# Heterogeneity of the Carnegie Effect<sup>\*</sup>

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#### Abstract

The Carnegie effect (Holtz-Eakin, Joualfaian and Rosen, 1993) refers to the idea that inherited wealth harms recipients' work efforts. Given that the income tax already have detrimental labor supply effects, taxation of intergenerational transfers can be seen as advantageous, as the amount available for consumption of leisure is reduced. However, as estimates of Carnegie effects are few, reflecting that such effects are hard to trace in data, there are doubts on how much weight to be given to this effect in overall assessments of the inheritance/estate tax. Most previous studies have relied on data from limited size sample surveys. Here we use information from a rich administrative data set (for the whole Norwegian population), which also makes it possible to investigate the variation in the Carnegie effects across groups of recipients. Mechanisms behind and magnitudes of the Carnegie response are discussed by estimating specifications derived from hypotheses on various forms of response diversity. We find that Carnegie effects vary according to the size of the transfer, the age of the recipients, the recipients' eligibility to other transfer programmes, and the existence of new heirs (children) in the family chain.

Keywords: inheritance, labor supply, heterogeneous responses JEL codes: D10, D80, D91, J22

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# 1 Introduction

The potential of harmful effects of intergenerational effects on donees was eloquently expressed by the 19th century industrialist Andrew Carnegie: "the parent who leaves his son enormous wealth generally deadens the talents and energies of the son, and tempts him to live a less useful and less worthy life than he otherwise would ..." (Carnegie, 1962).<sup>1</sup> Hence, even though bequests in many societies in the twenty-first century are more often recieved by offspring in their fifties rather than by young adults, and few bequests have the size of the wealth of Andrew Carnegie, detrimental effects of inheritance on donees' labor supply are often referred to as the "Carnegie conjecture" or the "Carnegie effect", see Holtz-Eakin et al. (1993).

Recently there has been a resurgence in the interest of optimal taxation of wealth transfers, with several studies suggesting that taxation of intergenerational transfer is preferable, see for example Golosov et al. (2003), Piketty and Saez (2013) and Kopczuk (2013a). In the optimal tax model of Kopczuk (2013a), the optimal bequest tax formula reflects two contradicting considerations: the positive externality of bequests following from the double utility production, both gaining parents and children, and the fiscal externality due to reduced efforts of children (the Carnegie response). Thus, the Carnegie effect possesses an important role in the discussion of tax design.

In this perspective it is surprising that relatively few Carnegie estimates are found in the literature; exemptions are Holtz-Eakin et al. (1993), Joulfaian and Wilhelm (1994), Brown et al. (2010) and Elinder et al. (2012). This is most likely due to the substantial obstacles in the empirical identification of effects. A major problem is that if the inheritance is expected, the standard life-cycle model predicts that the transfer will be fully absorbed in the life-cycle plan of the recipient. A perfectly foreseen inheritance would lower the heir's marginal utility from the first year of his economic life, yielding a downward shift in his entire life-cycle profile of labor. Permanent life-cycle adjustments are not easily identified in data.

However, there are several reasons for expecting labor supply effects (if there are any) to materialize shortly after the actual transfers of resources from parents or other donors. Firstly, there is uncertainty about both timing and amount of inheritance, which may generate a wealth shock, as argued by Brown et al. (2010). Recipients may receive larger and smaller inheritances than expected, dependent on how much of the wealth that is consumed by the parents, to what extent people or organizations outside the family, such as religious movements, are supported through

<sup>&</sup>lt;sup>1</sup>Carnegie gave or bequeathed most of his vast fortune to charity.

transfers inter vivos or through testament, and to what degree parents are able and willing to divide unequally between children. Secondly, although inheritances may be anticipated, credit constraints may prevent the heirs from incorporating the inheritance into their budget. Finally, risk averse recipients will avoid using money they do not fully control. Thus, given that inheritances are noe perfectly foreseen, and assuming a positive income effect on the consumption of leisure, we expect to observe reduced work shortly after the transfer.

The main ambition of the present study is to improve the understanding of how Carnegie effect works, given its key role in the intergenerational tax discussion. Even though the Carnegie effect may be measured with error, biased downward due to measurement problems because of anticipated bequests (life-cycle behavior), we indentify responses materializing in the time period shortly after the transfer, and, moreover, we add to the understanding of Carnegie effects by discussing empirical evidence of Carnegie mechanisms across population groups. This can be done as we have access to a large panel data set for the years 1997 to 2010, based on Norwegian administrative registers, which covers the whole population. Response differences in the population are informative about the working of the conjecture and its economic magnitude. Previous literature on Carnegie effects, such as Holtz-Eakin et al. (1993), Joulfaian and Wilhelm (1994) and Brown et al. (2010), have had limited scope for more detailed analysis, as they have been predominantly based on evidence from sample surveys, with smaller sample sizes.

The Carnegie effect is here measured by addressing information on three labor supply response indicators: inheritors' working hours, labor income, and early retirement take-up. Identification is based on comparing inheritors to non-recipients with similar characteristics, using propensity score matching (Rosenbaum and Rubin, 1983). To avoid possible anticipatory effects, the matching is done three years before receipt of inheritances. Moreover, to account for response inertia, we measure responses 1-6 years after receiving bequests. This is done by exploiting the panel dimension of the data and allocating a smaller time window (2000-2004) for bequeathing. From this empirical design it is straightforward, as a control, to use the same specification to describe inheritors' behavior 1-6 years prior to transfers, when no effects are expected.

The response heterogeneity is measured along several dimensions, based on both characteristics of the heirs and attributes of the setting in which agents make their decisions. Firstly, our comprehensive data makes it possible to examine the age dependency, highlighting that many recipients are in their fifties or sixties, and comparing them with recipients in other stages of life. The interaction with public transfer schedules, such as the early retirement scheme, is important in this perspective. Secondly, given that there are (fixed) costs of finding a new optimum, as is well-established in the labor market literature (see for instance Altonji and Paxson, 1992 and Chetty, 2012), we expect to observe a nonlinear relationship between responses and the size of the transfer, responses increasing at an increasing rate with the amount transferred. Thirdly, we also draw attention to the fact that inheritances may come with "strings attached". Parents may have expectations and aspirations for their child, which means that they have opinions on how the intergenerational transfers are used (Becker, 1991; Haveman and Wolfe, 1995; Chami, 1998); consumption of leisure may be seen as an inferior activity (along the line of Carnegie). In this perspective, intergenerational transfers follow a replication norm, where parents step into a chain of intergenerational transfers, which may be referred to as the "golden rule of bequests" (Bevan and Stiglitz, 1979) or indirect reciprocity (Arrondel and Masson, 2006). When such constraints are working, we expect recipients without children to show stronger responses than donees who are constrained by having own offspring.

Interestingly, one will find that real world inheritance tax schedules are differentiated with respect to some of the heterogeneity characteristics that we examine, although apparently not motivated by Carnegie effects. For example, one will often find that schedules are progressive (smaller transfers are tax exempt) and that there are separate schedules for heirs in a direct line to the deceased. Thus, in this sense, our results may also have implications with respect to the design of the inheritance tax schedule.

The paper is organized as follows. In Section 2 we discuss Carnegie effects from a tax perspective, whereas Section 3 presents findings from the literature on Carnegie effects and refer to some relevant perspectives and studies given the focus on response heterogeneity. The empirical approach is presented in Section 4, and results are discussed in Sections 5 and 6. First in Section 5 we present overall estimates of the Carnegie effect for all recipients and for recipients of large transfers. In Section 6 heterogeneity is further discussed by addressing age dependency, including responses of people being eligible to early retirement pension, and by providing separate estimates for people being potentially restricted by having own heirs. Robustness checks are conducted in Section 7, whereas Section 8 concludes the paper.

#### 2 The Carnegie effect in the tax account

Taxation of intergenerational transfers is controversial and opponents criticize the inheritance tax for being inefficient, for lacking legitimacy and for being unfair. Correspondingly, tax rates have been cut in several OECD countries, such as the US, the UK, Italy, and France (Piketty, 2010), and some countries, such as Canada, Australia, New Zealand, Sweden, Austria and Norway<sup>2</sup>, have abolished their bequest tax completely. However, the dominant picture, see Denk (2012) and Strawczynski (2014), is that one finds inheritance tax schedules in a majority of OECD-countries.

Recently, we have witnessed an increased focus on taxation of inheritance from a wealth concentration perspective, see for example, Kopczuk (2013b) and Piketty (2014). From a normative tax point of view, a major complication in the assessment of the inheritance tax is that the tax affects both donors and donees, and we are not sure how the different generations are linked together, or what motivates transfers. Models of intergenerational linkages include the altruism model (Barro, 1974; Becker, 1974), the strategic exchange model (Bernheim et al., 1985; Cox, 1987) and joy of giving (Andreoni, 1990). Altruism means that the parent takes the child's well-being into account when making decisions, whereas the strategic model focuses on bequests as payments for services that the donee delivers to the donor. The joy of giving (or warm glow) motive implies that act of giving itself provides benefits to the donor. In contrast to altruism, benefits to the donee from receiving bequests are not valued by the donor.

The case for taxation is enhanced if there is no specific transfer motive, and bequests are accidental, see surveys of the literature in Cremer and Pestieau (2006), Boadway et al. (2010) and Kopczuk (2013b). Under altruism, taxation harms the labor supply of a parent whose efforts in wealth accumulation is motivated by concern for the next generation.<sup>3</sup> However, the child may take advantage of the caring parent and free ride on their parents' altruism, which has been characterized as the Samaritan's dilemma of bequests (Bruce and Waldman, 1990). The quote from Andrew Carnegie in the Introduction indicates that he may have had such effects in mind when warning against bequests. Further, Becker's rotten-kid theorem (Becker, 1974) says that selfish child may find it optimal to behave in the interest of their altruistic parents, i.e. they will contribute to the maxmization of total family income, but Bergstrom (1989) warns that the rotten kid theorem may fail if kids also care about their activities. Thus, "a lazy rotten kid" may still take out too much leisure.

One finds support for not taxing bequests in key theoretical results against capital income taxation in general, see Chamley (1986) and Judd (1985), for arguments within a Ramsey type of framework, and the Atkinson-Stiglitz theorem (Atkinson

 $<sup>^{2}</sup>$ So far, Norway is last in the row, as the inheritance tax disappeared in 2014.

<sup>&</sup>lt;sup>3</sup>Very few have studied labor supply effects of estate taxation on the donor side (Gale and Slemrod, 2000); one exception is Holtz-Eakin (1999).

and Stiglitz, 1976). The Atkinson-Stiglitz theorem states that when preferences are separable between labor supply and goods, governments should abstain from taxing capital if nonlinear income taxation is an option. It follows that within a standard OLG-framework (thus, with no intergenerational links), and with a nonlinear income tax at hand, that there is no role for taxation of bequests. Present and future consumption are equally complementary to leisure, and capital income taxation is not helpful for alleviating the labor income taxation distortion. It only introduces an additional distortion. In addition, when bringing in a dynastic perspective and pure altruism, one finds that bequests instead may be subsidized, see Kaplow (2001) and Farhi and Werning (2010). This follows from the social value of inheritance to the recipients that is not taken into account by the donors.<sup>4</sup>

However, there are several recent examples of studies that modify the no-tax result, and assige attention to the labor supply effects of recipients. For example, Golosov et al. (2003) find a role for capital taxation in a dynamic Mirrleesian framework with individual income uncertainty and incomplete insurance markets. Welfare maximization involves a trade off between insurance and incentives to work, and extended to a setting with bequests, a tax on inheritance would be optimal, as by reducing wealth it increases the incentives to work for the next generation.

