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Non-Technical Summary

The vast majority of parents will experience grandparenthood well before their official retirement age. The birth of a grandchild may not only have consequences on parental labor supply, but also on the labor supply of grandparents. On the one side, grandparents might provide informal grandchild care and reduce their labor supply. On the other side, grandparents might extend their labor supply and support their offspring and grandchild financially. Surprisingly, up to now not much is known about which of these two channels is more important and how a grandchild affects the labor supply decision.

In this paper, we study the impact of grandchildren on the labor supply decision of grandmothers. Using high quality data for Austria, we estimate the effect on both the extensive margin, that is the arrival of a first grandchild, and the impact of additional grandchildren, the intensive margin, on the labor supply of women. Our estimation approach allows for possible intergenerational transmission of values and gives interesting insights how grandchildren can affect the labor supply decision.

Our results show that the arrival of a first grandchild decreases the labor supply of women by 8%. We investigate potential differences in the time pattern of the departure and find that grandmothers are more likely to leave the labor market at the end of the parental leave period and when the grandchild reaches schooling age. These results indicate that grandparents time their exit in such a way to provide child care when it is most valuable. On the intensive margin we find that further grandchildren decrease expected duration in the labor market for grandparents even further. We do not find evidence that formal child care is a substitute for informal child care.

Our results give a clear indication that demographic trends in fertility and labor market exit for retirement are strongly related. Grandmothers play a substituting role for their daughters' labor supply allowing the daughter a quicker return to the labor market after childbirth. Formal child care for children under the age of three – in its current fairly restrictive form – does not resolve this tension.

Grandmothers' Labor Supply*

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Abstract

The labor supply effects of becoming a grandmother are not well established in the empirical literature. We estimate the effect of becoming a grandmother on the labor supply decision of older workers. Under the assumption that grandmothers cannot predict the *exact* date of conception of their grandchild, we identify the effect of the first grandchild on employment (extensive margin). Our *Timing-of-Events* approach shows that having a first grandchild increases the probability of leaving prematurely the labor market. This effect is stronger when informal child care is more valuable to the mother. To estimate the effect of an additional grandchild (intensive margin), we assume that the incidence of a twin birth among the second generation is not correlated with unobserved determinants of the grandmother's labor supply (first generation). Our respective 2SLS estimation shows a significant effect of further grandchildren. Our results highlight the important influence of the extended family on the decisions of older workers and point to mediating effects of different institutional settings.

JEL Classification: J13, J14, J22
Keywords: grandchildren, female labor supply, timing of events, instrumental variables.

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1 Introduction

Over the last decades, a substantial amount of evidence on the relationship between fertility and maternal labor supply has accumulated.[1] In contrast, labor economists have paid comparably little attention to potential adjustments of other family members' allocation of time. A small number of papers examines paternal labor supply responses. These conclude that males' labor market behavior is quite inelastic to fertility.[2] The role of grandparents is the least studied aspect (Zanella, 2017). This gap in the literature is surprising given that the vast majority of parents will also experience grandparenthood, and given that this occurs typically before retirement. Women's median age at the birth of the first grandchild is about 47 years in Eastern Europe, 49 years in the USA, and 51 years in Western Europe (Leopold and Skopek, 2015). Given an average effective age of retirement of 63 years, the average overlap between grandparenthood and labor market activity is at least 12 years.[3] This timing suggests that the birth of a child may not only have consequences for parental labor supply, but also for the labor supply of their grandparents.

Grandparents play an important role in providing both money and time to their offspring and their grandchildren (Glaser et al., 2013; Ellis and Simmons, 2014)[4]. Survey data also reveal a strong association between grandparenthood and preferences for early retirement (Hochman and Lewin-Epstein, 2013). Thus, from a theoretically point of view, older workers' labor market response to becoming grandparents is ambiguous. On the one hand, they could substitute their own labor supply with time caring for their grandchild. This substitution effect would lead to a reduction in labor supply or even to an exit from the labor market. On the other hand, grandparents could focus on supporting their (grand)child by providing financial resources. In this case, grandparents may expand their labor supply to increase their financial resources. Which type of transfer is dominating is unclear, and not straightforward to quantify. The response may also differ between the arrival of a first versus further grandchildren, and across different types of institutional settings and families.

In this paper, we use high-quality administrative data covering the universe of Austrian births and workers to examine the effect of grandparenthood on female labor supply. These data allow us to link precise information on all relevant variables across three gen-

[1] See, for instance, Rosenzweig and Wolpin (1980*a*); Killingsworth and Heckman (1986); Bronars and Grogger (1994); Angrist and Evans (1998); Lundborg et al. (forthcoming); Herr (2015).

[2] See, for instance Lundberg and Rose (2000, 2002); Wulff Pabilonia and Ward-Batts (2007); Loughran and Zissimopoulos (2009); Vere (2011).

[3] For men grandparenthood occurs around three years later (Leopold and Skopek, 2015), and their average effective age of retirement is about 65 years.

