The effect of inheritance taxation on labour supply

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Preface

This thesis is a part of my master´s degree in Economics at the University of Bergen. My initial expression of gratitude is extended to my academic advisor, Anantha Divakaruni, whose invaluable guidance and counsel significantly shaped the development of this thesis.

I would also like to convey my heartfelt appreciation to my family, friends and girlfriend who, through their steadfast encouragement and motivation, played an integral part in this process. Their diligent proofreading and feedback have greatly enhanced the quality of this work.

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Abstract

This Master's thesis offers an empirical analysis of the causal impact of inheritance taxation on labour supply in Norway, utilising a regression discontinuity design. The research is underpinned by a comprehensive review of existing literature on the subject and the development of a theoretical framework grounded in economic theory. It then leverages a unique cross-sectional dataset from Microdata to analyse how changes in inheritance tax levels influence labour supply decisions, by using a regression discontinuity design. The robustness of the findings is explored through a series of placebo tests, bandwidth sensitivity analyses, and tests for manipulation around the treatment threshold. Contrary to common assumptions, the findings suggest that inheritance taxation may increase the labour supply of potential donors. However, the results' sensitivity to bandwidth selection signals the complexity of this relationship, providing a nuanced contribution to the ongoing policy debates surrounding inheritance taxation.

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1. Introduction

In recent years, inheritance taxation has emerged as a topic of significant interest in economic research and policy debates. Proponents of inheritance taxation argue that it can reduce wealth inequality and generate revenue for public services (Unneland, 2020). On the other side, opponents contend that inheritance taxation disincentivises wealth accumulation, distorts economic behaviour, and impedes intergenerational mobility (Dackling, 2020). However, despite the extensive discussions surrounding inheritance taxation, empirical evidence on its causal effects remains limited and inconclusive, both within an international context and notably within the specific context of Norway.

Thus, the research question is as follows: "Does inheritance taxation affect the labour supply of potential donors?"

This thesis aims seeks to augment the existing literature by examining the causal effects of inheritance tax on the labour supply of a person giving inheritance, using a regression discontinuity (RD) design. By exploiting the exogenous variation in inheritance tax liability around a specific threshold, the RD design allows for identifying causal effects in the presence of potential endogeneity and unobserved confounding factors (Cattaneo et al., 2019). The empirical analysis is based on a cross-sectional dataset from Microdata that includes information on individual wealth, tax liabilities, and other economic outcomes. My findings will provide insights into the short- and long-term consequences of inheritance taxation, which can inform policymakers and contribute to the ongoing debate on the optimal design of inheritance tax systems.

The remainder of this thesis is organized as follows: Chapter 1.1 provides a summary of the historical changes to inheritance taxation in Norway. Chapter 2 provides a literature review of previous studies on inheritance taxation and their findings, focusing on their underlying theories and policy implications. Chapter 3 describes the theoretical framework surrounding expected responses to taxation changes. Chapter 4 describes the data sources and sample selection process, as well as the choice of method and descriptive statistics. Chapter 5 reports the main results and their interpretations, while also examining their validity and robustness.

Chapter 6 summarizes the main findings, discussing their policy implications, and suggesting avenues for future research.

1.1 Background

Inheritance tax has been a prominent topic in Norwegian politics in recent decades. However, in 2009, the tax experienced was reduced at certain thresholds, and by 2014, it was eliminated in Solberg's cabinet's initial state budget proposal (Skatteetaten, n.d.-a). Table 1 displays the modifications made to inheritance tax regulations concerning inheritors.

Table 1 - Historical tax rate of inheritance tax in Norway

Year	Inheritance basis (in NOK)	Tax rate
2003-2008	0 - 250 000	0%
	250 000 – 550 000	8%
	550 000 -	20%
2009-2014	0 – 470 000	0%
	470 000 – 800 000	6%
	800 000 -	10%
2014-	0 -	0%

Table 1 demonstrates that from 2009, inheritances ranging between 250 000 NOK and 470 000 NOK were no longer subject to tax. It is crucial to note that the inheritance basis encompasses all gifts the beneficiary receives, both during the benefactor's lifetime and upon their death (Arveavgiftsloven, 1964). However, some exceptions apply, such as upbringing costs and investments in education. Furthermore, individuals can give gifts up to half the base amount in the national insurance scheme (G) annually without the amount being included in the inheritance basis. In 2009, this exemption was 36,440 NOK.

Until recently, there had been limited discourse on the matter following the removal of the inheritance tax. The debate has since resurfaced as LO, Norway's largest labour union, voted to reinstate the inheritance tax (Birkelund, 2022). "Fagforbundet" and several political parties, including SV, supported the reinstatement.

As previously stated, in 2009, inheritances under 470 000 NOK were no longer subject to tax. Consequently, individuals with a net worth of less than 470 000 NOK per beneficiary did not have to be concerned about their beneficiaries having to pay taxes on the inheritance received. Inheritance tax been perceived by some as a "tax upon tax" since it is levied on funds already taxed through labour and wealth taxes. Therefore, I contend that exploring the impact of inheritance tax on the labour supply of someone intending to leave an inheritance for their children later in life is a fascinating research subject. The 2009 amendment to Norwegian inheritance tax laws presents a valuable opportunity to investigate this, as individuals with a net worth per beneficiary slightly above and below 470 000 NOK were affected differently by the change.

2. Literature Review

In this chapter, I will present relevant literature for this study. The primary motive for this thesis is to look at responses to inheritance taxation, and therefore, I will present studies that show bequest motives and responses to inheritance tax. Due to the limited Norwegian literature on the topic of inheritance tax, I primarily use international studies that show bequest motives and responses to inheritance tax. In addition, I present some Norwegian studies that focus on other types of taxation, theorizing that individuals might have the same response to different types of wealth taxation.

Goupille-Lebret & Infante (2018) discovered that despite being aware of future changes in taxation, individuals in France do not proactively plan to optimise their inheritance. Interestingly, their research revealed that people tend to respond more to inheritance taxes as they approach the end of their lives. The authors attribute this behaviour to individuals´ reluctance to confront matters related to death until they reach an advanced age when they are more likely to come to terms with their mortality and thus, address issues like inheritance planning. The study also showed that inheritance taxation can play a significant role in reducing wealth inequality. They found that higher inheritance tax rates decreased wealth concentration among the top percentile, thus mitigating wealth inequality.

Niimi (2018) discovered that people in Japan exhibit a weak bequest motive, meaning a weak motive to change economic behaviour due to future inheritance donation. The research indicates that many individuals do not intend to shift new wealth towards consumption or lifetime gifts in reaction to a reduction in the basic deduction for inheritance tax. This observation is further supported by evidence that most individuals fail to utilise the gift tax exemption, where gifts up to a specified limit can be given without incurring taxes.

Joulfaian & Wilhelm (1994) discovered that in Michigan, individuals who receive an inheritance do not significantly alter their labour supply, and the corresponding increase in consumption is relatively small in relation to the size of the inheritance. Additionally, the study found that receiving an inheritance does not influence the decision to retire. However, Bø et al. (2019) used administrative data covering the entire Norwegian population to examine the labour supply of individuals who have inherited wealth. Their findings suggest that recipients of large inheritances significantly reduce their labour supply for up to six years after receiving the inheritance. The article suggests that introducing inheritance taxation will increase the labour supply from recipients of inheritance.

Løvdal & Molegoda (2020) found that the inheritance tax in Norway does not influence the decision to keep a firm in the family, while Ring (2020) investigates the Norwegian household´s response to capital taxation. The study found that wealth taxation causes households to increase their savings and that the savings are mainly due to increased labour supply. The article then goes on to suggest that the results imply that the income effect may dominate the substitution effect in Norwegian households' responses to taxation changes. Even though capital taxation and inheritance taxation represent distinct types of wealth taxation, their relationship can be considered as somewhat interconnected. Capital taxation is often suggested as an alternative to inheritance taxation, and my contention is that Norwegians might respond similarly to modifications in both types of tax, provided they perceive the taxes as sufficiently alike (Bjørnestad, 2021).

The articles in question examine various aspects of the impact of inheritance tax or similar taxes. The articles yield conflicting results, with Joulfaian & Wilhelm's 1994 study suggesting that labour supply remains unchanged upon receiving an inheritance, while Bø et al.'s 2019 research indicates a reduction in labour supply when wealth is inherited. One explanation for this is that the studies are based on different countries, and different countries and cultures might have individual responses to inheritance taxation. After all, it is more common in the United States to save for your children's college education than it is in Norway. The difference in time between the data of the two studies might also have had an impact, as Joulfaian & Wilhelm (1994) studied older data, and inheritance taxation responses might have changed over time. In addition, Bø et al. (2019) arguably had more comprehensive data, as it included the entire Norwegian population, while Joulfaian & Wilhelm (1994) had a more limited survey sample. However, it is essential to note that none of these articles specifically investigate the effect of inheritance tax on the labour supply of the person providing the inheritance, leaving room for further research.

The studies that focus on responses from the bequeathing individual find that, in general, individuals have little to no bequest motives. In addition, the bequest motives that exist seem to be larger the older the individual is. This is an interesting theory that I will examine in Chapter 5, where I present this thesis´ regression results.

3. Theoretical Framework

Economic theory provides insights into how individuals may respond to changes in taxation. These responses can be broadly classified into two categories: income effect and substitution effect (Snyder et al., 2015, p. 113). When taxes change, the individual's disposable income is affected. Conversely, if taxes increase, disposable income decreases, and vice versa. According to the income effect, individuals may feel compelled to work more to maintain their desired standard of living when disposable income decreases. On the other hand, if disposable income increases, they may work less as their desired standard of living can be achieved with fewer hours of work (Snyder et al., 2015, p. 116).

The substitution effect focuses on the relative price of leisure and work. The after-tax wage rate declines when taxes increase, making leisure cheaper than work. As a result, individuals may choose to substitute work with leisure, reducing their labour supply. On the other hand, when taxes decrease, the after-tax wage rate increases, making work more attractive compared to leisure. This may lead to an increase in labour supply (Snyder et al., 2015, p. 116).

Although the theoretical framework is relatively limited on the specific topic of inheritance taxation, it is possible to use the basis of the income and substitution effects to imagine two possible scenarios. First, let us imagine how the income effect relates to inheritance taxation. For example, suppose an individual knows their children will have to pay tax on their inheritance. In that case, some individuals might provide more labour to make sure their children inherit the same amount after the new increased taxation occurs. Moreover, vice versa, if one faces less inheritance taxation, one can work less for its children to inherit the same amount.

The other effect, which I argue is a version of the substitution effect, is commonly used by opposers of inheritance taxation. Again, if inheritance taxation increases, individuals will have to work more for their children to inherit the same amount of wealth. This line of thought argues that inheritance taxation provides an incentive to prioritise leisure over work. If an individual works to save money for their children, their after-tax income decreases if inheritance taxation increases. Conversely, if inheritance taxation increases, it becomes "cheaper" for an individual to save inheritance for their children, providing an incentive to prefer more work over leisure.