In the optimal tax model of Kopczuk (2013a), the Carnegie effect captures a key role. The optimization problem is simplified by letting parents be motivated to leave bequest because of "joy of giving". Thus, the transfer represents a benefit for both parents and children, but the internalization effect of altruism is missing. Moreover, utility is separable between income (or labor supply) and other goods. Kopczuk discusses optimal estate taxation by discussing a perturbation to the optimal tax schedule, i.e., in a small range of wages (income) and bequests, an increase in the marginal tax rate on bequest is paralleled by a decrease in the income tax. It turns out that there are only two (contradicting) effects which should be accounted for in the set-up.<sup>5</sup> Firstly, as already discussed, as there are benefits of bequests both on the donor and the donee side (double-blessed), and as the latter is non-internalized, there is a positive externality pushing towards subsidization.<sup>6</sup> On the other hand, the transfer has a fiscal externality effect, as parental bequests interact with the incentive constraints of the child, making it tighter. This latter detrimental effect of

<sup>&</sup>lt;sup>4</sup>However, this double-counting of the benefits is questionable on normative grounds, as discussed by Boadway and Cuff (2014), although, one may still tax bequests if inheritances are correlated with the wage rate of recipients Brunner and Pech (2012).

 $<sup>^5\</sup>mathrm{Remarkably},$  the effect of taxation on the size of bequest does not enter the optimal tax formula.

<sup>&</sup>lt;sup>6</sup>If there is correlation between wage rates of recipients and bequest, progressive subsidization is advantageous (Farhi and Werning, 2010)

bequests is the Carnegie effect, and enters into the balance because incentives of children are not fully internalized by parents.

In addition to its key role in the optimal tax account, we should note that the information about the magnitude of the Carnegie effect is important for other reasons, such as for understanding the development of wealth accumulation and the role of intergenerational transfers in wealth (Holtz-Eakin et al., 1993; Joulfaian and Wilhelm, 1994), for estimating if people save enough for retirement (Elinder et al., 2012) and for understanding how the labor supply of elderly will develop as the values of inheritances increase due to the increasing wealth in the last decades (Brown et al., 2010).

# 3 Carnegie magnitudes

# 3.1 Idiosyncratic income effect

In a model with perfect foresight, as the structural life cycle labor supply model of Heckman and MaCurdy (1980, 1982), inheritance is anticipated and fully absorbed, yielding a downward shift in the entire life cycle profile of labor, and no immediate response would follow the receipt of inheritance. Still, we expect to observe short term Carnegie effects. At least some recipients will time their labor supply responses to the period just after the actual transfer. Because some inheritances are unexpected, beneficiaries may be liquidity constrained (before the actual transfer) and risk averse recipients will avoid using money they do not have.

Even though the change in labor supply as a result of bequest resembles the income effect of the standard labor supply literature, see reviews of the latter in Blundell and MaCurdy (1999) and Keane (2011), there are several reasons for not using the average income effect as a response estimate; these are the idiosyncracies of intergenerational transfers under investigation here. In addition, there is substantial uncertainty about magnitudes of labor supply responses in general, see for instance the different assessments in Chetty (2012) and Keane and Rogerson (2012). Correspondingly, there is no general agreement concerning the size of the income effect (Kimball and Shapiro, 2008; Hines Jr, 2013).<sup>7</sup>

The first type of heterogeneity is inspired by findings of the labor supply literature,

<sup>&</sup>lt;sup>7</sup>One line of research uses information on winners of lotteries to obtain estimates. For example, Imbens et al. (2001) estimate the propensity to earn among lottery winners, and find propensities that range from -0.1 to -0.25, but on average approximately -0.11, and significantly more for those close to retirement age, whereas Kimball and Shapiro (2008) use hypothetical lottery winners (e.g. they ask a sample of people what they would do in the event of winning the sweepstakes) and arrive at estimates close to -0.3. Still, lottery winners may not be representative of the general population.

namely that there are fixed cost of adjustments, such as search costs and other adjustments costs, which means that agents can be expected to respond only to changes that are sufficiently large. A change in unearned income will only have effect if it exceeds the fixed costs of finding a new optimum, see for instance Altonji and Paxson (1992) and Chetty (2012). Thus, we expect to see responses increasing at an increasing rate with the size of the transfer, also because other studies, as Brown et al. (2010), report such effects.

Next, we discuss age dependency in the Carnegie response. Of course, the negative fiscal externality of bequests is particularily problematic if people at an early stage of life (who Carnegie had in mind) are affected, and there is persistence in the responses. On the extensive margin, an inheritance increases the reservation wage, which means that some recipients withdraw from the labor market. It is expected that those who already have high income in the non-work alternative are more responsive, for instance because of eligibility to other public transfer schedules, such as the early retirement scheme.

A reason for not treating donations from parents as conventional lump sum incomes for the beneficiaries is that they may come with strings attached. In the exchange model of intergenerational transfers (Bernheim et al., 1985; Cox, 1987) this is highlighted, as parents use transfers strategically to engender the desired behavior of children, for instance to obtain attention from their own children. Thus, the exchange model perspective focuses on intergenerational transfers as device for controlling children's actions. Similarly, under altruism it has been focused on the importance of "having the last word" or controlling the last actions in a temporal sequence (Hirshleifer, 1977) in order to derive the positive outcomes of the "rotten kid" behavior (see Section 2).

Tied transfers may also come from mutual obligations, resulting from the interactions of attitudes and expectations within the family (Haveman and Wolfe, 1995; Chami, 1998). There are several variants of this type of family ties in the literature, characterized by different concepts. For example, Arrondel and Laferrere (2001) use the term "indirect reciprocity", meaning a system of transfer between generations where emotions, expectations and obligations play important roles. "Impure altruism" is another characterization (Laferrère and Wolff (2006)).<sup>8</sup> Such behavior may also develop to laws of bequest related to the idea of a "golden rule of bequests" (Bevan and Stiglitz, 1979): people bequeath an equal amount to which they inherited themselves, plus or minus some adjustments for luck over the life-cycle. Irrespective

<sup>&</sup>lt;sup>8</sup>See also Gatti (2005) and Lindbeck and Nyberg (2006) on the relationship between altruistic parents and work incentives for children.

of the precise mechanism and what terms that are used, we expect that heirs outside a direct line of kinship are less affected, implying that such effects will manifest in larger labor supply effects among recipients who do not have children.

#### 3.2 Previous studies

The literature on Carnegie effects is relatively small and is based on limited size data sources. Most contributions focus on unanticipated bequests, similar to the approach of the present study. A notable exception to this is Joulfaian and Wilhelm (1994), where both models with unanticipateds bequest and models with perfect foresight are estimated. In the latter case, the inheritance variable is discounted back to age 25. Two datasets are exploited in the estimation of the model: the Michigan Panel Study of Income Dynamics (PSID), which include both inheritors and non-inheritors, and the Treasury's Estate-Income Tax Match Sample (EITM), which is a sample of wealthy descendents and their heirs. They find that the labor supply responses are small under either perfect foresight or unanticipated inheritance maintained hypotheses. One possible explanation put forward is that the PSID data does not adequately represent recipients of large transfers.

The EITM data are also used by Holtz-Eakin et al. (1993). They labor market behavior of recipients before and after they recieved inheritances is examined, such as transitions in and out of the labor force and income growth. Thus, identification of effects comes from response differences dependent on the size of the transfer. They find clear indications that large inheritances reduce labor force participation, whereas effects on labor earnings are smaller. Brown et al. (2010) focus on the binary work/retire decision. Using 1994-2002 American survey data from the Health and Retirement Study, they find a significantly increasing probability of retirement amongst those who receive inheritances. The probability also increases with the size of the inheritance. They have the possibility to split inheritances in expected and unexpected, and find higher responses to unexpected inheritances. The study by Elinder et al. (2012) uses a small panel of wealthy decedents and their children. They find immediate labor supply effects that increase in the age of the recipient and the size of the transfer. Moreover, compared to Joulfaian and Wilhelm (1994), effects are reported to be larger and longer lasting.

## 4 Empirical framework

## 4.1 Data descriptions

As already remarked, in contrast to the most of the previous literature, we use data from administrative registers, which means that we exploit data for the whole Norwegian population. However, given that the administrative data only include information about formal working hours and people's move out of employment (extensive margin responses) are not observed, we measure outcomes in terms of labor income and early retirement, in addition to working hours (on the intensive margin). We exploit that information from various administrative registers can be linked by using unique personal identification numbers. A key data source for the present analysis is the register of all Norwegian inheritances by recipient, the Inheritance statistics (StatisticsNorway, 2014). Inheritances are reported to tax authorities whether or not they are liable for inheritance taxation. It is difficult to avoid reporting as it is necessary to provide documentation of estate settlement in order to terminate the deceased's bank accounts, change deeds, etc. The only source of missing observations is that very small estates are not always electronically registered by the tax authorities.<sup>9</sup> Further, the Income statistics for persons and families (StatisticsNorway, 2012) gives register-based information about income (wage income and all other types of income), wealth, family composition and educational level. In addition, the Wage statistics (StatisticsNorway, 2006) provides data for weekly hours of work for a sub-sample of the population.<sup>10</sup>

An important element of our empirical design is that we want to follow inheritors over time, both before and after receipt, and we exploit information about both heirs and of non-heirs, with the latter group representing counterfactual outcomes.We assign a time window for the transfers to take place, and make sure that we have at least three years of observations both before and after the transfer. In the analysis, inheritance transfers in the time window 2000-2004 are used. What we in the following will refer to as the "year of receipt" therefore varies between the years from 2000 to 2004.<sup>11</sup>

Further, in the descriptions of effects, we refer to "before transfer" and "after

 $<sup>^{9}</sup>$ Our data includes few inheritances of less than 5,000 NOK (\$660 in 1998), as the tax authorities reduced the administrative burden by not registering estates that were far from generating inheritance tax.

<sup>&</sup>lt;sup>10</sup>Recall that this information is based on formal or contract weekly hours of work, not actual hours.

 $<sup>^{11}</sup>$ We have inheritance statistics covering the period 1998-2006. Persons from households that we know have inherited in the years outside of 2000-2004 (i.e., in the years 1998, 1999, 2005 and 2006) are excluded.

transfer" periods, to examine the behavior of recipients and non-recipients in the labor market (income, working hours, retirement) for up to six years before and six years after the transfer. As for the data from the Income statistics for persons and families, we primarily use information for the years from 1997 to 2010,<sup>12</sup> which means that a person inheriting in 2000 will be covered by data for three "before transfer" years (data for 1997, 1998 and 1999) and the six years of the "after transfer" period (2001-2006). As the recipients are spread around in the time window 2000-2004, we get data points scattered over the thirteen year period: the transfer year plus six years before and six years after the transfer.

As we will return to soon, a propensity score matching technique is used in the identification of the Carnegie effects. The year three years prior to the transfer year is used for the matching. Note that all income and wealth variables will be measured in terms of log transformations in the estimations.