[4] Hank and Buber (2009) use the first wave of the Survey on Health, Ageing and Retirement in Europe (SHARE) for European countries and find that 58 percent of grandmothers provide some care for a grandchild and 32 percent look almost weekly or more often after these children. Results show that these care-activities peak when the kids are between ages 1 and 5.

erations. Methodologically, we use two different identification strategies, to estimate the effect of a first grandchild (*extensive margin*) and an additional grandchild (*intensive margin*), respectively. To estimate the extensive margin we make use of the *Timing-of-Events* (ToE) approach by Abbring and van den Berg (2003). This allows us to non-parametrically estimate the treatment effect and account for unobserved heterogeneity under the identifying assumption that grandmothers cannot predict the *exact* date of conception of their first grandchild. To study the intensive margin, we exploit within an instrumental variable (IV) approach the effect of twin births in the second generation on the total number of grandchildren (third generation). Here, we have to assume that the incidence of a twin birth among the second generation is not correlated with unobserved determinants of the grandmother's labor supply (first generation). As our data set is subject to censoring — some (potential) grandmothers might not leave the labor market until the end of our observation period — we also apply a *Censored Two-stage Least Square* (c2SLS) approach suggested by Frandsen (2015).

We find a significant negative effect of grandparenthood on the labor supply at the extensive margin. The birth of the first grandchild increases the likelihood to leave the labor market by about 8 percent. Investigating potential differences in the time pattern of the treatment effect, we find evidence that grandmothers are more likely to exit the labor market at the end of their daughters' parental leave, and when the grandchild reaches schooling age. These results indicate that grandparents time their exit in such a way to provide child care when it is most valuable. On the intensive margin we find that further grandchildren decrease expected duration in the labor market for grandparents even further, and the quantitative effect is remarkably similar.

Along both margins, we find interesting patterns of treatment effect heterogeneity. As expected, reductions in labor supply happen predominantly in cases, when geographic distance between grandmother and grandchild is low. Somewhat unexpectedly, we find that grandmothers tend to reduce their labor supply more in communities with formal child-care institutions, as compared to communities without. This reaction could be due to fairly restrictive time-schedules of such facilities, which make formal care and grandparental informal care complements.

Existing research taking into account the extended family, mostly concentrates on the effect of grandparent-provided child care on parental labor supply. These papers consistently find that grandparent-provided child care increases labor force participation of parents (Cardia and Ng, 2003; Dimova and Wolff, 2011; Posadas and Vidal-Fernandez, 2013; Arpino et al., 2014; Bratti et al., 2016; Aassve, Arpino and Goisis, 2012). In contrast, very little is known about the effect of grandparenthood on grandparents' own labor supply. To the best of our knowledge there are only a handful of studies, which examine the effect of grandparenthood on labor supply. Most of these do not provide a design-based approach and point to interpret their results as associations rather than argue for causality. For instance, Ho (2015) examines the correlation between an additional grandchild and grandparents' labor supply in data from the *Health and Retirement Study* (HRS). She finds significant correlation at the extensive and the intensive margins, however, with varying signs depending on the grandparental characteristics, such as family status (i. e., single versus married). This suggests that some grandparents support their children as a caregiver and others help out with financial resources. Using the same data source, Lumsdaine and Vermeer (2015) show that the arrival of a new grandchild is associated with an increase in the retirement hazard of about eight percent. A similar qualitative conclusion is provided by Van Bavel and De Winter (2013), who use retrospective information on retirement and grandparenthood included in the cross-sectional data from the *European Social Survey*.[5] Thus, while these papers carefully document associations between grandparenthood and labor supply adjustment, it is hard to rationalize differences in findings across these studies, and one should not draw any causal conclusions. The birth of a grandchild may simply be correlated with unobserved determinants of grandparental labor supply. Or, the association may also reflect a reversed causal relationship, where the grandparental labor supply reduction, and the resulting availability of grandparental child care, triggers the fertility decision.[6]

The closest related work to our research are the analyses by Rupert and Zanella (2016) and Wang and Marcotte (2007). Both studies use in their empirical analyses US survey data from the *Panel Study of Income Dynamics* (PSID), but come to different conclusions. Wang and Marcotte (2007) use state-level variation in teenage birth ratios as well as welfare state generosity to instrument for grandmothers' caring decisions. They find an increase in labor supply in response to the birth of a grandchild. Rupert and Zanella (2016), on the other hand, exploit the sex of children of the grandparents as a exogenous source of variation in the timing of grandparenthood. Parents of girls become grandparents about two years earlier than parents of boys. The identifying assumption of their IV approach is that the sex of the child affects the labor supply of the grandparents only through the channel of grandparenthood, and that it is not correlated with any unobserved determinants of their labor supply. Considering results by Dahl and Moretti (2008), this is an assumption which may be questioned. They find that becoming a grandparent causes a reduction of the labor supply of grandmothers, but not for grandfathers. The effect is driven by women who are already working less than full-time at the time they become grandmothers. The effect at the extensive margin is more important than the corresponding intensive margin.