The income and substitution effect work in the opposite direction and the overall response of individuals to taxation changes might depend on the interplay between the two effects. In some cases, the income effect may dominate, increasing labour supply when taxes rise. In contrast, the substitution effect may prevail in other situations, reducing labour supply as taxes increase (Snyder et al., 2015, p. 117). Apart from these two primary effects, individuals may also engage in tax avoidance or tax evasion, seeking legal or illegal ways to minimise their tax liabilities in response to changes in taxation. Additionally, taxation changes may impact savings and consumption behaviour, entrepreneurship, investment decisions, and bequest motives.

One important thing to consider when trying to find the effect of inheritance taxation change is the motives individuals have for saving wealth for their children. OECD (2021, p. 54) propose four bequest motives, citing Cremer and Pestieau (2009). The first, accidental bequests, occurs when an individual passes away before they have had the chance to utilise their wealth fully (Abel, 1985, p. 777). In some cases, individuals might keep extra savings only to use in case of emergencies. Therefore, the reason to keep these savings has nothing to do with inheritance, and the accidental bequest does not provide any utility for the donor upon transfer. Also, the donor does not know what he bequests until death, and it is reasonable to believe that the donor feels no utility after they are dead. Thus, I suggest that individuals with this motive will not change their preferences when facing inheritance taxation changes.

The next motive proposed is a strategic motive. Bernheim, Shleifer and Summers (1985) suggest that in some cases, donors might transfer wealth to their heirs as a form of compensation for specific services. For instance, donors may motivate their heirs to act in particular ways, such as providing care for them during their later years. When considering individuals with this motive, I argue that they will not change their preferences due to inheritance taxation. If one is only focused on keeping wealth so that the inheritors will be kind before death, one does not care about how much the inheritor taxes when the time comes.

The third motive, altruistic bequests, proposes that some donors care about the utility of their children (Cremer & Pestieau, 2009, p. 10). Therefore, they save money to ensure that their inheritors and future generations live better. Individuals with this motive are prone to change their preferences in face of inheritance taxation. In theory, this would indicate that if someone cares deeply about the exact amount their children inherit, they will save more if taxation increases.

Lastly, Andreoni (1990) suggests that some individuals benefit from the act of gifting itself. This is known as a “joy of giving” or “warm glow giving” bequest and differs from altruistic bequests because the donor gets utility from the donation itself, rather than the awareness that the bequest will improve the beneficiaries' conditions as in the case of altruistic bequests. As with altruistic bequests, I argue that individuals with this motive will also change preferences as inheritance taxation changes. If one gets utility from gifting, it is logical to assume that one gets more utility the larger the gift is. Therefore, if inheritance taxation reduces the amount the gift is worth, one will be incentivised to save more to reach the original after-tax bequest amount.

As the bequest mote differs, predicting which motives will be prevalent in this study is difficult. Most likely, a combination of all these bequest motives is in play in the Norwegian society, and the effect of inheritance taxation will to some degree, be based on which motives the individuals values more. For example, if this study's results indicate no effect of inheritance taxation changes, accidental or strategic bequest motives might be assumed to be the dominating factor. Conversely, suppose the results indicate a change in labour supply due to inheritance taxation. This might indicate that altruistic or “joy of giving” bequests are the main force behind Norwegian individuals' bequest motives.

4. Data and Methodology

In this chapter, I will discuss the different methods available for researching the effect of inheritance taxation on labour supply. After settling on a regression discontinuity design, I will present the regression model and discuss some potential difficulties with using this regression method. I then present and discuss the data sources, before finally providing descriptive statistics from the acquired data.

4.1 Choice of method

This analysis intends to research if inheritance taxation has a causal effect on an individual's labour supply. If one knows that its children will no longer pay any taxes on the inheritance one bequests, is one more inclined to work, as any additional income one earns and saves for them is, in practice, "worth more"? There are several ways one could research this effect. First, one might think to compare parents with individuals without children. As inheritance taxation has changed over the years, these changes have affected individuals who have children greater than those without. The challenge with this analytical approach is that there could be unobservable disparities between the two groups. For example, one might choose not to have kids to chase a better career. The choice of having children might also correlate with socioeconomic status and education, among other factors. Consequently, the two groups will plausibly not have a common trend, and methods like the difference-in-difference approach might not be suitable for this analysis (Wing et al., 2018, p. 457).

Instead, I turn my vision towards a regression discontinuity approach. Since inheritance taxation in Norway was gradually reduced at different thresholds, individuals with wealth right above a cut-off can act as a control group, while individuals with wealth right below a cut-off act as the treatment group. With some additional assumptions, this empirical method will potentially find a causal effect if it exists.

4.2 Regression Discontinuity

Regression discontinuity (RD) design is a powerful quasi-experimental research method that allows for causal inference in observational data, first introduced by Thistlethwaite and

Campbell (1960). The RD design capitalises on the existence of a sharp or discontinuous change in the treatment assignment based on a pre-determined threshold within a continuous variable, known as the forcing or running variable. RD design aims to identify the treatment's local average treatment effect (LATE) on the outcome variable of interest by comparing the outcomes of units just above and below this threshold. In this thesis, the method will be based on regression discontinuity as presented in “A Practical Introduction to Regression Discontinuity Designs: Foundations” by Cattaneo et al. (2019).

There are three main components of a regression discontinuity design. The score, also called the running variable or assignment variable, is a continuous variable that determines the assignment of a treatment based on a threshold or cut-off point, which is the second main component. Units with scores above the threshold will either be or not be assigned to a treatment, and vice versa for the units below the threshold. This treatment is the third component of the design (Cattaneo et al., 2019). The connection between the three components is shown in Figure 1, acquired from Figure 1 in Lee and Lemieux (2010).

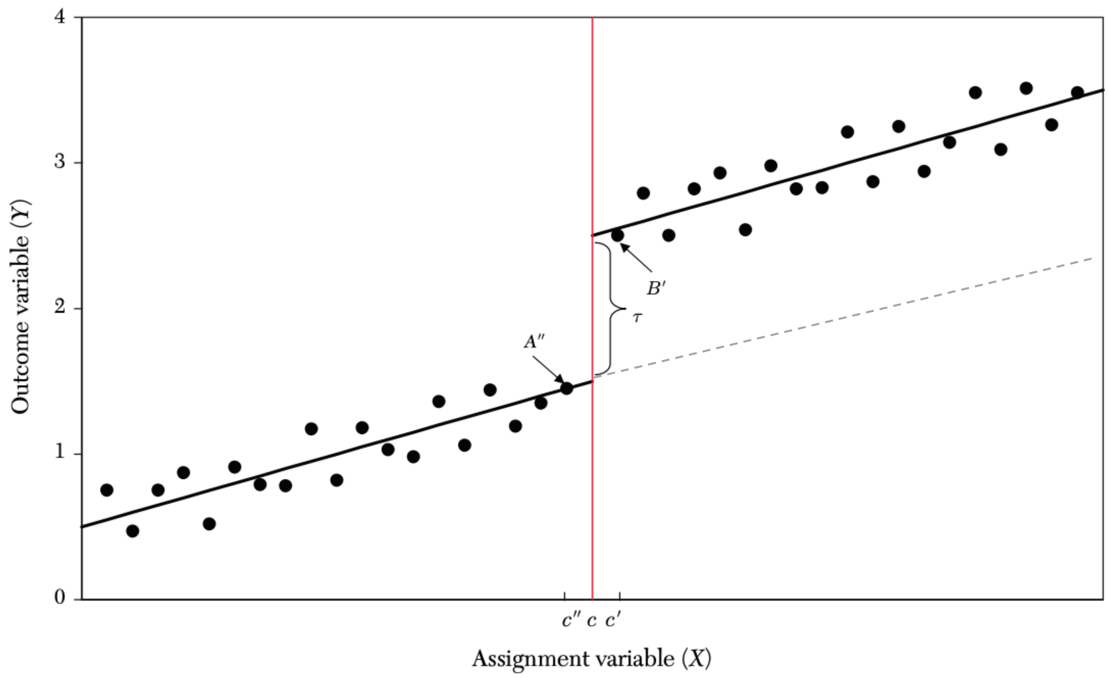


Figure 1 - Assignment and control variable in the presence of a cut-off

The variable along the x-axis is the running variable, denoted by X. The running variable correlates with the outcome variable, Y. The correlation between these two variables is continuous, except for at the cut-off, denoted by c. The central theorem in regression discontinuity proposes that individuals with a running variable value close to the cut-off should have nearly identical values on the outcome variable (Cattaneo et al., 2019). Therefore, the difference between individuals just over and under the cut-off value can be viewed as the effect of being treated, denoted by τ. If we use Figure 1 as an example, individuals with X-values of c´ and c´´ have B´ and A respectively´´ as corresponding Y-values. If there were no treatment at the cut-off, these individuals would assumably have equal Y-values. Therefore, the difference between B´ and A´´ is calculated as τ and is the estimated average treatment effect. An important assumption is that without treatment at the cut-off, the connection between the X- and Y-variable would have continued continuously along the stapled grey line (Lee & Lemieux, 2010, p. 286).

When examining Table 1, we see that the taxation on inheritance in 2009 started at 470 000 NOK, which means that the individuals right below this cut-off were not affected by inheritance tax, while the individuals above were. Using a regression discontinuity design, estimating the effect of inheritance taxation using these individuals might be possible. If the analysis only includes individuals with running variables as close to the cut-off as possible, the individuals should have similar characteristics, and thus, we avoid problems with heterogeneity. For example, an individual with a net worth of 480 000 NOK per child should be similar to someone with a net worth of 460 000 NOK per child along all other factors. Thus, the difference in labour supply between the groups should be an estimation of the effect of inheritance taxation (Cattaneo et al., 2019, p. 3).

4.2.1 Bandwidth

The next step of regression discontinuity design selecting choosing an appropriate bandwidth. The bandwidth is a crucial parameter that determines the range or window around the cut-off point of the running variable within which observations are used for the analysis (Cattaneo et al., 2019 p. 45). For example, if a bandwidth of 20 000 is chosen for this thesis, I would include all individuals with between 450 000 and 490 000 NOK net worth per child. I can balance the trade-off between bias and variance in estimating the causal treatment effect by selecting an appropriate bandwidth.

A narrow bandwidth includes only observations that are very close to the cut-off point, which helps to minimise potential bias in the estimation. This is, as discussed previously, because units near the cut-off are more likely to be similar in their observable and unobservable characteristics, except for the treatment assignment. However, a narrow bandwidth also leads to fewer observations being included in the analysis, which can result in a higher variability or noise in the estimated treatment effect. Meanwhile, a wider bandwidth includes more observations in the analysis, which might reduce the variability in the estimated treatment effect. However, it may also increase the potential for bias, as units further away from the cut-off may be less comparable in terms of their characteristics (Cattaneo et al., 2019, p. 46).