We limit the sample to persons who are between 18 and 66 years old (to avoid including children of school age and old age pensioners)<sup>13</sup> and exclude anyone not continuously present in the data for all years, except those who enter or exit the sample due to age. Self-employed<sup>14</sup> are left out, as we do not have register-based information on working hours for that group and because the bequest model for the self-employed may differ.<sup>15</sup> Individuals with zero income in the period leading up to the period of inheritance are also excluded.

These restrictions leave us with 1,684,967 persons followed over at least five years. For 317,945 of these indviduals we also have information about hours of work over the period 1998-2006, obtained from the Wage statistics. In comparison to earlier studies on labor supply and inheritance, we have access to much larger datasets,

For married couples where one of the partners receives an inheritance, findings from the labor supply literature (see, for example, Blundell and MaCurdy, 1999) suggest the that the spouses' labor supply is affected as well. An advantage of our paper, compared to the previous literature, is that we account for effects on both the heir and the spouse of the heir. We assume that couples have a common economy, implying that both spouses are defined as recipients. Persons who are living in a multiple-person household, but are classified as single, are excluded from the data

 $<sup>^{12}\</sup>mathrm{In}$  the construction of variables measuring previous income we use accumulated information over several years, also involving data from years prior to 1997.

<sup>&</sup>lt;sup>13</sup>Note that effect on early retirement is one of the outcomes we are interested in, but not standard retirement; the formal retirement age in Norway is 67.

<sup>&</sup>lt;sup>14</sup>Self-employment is defined as having higher total business income than wage income.

<sup>&</sup>lt;sup>15</sup>Transfer of firms to the next generation will often be examples of bequests coming with strings attached.

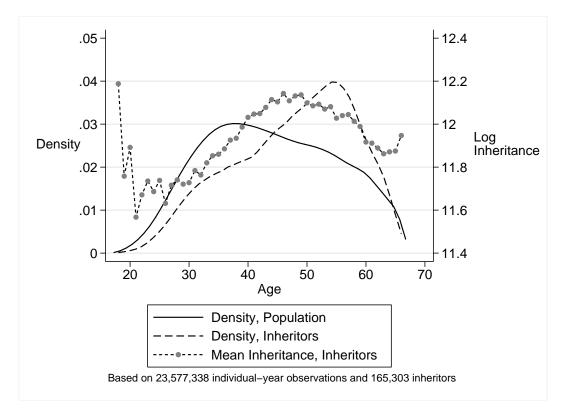


Figure 1. Population densities

set.<sup>16</sup>

<sup>&</sup>lt;sup>16</sup>These are mostly grown children registered as living in their parents' household, and does not represent a large number of observations.

	Non-	Inheritors	Inheritors
	inheritors		large transfers
$Mean values^2$			
Age	40.0	45.0	45.4
Wage	$218,\!116$	240,082	257,279
Capital income	$15,\!609$	22,242	29,519
Business income	$3,\!290$	$3,\!958$	4,013
Financial wealth	$140,\!125$	$221,\!989$	283,152
Housing wealth	77,026	$97,\!104$	105,099
Debt	$303,\!952$	290,119	308,74
Male	.481	.476	.48
No of adults	1.62	1.77	1.7
No of children	.823	.758	.76
High school	.471	.480	.46
University	.278	.323	.37
High school father	.337	.307	.33
High school mother	.322	.300	.32
University father	.100	.104	.13
University mother	.061	.061	.07
$Previous wage^3$	1,039,292	$1,\!218,\!084$	$1,\!310,\!75$
Previous capital $inc^3$	52,168	85,494	118,79
Previous business inc <sup>3</sup>	$27,\!839$	35,962	$36,\!93$
$Inheritance^4$			
Mean		$318,\!240$	668,55
Standard deviation		491,269	$678,\!29$
Median		198,871	495,86
No of persons	1,524,254	160,713	$58,\!30$

Table 1. Descriptive statistics, income and inheritance register data

-100 or persons 1,02 1,201 100,00  $^{-1}$  Inheritances over 300,000 NOK (\$1=7.55 NOK)

 $^{2}$  Measured in the last pre-transfer year (1999). All income and

wealth variables measured in 1998 NOK (\$1=7.55 NOK).

 $^3$  Summed over the period from 1993 to 1998.

<sup>4</sup> Transfers recieved in the period 2000-2004.

	Non-	Inheritors	Inheritors
	inheritors		large transfers <sup>1</sup>
Mean values <sup>2</sup>			
Age	42.2	45.8	46.2
Weekly hours of work	33.3	33.4	33.9
Wage	261,299	$268,\!158$	280,539
Capital income	6,533	7,841	9,131
Business income	1,925	2,722	2,950
Financial wealth	97,279	131,720	145,139
Housing wealth	88,800	99,085	106,365
Debt	$295,\!644$	259,380	266,907
Male	.403	.397	.414
No of adults	1.71	1.82	1.81
No of children	.931	.854	.854
High school	.412	.401	.372
University	.459	.496	.546
High school father	.355	.332	.352
High school mother	.348	.327	.356
University father	.113	.117	.146
University mother	.067	.070	.086
Previous wage <sup>3</sup>	$1,\!258,\!314$	$1,\!346,\!963$	1,416,700
Previous capital inc <sup>3</sup>	24,104	31,932	34,446
Previous business $inc^3$	14,207	19,511	19,704
$Inheritance^4$			
Mean		$320,\!524$	650,044
Standard deviation		465,937	623,241
Median		207,897	495,352
No of persons	$276,\!152$	37,274	14,082

Table 2. Descriptive statistics, subsample including hours of work

<sup>1</sup> Inheritances over 300,000 NOK (\$1=7.55 NOK)

 $^2$  Measured in the last pre-transfer year (1999). All income and wealth variables measured in 1998 NOK (\$1=7.55 NOK).

 $^3$  Summed over the period from 1993 to 1998.

<sup>4</sup> Transfers recieved in the period 2000-2004.

Table 1 and Table 2 show descriptive statistics for the full sample and the sample which is restricted by access to information about hours of work, respectively. Pointing forward to separate analyses for recipients of larger transfers, we also show separate figures for persons who have inherited more than 300,000 NOK (which is roughly the mean inheritance).<sup>17</sup>

The tables clearly suggest that the recipients are not similar to the rest of the population, reflecting that this is not a randomly selected group. This represents a major empirical challenge, also because we follow an identification strategy based on exploiting observations of non-recipients in the description of counterfactual outcomes. Recipients are different because they most likely have received other (unobservable) transfers from their parents, in the form of human wealth. Human wealth is influenced by favorable educational and environmental opportunities, which may also be interrelated to intergenerational transfers. Table 1 provide indications of such mechanisms: for example, inheritors (in 1999, one to five years before the transfer) have on average a higher level of education, higher earnings and higher wealth prior to inheritance. The fraction of inheritors that has high school as the highest level of education is about the same as for non-inheritors; 48 percent in the former group and 47 percent in the latter. However, there is a larger fraction of recipients (32 percent) that have attained college or university degrees than nonrecipients (28 percent), and this fraction is increasing with the size of the inheritance. For those who have received inheritances above 300,000 NOK, 38 percent of the recipients have a college or university degree. Pre-inheritance wage income and net wealth is also increasing in the level of inheritance.<sup>18</sup> Note also that for the subsample for which we have observations on working hours (Table 2), the differences between non-inheritors and inheritors are smaller (in particular for earnings), probably due to the requirement, of this data set, that all persons work continously throughout the whole period.

Figure 1 further elaborates on age differences, comparing age densities of inheritors with age densities of the general population (as represented by the data set established for the present analysis). The figure confirms that the population of inheritors is not representative of the general population. It also shows mean inheritance by age. Because of the natural timing of inheritances, inheritors are on average older that the rest of the population, which will result in higher observed pre-inheritance earnings and wealth in this group. On average the recipients are

 $<sup>^{17}</sup>$ All sums are deflated using the consumer price index, and given as Norwegian kroner (NOK) in 1998; 1=7.55 NOK according to the exchange rate in 1998.

<sup>&</sup>lt;sup>18</sup>This differs from the Swedish sample studied by Elinder et al. (2012), where high transfers are correlated with low wages.

46 years old in 1999, which means that they are on average 47-51 years old at the time of inheriting. As well as a higher average age, the distribution peaks at around age 55 for inheritors, whereas the general population peaks at age 35. In the next subsection we discuss how to obtain unbiased estimates of the Carnegie effect, given these differences between recipients and non-recipients.

#### 4.2 Data balancing with propensity score matching

One possible identification strategy is to study only the recipients over time (before and after the transfer), as done in Holtz-Eakin et al. (1993). However, results are then in danger of being confounded by unobserved time effects. As observations of non-recipients are exploited too, there exist various methods to handle the covariate differences just described. Instead of using parametric regressions to control for effects of covariates, we use techniques to improve the balance between the datasets of recipients and non-recipients. Matching techniques hold the promise of including the covariates in a more flexible way than standard parametric regression methods, as results of regressions may be vulnerable to the curse-of-dimensionality problem, i.e., it may be difficult to detect model inadequacies when different groups have covariates stretched thinly over a wide space, with their probability mass concentrated at different parts of the distribution, see for example Imbens (2004), Blundell and Dias (2009), Imbens and Wooldridge (2009) and Huber et al. (2013). Matching is explicitly a process of building a data set to obtain an unbiased estimate for the treatment by finding a sample of non-treated observations that are comparable to the treated observations. Applying matching methods makes it straightforward to discuss heterogeneous effects, by establishing balanced datasets for the various effects put forward here. In addition, we also combine matching with regression analysis in some parts of the analysis.

Thus, in the identification of Carnegie effects we exploit that there are many households that have the same characteristics and probability of inheriting as the households receiving transfers. A comparison along these lines could be achieved by matching persons with similar observed characteristics, except receiving intergenerational transfers. Such a matching procedure is cumbersome and requires a number of more or less justified choices concerning who are considered to be "equal". Instead of comparing individuals who have similar values on variables such as age, education, previous earnings and wealth, we may use the variables to construct the propensity score (Rosenbaum and Rubin, 1983). This is the estimated probability that a person receives an inheritance given the values of all the confounding variables. Then persons with similar propensity scores are used the obtain effects of inheritance on the dependent variables. As the propensity score function is not directly related to the outcome variables, estimates of effects obtained via propensity score matching are expected to deliver results which are more robust to misspecification, compared to results of standard methods, such as linear regression (Huber et al., 2013).

In the propensity score method, a single composite score is created from all observed baseline covariates, **X**. Units are then matched on the basis of that one-dimensional score alone. The propensity score is in our case defined as the conditional probability of inheritance receipt in a time period, given the observed covariates **X**, that is,  $E(\mathbf{X}) = \Pr(D = 1 | \mathbf{X})$ , where D is a dichotomous treatment indicator variable.

The two main identification assumptions in matching are unconfoundedness and overlap (or common support) (Imbens, 2004). The assumption of unconfoundedness means that, conditional on the propensity score, the potential outcomes are independent of treatment. That is, there are no unobservable variables influencing both the assignment to treatment and the outcome. The overlap assumption ensures that over the whole range of  $\mathbf{X}$ , there is the possibility for matches, i.e., similar persons with different treatment status. These two assumptions are referred to as strong ignorability. Rosenbaum and Rubin (1983) showed that if treatment assignment is strongly ignorable, given observed covariates, it is also strongly ignorable given the propensity score,  $Y(0), Y(1) \perp D|e(\mathbf{X})$ . This implies that instead of using the overall set of covariates, we may employ a single composite for balancing baseline differences in covariates, and multivariate matching techniques can be replaced by univariate propensity score matching techniques.