[5] See also Reinkowski (2013) using data from SHARE.

[6] There are several observational studies highlighting this effect (see, e. g., Lehrer and Kawasaki, 1985; Kaptijn et al., 2010; Aassve, Meroni and Pronzato, 2012), and more recently, there is also evidence for it from design-based papers, which exploit pension reforms to obtain exogenous variation in the timing of grandparental retirement in Italy (Aparicio-Fenoll and Vidal-Fernandez, 2014; Battistin et al., 2014) and Germany (Eibich and Siedler, 2016). See also Zamarro (2011) using data from SHARE.

Our contribution uses administrative data for all potential grandmothers in Austria, examines at the extensive as well as the intensive margin, using different methodologies. We also explore heterogeneity across different institutional settings, which make the occurrence of such intergenerational sharing more or less probable, e.g. the availability of formal early child-care institutions. Our study and our findings thus bring together political discussions about child-care reform and declining fertility with imminent demographic problems in pay-as-you-go pension systems. Showing a clear connection between changes in fertility, child-care costs and costs of the pension system is a new way to bring these demographic issues together: while there may be interactions between reforms in child care and — current — pension inflows, there may also be other interactions, e.g. changes in the pension system might have effects on fertility and, thus, long-term effects on the sustainability of the pension system.

The remainder of the paper is organized as follows. Section 2 outlines the relevant institutional background and describes our data sources. Section 3 discusses the ToE approach, which we use to identify the causal effect of the first grandchild (the extensive margin) and reports our main estimation results. Section 4 focuses on the effect of further grandchildren (the intensive margin) estimated with an IV approach. Section 5 explores heterogenous treatment effects along both margins. Section 6 offers concluding remarks.

2 Institutional background and data sources

To understand labor supply adjustments by grandmothers, several aspects of the institutional background have to be considered. In this section, we briefly describe Austrian regulations regarding maternity leave and parental leave, the availability of formal child-care, and pension regulations.

Maternity and parental leave After child birth, employed parents are eligible for substantial leave. Right after birth statutory maternity leave actually prohibits maternal employment for 2 months. Following this period, either parent can go on paid and job-protected parental leave until the child's second birthday.[7] While the exact regulations have varied over time, parental leave has always been almost universal. Thus, during the first two years after child birth, grandparental child-caring is certainly appreciated by the parents, however, it is not as crucial given the generous leave regulations.

Formal child care The Austrian system of formal child care distinguishes between facilities for children below the age of three (nurseries, *Kinderkrippe/Krabbelstube*) and for those aged three to six (kindergarden, *Kindergarten*). While the vast majority of

[7]There have been several changes in the maximum duration of cash benefits during our observation period. A reform in 1996 reduced the duration of cash benefits to 18 months, while a second reform in 2000 extended this duration to 30 months. Additional 6 months of cash benefits are granted if the partner goes on parental leave. Both reforms, however, kept the job protection duration of two years unchanged.

communities have a kindergarden facility since the 1980s, the local availability of nurseries has been traditionally much lower. In 1990, only around 33 percent of the population had access to a nursery. Existing nurseries often had only short opening hours (until noon) and long holidays. Thus, the typical parent, who wanted to return to the labor market after parental leave has elapsed on the child's second birthday, faced problems finding a suitable formal-care arrangement. In such a situation, the extended family is the main source of child care, with a potentially important role for grandparents. This is confirmed by recent survey data. Baierl and Kaindl (2011) provide statistics about the actual situation of the demand and supply of child-care facilities in Austria. Evidence from survey data shows that grandparents indeed play an important role in providing child care in Austria, especially working-age grandparents, and that grandparental support is not only an Austrian phenomena (Kaindl and Wernhardt, 2012).

Pension regulation Compared to other OECD countries, Austria shows a relatively low retirement age and high replacement rates. Replacement rates reach up to 80 percent of the assessment basis (best 15 years of earnings), given the worker had 45 contribution years. While normal retirement age is 65 for men and 60 for women, there is also the possibility for early retirement before that age. If the worker had 35 contribution years, men could claim retirement as early as age 60, women at age 55. These possibilities for early retirement were gradually phased out in two reforms 2000 and 2003, leading to a full abolishment for men born in the cohort 1952 and women born in 1957 (Staubli and Zweimüller, 2013). Due to these possibilities of early retirement, but also due to early retirement options like disability pensions and early retirement as a result of long-time unemployment, the average pension entry age was 59.2 for men and 57.3 for women in 2011 (Stiglbauer, 2013).

Data sources Our empirical analysis is based on administrative data sources from Austria. The Austrian Social Security Database (ASSD) are administrative records to verify pension claims and are structured as a matched employer-employee data set. They cover all Austrian workers. The Austrian Child Allowance database documents the child allowance take-up of Austrian families and includes a comprehensive link of parents and their children. This enables us to identify the three generations (grandmother, parent, possible grandchild) and provides us with birth-date related information.