Selecting an optimal bandwidth is an important step in RD design, as it can significantly influence the validity and robustness of the causal inference. Following Chapter 4.2.2 in Cattaneo et al. (2019), it is suggested to use a data-driven method to choose an optimal bandwidth. However, due to limitations in Microdata discussed later on in this chapter, I cannot use any of the suggested methods. Specifically, The Stata and R package 'rdrobust', developed by Calonico et al. (2017), would be beneficial as an automatic way to choose bandwidth etc. and is the primary method suggested in the paper. This would be an excellent way to solidify the robustness of the analysis further, but it is sadly yet to be implemented in Microdata at the writing of this thesis. Consequently, I must manually select an appropriate bandwidth that balances bias and variance in estimating the treatment effect. In Chapter 5.2, I will present robustness checks that compare different bandwidth selections to research if I get consistent results across bandwidths.

4.2.2 Sharp RD vs Fuzzy RD

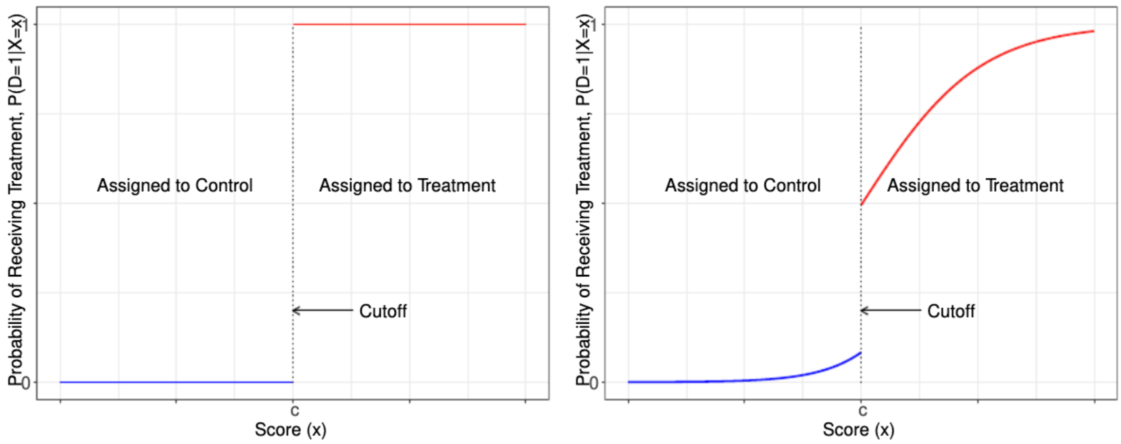
The examples I have used in this chapter are based on the assumption that everyone on one side of the cut-off gets assigned to the treatment and vice versa. This is called a sharp regression discontinuity design, where the treatment assignment is deterministic at the cut-off point (Cattaneo et al., 2019, p. 4). This can be shown as

$$D_i = \begin{cases} 1 \; if \; X_i \geq c \\ 0 \; if X_i < c \end{cases}$$

, where D is an indication of receiving treatment. D is equal to 1 if the individuals' running variable is equal to or above the cut-off, and 0 otherwise. When looking at this thesis, inheritance taxation might happen many years after the taxation change is introduced. It is plausible to imagine that some individuals might not care about the taxation even though they are in the treatment group, as they assume they will not be in the treatment group when the inheritance gift is given. Some might assume they will increase their savings, while some might assume they will spend more when retired. Therefore, sharp RD might not fit the analysis, as the cut-off might not be deterministic, even though the numerical value is.

In addition, the running variable chosen in this thesis, net worth per child, is taken from an older method of measuring net wealth (Microdata, n.d.-a). In 2010, the Norwegian government introduced a new and improved method to calculate taxable wealth, largely changing how they assess house prices (Ring, 2021, p. 6). This new method has not been implemented backwards, and therefore it, unfortunately, does not apply to the data from 2009 I am using in this thesis. This is another reason I argue against using Sharp RD for this thesis, as not all individuals have a perfectly estimated net wealth, leading to uncertainty if all individuals above the estimated cut-off are truly above the cut-off.

An alternative to sharp RD is fuzzy RD, which can be viewed as no longer deterministic at the cut-off point Although the cut-off still is deterministically chosen, compliance with it is no longer perfect (Cattaneo et al., 2023, p. 53). Some units above the cut-off might not receive the treatment, while others below the cut-off might receive it. This non-compliance with the treatment assignment introduces a degree of fuzziness in the discontinuity, making estimating the causal treatment effect more complex. The difference between the two regression discontinuity methods is shown in Figure 2 as depicted in Figure 3.1 in Cattaneo et al. (2023).



(a) Sharp RD (b) Fuzzy RD

Figure 2 - Difference between Sharp RD and Fuzzy RD

There are two primary strategies to consider when adopting a fuzzy regression discontinuity approach (Cattaneo et al., 2023, p. 57). The first approach centre on the effect of treatment assignment, commonly called the "intention-to-treat" (ITT) method. The ITT method treats the fuzzy RD design as a sharp RD design by comparing the outcomes of units just above and below the cut-off based on treatment assignment rather than treatment receipt. The second approach emphasises the effect of receiving the treatment, which necessitates a more complex regression analysis. As Cattaneo, et al. (2023, p. 61) suggest, *"A policy maker who is interested in assessing whether the program affects labour supply decisions will be interested primarily in the effect of program eligibility on household income, not on the effect of the cash transfer itself."* Although this thesis examines a slightly different subject matter, I contend that concentrating on the intention-to-treat when evaluating policies is the optimal choice.

4.2.3 Regression model

To summarise, the method I have chosen for this analysis is a fuzzy regression discontinuity design with a focus on the intention-to-treat effect. With a linear running variable and no control variables, the regression model for estimating the treatment effect would look like this:

$$Y_i = \alpha + \beta x_i + \tau D_i + \varepsilon_i (1)$$

Here, Y is the outcome variable, in our case, labour supply. D is the dummy variable indicating if an individual has received treatment. In this analysis, $D_i = 1$ if the individual´s net wealth per child is below 470 000 NOK. τ is the measured effect of being in the treatment group. ε_i is the error term, and x_i is the running variable; net wealth per child. However, it is often suggested to use a polynomial running variable (Cattaneo et al., 2019, p. 40). Commonly, one looks at a visual plot of the relationship between the outcome and running variable to decide on polynomial order. However, one cannot visually determine this as only a hexbin plot is available with Microdata. Therefore, I have chosen to employ a cubic polynomial of the running variable as I argue that this strikes a balance between having a linear model and having a too-high polynomial order. When also adding control variables, I present the following regression discontinuity model:

$$Y_i = \alpha + \beta_1 x_i + \beta_2 x_i^2 + \beta_3 x_i^3 + \tau D_i + \gamma Z_i + \varepsilon_i \ (2)$$

Equation 2 is the main equation used for the analysis in this thesis. If Column 3 in Table 3 is used as an example, it is possible to rewrite Equation 2 as:

$$Income_i = \alpha + \beta_1 (nwpc)_i + \beta_2 (nwpc)_i^2 + \beta_3 (nwpc)_i^3 + treatment\ effect(D_i) + \gamma Z_i + \varepsilon_i \ (3)$$

With Equation 3, one can see that the coefficient of the dummy variable D_i, indicating if treatment is received, is the measure of the effect inheritance tax has on an individual's labour supply. "nwpc" in Equation 3 stands for net worth per child, the running variable chosen for this analysis.

4.2.4 Critiques of the Regression Discontinuity Design

While the regression discontinuity design is a powerful tool for causal interference, it is not without its limitations and critics. The design is based on several assumptions, and some of these assumptions are impossible to test. For instance, I previously discussed the assumption of continuity in absence of the treatment effect, as illustrated by the stapled grey line in Figure 1. As most individuals with a running variable over the cut-off are assumed to be affected by the treatment, the grey line is only an image of what would happen if treatment would not occur (Angrist & Pischke, 2015, p. 153). If, for some reason, there is a discontinuity occurring at the cut-off point of the running variable, unrelated to the treatment, this would lead to bias in the estimations if not accounted for. While the assumption of continuity is plausible in many situations, arguably including the situation in this thesis, the assumption is inherently untestable, leaving room for potential bias if violated.

As previously discussed, the selection of an assumed optimal bandwidth is also a potential issue with the regression discontinuity design. Anonymity concerns in Microdata that I will discuss later in this chapter lead me unable to use data-driven methods to select an optimal bandwidth, increasing the chance for potential bias to affect the results. To accommodate this, I present a robustness check of bandwidth choice in Chapter 5.2 and keep potential shortcomings in mind when discussing the results from the regression discontinuity design. The objective of choosing a bandwidth is not about pinpointing an ideal bandwidth, rather, it's to demonstrate that the results produced from a specific bandwidth selection aren't merely coincidental or accidental (Angrist & Pischke, 2015, p. 162).

Another critique revolves around the local nature of regression discontinuity designs. It estimates the treatment effect at the threshold, implicitly assuming that this local effect is somewhat representative of the overall treatment effect (De la Cuesta & Imai, 2016, p. 389). The treatment effect tends to have limited external validity, as the RD effect is generally not representative of the population with scores far from the cut-off (Cattaneo et al., 2019, p. 40). The more different the bandwidth population in a RDD is from the overall population, the poorer the external validity is assumed to be. To account for this I present Table 2 later in this chapter, comparing the selected bandwidth population with the overall population of Norwegian parents across different metrics, including wage income, net wealth per child, and other characteristics. If the comparison shows significant discrepancies in the average value for these characteristics, the problem with external validity is something to keep in mind when discussing the results from the regression discontinuity design.

4.3 Different inheritance taxation changes

As shown in Table 1, we see several changes in inheritance taxation over different points in time. For instance, a received inheritance gift of 350 000 NOK in 2008 would be taxed with 8000 NOK ((350 000 – 250 000) * 0.08). The same inheritance gift would not be taxed in 2009, as the cut-off for taxation was raised above 350 000 NOK. For another example, a received inheritance gift in 2013 of 570 000 NOK would be taxed with 6000 NOK ((570 000 – 470 000) * 0.06). The same gift would not be taxed in 2014, as all inheritance taxation had been removed. This leads to an interesting choice; which of the changes in inheritance taxation should be the main focus for this study?

I argue that the lower change in 2009 is optimal for the regression discontinuity approach. All received inheritance between 250 000 and 470 000 NOK was no longer taxed. In addition, all received inheritance between 470 000 and 550 000 NOK was reduced from 8 to 6 per cent. Looking at 470 000 NOK as a cut-off, we can see that taxation on inheritance right below this point went from 8 to zero per cent, while inheritance right above went from 8 to 6 per cent. While this taxation change is not perfect, as the control group is also slightly affected by the shift, I argue that it is better than the other changes in the 2009-2014 period.