Using the treatment terminology, and denoting that we use nearest-neighbour matching, the Carnegie effect (CE),  $\alpha^{CE}$ , can be seen as an estimate of the average treatment effect on the treated,<sup>19</sup>

$$E\left[Y_{i}^{1} - Y_{i}^{0}|D=1\right] = \alpha^{CE} = \frac{1}{N^{R}} \sum_{i \in R} \left\{Y_{i} - \sum_{j \in NR(i)} Y_{j}\right\},$$

where  $Y_i^1$  is the potential outcome for individual *i* if inheriting, which is compared to the potential outcome,  $Y_i^0$ , when there is no inheritance for person *i*. In the empirical estimator, the identification relies on the matched individuals providing the counterfactual outcome of not recieving bequests; the sample counterpart for the missing observation of the behavior of individual *i* belonging to the group of recipients (*R*) is obtained from the group of non-recipients (*NR*). In the present

 $<sup>^{19}\</sup>mathrm{As}$  the recipients belong to a selected group of the population the effects derived can not be interpreted as overall average effects.

study, this means finding one match for the receipient (by the propensity score); thus, no weights are involved and the number of recipents dictates the number of matches,  $N^R$ . This means that control variables are used to design data sets which consist of "treated" (those who receive bequests) and a relevant, "non-treated" comparison group, where the treatment is the only observable difference. In the case where the two groups are perfectly balanced this estimator will also be equal to  $\bar{Y}_i - \bar{Y}_i$  and  $\alpha^{CE}$  can be consistently estimated by OLS.

The propensity score in our case is the estimated probability that a person lives in a family that receives an inheritance, given the values of the confounding variables. We argue that the timing of inheritance recipt is to a large degree coincidental, and that when conditioning on the large set of variables available, the unconfoundedness assumption holds. The matching is done three years before the receipt of inheritance, in order to avoid possible anticipatory effects (people adjusting to the transfer in advance). Since our treatment group consists of persons who inherit in a year that varies from 2000 to 2004, and we want to compare outcomes for the years after receipt, we also need to assign a specific "year of inheritance receipt" to our control persons. After matching, the control observation is assigned the same year of inheritance as its match. For this reason, the nearest-neighbor matching is done without replacement.<sup>20</sup>, benefitting from having access to a large data set with a rich set of observable characteristics for each person.

Given the outcomes we investigate, pre-inheritance earnings is an important matching variable. Further, as inheritors are older and have higher education than non-inheritors (see Table 1), and being in a couple increases the probability of inheriting since two are more likely to inherit than one, these variables are obvious candidates in the estimation of the propensity score. We have explored several different specifications to find the best fit. To guide the specification we have looked at how closely the covariates of the matched treated and control group fit, using t-tests. In addition, inspired by Dehejia and Wahba (2002), we have split the sample into 10 equally large groups sorted on propensity score, and looked at the balance of covariates within the groups. The preferred specification uses a logit procedure with the following explanatory variables: log of wage, capital and business income; log of financial wealth, housing wealth and debt; log aggregated wage, capital and business income for a period before the matching (from 1993 to the the year before matching); log square terms for the previous variables; age dummies; sex; a dummy for marriage/cohabitation; an interacted term of sex and marriage; and dummies for

 $<sup>^{20}</sup>$  As a recipient year is assigned to the control observations, this procedure would potentially be problematic if one control was matched to several treated observations. However, as we have many control persons available for comparison, not using replacement should not affect results.

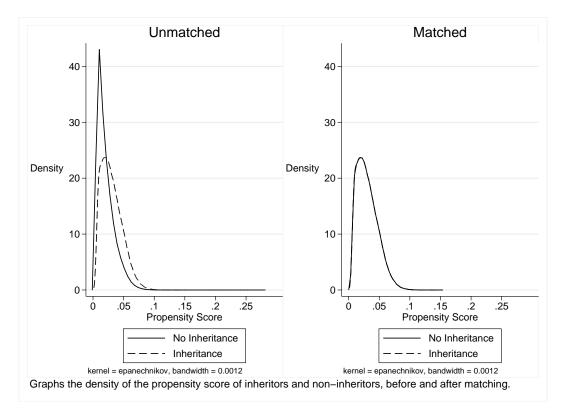


Figure 2. Propensity score densities before and after matching

high school and university education, for the person as well as for the person's father and mother.<sup>21</sup> The results for the participation model is presented in Appendix A, see Table A.1 along with mean equality tests in Table A.2. The mean equality test shows that our matching procedure is successful in balancing the dataset over the dimensions included in the model.

In Figure 2, the propensity score densities of inheritors and non-inheritors are displayed.<sup>22</sup> As shown in the left diagram of the figure, the distribution is massed at higher levels of propensity score for inheritors than for non-inheritors, which means that the propensity score does have some predictive power. The plot also reveals a clear overlapping of the distributions, which is an indication of common support for all treated observations (Caliendo and Kopeinig, 2008). In addition, the right diagram shows that the matching procedure is able to find matches over the whole distribution of inheritors.

In the following we shall discuss the heterogeneity of the Carnegie effect, examining how it varies with respect to the size of the transfer, the age of recipients, the

 $<sup>^{21}</sup>$ The matching is implemented in Stata 12 with the package psmatch2 (Leuven and Sianesi, 2014).

 $<sup>^{22}{\</sup>rm Similar}$  figures for the other matches are available on request. They all share roughly similar characteristics.

existence of new heirs in the chain, and the recipients' eligibility to early retirement. The effect of early retirement is discussed by using early retirement pension take-up as the dependent variable, whereas income or working hours are used as dependent variables for the other dimensions.

The empirical strategy regarding effects of age and new heirs, presented in Section 6, combines propensity score matching and OLS regressions.<sup>23</sup> Given that we believe we have obtained a balanced matched dataset, it should be straightforward to include interaction effects in the inheritance impact, here illustrated in the case with two characteristics,  $X_1$  and  $X_2$ ,

$$Y = \beta_0 + \beta \mathbf{X} + \delta D + \delta_1 X_1 D + \delta_2 X_2 D + \delta_{12} X_1 X_2 D + e.$$

Therefore, in contrast to the more common practice of examining subgroups one at a time, we estimate an equation where we (in practice) let the Carnegie effect,  $\alpha^{CE}$ , be explained by different characteristics (and interactions between them), dummies for age group and whether the recipient has own heirs or not included,<sup>24</sup>

$$\alpha^{CE} = \delta + \delta_1 \bar{X}_{1D=1} + \delta_2 \bar{X}_{2D=1} + \delta_{12} \left( \overline{X_1 X_2} \right)_{D=1}$$

#### 5 Size and non-linearity of the Carnegie effect

First, we establish to what extent we are able to observe Carnegie effects in general and to see how the Carnegie effect varies over time and according to the size of the transfer. As the donees may need sizeable amounts in order to overcome the fixed costs of finding a new optimum, we expect to find relatively larger Carnegie responses for larger transfers. We discuss the heterogeneity of the Carnegie effect with respect to size of the transfer by employing a separately matched data set

<sup>&</sup>lt;sup>23</sup>Many authors have discussed the benefits of combining matching or propensity score weighting and linear regression. Most of the discussion is aimed at ways in which regression adjustment can improve efficiency of the matching method. The intuition behind using both methods is that regression adjustment can be used to alleviate the effects of remaining covariate imbalances. Supplementary regression analysis can increase efficiency (Heckman et al. (1997); Rubin and Thomas (2000); Abadie and Imbens (2006)Heckman et al., 1997; Rubin and Thomas, 2000; Abadie and Imbens, 2006 ). The additional regression method is mainly aimed at situations where the treament and comparison groups are unequally sized (matching with replacement), and one may use a weighted regression where the comparison units are weighted by the number of times that they are matched to the treated unit. Since we have the advantage of a very large population with ample possibilities of finding suitable matches, we can use matching without replacement and obtain a fully balanced sample, and therefore we will not benefit from regression adjustment. Regressions are, however, used in the discussion of heterogenity of the Carnegie effect.

<sup>&</sup>lt;sup>24</sup>The setup is similar to Djebbari and Smith (2008), although they also controlled for idiosyncratic heterogeneity. Another difference is that we estimate a full interaction of all covariates.

(whereas we in the next section shall study heterogeneity by adding in explanatory variables directly in regressions based on the matched samples).

The first column of Table 3 presents estimates of the effect on wage income of receiving an inheritance by reporting average differences between receipients and non-recipients over the thirteen year time period: six years before and six years after the transfer year.<sup>25</sup> Given the identification strategy, it is reassuring to see that there are no signs of effects on income prior to the transfer. Moreover, we see a drop in earnings among inheritors after the transfer, in accordance with the Carnegie conjecture and previous findings in the literature (Holtz-Eakin et al., 1993; Joulfaian and Wilhelm, 1994). There seems to be a gradual and temporary wage response to the receipt of an inheritance: the coefficients turn negative at the year of receipt and increases gradually thereafter until the second to third year. The point estimates suggest that the inheritors reduce their income by approximately 2 percent 3 years after the transfer. However, none of the estimates are statistically significant.

All inhe	ritances	Above mean				
		inherita	$ances^1$			
Est.	SE	Est.	SE			
.0032	.0166	.0253	.0246			
.0016	.0130	.0008	.0198			
0032	.0111	0046	.0174			
.0013	.0100	0117	.0160			
.0021	.0103	0067	.0163			
.0146	.0109	.0019	.0174			
0041	.0117	0209	.0188			
0219	.0126	$0504^{*}$	.0206			
0226	.0134	0739**	.0219			
0196	.0142	0638**	.0233			
0120	.0153	$0511^{*}$	.0250			
0005	.0163	0376	.0267			
0061	.0173	0506	.0283			
No of matches <sup>3</sup> 143,000 $51,669$						
<sup><math>1</math></sup> Inheritances larger than 300,000 NOK ( $1=7.55$ NOK).						
$^{2}$ Year of matching.						
<sup>3</sup> Maximum number of matches, i.e. from the year of						
	Est. .0032 .0016 0032 .0013 .0021 .0146 0041 0219 0226 0196 0120 0005 0061 143 ger than 3 g. per of mat	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{c c c c c c c c c c c c c c c c c c c $			

**Table 3.** Effect of inheritance on wage income. Average differences in propensity scored matched sample

matching until one year after receipt.

\* p < 0.05 \*\* p < 0.01

 $<sup>^{25}</sup>$ Remember that the matching is based on individual characteristics three years before inheritance.

Table 1 shows that mean inheritance is approximately 40 percent higher than mean wage income for the recipients, while the median inheritance is lower than the mean wage. In other words, there is a substantial share of inheritances that are smaller than the average wage income. If there are fixed adjustment costs in the optimization process, as suggested by several studies of the labor supply literature, it is likely that smaller inheritances have small or no effect on labor supply. Table 3 presents separate estimates for inheritances above 300,000 NOK (somewhat above the mean).<sup>26</sup> For larger inheritances we find a much more distinct pattern than for the full sample, in accordance with the hypothesis of adjustment costs. Again we find a gradually stronger negative effect on wage income in the first years after the transfer, reaching a maximum effect of about 7 percent two to three years after inheriting. In the following years, the effect seems to diminish, until it is no longer statistically significant five to six years after the transfer. Figure 3 provides a graphical representation of the results of Table 3.