We select all potential grandmothers born between 1950 and 1960 with at least one offspring, whose first-born is of cohort 1978 or later. For each grandmother we can observe on a daily base if she is employed, unemployed, out of labor force or retired. We also have detailed information on work experience and tenure to assess grandmothers' labor market attachment. Information on earnings is provided per year and per employer.[8] The details on sample selection are summarized in Section 3.2 for the extensive margin

[8] The limitations of the data are top-coded wages and no information on working hours (Zweimüller et al., 2009).

analysis, and, correspondingly in Section 4.3 for the intensive margin analysis.

3 The effect of the first grandchild

3.1 Estimation strategy

The estimation of the treatment effect of the first grandchild on grandmaternal labor supply involves two main challenges. *First*, there is a potential correlation between unobserved heterogeneity determining the duration until labor force exit and the duration until becoming a grandmother. The probability of becoming a grandmother depends on her daughter's/son's attitude towards children and career. It is likely that career-oriented mothers also have more career-oriented children. If this holds true, then labor market outcomes of the potential grandmother and the probability of becoming a grandmother are negatively correlated. *Second*, even after accounting for unobserved heterogeneity, the arrival of a grandchild is not completely random, since grandmothers might hold certain beliefs when to expect a grandchild.

We overcome these challenges by applying the *Timing-of-Events* approach (ToE) proposed by Abbring and van den Berg (2003) and model the duration until having a grandchild and the duration until labor market exit jointly by means of a bivariate mixed proportional hazard model. This approach allows us to identify the effect of a first grandchild without any exclusion restrictions. The most important underlying assumption of our model is the 'no anticipation' of the treatment.[9]

The *No-anticipation assumption* requires that the treatment occurs with a certain amount of randomness. It is not necessary that the treatment is randomly assigned or strictly exogenous. Potential grandmothers are allowed to hold certain beliefs over the possibility of getting treated, as long as the exact treatment date is sufficiently random. In our particular setting, the no-anticipation assumption translates into the supposition that grandmothers do not know the *exact* date of conception; and before the actual date, the conception does not have any effect on the exit hazard. Notably, this framework does not rule out potential bargaining over how the grandmother will adjust her labor supply once the grandchild is conceived.

To assess the no-anticipation assumption in our context it is necessary to understand the process of fecundability. The probability of conception strongly varies over the woman's monthly cycle and the correct timing of sexual intercourse (Wilcox et al., 1995; Colombo and Masarotto, 2000). But even with regular unprotected intercourse, conception occurs with a certain amount of randomness and is far from deterministic, although the probability of a pregnancy increases over time (Slama et al., 2012). It seems sug-

[9] Other imposed conditions are of a more technical nature, such as finite moments of the heterogeneity terms, see Abbring and van den Berg (2003).

gestive that unobserved heterogeneity, which might be attributable to biological factors, plays an important role (Heckman and Walker, 1990; Larsen and Vaupel, 1993). Besides the evidence from the literature that conception is sufficiently random to the coming parents, we think it is reasonable to assume that daughters/sons do not communicate their reproduction intentions on a daily basis with the potential grandmothers. Even if the information is available to the parents-to-be, the grandmother will be in the dark for some time. But even if there is anticipation, Richardson and van den Berg (2013) argue that the effect on the treatment is likely to be negligible if the time between anticipation and the actual treatment is short compared to the total duration. This argument can also be applied in our setting.

While we assume that there is no anticipation on the side of the grandmother it might be possible that the daughter/son strategically decides to conceive a child; in particular at a point in time, when the grandmother's retirement date approaches. In the Section 3.4, we restrain our analysis to cases, where early retirement of the grandmother is not possible – and find no evidence for this hypothesis.

We assume that the transition rate from work to exit has a mixed proportional hazard specification. For a realized spell with duration T until exit and duration D until the first grandchild, the exit rate is defined as

$$\theta_E(T|x, \nu_E, D) = \lambda_E(T) exp(x'\beta_E + \delta(T - D)\mathbb{1}(T > D) + \nu_E) \tag{1}$$

In our exit hazard, the baseline hazard $\lambda_E(T)$ represents individual duration dependence, the vector x consists of individual observable characteristics and ν_E captures the unobserved heterogeneity on the exit rate. The parameter of interests is $\delta(T-D)$, which captures the shift in the exit hazard due to the arrival of a grandchild. This shift represents our treatment effect. In a more general setting, we allow $\delta(T - D)$ to depend on the elapsed time since treatment by modelling it as a piecewise constant function $\delta(T - D) = \sum_k \delta_k \mathbb{1}_k(T - D)$, where k denote the time intervals, and other covariates.[10]

Likewise the rate at which a grandchild is conceived (treatment hazard) is modeled as

$$\theta_G(D|x, \nu_G) = \lambda_G(D) exp(x'\beta_G + \nu_G) \tag{2}$$

Here ν_G captures the unobserved heterogeneity on the treatment hazard and the vector x consists of possible confounding factors.