If we instead imagine an inheritance of 800 000 NOK in 2009 as the cut-off, the inheritance taxation right below is reduced from 20 to 6 per cent. Although this is a more significant change than the 470 000 NOK cut-off, it has several problems. Firstly, inheritance is still taxed after the change. This might lead some individuals to not respond to the taxation reduction, as their inheritance still gets taxed in contrast to the lower cut-off point of 470 000 NOK. In addition, the control group of this cut-off moves from 20 to 10 per cent taxation. Again, this is a much more significant reduction than the control group of the 470 000 NOK cut-off experiences, which increases the chance of over- or underestimation of the actual effect.

Another option is to choose a cut-off in 2014 instead. At the start of this year, all inheritance taxation was removed. For example, taxation on the inheritance of right above 470 000 NOK went from 6 to zero per cent, while taxation on everything below 470 000 NOK stayed at zero per cent. The problem with choosing a cut-off this year is that the control and treatment groups are different before the changes, and then become equal after. Given that I'm examining labour income in the year following the change, this type of analysis would not yield valuable insights because the two groups would essentially be identical.

In summary, the 470 000 NOK cut-off in 2009 seems like the best option to be the main focus of the analysis. There are some problems with it, such as the control group changing and different cut-off points at the same time. However, I argue that since I chose a narrow bandwidth as suggested in Chapter 4.2.2 by Cattaneo et al. (2019), the fact that there is another cut-off point at 800 000 NOK should not be of interest for the individuals with net wealth per child of approximately 470 000 NOK. Still, some individuals might be affected by the higher cut-off, and this, coupled with the fact that the control group also gets affected by taxation changes, leads to the fact that the causal effect in this analysis might be over- or underestimated. This is something to consider when looking at the results.

4.4 Microdata

For the analysis, I am using Microdata as the source for my data. Microdata is a cooperation between the Norwegian Agency for Shared Services in Education, and Research and Statistics Norway (Microdata, n.d.-b). The goal of this site is to provide extensive, unmanipulated register data to users who must belong to an approved research institution, ministry, or directorate. By working with the data through "metadata", I can get a large data sample for my analysis that includes all Norwegian residents through the relevant years. Furthermore, the site makes adding new data to the dataset very simple, and therefore I have done several extensions to my analysis without having to search or apply for additional data.

There are, however, some drawbacks to using Microdata. Due to the large amount of personal information, one can potentially harvest from the data, multiple safety and anonymity-strengthening features have been added to the site (Microdata, 2020, Appendix C). One such feature is the 98%-winsorisation of the data. This means that the upper and lower 1% of data get bunched up on their respective ends when looking at descriptive statistics. Histograms and similar visual data in my thesis might therefore look strange with unnaturally large columns on each end. In addition, winsorisation will slightly affect the mean and standard errors in descriptive statistics, as many variables are skewed with long tails to the right. Since the extreme data values are bunched up to the 99th percentile, the shown mean and standard deviation will often be lower than the actual numbers. This is, however, only a problem for the descriptive statistics, as winsorisation is not used when running regressions in Microdata (Microdata, 2020, Appendix C). Also, I have to include at least 1000 observations in my regressions, as Microdata does not allow analysing subpopulations of less than 1000 individuals.

Another difficulty with Microdata is the inability to view the dataset I am working with. Whenever I want to change a variable, for example, subtracting net worth by the number of children. I can view the new variable in other programs, such as Stata, and visually check that the change worked adequately. However, carrying out such a procedure in Microdata requires alternative methods to ensure accuracy in the steps taken. A workaround for this challenge is suggested in a user tutorial provided by Microdata. (Microdata, 2020). If I use my previous example of dividing net worth by the number of children, I first need to find the mean of the original variable, net worth. Then, I should be able to subtract the numbers by finding the mean of the number of children variable. If the number I get on my calculator is close to the mean number from the new net worth per child variable, I can be confident that the operation is done correctly. As mentioned in the previous paragraph, winsorisation leads to a problem where the shown mean is not equal to the true mean. This tells us there is little chance that the mean net worth per child I calculate is the same as the mean Microdata shows. Therefore, I can never be truly certain that every command I make in Microdata leads to the desired outcome. However, if I follow the user manual closely and get close to identical results when calculating means etc., by hand, I am confident that my commands are correct.

4.5 Description of variables

All variables used in the thesis are acquired from Microdata. I use "pensjonsgivende inntekt" for labour supply, which includes all wage income from labour, sole proprietorship etc. Net wealth is acquired from "skattepliktig nettoformue", which is taxable wealth minus debt. SSB measures this variable yearly, so to get the most accurate measure of an individual's net worth at the time of the taxation change, I choose the year of 2008. This ensures that the net worth variable is measured on December 31st 2008, the day before the taxation change occurs. The treatment variable is created as a dummy variable indicating whether an individual has less than 470 000 NOK net wealth per child.

Even though regression discontinuity designs are assumed to remove many problems with unobserved heterogeneity, adding control variables in the regression is still advised (Cattaneo et al., 2019, p. 78). I have included several control variables and some fixed effects for this regression. The first three control variables I have included are three binary variables to indicate whether an individual is married, is male and whether the individual has a higher education degree, all acquired from Microdata and modified to become dummy variables. The variables are all 1 if an individual has the aforementioned characteristics and 0 otherwise. The cut-off I have chosen for higher education is whether a person has finished a university degree of at least four years. In addition, I have added the individuals' age as a control variable. Finally, I added dummy variables for each Norwegian county to control for effects specific to each region. For example, Norwegian housing prices differ from county to county, and some counties have a more rapid rise in housing prices, causing the estimated wealth taxation to differ between counties (Ring, 2020, p.6)

4.6 Wealth per child

The inheritance tax is calculated per inheritor (Skatteetaten, n.d.-a). This means that each inheritor of the person giving the inheritance can be gifted up to the threshold without paying the inheritance tax. Since I am looking at the labour supply of the person giving the inheritance in later years, I need to modify the wealth variable to accommodate this. As mentioned, I propose that the wealth variable is the best way to quantify how much inheritance an individual thinks it will donate. Since inheritance taxation is per inheritor, I divide wealth by how many children an individual has. This will adjust the wealth variable to show how much an individual calculates that each of their children will inherit.

There are some issues with modifying the wealth variable in the aforementioned way. First, this change removes all individuals in the data without children, as it is impossible to divide by zero. Since the analysis focuses on the inheritance taxation's effects on a parent's labour supply, I would adjust the dataset to only look at individuals with children, and therefore it poses no big problem. Secondly, modifying and selecting the appropriate running variable leads to another essential assumption of the analysis; most married individuals assumes that all wealth given to their spouse as inheritance will later be given to their children. I argue that this assumption holds in most cases. If one were to look at its wealth to see how much its children will inherit, one will most likely not care that some of it go through the spouse, as its children will eventually inherit that amount when the spouse passes on. Even if this holds for most cases, some individuals have children with different partners etc., in which case not all inheritance that goes via the spouse is passed on to its children. This is another argument for using a Fuzzy RD approach to the analysis, as the cut-off only increases the likelihood of an individual being affected by the taxation, but it does not guarantee it.

4.7 Threshold taxation dynamics

One thing to keep in mind is that taxation only applies to any inheritance over the threshold. This means that if one inherits a gift of, for example, 500 000 NOK in 2009, one will only have to pay taxes on the amount above 470 000 NOK. At first glance, this seems to cause a problem for the analysis: as we are only looking at the individuals right around 470 000 NOK wealth per child, the ones above would have to pay an insignificant tax amount and thus might not care about the taxation change. However, I argue that this does not pose a significant issue for the analysis. As mentioned, the ones above the cut-off would only have to pay tax on additional inheritance. However, since they already are above the cut-off, any additional income the parent earns will be taxed. The ones with an inheritance just below the threshold would still, at the margin, be able to increase their income until they reach the cut-off threshold without affecting any inheritance taxation. Since this analysis looks at the labour supply of individuals facing inheritance taxation, any change in the labour supply at the margin will be affected by the entire taxation change, even though the total tax amount is very similar between the groups.

4.8 Descriptive statistics

Table 2 shows descriptive statistics for the full sample of Norwegian parents in 2009 and the sample restricted by the selected bandwidth of h=5000.

Table 2 - Descriptive statistics of entire population of Norwegian parents in 2009, and the selected bandwidth of h=5000 for the RDD

Mean values	Entire population	Selected bandwidth
Wage income	343	433
Net wealth per child	-59	470
No of childen	2.25	2.01
Married	.52	.71
Male	.48	.55
Age	43.2	52.6
High Education	.077	.103
No of persons	2,474,651	3667

Wage income is an individual's income in 2009, and net wealth per child is at the end of 2008. Both variables are measured in 1000 NOK. As expected, we see that the mean wage income is larger for the selected bandwidth, as these individuals have a higher mean net worth per child. The number of children is lower for the selected bandwidth. However, the percentage of male individuals, the percentage of individuals married, the average age and the percentage of individuals with a high education are all higher in the selected bandwidth. This is also in accordance with economic theory that states that individuals with a higher wealth have a higher expected value of these characteristics. The table indicates that the selected bandwidth group for the analysis is not a perfectly representative population for all Norwegian parents. This is something to keep in mind when looking at the regression results, as the inheritance taxation responses of this subpopulation might not be perfectly equal to the response of the rest of the population.

5. Results and Robustness Checks

In this chapter, I examine the primary results and undertake various robustness checks to validate the Regression Discontinuity (RD) design used in the study, following the guidelines from Cattaneo et al. (2019). Firstly, I assess the potential impact of inheritance taxation changes. I both test for the entire population of Norwegian parents, and an additional test where I have narrowed the data down to only individuals above 55 years old. I then move over to the robustness checks, where I check the validity and robustness of my analysis.

5.1 Results

5.1.1 Visual Results

The first and easiest way to assess if there are any signs of discontinuity at the cut-off is with a visual approach (Cattaneo et al., 2019, p. 20). In Figure 3, I present a hexbin plot showing the correlation between a Norwegian individual's income in 2009 and their wealth by the end of 2008. In a hexbin plot, each hex represents a certain number of individuals. The darker the hex is, the more individuals are in that specific combination of income and wealth.