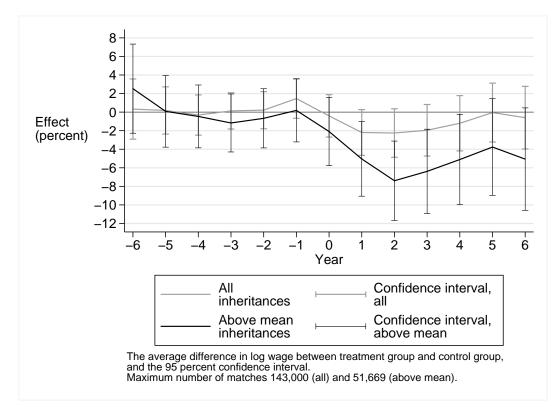


Figure 3. The effect of inheritance on wage income

As denoted by the literature focusing on the measurement of income responses to changes in taxes (see Saez et al., 2012, for a survey), income responses reflect a diversity of behavioral responses. To obtain separate estimates for the effect

 $<sup>^{26}{\</sup>rm The}$  matching is done separately for each subgroup, which means that recipients of large inheritances are matched with persons based on a different participation model.

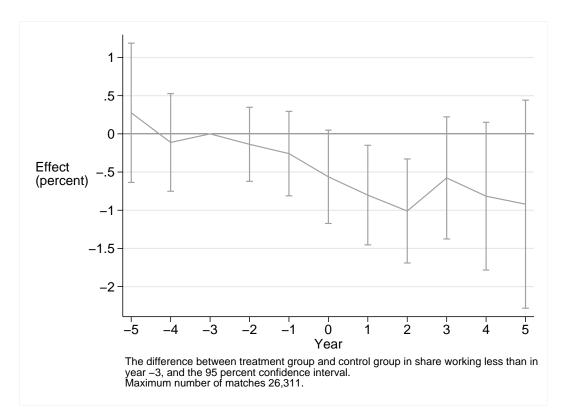


Figure 4. The effect of inheritance on the probability of reducing working hours

on working hours at the intensive margin, we use the subsample were we have information about hours of work over the period 1998-2006. Being in the sample is conditional on working over the whole observation period, and we only have information about contractual working hours for a subsample of persons, so there are data limitations. People who retire or completely stop working will not show up in this sample, which implies that effects on the intensive margin are obtained.

When using the same identification strategy as for income, we obtain results which are very hard to interpret due to huge standard errors (see Table A.4 in the Appendix). We therefore use a somewhat modified empirical strategy to study whether there is an effect on hours of work. The matching procedure is the same, but the outcome variable is different. Now the outcome variable is a dummy indicator taking the value 0 if working time is reduced from its level in the year of matching and 1 if it is the same or higher. The results are presented in Figure 4, showing that the share of people cutting their working time is up to one percentage point larger for recipients. However, the effect is only statistically significant in the two years directly following the transfer.

Our results, though using different methods, are qualitatively similar to Joulfaian and Wilhelm (1994) in finding a very small change in working hours, and a somewhat larger change in earnings. We also confirm the result from Holtz-Eakin et al. (1993) that larger inheritances leads to larger labor supply response. Quantitatively, our estimates of the effect on labor earnings are larger than in both of these papers. The time pattern of the labor supply responses is similar to the findings of Elinder et al. (2012); the impact is strongest after a couple of years, then decreasing over time.

### 6 Further response heterogeneity

In order to investigate how Carnegie effects differ across groups, a standard procedure would be to split into subsamples and making new matches for each subsample. Until now we have split the initial sample into recipients with an inheritance smaller than mean inheritance (smaller than 300,000 NOK) and recipients with above mean inheritance (and their comparable units). When we in the following discuss how Carnegie effects vary with respect to the age of recipients and the existence of new heirs, we use the "large transfer" subsample and employ the propensity score matching technique in combination with regression analysis, as discussed in Section 4. Estimation results are obtained for an equation including the inheritance indicator and its interactions with dummies for age group and whether the recipient has own heirs or not. In addition, we present estimation results for the effects of gender, marital status and educational level.

Note that the specification includes direct effects of all additional covariates and all possible interactions between the covariates. With a fully flexible model where all characteristics are allowed to interact with each other it is difficult to evaluate the point estimates. Therefore we compute the predicted marginal effect of inheriting for each subgroup. Table 4 shows these marginal effects of inheriting by age, existence of heirs, marital status, and level of education, together with the benchmark: the overall marginal effect of inheritance (the first line of Table 4). In the table, results for selected years are presented in order to reduce the dimensionality of the table.

	Year of	λ	ears after	r inheritin	ıg
	inheritance	1 year	2 years	4 years	6 years
Inheriting	045*	077**	100**	080**	078**
Age $21-42^1$	115**	163**	171**	114*	188**
Age $43-49^1$	033	043	015	.031	.080
Age $50-55^{1}$	023	025	052	021	.043
Age $56-60^{1}$	025	079*	139**	172**	222**
No heirs	206**	257**	338**	216**	199*
Heirs	024	053*	072**	066**	069*
Male	.001	023	048	064	041
Female	081**	119**	143**	096**	118**
Couple	030	053*	068**	067*	075*
Single	087*	150**	208**	135**	107
Elementary school	.109	.035	006	039	.011
High school	075**	112**	143**	126**	143**
Higher education	065*	072*	082*	044	045

Table 4. Marginal effects of inheritance on wage income

Note: propensity score method in combination with regression.

<sup>1</sup> Age in the year of inheritance.

\* p < 0.05 \*\* p < 0.01

In Table 4 we show Carnegie effects for four age groups. The average age of heirs (at receipt) is about 49 years, which is probably a higher age than that of the sons who Andrew Carnegie had in mind when he was concerned about a "general deadening of talents and energies". Table 4 confirms that responses vary across age-groups, with the youngest and oldest age groups responding,<sup>27</sup> and recipients in their forties and early fifties not showing any significant behavioral change. It seems transfer magnitudes are not large enough to move middle-aged people away from their stable position in the labor market. For the eldest inheritors we see a pattern of steadily declining earnings over the entire period we are studying. The largest response with respect to age is seen for the oldest age group: recipients reduce their income by 22 percent, compared to the non-recipients of that age group.

An interpretational challenge concerning the results reported in Table 4 is that they are not informative about the significance of differences in the marginal effects between groups. Therefore, in Table 5, we provide results of F-tests for the differences between groups. The asterisk indicates rejection of the null hypothesis that the

 $<sup>^{27}</sup>$ One may speculate that younger households respond more temporarily. Although we restrict the following analysis to larger inheritances (above mean inheritance), it is unlikely that the transfers are so large that they will support a permanent non-working life.

marginal effects in the pairwise comparison are equal, at different significance levels. According to the table, the youngest and the oldest age groups have long run marginal responses to inheriting which significantly differ from the middle aged groups; see the results for six years after inheriting.

Table 5.	Differences in	marginal	effects	between	groups -	statistical	significance

	Year of	Years a	fter inhe	riting	
	inheritance	One	Two	Four	Six
Age 21-42 vs age $43-49^1$	1.91	3.42	$5.33^{*}$	3.68	10.5**
Age 43-49 vs age $50-55^1$	0.03	0.09	0.35	0.54	0.22
Age 50-55 vs age $56-60^1$	0.01	1.12	2.50	$5.93^{*}$	$14.5^{**}$
Heirs vs no heirs	$9.05^{**}$	9.59**	$14.6^{**}$	3.63	2.17
Males vs females	$5.03^{*}$	$5.82^{*}$	$5.07^{*}$	0.45	2.08
Singles vs couples	1.68	4.14*	$7.65^{**}$	1.41	0.23
Elementary vs high school	$11.7^{**}$	$6.26^{*}$	$4.89^{*}$	1.49	3.71
High school vs higher edu.	0.06	0.81	1.82	2.49	2.87

Note: F-test for differences in the marginal effects between groups

<sup>1</sup> Age in the year of inheritance.

\* p < 0.05 \*\* p < 0.01

Since we observe a pattern of steadily declining earnings for the age group approaching retirement it is reasonable to conjecture that this is influenced by responses on the extensive margin, i.e. that some individuals in this group use the transfer to withdraw from the labor market. It is likely that the choice of when to retire may be affected by the sudden receipt of an inheritance. Even though we readily acknowledge that this type of behavioral response is far from Alfred Carnegie's original notion, we investigate extensive margin responses for this age group by providing estimation results for the probability of retirement before normal retirement age.<sup>28</sup>

The findings are reported in Figure 5, where the outcome variable is now the difference in the share of inheritors and non-inheritors who have taken early retirement. The results show an increase in the uptake of early retirement in the years after inheritance receipt, and the results show a pattern that is stable over time. The share of inheritors that retire early is around two percentage points higher than the share among non-inheritors, and the difference in shares is statistically significant for most years following receipt. The results coincide with the findings of Brown et al. (2010), who show a signifiant increase in the probability of retirement for inheritors, increasing with the size of the inheritance.

 $<sup>^{28}</sup>$ Uptake of an early retirement pension before the formal retirement age (67), given to employees that participate in a pension scheme through a collective agreement, called AFP.

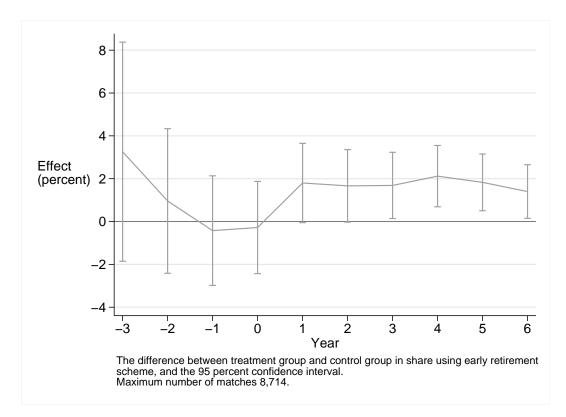


Figure 5. Estimation results, early retirement

Returning to the other results of Table 4, we see results which accord with a "strings attached" conjecture; see several reasonings behind this pattern in Section 3. The marginal effects for the group with no direct heirs show the largest response of all subgroup-responses reported in Table 4. This suggests that family obligations, which follow from the interactions of attitudes and expectations within the family, or the golden rule of bequests, may be of importance. Note that (see Table 5) significant differences between recicipents with and without offspring are obtained for the first two years after the transfer; thereafter effects are positive, but non-significant.

As seen in Table 4, we have also looked more closely at effects of the gender of the recipient, whether the recipient is single or in a couple (married/cohabiting) and educational level. Educational level is included since it may be a proxy for high income, or may influence financial literacy and ability to plan. We note that higher female labor supply responses are in line with the literature on labor supply elasticities, which typically find that female's labor supply is more elastic than men's labor supply (Blundell and MaCurdy, 1999; Keane, 2011). Regarding education, it seems that the main difference is between recipients with elementary school level and recipients with high school level; the latter group being more responsive. Overall, the least responsive group is highly educated couples in their fifties, with direct heirs.