In our model we allow for selectivity and do not impose any restrictions on the correlation of the unobserved components ν_E and ν_G. This means that selection into treatment

[10] The identification of this model with treatment effect heterogeneity was proven in Richardson and van den Berg (2013).

can affect the exit transition and vice versa. We assume the distribution of heterogeneity to be unknown and approximate it by means of a discrete distribution (Heckman and Singer, 1984). The associated probability for having M possible mass points is parametrized in the following fashion which helps us to avoid the use of constrained maximization

$$p_m = P(\nu_E = \nu_E^m, \nu_G = \nu_G^m) = \frac{exp(\alpha_m)}{\sum_{m=1}^{M} exp(\alpha_m)}$$

In our empirical specification we model the individual duration dependence in a flexible way via a piecewise constant function $\lambda_j(T) = exp(\sum_{k=1}^{9} \lambda_{j,k} \mathbb{1}_k(T))$ for $j = E, G$. In total we distinguish nine time intervals: 0-6 years, 6-8 years, 8-10 years, 10-12 years, 12-14 years, 14-16 years, 16-18 years, 18-20 years and $20 - \infty$. For estimation purpose we normalize $\lambda_{E,0} = \lambda_{G,0} = 0$ and $\alpha_1 = 0$.

We estimate the parameters by means of maximum likelihood. Having N individuals in total and observing the time until exit T_i (or censoring) and the time until the conception of the grandchild $D_{i,}$ (or censoring) for each of these individuals, the log-likelihood function for our empirical model is defined as

$$\begin{aligned} L = \sum_{i=1}^{N} \log \Bigg\{ \sum_{m=1}^{M} p_m \; \theta_E(T_i|x_i, \nu_E^m, D_i)^{\Delta_{i,E}} exp\left(-\int_0^{T_i} \theta_E(T_i|x_i, \nu_E^m, D_i)\right) \\ \theta_G(D_i|x_i, \nu_G^m)^{\Delta_{i,G}} exp\left(-\int_0^{D_i} \theta_G(D_i|x_i, \nu_G^m)\right) \Bigg\} \end{aligned} \quad (3)$$

$\Delta_{i,E}$ and $\Delta_{i,G}$ are the censoring dummies, which take a value of 1 if we observe an exit from the labor market or an arrival of a grandchild, respectively.

When optimizing the likelihood over all unknown parameters we follow the suggestions in Gaure et al. (2007*a*) and Gaure et al. (2007*b*). We start with a single mass point and increase the number of support points until we do not find any improvement in the log likelihood. We then choose our model according to the Akaike Information Criterion. Gaure et al. (2007*a*) present Monte Carlo evidence that parameters obtained in this fashion are consistent and normally distributed.

3.2 Estimation sample and descriptive statistics

We are interested in the effect of the arrival of a first grandchild on the labor supply decision of grandmothers. To allow for sufficient time between treatment and a possible exit we restrict our sample to (potential) grandmothers who had at least one 15 year old offspring between 1993 and 1998. In our analysis we use the 15th birthday of the offspring with the *first* child as the reference date, from which on we measure all durations. We take the 15th birthday of the oldest offspring as the reference date if there are no grandchildren born until the end of 2013. In more than 70 percent of the cases the offspring with the first child is also the oldest one.[11] As we are interested in the effect on the labor supply decision of individuals who are attached to the labor market, we require that (potential) grandmothers have accumulated at least 2.5 years of labor market experience within 3 years before the reference date.

For each of those potential grandmothers, we observe their labor market outcomes as well as the conception date and the birth date of the first grandchild until the end of December 2013. We define a labor market exit as the first observed state of non-employment with a minimum duration of 12 months after our reference date. Notice that this also includes unemployment spells as well as transitions between jobs. If the grandmother has not exited the labor market until the 31th of December 2013 she is regarded as censored. Likewise we calculate the elapsed days between the 15th birthday of the offspring and the conception date of the first grandchild as time until treatment. If the conception occurred after the first labor market exit or after the 31th of December 2013 the individual is regarded as non-treated.

Table 1 provides an overview over the sample and separate statistics by treatment status. In total, our sample consists of $72,935$ women. For each woman, we observe $T = min\{T_{exit}, C_{exit}\}$ where T_{exit} is the time until exit from the labor market and C_{exit} is the censoring point. Around 56 percent of the women in our sample leave the labor market before the 31th of December 2013. Furthermore, we observe $D = min\{D_{grandchild}, T\}$, where $D_{grandchild}$ is the conception date of the grandchild. A grandmother is considered as treated if $T > D$. About 48 percent of the women in our sample become grandmothers before the first long-term exit from the labor market. Those who become grandmothers tend to be younger, have slightly lower education, and tend to have more children. Moreover, our summary statistics show that those who finally become grandmothers tend to have slightly less experience in the labor market.

