			(0.052)
5-NN-Caliper	-2.831	-3.672	0.841	0.434	0.243	0.192
			(0.199)			(0.053)
Mahalanobis	-2.831	-3.681	0.850***	0.434	0.166	0.269***
			(0.289)			(0.066)

***, **, * = denote significance levels at the 1%, 5% and 10% level respectively.

T = treated firms, C = comparison firm. The numbers in brackets denote those firms outside the common support. Standard errors for the ATT are given in brackets.

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