# 7 Robustness checks

## 7.1 Unobserved heterogeneity

A disadvantage of propensity score matching estimator is that it only accounts for observed (and observable) covariates. If there are unobserved factors that simultaneously affect the probability of inheriting and the earnings outcome (selection on unobservables), the usual matching estimator can be seriously biased. In the presence of longitudinal data, Heckman et al. (1997) has proposed a combination of matching methods and difference-in-differences techniques that may accommodate selection on unobservables and weaken the strong underlying assumptions of both methods (Blundell and Dias (2009)). Time independent unobservable individual effects can be cancelled out by taking differences over time. This alternative estimation by a matching difference-in-differences (MDID) technique implies comparing the development of recipients with that of non-recipients over an observation period  $(t_0, t_1)$ . The matching estimator now becomes

$$\alpha^{CE} = \sum_{i \in R} \left\{ (Y_{it_1} - Y_{it_0}) - \sum_{j \in NR(i)} (Y_{jt_1} - Y_{jt_0}) \right\}.$$

Table 6 shows results when applying the MDID for estimating the effect of receiving a large transfer (thus, the sample based on above mean inheritances is used here too). Since we have many observation periods, one must make a choice with respect to the observation period  $(t_0, t_1)$ . The table shows results for two alternatives: one where  $t_0$  is the year before inheriting, and another where the initial level is based on the average earnings in the three years before inheriting.

			Diff. from mean
		Diff. from year	of the 3 years
	Level	before inheriting	before inheriting
Year of inheriting	020 (.018)	-	-
1 year after	050* (.021)	$052^{**}$ (.015)	044** (.016)
2 years after	073** (.022)	066** (.018)	062** (.018)
3 years after	066** (.024)	057** (.020)	053** (.020)
4 years after	054* (.025)	043 (.022)	040 (.022)
5 years after	035 (.027)	030 (.024)	027 (.024)
6 years after	044 (.029)	039 (.026)	034 (.026)

Table 6. Effects on wage in levels and long differences, alternative estimator

Note: Standard errors in parentheses.

\* p < 0.05 \*\* p < 0.01.

The results of Table 6 are encouraging, as estimates based on the differenced matching technique are close to the estimates based on levels. These results therefore do not indicate that unobserved heterogeneity represents a major source of bias. Also under this specification, the effect is clearly negative in the years after inheriting. The overall negative effect on earnings of inheritors after the (large) transfer is approximately five percentage points.<sup>29</sup> However, needless to say, the MDID method also relies on assumptions which may not hold.

## 7.2 Testing familiy ties with more parental information

In the previous section we found that inheritors with no own heirs reduced their work effort more than inheritors with heirs. We suggested than an explanation could be a sense of obligation towards later generations that discouraged recipients with heirs from using the inheritance on own consumption of goods and leisure. In order to obtain a more exhaustive test of this hypothesis, one would ideally require that the bequest is given by a parent and not from others. In the previous sections we have included all inheritances, irrespective of family ties, though bequests predominantly go from parents to children or grandchildren. The main reason for not restricting on family ties is that the register data is not complete with respect to family linkages, and conditioning on information about parental transfers would cause a large drop in the number of observations.

		, 1	1 1		11 1 '	2
	Restric	cted san	iple	Fi	ull sample <sup>2</sup>	2
	No heirs	Heirs	Diff.	No heirs	Heirs	Diff.
	Marg. e	effect	F-test	Marg.	effect	F-test
1 year before	027	.048	0.58	133*	001	$5.49^{*}$
Year of receipt	105	.011	1.72	206**	024	$9.05^{**}$
1 year after	232**	.002	$6.13^{*}$	257**	053*	9.59**
2 years after	237*	.015	$6.19^{*}$	338**	072**	$14.6^{**}$
3 years after	189	.019	3.37	267**	072**	6.99**
4 years after	149	.051	3.02	216**	066**	3.63
5 years after	106	021	0.48	154	067*	1.07
6 years after	148	025	0.89	199*	069*	2.17

 Table 7. Marginal effects for recipients with and without own heirs

<sup>1</sup>Inheritances larger than 300,000 NOK from own parents. Comparison group with at least one live parent.

<sup>2</sup>Inheritances larger than 300,000 NOK

\* p < 0.05 \*\* p < 0.01

 $<sup>^{29}\</sup>mathrm{The}$  MDID estimator implies that results now are presented in terms of differences, measured in percentage points.

Nevertheless, it is of interest to check whether the interaction results for inheritors with and without own heirs are replicated in a sample where we impose stricter conditions. For the inheritors we require that the inheritance is left by the last surviving parent, and for the comparison group we require that at least one parent is alive during the entire comparison period (which is up to six years after the assigned year of inheritance receipt). Table 7 presents the results for this smaller sample and compare results to the initial estimates for heirs/no heirs, obtained from Table 4. We see that the F-tests for significant differences are weakened with the smaller sample, but that the overall results stand. We still find that recipients with no heirs have a larger propensity to use the inheritance on own leisure, and that this propensity differs significantly from responses of recipients with heirs in the first years after inheriting.

# 7.3 Entrepreneurship

Initially we excluded self-employed and restricted the analysis to wage earners, defined as those having had higher wage income than business income in the years before matching. However, we cannot rule out that some inheritors may have used the acquired funds to start up a new business. Thus, part of the decline in earnings could be attributed not to increased leisure, but to a transition into self-employment and a start-up period, in which the person allocates very little as wage to himself/herself. Some may also have inherited the ownership of a small family business and for that reason changed from being an ordinary wage earner to becoming self-employed. There are some studies that report positive effects of windfall gains (both lotteries and inheritance) on the probability of entering self-employment; see Lindh and Ohlsson (1996), Blanchflower and Oswald (1998) and Evans and Leighton (1989). A standard interpretation of the positive windfall impact on entrepeneurship is that the windfall relaxes the liquidity constraint.

We check this by studying how the receipt of an inheritance affects the probability of becoming self-employed. Results are derived when restricting the data to large inheritances, since we expect such behavioral responses to be dependent on large transfers. Figure 6 uses the same matching procedure as previously presented in figure 3, but the outcome is the difference in the share of self-employed for the years before and after inheritance. The figure shows very small effects, and no clear upward trend in self-employment following the receipt of inheritance.

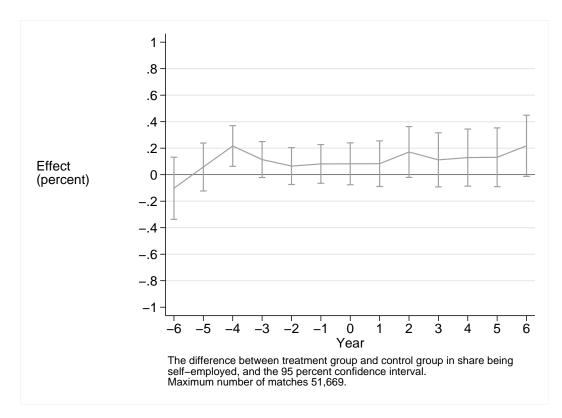


Figure 6. Estimation results, self-employment

# 8 Summary

Taxation of intergenerational transfers is under pressure in many countries, and Norwegian politicians decided to abolish the scheme in 2014. One often neglected potential positive effect of the inheritance tax is that it may increase the labor supply of recipients, as bequests are expected to increase the consumption of leisure. This is often referred to as the Carnegie effect. Recent discussions of the estate tax/inheritance in an optimal perspective, as in Kopczuk (2013a), assign a key role for the Carnegie effect in the overall judgment.

In this perspective it is problematic that the literature providing estimates of the Carnegie effects is rather limited. One reason is that some bequests are perfectly foreseen and accounted for in the life-cycle plan of the recipients. Thus, the results of the present study may for this reason underestimate the overall Carnegie effect. Nevertheless, we find clear evidence of recipients using bequests to reduce increase their consumption of leisure also shortly after the transfer. Moreover, a main advantage of the present study is that we have had access to large datasets, obtained from administrative registers. This means that have been able to present a broader picture of the labor supply responses induced by inheritances.

The diversity of behavioral responses also point to factors that constrain the

Carnegie effect. We see evidence in accordance with adjustments costs in finding new optima resulting in smaller negative labor supply effects and, notably, find results which support that recipients may not feel eligible to use intergenerational transfers only on their own consumption of leisure when there is a new generation awaiting support. One important implication of our finding is that income effects on recipients of bequests are idiosyncratic: simply adopting income effects from other labor supply studies can be highly misleading. Finally, these findings give support for two rather common features of the inheritance tax, given that one would like to limit the Carnegie effect: progressive schedules and higher tax rates for heirs not in the direct line from the deceased.