Figure 1 depicts estimated yearly transition rates into leaving the labor force (solid line) and treatment state (dashed line), respectively. One can see that the exit hazard does not change much during the first 12 years of our observation period when the majority of our individuals are well below the age of 50. In contrast, we observe a steady increase of the treatment hazard over the same time period which reaches a maximum around 14 years after the start of our observation period. At this time the relevant offspring is around 29 years of age. The treatment hazard falls strongly after this date while the exit hazard increases sharply. The descriptive estimates presented here supports our 'no anticipation' assumption and we provide further evidence about that in our analysis in Section 3.4.

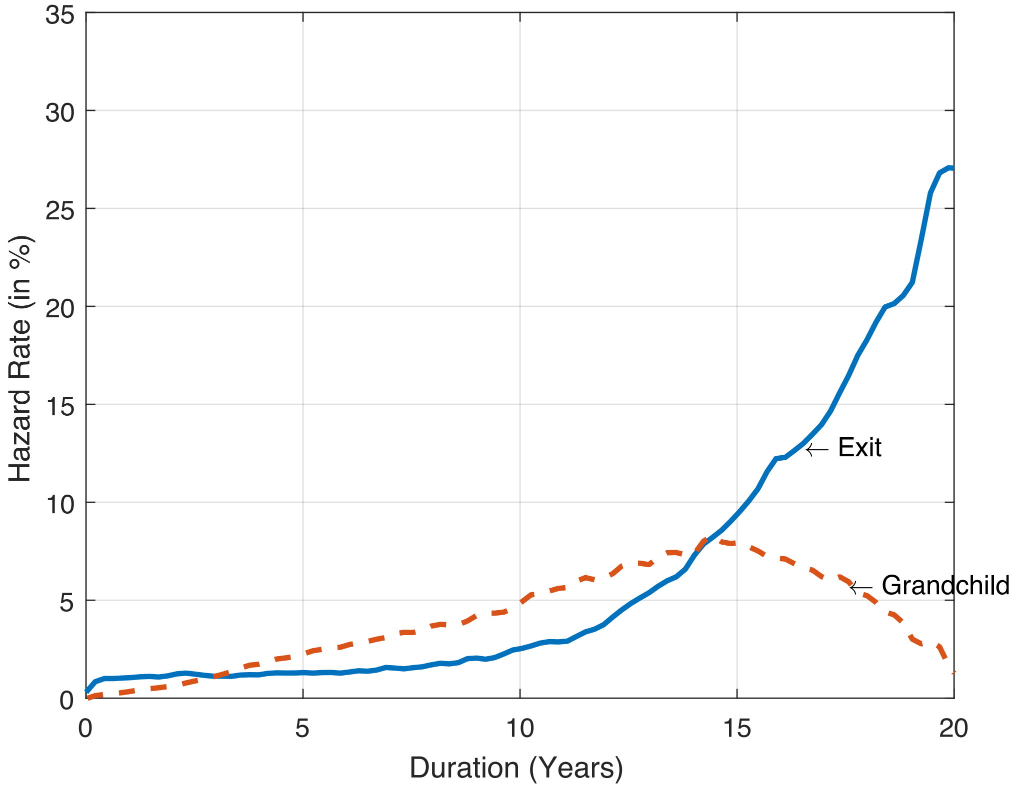
[11] Concentrating only on the oldest offspring does not change our conclusions.

Table 1: Mean of variables in the ToE estimation sample, overall and by Treatment status

	(I)	(II)	(III)	(IV)	(V)
	Overall sample:	*By Grandmother status:*			
		Grandchild	No Grandchild	Diff.	P-value
Labor market exit observed (shares)					
Labor market exit	0.56	0.48	0.63	0.15***	0.00
Duration until exit					
Duration to labor market exit	13.01	15.34	11.66	3.68***	0.00
Grandmother's characteristics					
First grandchild by son (vs. daughter)	0.21	0.39	0.07	0.32***	0.00
Age < 40 Years	0.53	0.61	0.46	0.15***	0.00
40 ≥Age < 45 Years	0.41	0.36	0.45	−0.09***	0.00
45≥Age	0.06	0.03	0.08	−0.05***	0.00
Labor market characteristics					
Wage (in Euro)	40.83	39.79	41.62	−1.84***	0.00
Missing wage is imputed	0.16	0.14	0.18	−0.04***	0.00
Experience (in years)	14.74	14.17	15.17	−0.99***	0.00
Educational attainment (shares)					
Level 1	0.06	0.07	0.05	0.02***	0.00
Level 2	0.09	0.09	0.08	0.01*	0.08
Level 3	0.08	0.07	0.09	−0.02***	0.00
Level 4	0.03	0.03	0.04	−0.01***	0.00
Level 5	0.04	0.03	0.05	−0.02***	0.00
Level 6	0.02	0.01	0.02	−0.01***	0.00
Level 7	0.68	0.70	0.66	0.04***	0.00
Number of children (shares):					
Has 1 Child	0.29	0.22	0.34	−0.12***	0.00
Has 2 Children	0.51	0.54	0.49	0.05***	0.00
Has 3 Children	0.15	0.18	0.13	0.05***	0.00
Has 4 Children or More	0.04	0.06	0.04	0.02***	0.00
State of residence (shares)					
State 1	0.04	0.04	0.04	0.00	0.63
State 2	0.06	0.06	0.07	−0.01***	0.00
State 3	0.20	0.22	0.20	0.02***	0.00
State 4	0.16	0.17	0.15	0.02***	0.00
State 5	0.06	0.07	0.06	0.01	0.24
State 6	0.15	0.15	0.15	−0.00	0.31
State 7	0.06	0.05	0.06	−0.01***	0.00
State 8	0.04	0.03	0.04	−0.01**	0.02
State 9	0.22	0.21	0.23	−0.020***	0.00
Number of observations	72,935	31,373	41,562		