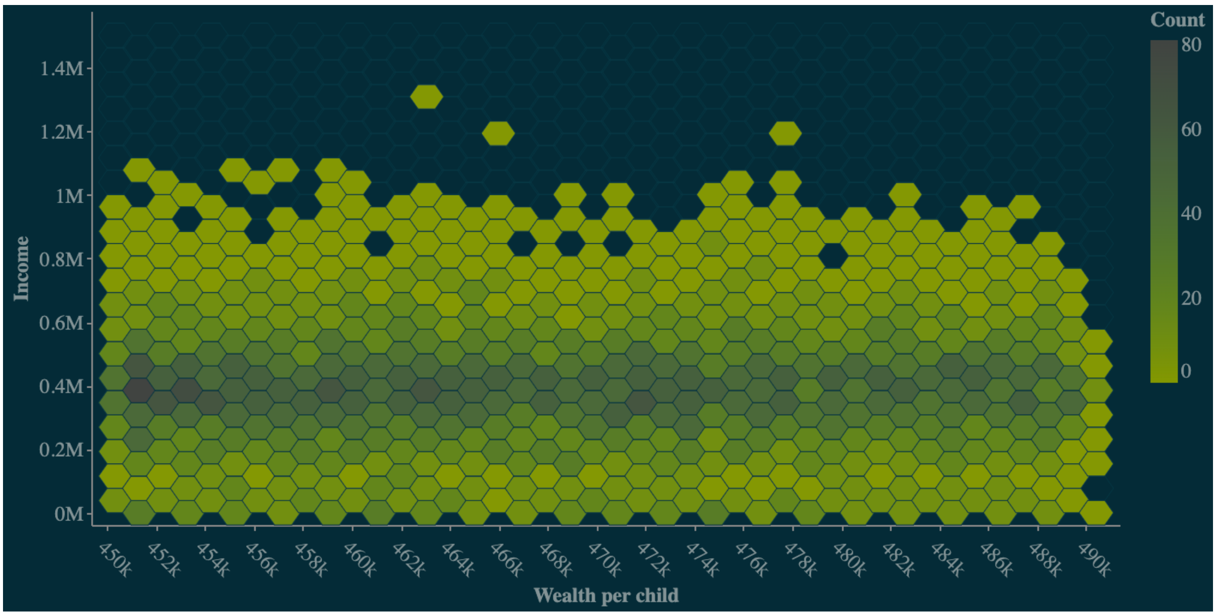


Figure 3 - Visual RD approach

Looking at Figure 3, it is not easy to see any discontinuity at the cut-off of 470 000 NOK wealth per child. This observation might imply that inheritance tax has no effect on the inheritance givers' labour supply. Nevertheless, it is essential to note that while the hexbin plot provides a functional graphical representation, formal statistical tests and regression analysis are needed to quantify the treatment effect and determine its statistical significance rigorously.

5.1.2 Regression results

When running my primary analysis presented in Table 3, I use the regression discontinuity method proposed in Chapter 4. In column 1, I have only included the treatment and the polynomial running variables. Then, in column 2, I added the previously discussed control variables, and control for region-fixed effects in column 3 by adding a dummy indicating if the individual resides in a specific county.

Table 3 - Main analysis results with RD

RD estimates with polynomial wealth			
	(1)	(2)	(3)
Treatment (Under Cutoff)	-0.18**	-0.19***	-0.19***
	(0.07)	*(0.07)*	*(0.07)*
Running Variable (LnWPC)	-1.34***	-1.28***	-1.24***
	(0.41)	*(0.39)*	*(0.39)*
Running Variable^2 (LnWPC)	-2.67***	-2.57***	-2.47***
	(0.83)	*(0.79)*	*(0.79)*
Running Variable^3 (LnWPC)	-4.01***	-3.85***	-3.71***
	(1.24)	*(1.18)*	*(1.18)*
Control variables		x	x
Region fixed effects			x
Adj. R-squared	0.003	0.087	0.096
N	3667	3667	3667

*Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 3 shows that being in the treatment group has a statistically significant negative effect on income. By looking at the stars that indicate statistical significance levels based on p-values, the effect is statistically significant with 95% certainty when no control variables or fixed effects are included. The treatment effect is negatively statistically significant with 99% certainty when these are added.

When looking at the coefficients for the treatment group, one quickly notices that these are negative. This indicates that individuals in the treatment group, i.e., those affected by the removal of inheritance taxation in 2009, actually have a lower income than those in the control group. The difference is relatively small, which might explain why no significant jump at the cut-off is found in Figure 3. Although it is small, the effect indicates that an individual who does not face inheritance taxation will provide less labour supply than if facing inheritance tax. This result presents an intriguing observation that contradicts the prevailing theory suggesting that inheritance taxation leads to a reduction in individuals' savings.

The adjusted R-squared value is relatively low, maxing at around 10% when covariates and fixed effects are added. This is reasonable and expected, as it tells us other factors play a part in deciding an individual's income other than wealth, inheritance taxation and the added control variables and fixed effects.

Table 4 - Labour supply from individuals over the age of 55

RD estimates with polynomial wealth and age > 54			
	(1)	(2)	(3)
Treatment (Under Cutoff)	-0.33***	-0.34***	-0.34***
	(0.11)	*(0.11)*	*(0.11)*
Running Variable (LnWPC)	-1.87***	-1.71***	-1.66***
	(0.68)	*(0.63)*	*(0.63)*
Running Variable^2 (LnWPC)	-3.75***	-3.42***	-3.33***
	(1.37)	*(1.26)*	*(1.26)*
Running Variable^3 (LnWPC)	-5.62***	-5.13***	-4.99***
	(2.05)	*(1.90)*	*(1.89)*
Control variables		x	x
Region fixed effects			x
Adj. R-squared	0.004	0.143	0.159
N	1869	1869	1869

*Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 4 represents the primary analysis; however, it now only includes individuals of at least 55 years old. As discussed in Chapter 2, some studies have found evidence that individuals have more significant bequest motives later in life. The regression results are presented the same way as in table 5.1, with column 1 only including treatment and a polynomial running variable, then adding control variables in column 2, before finally adding fixed effects in column 3.

When comparing the results, we see that the coefficients for the treatment variable are even lower in this table than in the previous one. This indicates that inheritance taxation has a more substantial effect on individuals over 55 years old. In addition, the results are statistically significant at a 99 per cent certainty, like the results from the primary analysis. One thing to be aware of is the reduced number of observations. As the only difference between this regression and the regression presented in Table 3 is the removal of individuals under 55 years old, it is logical that the number of reductions is substantially reduced. However, the number is still close to 2000, which I argue is still a sufficient amount of observations for this analysis.

5.2 Robustness checks

In empirical research, the robustness of findings is a crucial aspect that reinforces the validity and reliability of the study's conclusions Cattaneo, et al. (2019, p. 88). Using the guidelines from Cattaneo et al. (2019), this subchapter aims to meticulously examine the robustness of the regression discontinuity design used in this thesis, scrutinising the potential impact of various factors and the sensitivity of the results to changes in these elements.

Firstly, I explore the potential implications of contemporaneous taxation changes. The period under study witnessed income and wealth tax alterations alongside the inheritance tax reform. While these changes, at first glance, could appear to confound the results, I investigate their impact and argue for the resilience of the primary analysis. The subchapter then evaluates the robustness of the findings against placebo tests and manipulation tests, integral components of any RD design study (Cattaneo et al., 2019, p. 88). Placebo tests allows me to establish the specificity of our treatment effect, assessing whether similar effects surface at artificial thresholds. Manipulation tests, on the other hand, explore the potential for strategic positioning by individuals around the cut-off. Lastly, the subchapter delves into the sensitivity of the analysis to bandwidth choices. The bandwidth selection in an RD design is a critical decision that can influence the results. By re-running the analysis with a spectrum of bandwidths, I gauge the stability of our findings.

Through this comprehensive exploration, this subchapter seeks to reinforce the robustness of the RD design and, by extension, the findings of this thesis. The objective is to ensure that the conclusions drawn are not artefacts of specific assumptions or methodological choices but instead, robust insights into the effects of inheritance tax changes on labour supply.

5.2.1 Other taxes

A potential issue with the analysis is that other taxation changes might occur during the same period. For instance, income tax was increased slightly at the start of 2009 (Skatteetaten, n.d.-b). The tax, called “toppskatt”, taxed all income above the first threshold at 9% and all income above the second threshold at 12%, including the initial 9%. In 2009, the first threshold increased from 420 000 to 441 000 NOK, while the second increased from 682 500 to 716 600 NOK. These are increases of respectively 5% and approximately 4.5%, which are higher than inflation and wage growth in 2009 (Norges Bank, 2009) and thus affect more individuals than in previous years. Although a relatively small taxation increase, one could imagine it still affects an individual's choice of labour supply.

I argue, however, that this change should not pose a massive problem for the analysis. Firstly, income taxation should equally affect those above and below 470 000 NOK net worth per child. The change in taxation is based on income, not wealth, as the inheritance tax is "based" on. One of the benefits of regression discontinuity, as discussed previously, is that individuals right above and below the cut-off should be practically equal across all other factors. Thus, their income preferences should also be approximately equal, and they will be affected the same way by the income taxation changes.

Further, Table 3 provides evidence that those above 470 000 NOK net worth per child increase their labour supply. These individuals might therefore be affected by the income tax changes if they had been right below the threshold if the inheritance taxation changes did not occur. Therefore, assuming that higher income tax leads to less incentive to supply labour, this will lead to underestimating the actual effect of inheritance taxation. However, the chance of an individual being right on the cut-off of changes in inheritance taxation and income taxation is very slim, so this scenario will not significantly impact the results of my analysis.

Another change in taxation in 2009 was increased wealth taxation, called "formueskatt". (Skatteetaten, n.d.-c). In 2008, individuals were taxed 0.9% on all net worth above 350 000 kr. They were then taxed an additional 0.2% on all net worth above 540 000 kr. The wealth taxation was then changed to a single tax level of 470 000 NOK, where all net worth over this threshold was taxed at 1.1%. This means that individuals with a net worth of 470 000 NOK had to pay 1.1% on all extra income, which increased from the 0.9% they had to pay in 2008. In addition, individuals below 470 000 NOK could earn extra income without paying wealth tax; again, individuals above 470 000 NOK would have to pay 1.1% wealth tax on all additional income.

The wealth taxation changes in 2009 leads to some complications with my analysis. As the cut-off point is precisely the same as the inheritance taxation cut-off point, it is not certain which of the two taxation changes individuals respond to and is causing the statistically significant effect we found in Table 3. However, I can still check if the change in inheritance taxation has any effect on labour supply. The wealth taxation is set up so that if an individual is married, the married couple adds their net worth together and divides it in two to form a single collective net worth on which they base their taxation levels (Skatteetaten, n.d.-b). This means that if an individual in my dataset is married, the individual is arguably no longer affected by the change in wealth taxation as there is only a minimal chance that their partner also has a net worth of the same amount. Therefore, a married individual will most likely not be right around the wealth taxation cut-off of 470 000 NOK, even though his individual net worth is at that amount. In addition, the inheritance tax is based on net worth per child, so individuals with two or more children will not have a base net worth of 470 000 NOK. Recall that when I prepared the data, I divided net worth by the number of children, so the net worth variable I am working with is per child.