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# A The participation model

A.1 Logit results	5
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Log capital income $29128213$ $.21296642$ $-1.36773$ Log financial wealth.00196621.41085275.0047850Log debt.3233201.64224324.5034233Log housing wealth $-8.4310527$ .72464954 $-11.6346$ Log business income.14830162 $3.4524141$ .0429550Male $-01910904$ .05324444 $358892$ Housh. size.53336845.0210742125.30903Male*Housh. size $05460765$ .03009494 $-1.814511$ Wage equals zero.11131634.11823463.941650High school.11318758.016485986.865686University.19599449.0191854210.21580High school father.1129047.015878177.110683University father.22533329.030227037.454694Age 18 <sup>1</sup> $87974073$ .32868695 $-2.67653$ Age 19.1.3062156.26065865 $-5.01121$ Age 20.1.1404213.16709006 $-6.82518$ Age 21.1.178634.13471368 $-8.74917$ Age 22.1.0553106.07026382.15.0192Age 23.1.0553106.07026382.15.0192Age 24.1.0992844.08033906.13.6830Age 25.1.0553106.056397672.16.1874Age 27.1.0290123.0601584.17.1050Age 2896816731.05641777.17.1666Age 3094536366.05371912.17.5982Age 3188170786 <th></th> <th>Coefficient</th> <th>SE</th> <th>t-stat</th>		Coefficient	SE	t-stat
Log financial wealth       .00196621       .41085275       .0047850         Log debt       .3233201       .64224324       .5034233         Log housing wealth       -8.4310527       .72464954       -11.6346         Log business income       .14830162       3.4524141       .0429553         Male       -0.01910904       .05324444      358892         Housh. size       .53336845       .02107421       25.30903         Male*Housh. size      05460765       .0309494       -1.81451         Wage equals zero       .1113634       .11823463       .941656         High school       .11318758       .01648598       6.865686         University       .19599449       .01918542       10.21580         High school father       .1126047       .01587817       7.110683         University father       .2253329       .03022703       7.454694         Age 18 <sup>1</sup> 87974073       .32868695       -2.67653         Age 19       .113062156       .26065865       -5.01121         Age 20       .11404213       .16709006       -6.82518         Age 21       .1.178634       .13471368       -8.74917         Age 22       .1.157025       .09381522       -12.	Log wage income	.62361832	2.0986603	.29715067
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Log housing wealth $-8.4310527$ $.72464954$ $-11.6346$ Log business income $.14830162$ $3.4524141$ $.0429553$ Male $01910904$ $.05324444$ $358892$ Housh. size $.53336845$ $.02107421$ $25.30903$ Male*Housh. size $05460765$ $.03009494$ $-1.814511$ Wage equals zero $.11133634$ $.11823463$ $.941650$ High school $.11318758$ $.01648598$ $6.865686$ University $.19599449$ $.01918542$ $10.21586$ High school father $.1129047$ $.01587817$ $7.110683$ University father $.2253329$ $.03022703$ $7.454694$ Age 18 <sup>1</sup> $87974073$ $.32868695$ $-2.67653$ Age 19 $-1.3062156$ $.26065865$ $-5.01121$ Age 20 $-1.1404213$ $.16709006$ $-6.82518$ Age 21 $-1.172977$ $.10858234$ $-10.3819$ Age 23 $-1.1557025$ $.09381522$ $-12.3189$ Age 24 $-1.0992844$ $.08033906$ $-13.6830$ Age 25 $-1.0553106$ $.07026382$ $-15.0192$ Age 26 $-1.0356195$ $.06397672$ $-16.1874$ Age 29 $-96816731$ $.05641777$ $-17.1606$ Age 30 $94536366$ $.053711912$ $-17.982$ Age 31 $88170786$ $.05225194$ $-16.8741$ Age 33 $80876987$ $.05116891$ $-15.8058$ Age 34 $74966194$ $.05065301$ $-14.0851$	Log financial wealth	.00196621	.41085275	.00478568
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Housh. size.53336845.0210742125.30903Male*Housh. size05460765.03009494-1.81451Wage equals zero.11133634.11823463.941656High school.11318758.016485986.865686University.19599449.0191854210.21586High school father.13662074.01568448.710614High school mother.1129047.015878177.110688University father.23189255.025072279.248964University mother.22533329.030227037.454694Age 18187974073.32868695-2.67653Age 19-1.3062156.26065865-5.01121Age 20-1.1404213.16709006-6.82518Age 21-1.178634.13471368-8.74917Age 22-1.127297.10858234-10.3819Age 23-1.0553106.07026382-15.0192Age 24-1.0992844.08033906-13.6830Age 27-1.0250123.0601584-17.1050Age 2896816731.05641777-17.1666Age 2996585232.0548832-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3280876987.05116891-15.8058Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.0504532-14.0551	Log business income	.14830162	3.4524141	.04295592
Male*Housh. size05460765.03009494-1.81451Wage equals zero.11133634.11823463.941650High school.11318758.016485986.865680University.19599449.0191854210.21580High school father.13662074.01568448.710614High school mother.1129047.015878177.110683University father.23189255.025072279.248964University mother.22533329.030227037.454694Age 18187974073.32868695-2.67653Age 19-1.3062156.26065865-5.01121Age 20-1.1404213.16709006-6.82518Age 21-1.178634.13471368-8.74917Age 22-1.127297.10858234-10.3819Age 23-1.1557025.09381522-12.3189Age 24-1.0992844.08033906-13.6830Age 25-1.0553106.07026382-15.0192Age 26-1.0356195.06397672-16.1874Age 27-1.0290123.0601584-17.1050Age 2896816731.05641777-17.1666Age 2996585232.0548832-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3280876987.05116891-15.8058Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 357	Male	01910904	.05324444	35889274
Wage equals zero.11133634.11823463.941650High school.11318758.016485986.865680University.19599449.0191854210.21580High school father.13662074.01568448.710614High school mother.1129047.015878177.110683University father.23189255.025072279.248964University mother.22533329.030227037.454694Age 18187974073.32868695-2.67653Age 19-1.3062156.26065865-5.01121Age 20-1.1404213.16709006-6.82518Age 21-1.178634.13471368-8.74917Age 23-1.1557025.09381522-12.3189Age 24-1.0992844.08033906-13.6830Age 25-1.0553106.07026382-15.0192Age 26-1.0356195.06397672-16.1874Age 27-1.0290123.0601584-17.1050Age 2894536366.05371912-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.0504532-14.0851	Housh. size	.53336845	.02107421	25.309058
High school.11318758.01648598 $6.865680$ University.19599449.0191854210.21580High school father.13662074.0156844 $8.710614$ High school mother.1129047.01587817 $7.110683$ University father.23189255.02507227 $9.248964$ University mother.22533329.03022703 $7.454694$ Age $18^1$ 87974073.32868695 $-2.67653$ Age 19-1.3062156.26065865 $-5.01121$ Age 20-1.1404213.16709006 $-6.82518$ Age 21-1.178634.13471368 $-8.74917$ Age 23-1.127297.10858234 $-10.3819$ Age 24-1.0992844.08033906 $-13.6830$ Age 25-1.0553106.07026382 $-15.0192$ Age 26-1.0356195.06397672 $-16.1874$ Age 2996816731.05641777 $-17.1606$ Age 2996585232.0548832 $-17.5983$ Age 3188170786.05225194 $-16.8741$ Age 3289266276.05239001 $-17.0387$ Age 3380876987.05116891 $-15.8058$ Age 34.74966194.05065301 $-14.7999$ Age 3571193691.05054532 $-14.0851$	Male*Housh. size	05460765	.03009494	-1.8145126
University.19599449.0191854210.21580High school father.13662074.01568448.710614High school mother.1129047.015878177.110683University father.23189255.025072279.248964University mother.22533329.030227037.454694Age 18187974073.32868695-2.67653Age 19-1.3062156.26065865-5.01121Age 20-1.1404213.16709006-6.82518Age 21-1.178634.13471368-8.74917Age 22-1.127297.10858234-10.3819Age 23-1.1557025.09381522-12.3189Age 24-1.0992844.08033906-13.6830Age 25-1.0553106.07026382-15.0192Age 26-1.0256195.06397672-16.1874Age 27-1.0290123.0601584-17.1050Age 2896816731.05641777-17.1606Age 2996585232.0548832-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.0504532-14.0851	Wage equals zero	.11133634	.11823463	.941656
High school father $.13662074$ $.0156844$ $8.710614$ High school mother $.1129047$ $.01587817$ $7.110683$ University father $.23189255$ $.02507227$ $9.248964$ University mother $.2253329$ $.03022703$ $7.454694$ Age $18^1$ $87974073$ $.32868695$ $-2.67653$ Age $19$ $-1.3062156$ $.26065865$ $-5.01121$ Age $20$ $-1.1404213$ $.16709006$ $-6.82518$ Age $21$ $-1.178634$ $.13471368$ $-8.74917$ Age $22$ $-1.127297$ $.10858234$ $-10.3819$ Age $23$ $-1.1557025$ $.09381522$ $-12.3189$ Age $24$ $-1.0992844$ $.08033906$ $-13.6830$ Age $25$ $-1.0553106$ $.07026382$ $-15.0192$ Age $26$ $-1.0356195$ $.06397672$ $-16.1874$ Age $27$ $-1.0290123$ $.0601584$ $-17.1050$ Age $29$ $96585232$ $.0548832$ $-17.5983$ Age $30$ $94536366$ $.05371912$ $-17.5982$ Age $31$ $88170786$ $.05225194$ $-16.8741$ Age $32$ $89266276$ $.05239001$ $-17.0387$ Age $33$ $80876987$ $.05116891$ $-15.8058$ Age $34$ $74966194$ $.05065301$ $-14.7999$ Age $35$ $71193691$ $.05054532$ $-14.0851$	High school	.11318758	.01648598	6.8656866
High school mother $.1129047$ $.01587817$ $7.110683$ University father $.23189255$ $.02507227$ $9.248964$ University mother $.22533329$ $.03022703$ $7.454694$ Age $18^1$ $.87974073$ $.32868695$ $-2.67653$ Age $19$ $-1.3062156$ $.26065865$ $-5.01121$ Age $20$ $-1.1404213$ $.16709006$ $-6.82518$ Age $21$ $-1.178634$ $.13471368$ $-8.74917$ Age $22$ $-1.127297$ $.10858234$ $-10.3819$ Age $23$ $-1.1557025$ $.09381522$ $-12.3189$ Age $24$ $-1.0992844$ $.08033906$ $-13.6830$ Age $25$ $-1.0553106$ $.07026382$ $-15.0192$ Age $26$ $-1.0356195$ $.06397672$ $-16.1874$ Age $27$ $-1.0290123$ $.0601584$ $-17.1050$ Age $29$ $96585232$ $.0548832$ $-17.5983$ Age $30$ $94536366$ $.05371912$ $-17.5982$ Age $31$ $88170786$ $.05225194$ $-16.8741$ Age $32$ $89266276$ $.05239001$ $-17.0387$ Age $33$ $80876987$ $.05116891$ $-15.8058$ Age $34$ $74966194$ $.05065301$ $-14.7999$ Age $35$ $71193691$ $.05054532$ $-14.0851$	University	.19599449	.01918542	10.215801
University father $.23189255$ $.02507227$ $9.248964$ University mother $.22533329$ $.03022703$ $7.454694$ Age $18^1$ $.87974073$ $.32868695$ $-2.67653$ Age 19 $-1.3062156$ $.26065865$ $-5.01121$ Age 20 $-1.1404213$ $.16709006$ $-6.82518$ Age 21 $-1.178634$ $.13471368$ $-8.74917$ Age 22 $-1.127297$ $.10858234$ $-10.3819$ Age 23 $-1.1557025$ $.09381522$ $-12.3189$ Age 24 $-1.0992844$ $.08033906$ $-13.6830$ Age 25 $-1.0553106$ $.07026382$ $-15.0192$ Age 26 $-1.0356195$ $.06397672$ $-16.1874$ Age 27 $-1.0290123$ $.0601584$ $-17.1050$ Age 28 $96816731$ $.05641777$ $-17.1606$ Age 30 $94536366$ $.05371912$ $-17.5982$ Age 31 $88170786$ $.05225194$ $-16.8741$ Age 32 $80876987$ $.05116891$ $-15.8058$ Age 34 $74966194$ $.05065301$ $-14.7999$ Age 35 $71193691$ $.05054532$ $-14.0851$	High school father	.13662074	.0156844	8.7106146
University mother $.22533329$ $.03022703$ $7.454694$ Age $18^1$ $.87974073$ $.32868695$ $-2.67653$ Age 19 $-1.3062156$ $.26065865$ $-5.01121$ Age 20 $-1.1404213$ $.16709006$ $-6.82518$ Age 21 $-1.178634$ $.13471368$ $-8.74917$ Age 22 $-1.127297$ $.10858234$ $-10.3819$ Age 23 $-1.1557025$ $.09381522$ $-12.3189$ Age 24 $-1.0992844$ $.08033906$ $-13.6830$ Age 25 $-1.0553106$ $.07026382$ $-15.0192$ Age 26 $-1.0356195$ $.06397672$ $-16.1874$ Age 27 $-1.0290123$ $.0601584$ $-17.1050$ Age 28 $96816731$ $.05641777$ $-17.1606$ Age 30 $94536366$ $.05371912$ $-17.5982$ Age 31 $88170786$ $.05225194$ $-16.8741$ Age 32 $89266276$ $.05239001$ $-17.0387$ Age 33 $80876987$ $.05116891$ $-15.8058$ Age 34 $74966194$ $.05065301$ $-14.7999$ Age 35 $71193691$ $.0504532$ $-14.0851$	High school mother	.1129047	.01587817	7.1106855
Age 18187974073.32868695-2.67653Age 19-1.3062156.26065865-5.01121Age 20-1.1404213.16709006-6.82518Age 21-1.178634.13471368-8.74917Age 22-1.127297.10858234-10.3819Age 23-1.1557025.09381522-12.3189Age 24-1.0992844.08033906-13.6830Age 25-1.0553106.07026382-15.0192Age 26-1.0356195.06397672-16.1874Age 27-1.0290123.0601584-17.1050Age 2896816731.05641777-17.1606Age 3094536366.05371912-17.5983Age 3188170786.05225194-16.8741Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.0504532-14.0851	University father	.23189255	.02507227	9.2489644
Age 19-1.3062156.26065865-5.01121Age 20-1.1404213.16709006-6.82518Age 21-1.178634.13471368-8.74917Age 22-1.127297.10858234-10.3819Age 23-1.1557025.09381522-12.3189Age 24-1.0992844.08033906-13.6830Age 25-1.0553106.07026382-15.0192Age 26-1.0356195.06397672-16.1874Age 27-1.0290123.0601584-17.1050Age 2896816731.05641777-17.1606Age 2996585232.0548832-17.5983Age 3188170786.05225194-16.8741Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 34.74966194.05065301-14.7999Age 35.71193691.05054532-14.0851	University mother	.22533329	.03022703	7.4546947
Age 20-1.1404213.16709006-6.82518Age 21-1.178634.13471368-8.74917Age 22-1.127297.10858234-10.3819Age 23-1.1557025.09381522-12.3189Age 24-1.0992844.08033906-13.6830Age 25-1.0553106.07026382-15.0192Age 26-1.0356195.06397672-16.1874Age 27-1.0290123.0601584-17.1050Age 2896816731.05641777-17.1606Age 2996585232.0548832-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 34.74966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age $18^1$	87974073	.32868695	-2.6765308
Age 21-1.178634.13471368-8.74917Age 22-1.127297.10858234-10.3819Age 23-1.1557025.09381522-12.3189Age 24-1.0992844.08033906-13.6830Age 25-1.0553106.07026382-15.0192Age 26-1.0356195.06397672-16.1874Age 27-1.0290123.0601584-17.1050Age 2896816731.05641777-17.1606Age 2996585232.0548832-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3280876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age 19	-1.3062156	.26065865	-5.0112113
Age 22-1.127297.10858234-10.3819Age 23-1.1557025.09381522-12.3189Age 24-1.0992844.08033906-13.6830Age 25-1.0553106.07026382-15.0192Age 26-1.0356195.06397672-16.1874Age 27-1.0290123.0601584-17.1050Age 2896816731.05641777-17.1606Age 2996585232.0548832-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3280876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age 20	-1.1404213	.16709006	-6.8251897
Age 23-1.1557025.09381522-12.3189Age 24-1.0992844.08033906-13.6830Age 25-1.0553106.07026382-15.0192Age 26-1.0356195.06397672-16.1874Age 27-1.0290123.0601584-17.1050Age 2896816731.05641777-17.1606Age 2996585232.0548832-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3280876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age 21	-1.178634	.13471368	-8.7491788
Age 24-1.0992844.08033906-13.6830Age 25-1.0553106.07026382-15.0192Age 26-1.0356195.06397672-16.1874Age 27-1.0290123.0601584-17.1050Age 2896816731.05641777-17.1606Age 2996585232.0548832-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age 22	-1.127297	.10858234	-10.381955
Age 25-1.0553106.07026382-15.0192Age 26-1.0356195.06397672-16.1874Age 27-1.0290123.0601584-17.1050Age 2896816731.05641777-17.1606Age 2996585232.0548832-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age 23	-1.1557025	.09381522	-12.318924
Age 26-1.0356195.06397672-16.1874Age 27-1.0290123.0601584-17.1050Age 2896816731.05641777-17.1606Age 2996585232.0548832-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age 24	-1.0992844	.08033906	-13.683062
Age 27-1.0290123.0601584-17.1050Age 2896816731.05641777-17.1606Age 2996585232.0548832-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age 25	-1.0553106	.07026382	-15.019261
Age 2896816731.05641777-17.1606Age 2996585232.0548832-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age 26	-1.0356195	.06397672	-16.187445
Age 2996585232.0548832-17.5983Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age 27	-1.0290123	.0601584	-17.105048
Age 3094536366.05371912-17.5982Age 3188170786.05225194-16.8741Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age 28	96816731	.05641777	-17.160679
Age 3188170786.05225194-16.8741Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age 29	96585232	.0548832	-17.598323
Age 3289266276.05239001-17.0387Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age 30	94536366	.05371912	-17.598272
Age 3380876987.05116891-15.8058Age 3474966194.05065301-14.7999Age 3571193691.05054532-14.0851	Age 31	88170786	.05225194	-16.874165
Age 34      74966194       .05065301       -14.7999         Age 35      71193691       .05054532       -14.0851	Age 32	89266276	.05239001	-17.038796
Age 3571193691 .05054532 -14.0851	Age 33	80876987	.05116891	-15.805886
-	Age 34	74966194	.05065301	-14.799949
Age 3664913572 .05010278 -12.9560	Age 35	71193691	.05054532	-14.085121
	Age 36	64913572	.05010278	-12.956083