*,**,*** indicate a significance difference in the sample means defined by twin status at a 1%, 5% and 1% level. All variables on the grandmother level are measured at the 15th birthday of the reference child. All variables on the offspring level are measured at birth of first child.

Figure 1: Kaplan-Meier transition rates



Notes: The solid line represents the estimated yearly transition rate out of labor force (outcome: labor market exit), the dashed line the yearly transition rate into grandparenthood (treatment: conception of first grandchild). The sample consists of all (potential) grandmothers with at least one child aged 15 in 1993-1998 and 2.5 years of labor market experience before the birth of the reference child.

3.3 Estimation results

Table 2 summarizes estimation output for our two different specifications. Model (I) refers to our estimation model under the assumption of a homogeneous, i. e. constant, treatment effect. Model (II) allows the treatment effect to vary with the elapsed time since treatment. For both models, we report the estimated effects on the exit hazard (θ_E) and the treatment hazard (θ_G) along with standard errors in parentheses. Both models define a labor market exit if it lasted at least 12 months. In our discussion of the results, we proceed in three steps. First, we discuss the correlation between exit and treatment hazards and the duration dependence. It turns out that the hazards are significantly correlated implying that the arrival of a grandchild should not be treated as exogenous. Second, we discuss the estimated effects of our covariates. Third, we present our main estimates on the effect of grandparenthood on female labor supply.

Table 2: Results for Full Sample

	Model (I) Homogenous Effect				Model (II) Time-Dependent Effect			
	Exit hazard θ_E		Treatment hazard θ_G		Exit hazard θ_E		Treatment hazard θ_G	
Panel A: Treatment effects								
δ	0.08	(0.01)						
$\delta_{[0-9]\ months}$					0.03	(0.03)		
$\delta_{(9-33]\ months}$					0.11	(0.02)		
$\delta_{(33-45]\ months}$					0.10	(0.03)		
$\delta_{(45-87]\ months}$					0.08	(0.02)		
$\delta_{(87-]\ months}$					0.08	(0.02)		
Panel B: Unobserved heterogeneity								
ν_1	−5.59	(0.06)	−4.09	(0.05)	−5.63	(0.06)	−4.10	(0.05)
ν_2	0.71	(0.01)	−4.54	(0.25)	0.69	(0.08	−4.51	(0.26)
ν_3	−1.09	(0.07)	−3.76	(0.07)	−1.18	(0.11)	−3.28	(0.33)
ν_4					−1.02	(0.12)	−5.17	(1.51)
$\Pr_{\nu_1}$	0.90	(0.00)			0.90	(0.00)		
$\Pr_{\nu_2}$	0.03	(0.00)			0.03	(0.00)		
$\Pr_{\nu_3}$	0.07	(0.00)			0.04	(0.02)		
$\Pr_{\nu_3}$					0.03	(0.02)		
Panel C: Duration dependence								
$\lambda_{(0-6]}$	ref.							
$\lambda_{(6-8]}$	1.23	(0.04)	1.01	(0.02)	1.24	(0.04)	1.01	(0.02)
$\lambda_{(8-10]}$	2.00	(0.04)	1.33	(0.02)	2.02	(0.04)	1.34	(0.02)
$\lambda_{(10-12]}$	2.77	(0.05)	1.72	(0.02)	2.78	(0.05)	1.73	(0.02)
$\lambda_{(12-14]}$	3.64	(0.05)	2.05	(0.02)	3.66	(0.05)	2.06	(0.02)
$\lambda_{(14-16]}$	4.50	(0.05)	2.27	(0.02)	4.52	(0.05)	2.27	(0.02)
$\lambda_{(16-18]}$	5.24	(0.05)	2.14	(0.03)	5.26	(0.05)	2.15	(0.03)
$\lambda_{(18-20]}$	5.98	(0.06)	1.69	(0.06)	5.99	(0.06)	1.70	(0.06)
$\lambda_{(20-\infty)}$	6.58	(0.07)	−0.33	(0.58)	6.61	(0.07)	−0.32	(0.58)
Panel D: Covariate effects								
First grandchild by son	−0.04	(0.02)	1.29	(0.01)	−0.04	(0.01)	1.29	(0.01)
Age < 40 Years	−3.07	(0.03)	0.33	(0.03)	−3.07	(0.03)	0.33	(0.03)
40 ≥Age < 45 Years	−1.57	(0.02)	0.13	(0.03)	−1.57	(0.02)	0.13	(0.03)
45≥Age	ref.							
Wage (in Euro)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.000)
Missing wage is imputed	−0.35	(0.02)	−0.28	(0.02)	−0.34	(0.02)	−0.28	(0.02)
Experience (in years)	0.10	(0.01)	0.00	(0.00)	0.10	(0.00)	0.00	(0.00)
Has 1 Child	−0.53	(0.03)	−1.13	(0.03)	−0.53	(0.03)	−1.13	(0.03)
Has 2 Children	−0.47	(0.03)	−0.70	(0.03)	−0.46	(0.03)	−0.70	(0.03)
Has 3 Children	−0.27	(0.03)	−0.35	(0.03)	−0.25	(0.03)	−0.35	(0.03)
Has 4 Children or more	ref.							