Table 5 - Labour supply excluding single parents with one child

RD estimates with polynomial wealth		
	Exludes single parents w/ one child	
	(1)	(2)
Treatment (Under Cutoff)	-0.19***	-0.22***
	(0.07)	*(0.07)*
Running Variable (LnWPC)	-1.24***	-1.43***
	(0.39)	*(0.39)*
Running Variable^2 (LnWPC)	-2.47***	-2.85***
	(0.79)	*(0.84)*
Running Variable^3 (LnWPC)	-3.71***	-4.28***
	(1.18)	*(1.26)*
Control variables	x	x
Region fixed effects	x	x
Adj. R-squared	0.096	0.118
N	3667	3255

*Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

In summary, the wealth taxation changes only affect the individuals in my data that are not married and, at the same time, only have one child. I argue that if I remove these individuals from the analysis, I can re-run the analysis to see if there are still statistically significant results of the inheritance taxation changes. The results of this new analysis are presented in

Table 5. I find that even when removing the individuals affected by wealth taxation changes, the cut-off variable stays statistically significant and negative. By removing some individuals, I remove 412 observations, but the n is still at a healthy amount of over 3000 individuals. Therefore, I argue that the results still show that might be an effect on labour supply due to changes in inheritance tax, even though it is harder to tell exactly how large or small this effect is due to changes in wealth taxation at the same period.

5.2.2 Placebo test

The placebo tests are an essential step in checking the validity and robustness of a regression discontinuity design (Cattaneo et al., 2019, p. 100). The primary purpose of these tests is to examine whether any "treatment effects" appear at artificial thresholds away from the actual cut-off. Finding no statistically significant results in these placebo tests would provide evidence that the estimated treatment effect is specific to the actual threshold.

I redo the primary regression from Table 3 to run the placebo tests with one crucial difference. Instead of using the actual cut-off, I have selected some artificial thresholds above and below the actual threshold. Another difference from Table 3 is that I have changed the parentheses rows to represent p-values instead of standard error, as it is easier to induce statistical significance from the p-values. The results are presented in Table 6.

Table 6 - Placebo tests

RD estimates with polynomial wealth									
	Cut-off = 470 000			Cut-off = 467 000			Cut-off = 473 000		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (Under Cutoff)	-0.18**	-0.19***	-0.19***	0.09	0.10*	0.08	-0.04	-0.03	-0.02
	(0.01)	*(0.006)*	*(0.006)*	*(0.15)*	*(0.10)*	*(0.14)*	*(0.45)*	*(0.61)*	*(0.71)*
Running Variable (LnWPC)	-1.34***	-1.28***	-1.24***	-0.15	-0.02	-0.02	-0.57**	-0.42*	-0.36
	(0.001)	*(0.001)*	*(0.001)*	*(0.61)*	*(0.94)*	*(0.95)*	*(0.02)*	*(0.08)*	*(0.13)*
Running Variable^2 (LnWPC)	-2.67***	-2.57***	-2.47***	-0.30	-0.04	-0.04	-1.13**	-0.84*	-0.72
	(0.001)	*(0.001)*	*(0.001)*	*(0.61)*	*(0.94)*	*(0.95)*	*(0.02)*	*(0.08)*	*(0.13)*
Running Variable^3 (LnWPC)	-4.01***	-3.85***	-3.71***	-0.44	-0.06	-0.05	-1.70**	-1.26*	-1.08
	(0.001)	*(0.001)*	*(0.001)*	*(0.61)*	*(0.94)*	*(0.95)*	*(0.02)*	*(0.08)*	*(0.13)*
Control variables		x	x		x	x		x	x
Region fixed effects			x			x			x
Adj. R-squared	0.003	0.087	0.096	0.001	0.087	0.094	0.0009	0.086	0.094
N	3667	3667	3667	3667	3667	3667	3667	3667	3667

*P-values in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

The first three columns represent the main analysis findings with the actual cut-off. The p-values on the treatment variable range from 0.01 to 0.006, indicating a statistical significance of at least 95 per cent certainty. Moving on, columns 4 to 9 represent the same regression as in columns 1 to 3. Using an artificial cut-off of 467 000 NOK and then 473 000 NOK, the regression is run the same way with first only a treatment and running variable, then with control variables and finally with region-fixed effects. The point estimates for the treatment variable are not only smaller along the placebo cut-offs, but none of the estimates are statistically significant at a 95 per cent certainty, with p-values ranging from 0.10 to 0.71.

In conclusion, the results of the placebo tests provide evidence that the estimated treatment effect of inheritance taxation on labour supply is specific to the actual threshold and not any artificially selected cut-offs. Furthermore, the lack of statistically significant results on the placebo tests suggests that the analysis´s RD design is valid and increases the chance that the results can be interpreted as causal effects. This strengthens the credibility of the analysis and its policy implications.

5.2.3 Manipulation

The manipulation test is another vital robustness check in the regression discontinuity design (Cattaneo et al., 2019, p. 97). It checks whether individuals have manipulated their running variables to be placed on one side of the cut-off. As it is beneficial for individuals to be placed on one side of the cut-off, it would pose a problem for the analysis if one could precisely place itself on the "best" side. When looking at this thesis, a problem would occur if individuals could control their net worth per child to stay below 470 000 NOK. Theoretically, it is possible to micromanage wealth to ensure one stays on one side of the cut-off. However, I argue that this is hard to do in practice, due to the random nature of income and expenses. The standard way to check whether this problem occur is to run a manipulation test. This is a simple test where a histogram of the running variable is produced. Suppose the density of the running variable is significantly more prominent on one side of the cut-off in the histogram. In that case, this suggests that individuals could precisely modify their running variable to benefit from the treatment. This scenario is presented in Figure 18(b) in Cattaneo et al. (2019).

To do the manipulation test for the regression discontinuity design in this thesis, I have produced a histogram of the density of the running variable, net worth per child, around the cut-off. The histogram is presented in Figure 4.

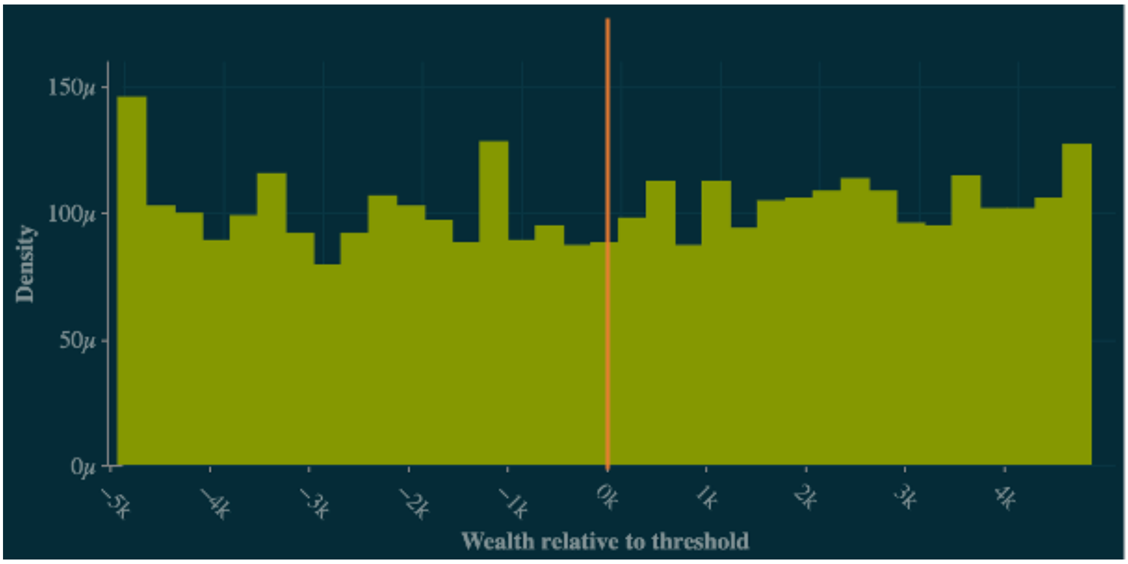


Figure 4 - Manipulation test

From the observed data, we find no indication of bunching below the threshold, consistent with the absence of manipulation in treatment assignment, as theorised. Theoretically, it is possible to micromanage wealth to ensure one stays on one side of the cut-off. Another way to do a manipulation test, suggested by Cattaneo, et al. (2019, p. 97), is that "researchers should explore the assumption more formally using a statistical test, often called a density test". As discussed previously, Microdata has its limitations due to anonymity. None of the suggested statistical tests are doable, and the automatic test with rdrobust is also unavailable (Calonico, et al., 2017). However, I argue that the visual manipulation test, Figure 4, provides significant evidence that there is no manipulation in the density of the running variable.

5.2.4 Sensitivity to Bandwidth Choice

In Chapter 4, I discussed the importance of a proper bandwidth choice. In the primary regression, I selected a bandwidth of h=5000, which provided a good number of observations of 3667 and, at the same time, were narrow enough to account for heterogeneity effects. In this chapter, I will present regression results with different bandwidth choices to see how sensitive the analysis is to this choice. Implementing this is straightforward, as I re-run the analysis from Column 3 in Table 3 with different bandwidth lengths instead of the previously chosen h=5000. The results are presented in Table 7.

Table 7 - Bandwidth sensitivity analysis

Bandwidth sensitivity						
	h = 5000	h = 1500	h = 4500	h = 5500	h = 8500	h= 10000
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (Under Cutoff)	-0.19***	-0.22*	-0.17**	-0.14**	-0.05	-0.05
	(0.006)	*(0.09)*	*(0.02)*	*(0.04)*	*(0.31)*	*(0.32)*
Running Variable (LnWPC)	-1.24***	-3.58	-1.11**	-0.76**	-0.12	-0.08
	(0.001)	*(0.14)*	*(0.01)*	*(0.02)*	*(0.50)*	*(0.56)*
Running Variable^2 (LnWPC)	-2.47***	-7.16	-2.22**	-1.52**	-0.23	-0.16
	(0.001)	*(0.14)*	*(0.01)*	*(0.02)*	*(0.50)*	*(0.56)*
Running Variable^3 (LnWPC)	-3.71***	-10.74	-3.33**	-2.29**	-0.35	-0.23
	(0.001)	*(0.14)*	*(0.01)*	*(0.02)*	*(0.50)*	*(0.56*
Control variables	x	x	x	x	x	x
Region fixed effects	x	x	x	x	x	x
Adj. R-squared	0.096	0.089	0.093	0.102	0.105	0.107
N	3667	1081	3300	4017	6219	7329

P-values in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

Column 1 is replicated from Column 3 in Table 3 as a reference point with the primary analysis bandwidth choice. Columns 2 to 5 represent the same regression, ran with different bandwidth choices. Column 2 represents the lowest bandwidth choice I am allowed to use in Microdata. I remind the reader that I cannot analyse populations with an n lower than 1000, as discussed in Chapter 4. The following columns present bandwidths increasing in size until column 5 with a bandwidth of 10 000, twice as large as the one in the primary analysis. We see that the coefficients for the treatment variable in columns 2 to 4 stay relatively consistent with the findings in column 1. The p-value is slightly lower; however, it is still large enough to suggest a statistical significance of at least 90 per cent certainty. The regressions represented in Tables 6 and 7 are shown with control variable coefficients and standard errors in Appendix B.1.