Age 37	5950899	.04984145	-11.939658
Age 38	55122948	.04950463	-11.134907
Age 39	43114076	.04790064	-9.0007312
Age 40	36263031	.04704361	-7.7083866
Age 41	28998817	.04602845	-6.3001947
Age 42	20540018	.04484019	-4.5807157
Age 43	16619236	.04431328	-3.7503959
Age 44	10083681	.04355358	-2.3152357
Age 45	01295133	.04246701	30497396
Age 46	.04794895	.04192119	1.143788
Age 47	.11649358	.04129042	2.8213221
Age 48	.1678171	.0407078	4.12248
Age 49	.22191555	.04014893	5.527309
Age 50	.2607717	.03967556	6.5726032
Age 51	.2719302	.0394738	6.8888788
Age 52	.31459705	.03900491	8.0655757
Age 53	.29628285	.03943646	7.5129174
Age 54	.30324728	.03998376	7.5842608
Age 55	.30992806	.04080823	7.5947444
Age 56	.24471886	.04309405	5.6787154
Age 57	.22637675	.04451159	5.0857934
Age 58	.15127026	.04650967	3.2524472
Log previous wage inc.	2.3558405	3.7180784	.63361778
Log previous business inc.	-2.3199333	4.5414531	51083502
Log previous capital inc.	39078764	.39739158	98338177
One child	04786599	.01817087	-2.6342157
Two children	08957406	.02022306	-4.4293023
Three children	1293405	.02792339	-4.6319768
Four or more children	20246249	.05520062	-3.6677574
Square log wage inc.	30485163	1.0490815	29058908
Square log capital inc.	.14617405	.10590098	1.3802898
Square log financial w.	.00524918	.20501356	.02560409
Square log debt	16538261	.32108827	515069
Square log housing w	4.2173968	.3627762	11.62534
Square log business inc	07200087	1.7262135	04171029
Square log previous wage inc.	-1.1688629	1.8589386	62877971
Square log previous business inc.	1.1594082	2.2707638	.51058069
Square log previous capital inc.	.20952808	.1982205	1.0570454
Region 1	25198958	.06226014	-4.0473661
Region 2	.17765505	.05703015	3.1151076

Region 3.16030741.037200903.1320341Region 4.29384768.061682234.7638948Region 5.09752066.062720291.5548503Region 6.33599069.059471985.6495633Region 7.63661201.0591302710.766263Region 8.28125792.062263474.5172219Region 9.18457957.067249052.7447165Region 10.43740846.061918437.0642689Region 11.33362136.057685275.7834756Region 1210086192.05833076-1.7291379Region 13.15100341.068254332.2123636Region 1414879022.06168756-2.4119971Region 1515841103.06117867-2.5893179Region 16.07553585.066524461.1354598Region 1701411953.0617482122866302Region 18.44699359.062298067.175081Constant-5.4712723.13318904-41.078997	Domion 2	19050741	05796606	2 1590241
Region 5.09752066.062720291.5548503Region 6.33599069.059471985.6495633Region 7.63661201.0591302710.766263Region 8.28125792.062263474.5172219Region 9.18457957.067249052.7447165Region 10.43740846.061918437.0642689Region 11.33362136.057685275.7834756Region 1210086192.05833076-1.7291379Region 13.15100341.068254332.2123636Region 1414879022.06168756-2.4119971Region 1515841103.06117867-2.5893179Region 16.07553585.066524461.1354598Region 18.44699359.062298067.175081Constant-5.4712723.13318904-41.078997	Region 3	.18050741	.05726696	3.1520341
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Region 1701411953.0617482122866302Region 18.44699359.062298067.175081Constant-5.4712723.13318904-41.078997	Region 15	15841103	.06117867	-2.5893179
Region 18         .44699359         .06229806         7.175081           Constant         -5.4712723         .13318904         -41.078997	Region 16	.07553585	.06652446	1.1354598
Constant -5.4712723 .13318904 -41.078997	Region 17	01411953	.06174821	22866302
	Region 18	.44699359	.06229806	7.175081
Matches 143,000	Constant	-5.4712723	.13318904	-41.078997
	Matches		143,000	

Parameters represent the weighted results of logit estimation, weighted by the numbers of matches each year. Weights: .228, .220, .209, .182, .161. <sup>1</sup>The variable Age 18 fully predicts failure in one year. Matches/weights: 119,931/.271, .262, .249, .217, 0

A.2 T-test

	Inheritors (mean)	Non-inheritors (mean)	t-stat		
Log wage income	11.61	11.61	.0768		
Log capital income	6.638	6.638	0011		
Log financial wealth	9.828	9.829	0089		
Log debt	8.354	8.339	3035		
Log housing wealth	5.518	5.499	3867		
Log business income	.6716	.6735	.0661		
Male	.4596	.4603	.1679		
Housh. size	1.773	1.773	.1266		
Male <sup>*</sup> Housh. size	.8164	.8177	.1667		
Wage equals zero	.0450	.0447	2125		
High school	.4801	.4823	.5252		
University	.3161	.3151	2448		
High school father	.3079	.3067	3154		
High school mother	.2987	.2993	.1184		
University father	.1027	.1023	1818		
University mother	.0598	.0593	2946		
Age	44.85	44.86	.0545		
Log previous wage inc.	13.44	13.44	.0939		
Log previous business inc.	1.478	1.481	.0594		
Log previous capital inc.	8.384	8.384	.0069		
Number of children	.7727	.7637	-1.0470		
Matches	143,000				

The weighted values of observable characteristics for inheritors and non-inheritors, as well as the t-statistic of a mean equality test, weighted by the numbers of matches each year. Weights: .228, .220, .209, .182, .161.

	All inheritances		Above mean	
			$inheritances^1$	
	Est.	SE	Est.	SE
6 years before	2819	.1518	2787	.2167
5 years before	0554	.1010	2369	.1490
4 years before	0136	.0804	0789	.1185
$3 \text{ years before}^2$	.0012	.0666	0727	.1016
2 years before	0500	.0666	0761	.1021
1 year before	1097	.0669	0331	.1026
Year of receipt	1098	.0664	0950	.1036
1 year after	1596	.0668	1689	.1042
2 years after	0914	.0655	0192	.1030
3 years after	1130	.0736	.0293	.1169
4 years after	1572	.0895	0337	.1449
5 years after	1595	.1261	1135	.2054
No of matches <sup>3</sup>	26,312		10,303	

A.3 Effect of inheritance on weekly hours of work, intensive margin

 $^{1}$  Inheritances larger than 300,000 NOK

 $^2$  Year of matching.

<sup>3</sup> Maximum number of matches, i.e. from the year of

matching until one year after receipt.

\* p < 0.05 \*\* p < 0.01