However, potential concerns with the bandwidth choice arise in columns 5 and 6. When increasing the bandwidth, the effect of removing inheritance taxation is no longer statistically significant. In addition, the coefficient is changed from -0.19 in column 1 to -0.05, a relatively large change. Following Cattaneo et al. (2019, p. 97), it is expected that the results change when increasing the bandwidth, as “bandwidths much larger than the MSE-optimal bandwidth will lead to estimated RD effects that have too much bias”. However, I suspect that the difference in p-value when increasing bandwidth is more extensive than expected, and the regression discontinuity design I use in the thesis might have problems with unobserved heterogeneity. I suggest that it would be beneficial to redo the analysis with automatic bandwidth selection when rdrobust is available in Microdata or by acquiring a dataset similar to the one in this thesis that one can use in Stata, R or similar programs (Calonico et al., 2017).

6. Discussion

6.1 Results considering the theoretical framework

As discussed in Chapter 3, the effect of inheritance taxation on labour supply might have depended on the income and substitution effects. The results in Column 3 in Table 3 indicate that decreased inheritance taxation negatively affects labour supply. From this, one can imagine that if inheritance taxation was to increase, individuals planning to bequeath their wealth would provide more labour supply. This indicates that the income effect is the dominant one, as this is the one suggesting that individuals will provide more labour in response to increased taxation.

It is plausible to imagine that the income effect takes place, as it follows the bequest motive of both “warm glow giving” proposed by Andreoni (1990) and the altruistic bequest proposed by Cremer & Pestieau (2009). To recap, “warm glow giving” or “joy of giving” suggest that some individuals motivate their decisions on some desire to gain prestige, respect etc. Altruistic bequests suggest that some individuals care deeply about their inheritors' wealth and utility and gain utility from bequeathing to improve their inheritors' lives. Following this theory, one can imagine that some parents prioritise their children’s future wealth over their labour supply preferences, resulting in increased labour supply when inheritance taxation increases.

The result from this thesis also fits with the findings of Ring (2020), who found that Norwegian individuals increase their savings due to increased wealth taxation. Furthermore, the findings suggest that individuals save more to have the same amount after tax as they would have without the tax. As with the regression results from this thesis, this indicates that the income effect plays a more significant role than the substitution effect in the decision-making of Norwegian individuals.

The regression results also provided evidence that bequest motives are larger later in life. The coefficients for treatment, i.e., not being impacted by inheritance taxation, were larger when looking at the subpopulation of individuals at least 55 years old. These findings align with Goupille-Lebret & Infante (2018), who found that people respond more to inheritance taxation later in life. I argue that this is a logical assumption, as it is plausible to believe that one does not consider what happens after death until closer to the end of life.

However, the study of this specific subpopulation is more prone to undiscovered heterogeneity. As the data sample size is closer to half of the primary regression from Table 3, there is a chance that individual randomness creating noise in the regression is increased. One way to deal with this is to increase the bandwidth of the sample size. However, as discussed in previous chapters, increasing bandwidth introduces more bias in the regression and might not be beneficial. To find the optimal bandwidth, I again suggest rerunning the analysis when rdrobust is available in Microdata or by acquiring data that can be used in Stata, R etc., where rdrobust is available (Calonico et al., 2017).

6.2 Interpreting the coefficient.

When interpreting the regression results in Table 3, it might be tempting to quantify the coefficient of the treatment variable to find an exact numeral value to find the exact effect of inheritance taxation. For example, if one does that using column 3 in Table 3 in this thesis, one could interpret the taxation change from 8 to zero per cent as leading to a decrease in labour income of 19%. However, there are multiple reasons to avoid trying to find the exact size of the effect. One thing to remember is that the individuals in the control group of this analysis also got affected by inheritance taxation changes. While not as heavy as the ones in the treatment group who went from 8 to zero per cent, individuals in the control group had the inheritance taxation reduced from 8 to 6 per cent. Since we are comparing these two groups, it is impossible to say that the change from 8 to zero per cent inheritance taxation is a 19 per cent decrease in labour supply. This is because such an assumption is based on the control group staying at 8 per cent, which it is not. Furthermore, when the control group preferences change, its trend is no longer equal to the treatment group trend if not affected by taxation, so it is no longer a perfect representation of the assumed trend.

In addition, it is shown in Table 2 that the specific subpopulation used for the analysis in this thesis, individuals with a net worth per child of around 470 000 NOK, differs from the overall population of Norwegian parents. As discussed in Chapter 4, this leads to some doubts about external validity, as it is not possible to be sure that the overall population will respond the same way as the subpopulation used in the analysis. This is an additional reason to be careful about interpreting the coefficient.

Another aspect to consider is the transformation of income into its logarithmic form. For continuous variables, the typical approach involves multiplying the variable's coefficient by 100 and interpreting the result as the percentage effect on Y due to a slight change in the continuous variable (Halvorsen & Palmquist, 1980). However, it is essential to recognise that dummy variables are not continuous. Halvorsen and Palmquist (1980) propose an alternative formula for estimating the impact of a dummy variable. Suppose the dummy variable's coefficient is negative. In that case, as in column 3 of Table 3, the relative effect using their formula is expected to be smaller than the effect calculated as though it were a continuous variable.

With these factors taken into account, I would advise against attempting to quantify the impact of inheritance taxation. It is unclear to what extent the control group's labour supply preferences were altered, due to the change in inheritance taxation from 8% to 6%, and the conventional interpretation of the coefficient is not advisable when dummy variables are present. Nevertheless, the treatment group's shift from 8% to 0% is more substantial than the control group's change from 8% to 6%. Given that the adjustment in interpreting dummy variable coefficients is relatively minor, viewing the treatment coefficient as indicative of a negative effect should still be possible. In other words, inheritance taxation may result in increased labour supply from parents intending to bequeath an inheritance.

6.3 No negative effect of labour

While arguing how to interpret the results from the regression, it is important to remember the original motivation for this analysis. In Chapter 1, I mentioned that opponents of inheritance taxation argue that this form of taxation might reduce the incentive for donors to provide labour supply, as the money they save for their inheritors are worth less. While the regression findings suggest that inheritance taxation could potentially boost donors' labour supply, the data does not indicate that individuals in Norway would decrease their labour supply in response to inheritance taxation. If the results were to show a decrease in labour supply due to inheritance taxation, the coefficient for the treatment variable would have to be positive. I remind the reader that being in the treatment group means no inheritance taxation. Note that across all regression results in this thesis, not even one has a positive coefficient for the treatment variable. As such, I conclude that there is no evidence of an increase in labour supply when individuals no longer had to worry about inheritance taxation in 2009. This is a vital takeaway from this thesis as it does not corroborate the abovementioned argument about individuals decreasing labour supply when facing inheritance taxation.

7. Conclusion

This thesis provides a nuanced understanding of the effects of inheritance taxation on labour supply using robust empirical methods. The findings do not support the commonly held argument that increased inheritance taxation decreases the labour supply of potential donors. Contrarily, regression results indicate that inheritance taxation might increase donors' labour supply. While the study's findings add to the body of knowledge on inheritance taxation and labour supply, the analysis' sensitivity to bandwidth selection highlights the complexity of these economic relationships. Future research could further refine these results by exploring heterogeneous treatment effects and alternative functional forms to capture more accurately the relationship between inheritance taxation and labour supply.

Ultimately, this thesis underscores the importance of empirical evidence in informing the policy debate on inheritance taxation, encouraging a move beyond simplified assumptions and towards a more nuanced understanding of economic behaviour.

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Appendix

A.1 Microdata script

Script used for analysis in www.microdata.no

```
//Connects to database
require no.ssb.fdb:19 as fdb1
//Creates dataset
create-dataset dbfar09
import fdb1/BEFOLKNING_FAR_FNR as fnr_far
import fdb1/BEFOLKNING_DOEDS_DATO as doedsdato
generate doedsaar = int(doedsdato/10000)
drop if doedsaar < 2009
generate antallfar09 = 1
collapse(sum) antallfar09, by(fnr_far)
//Creates dataset
create-dataset dbmor09
import fdb1/BEFOLKNING_MOR_FNR as fnr_mor
import fdb1/BEFOLKNING_DOEDS_DATO as doedsdato
generate doedsaar = int(doedsdato/10000)
drop if doedsaar < 2009
generate antallmor09 = 1
collapse(sum) antallmor09, by(fnr_mor)
//Creates dataset
create-dataset dbmain
//Importing variables to the dataset
import fdb1/BEFOLKNING_FOEDSELS_AAR_MND as faarmnd
import fdb1/BEFOLKNING_KJOENN as kjønn
import fdb1/BEFOLKNING_STATUSKODE 2009-01-01 as regstatus
keep if regstatus == '1'
import fdb1/SIVSTANDFDT_SIVSTAND 2009-01-01 as sivstand
import fdb1/SKATT_NETTOFORMUE 2008-12-31 as formue
```

```
import fdb1/BEFOLKNING_DOEDS_DATO as doedsdato
import fdb1/INNTEKT_PGIVINNT 2009-12-31 as inntekt09
import fdb1/BOSATTEFDT_BOSTED 2009-01-01 as kommune
import fdb1/NUDB_BU 2009-01-01 as utdanning
//Replacing missing values with 0
replace inntekt09 = 0 if sysmiss(inntekt09)
//Generating variable for age in 2009
generate alder = 2009 - int(faarmnd/100)
//Dropping non-adults
keep if alder >=18 & alder <67
//Generating variable for year of death
generate doedsaar = int(doedsdato/10000)
//Dropping individuals who died before 2009
drop if doedsaar < 2009
//Merging children data onto father dataset
use dbfar09
merge antallfar09 into dbmain on PERSONID_1
//Merging children data onto father dataset
use dbmor09
merge antallmor09 into dbmain on PERSONID_1
//Switching dataset
use dbmain
//Replacing missing values with 0
replace antallfar09 = 0 if sysmiss(antallfar09)
replace antallmor09 = 0 if sysmiss(antallmor09)
//Generating antallvariable
generate antall09 = antallfar09
//Replacing missing values with 0
replace antall09 = 0 if sysmiss(antall09)
replace inntekt09 = 0 if sysmiss(inntekt09)
replace formue = 0 if sysmiss(formue)
//Adding children to women in dataset
replace antall09 = antallmor09 if antall09==0
//Creating net worth per child
```

```
generate formueprbarn = formue
drop if antall09 == 0
replace formueprbarn = formue/antall09
//Generating cutoff variable
generate u470 = 0
replace u470 = 1 if formueprbarn < 470000
generate u467 = 0
replace u467 = 1 if formueprbarn < 467000
generate u473 = 0
replace u473 = 1 if formueprbarn < 473000
//Generating high education variable
generate utdanningsnivå = substr(utdanning,1,1)
drop if utdanningsnivå == 9
destring utdanningsnivå
generate utdanninghøy = 0
replace utdanninghøy = 1 if utdanningsnivå >=7
//Converting variables from text- to numberformat
generate mann = 0
replace mann = 1 if kjønn == "1"
generate gift = 0
replace gift = 1 if sivstand == "2"
//Table 2, column 1
summarize inntekt09 formueprbarn antall09 gift mann alder utdanninghøy
//Generate wealth around cutoff
generate formue470 = formueprbarn - 470000
drop if formue470 > 20000
drop if formue470 < -20000
//Figure 3
hexbin inntekt09 formueprbarn
//I change these to 1500, 4500, 5500, 8500 and 10000 to do the bandwidth sensitivity
analysis, and represent the results from table 3, column 3 with each of these bandwidths
individually
drop if formue470 > 5000
drop if formue470 < -5000
```

```
generate formue470s2 = formue470^2
generate formue470s3 = formue470^3
//Generating county variable
generate fylke = substr(kommune, 1, 2)
//Generating ln of income and wealth
drop if inntekt09 <= 0
generate lnint09 = ln(inntekt09)
generate formue2  = formueprbarn^2
generate formue3 = formueprbarn^3
generate lnformue = ln(formueprbarn)
generate lnformue2 = ln(formue2)
generate lnformue3 = ln(formue3)
//Table 2, column 2
summarize inntekt09 formueprbarn antall09 gift mann alder utdanninghøy
//Regressions
//Table 3, column 1
regress lnint09 u470 lnformue lnformue2 lnformue3, robust
//Table 3, column 2
regress lnint09 u470 lnformue lnformue2 lnformue3 gift mann alder utdanninghøy, robust
//Table 3, column 3
regress lnint09 u470 lnformue lnformue2 lnformue3 gift mann alder utdanninghøy i.fylke,
robust
//Table 6, column 4
regress lnint09 u467 lnformue lnformue2 lnformue3, robust
//Table 6, column 5
regress lnint09 u467 lnformue lnformue2 lnformue3 gift mann alder utdanninghøy, robust
//Table 6, column 6
regress lnint09 u467 lnformue lnformue2 lnformue3 gift mann alder utdanninghøy i.fylke,
robust
//Table 6, column 7
regress lnint09 u473 lnformue lnformue2 lnformue3, robust
//Table 6, column 8
regress lnint09 u473 lnformue lnformue2 lnformue3 gift mann alder utdanninghøy, robust
//Table 6, column 9
```

```
regress lnint09 u473 lnformue lnformue2 lnformue3 gift mann alder utdanninghøy i.fylke, robust
//Table 4, column 1
regress lnint09 u470 lnformue lnformue2 lnformue3 if alder >=55, robust
//Table 4, column 2
regress lnint09 u470 lnformue lnformue2 lnformue3 gift mann alder utdanninghøy if alder >=55, robust
//Table 4, column 3
regress lnint09 u470 lnformue lnformue2 lnformue3 gift mann alder utdanninghøy i.fylke if alder >=55, robust
//Figure 4
histogram formue470
//Dropping single parents with one child for table 5
drop if gift == 0 & antall09 == 1
//Table 5, column 2
regress lnint09 u470 lnformue lnformue2 lnformue3 gift mann alder utdanninghøy i.fylke, robust
```

B. Detailed regression results

In Appendix B, I detail the table of regression results from the primary analysis, complete with the coefficients for the covariates and region fixed effects. Table 3 includes the main regression results referenced in our discussion, and here, I've also incorporated the coefficients for all the dummy variables denoting whether an individual lives in a particular county. However, these dummy variables, which merely control for county-fixed effects, are not addressed in this thesis, so I opt not to display them in the other regression result tables within Appendix B. I assert that including these would only congest the Appendix and reduce the readability of the tables without contributing any relevant information to the thesis. Furthermore, I have adjusted the parentheses to display standard errors in contrast to some counterparts in Chapter 5.2, which show p-values in parentheses for ease of comprehension during robustness check discussions.

B.1 Main analysis

Table B. 1 - Recreated from Table 3 with coefficients for dummy variables and counties. Østfold is used as the reference county.

RD estimates with polynomial wealth			
	(1)	(2)	(3)
Treatment (Under Cutoff)	-0.18**	-0.19***	-0.19***
	(0.072)	*(0.069)*	*(0.069)*
Running Variable (LnWPC)	-1.34***	-1.28***	-1.24***
	(0.413)	*(0.393)*	*(0.393)*
Running Variable^2 (LnWPC)	-2.67***	-2.57***	-2.47***
	(0.827)	*(0.787)*	*(0.786)*
Running Variable^3 (LnWPC)	-4.01***	-3.85***	-3.71***
	(1.240)	*(1.180)*	*(1.178)*
Married		0.10***	0.09***
		(0.035)	*(0.035)*
Male		0.34***	0.35***
		(0.033)	*(0.033)*
Age		-0.02***	-0.02***
		(0.002)	*(0.002)*
High Education		0.55***	0.53***
		(0.048)	*(0.049)*
Vest-Agder			-0.19*
			(0.112)
Rogaland			0.11
			(0.088)
Hordaland			-0.03
			(0.089)
Sogn of Fjordane			-0.09
			(0.114)
Møre og Romsdal			0.05
			(0.089)
Sør-Trøndelag			-0.01
			(0.097)
Nord-Trøndelag			0.10
			(0.114)
Nordland			-0.05
			(0.108)
Troms			-0.21
			(0.142)
Akershus			0.14*
			(0.079)
Finnmark			*-0.02*
			(0.158)
Oslo			0.04
			(0.091)
Hedmark			-0.13
			(0.099)
Oppland			-0.23**
			(0.104)
Buskerud			0.07
			(0.098)
Vestfold			0.09
			(0.092)
Telemark			-0.27**
			(0.14)
Aust-Agder			-0.12*
			(0.139)
Adj. R-squared	0.003	0.088	0.096
N	3667	3667	3667

*Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table B.1 shows that the added covariates, indicating gender, married status, age, and high education have a statistically significant effect. In addition, few of the dummy variables indicating whether an individual resides in a specific country have any statistically significant effect. The few exceptions are some rural counties that are negatively statistically significant with 95% certainty.

B.2 Other Tables

Table B. 2 - Placebo tests with standard errors and coefficients for covariates.

Placebo test									
	Cut-off = 470 000			Cut-off = 467 000			Cut-off = 473 000		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (Under Cutoff)	-0.18**	-0.19***	-0.19***	0.09	0.10*	0.08	-0.04	-0.03	-0.02
	(0.072)	*(0.069)*	*(0.069)*	*(0.061)*	*(0.058)*	*(0.057)*	*(0.058)*	*(0.056)*	*(0.055)*
Running Variable (LnWPC)	-1.34***	-1.28***	-1.24***	-0.15	-0.02	-0.02	-0.57**	-0.42*	-0.36
	(0.413)	*(0.393)*	*(0.392)*	*(0.292)*	*(0.278)*	*(0.278)*	*(0.251)*	*(0.240)*	*(0.240)*
Running Variable^2 (LnWPC)	-2.67***	-2.57***	-2.47***	-0.30	-0.04	-0.04	-1.13**	-0.84*	-0.72
	(0.827)	*(0.787)*	*(0.786)*	*(0.584)*	*(0.557)*	*(0.555)*	*(0.502)*	*(0.479)*	*(0.480)*
Running Variable^3 (LnWPC)	-4.01***	-3.85***	-3.71***	-0.44	-0.06	-0.05	-1.70**	-1.26*	-1.08
	(1.240)	*(1.180)*	*(1.179)*	*(0.875)*	*(0.835)*	*(0.833)*	*(0.753)*	*(0.712)*	*(0.719)*
Married		0.10***	0.09***		0.10***	0.09**		0.10***	0.09**
		(0.035)	*(0.035)*		*(0.035)*	*(0.035)*		*(0.035)*	*(0.035)*
Male		0.34***	0.35***		0.34***	0.35***		0.34***	0.34***
		(0.033)	*(0.032)*		*(0.033)*	*(0.033)*		*(0.033)*	*(0.033)*
Age		-0.02***	-0.02***		-0.02***	-0.02***		-0.02***	-0.02***
		(0.002)	*(0.002)*		*(0.002)*	*(0.002)*		*(0.002)*	*(0.002)*
High Education		0.55***	0.53***		0.55***	0.53***		0.55***	0.53***
		(0.048)	*(0.049)*		*(0.048)*	*(0.049)*		*(0.048)*	*(0.049)*
Dummy variables for counties			x			x			x
Adj. R-squared	0.003	0.087	0.096	0.001	0.087	0.094	0.0009	0.086	0.094
N	3667	3667	3667	3667	3667	3667	3667	3667	3667

*Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table B.2 and Table B.3 are recreations of respectively Table 6 and Table 7 with standard errors instead of p-values in parentheses. In addition, I have included covariates coefficients, and the results show that these covariates are very similar to the covariates in Table B.1, providing further evidence that the regression is consistent when changing parts of it.

Table B. 3 – Bandwidth sensitivity analysis with standard errors and coefficients for covariates.

Bandwidth sensitivity						
	h = 5000	h = 1500	h = 4500	h = 5500	h = 8500	h= 10000
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (Under Cutoff)	-0.19***	-0.22*	-0.17**	-0.14**	-0.05	-0.05
	(0.069)	*(0.132)*	*(0.072)*	*(0.065)*	*(0.051)*	*(0.047)*
Running Variable (LnWPC)	-1.24***	-3.58	-1.11**	-0.76**	-0.12	-0.08
	(0.392)	*(2.418)*	*(0.454)*	*(0.340)*	*(0.172)*	*(0.136)*
Running Variable^2 (LnWPC	-2.47***	-7.16	-2.22**	-1.52**	-0.23	-0.16
	(0.786)	*(4.836)*	*(0.907)*	*(0.681)*	*(0.344)*	*(0.271)*
Running Variable^3 (LnWPC	-3.71***	-10.74	-3.33**	-2.29**	-0.35	-0.23
	(1.179)	*(7.254)*	*(1.361)*	*(1.021)*	*(0.516)*	*(0.407)*
Married	0.09***	0.15**	0.09**	0.13***	0.11***	0.12***
	(0.035)	*(0.072)*	*(0.037)*	*(0.035)*	*(0.027)*	*(0.025)*
Male	0.35***	0.29***	0.33***	0.35***	0.36***	0.37***
	(0.032)	*(0.062)*	*(0.034)*	*(0.031)*	*(0.025)*	*(0.023)*
Age	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.002)	*(0.004)*	*(0.002)*	*(0.002)*	*(0.002)*	*(0.001)*
High Education	0.53***	0.46***	0.51***	0.53***	0.57***	0.59***
	(0.049)	*(0.101)*	*(0.053)*	*(0.046)*	*(0.033)*	*(0.030)*
Dummy variables for countie	x	x	x	x	x	x
Adj. R-squared	0.096	0.089	0.093	0.102	0.105	0.107
N	3667	1081	3300	4017	6219	7329

*Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*