The sample consists of (potential) grandmothers with at least one child aged 15 in 1993-1998 and 2.5 years of labor market experience with a total of 72,935 observations. Standard Errors are reported in parentheses. Standard errors for the probabilities are calculated using the delta method. In addition to the listed covariates, education, residential, and time dummies are included in the estimation. Model (I) assumes a homogenous treatment effect and Model (II) allows the treatment effect to vary with the elapsed time since the birth of the grandchild.

3.3.1 Unobserved heterogeneity and duration dependence

The estimated unobserved heterogeneity ν_m is summarized in Panel B. We find three points of support for the joint distribution for Model (I) and four support points when estimating Model (II). These imply the existence of three and four groups in the population, respectively. The estimated groups are quite comparable across the two specifications. In particular, the third and fourth group in Model (II) are very much alike the third group in Model (I). Thus, for the sake of brevity, we discuss the implications only for Model (I).

The first group in Model (I) can be considered as quite attached to the labor market with a low treatment arrival rate. These grandmothers have a steady career and also the highest probability mass ($Pr_{\nu_1} = 0.90$, hence 90 percent). The second group has a very high exit rate and the lowest treatment rate, implying only a loose connection to the labor market. The third group is somewhat in the middle between both extremes. It has a relatively high exit and a relatively low treatment rate.

In general, our estimates imply that unobserved heterogeneity in the exit rate is positively correlated with unobserved heterogeneity in the arrival of treatment. A model without correcting for correlations between unobserved characteristics would overestimate the effect of grandparenthood on the labor market exit probability. Indeed, when we estimate the model ignoring the potential correlation between the treatment and exit hazard our treatment coefficient is around 14 percent higher as compared to our preferred estimate.[12]

The estimated duration dependence summarized in Panel C of Table 2 is essentially identical for the wo models. The time structure of the duration dependence terms follows largely the pattern of the Kaplan-Meier transition rates shown in Figure 1. The hazard for exits out of the labor force is increasing for all our specified intervals, while the hazard for the arrival of a grandchild is increasing up to 14 years and declining thereafter.

3.3.2 Effect of covariates

The estimated coefficients on our covariates are listed in Panel D. The estimated effects are very similar across models and all show the expected signs for both hazards. Both hazards increase with age. Less experienced women are also less likely to leave the labor force. This is not surprising as these potential grandmothers are in the middle of their career and have more to lose in terms of future labor market outcomes compared to those at the end of their working lives. Similarly, having more children increases the risk of becoming a grandmother, but it also does so for leaving the labor force. Finally, it also matters whether the daughter or the son has become a parent. The labor market exit

[12]In contrast, the estimated treatment effect is not sensitive to the exact number of masspoints included in the estimation.

hazard is 3 percent higher in the case of the daughter's child (as compared to the son's child)

3.3.3 Effect of a grandchild on labor market exit

Our main parameter of interest, δ, reflects the arrival of a first grandchild on the exit hazard of the grandmother. These estimates are reported in Panel A of Table 2. Assuming constant effects as in Model (I), becoming a grandmother increases the probability of exiting the labor market by approximately 8.5 percent.[13] This effect is highly statistically significant and indicates that the fertility decision of the direct family has an important influence on the working behavior of grandmothers.

Our estimated coefficient is similar to the results reported by Lumsdaine and Vermeer (2015), who estimate the effect of providing child care on retirement.[14] Relating our results to the ones reported in Rupert and Zanella (2016) is complicated. First, they estimate a local average treatment effect (LATE) rather than an average treatment effect (ATE). Second, in their survey data, they only find significant effects for hours worked, but not for labor supply at the extensive margin - although their point estimate is similar to ours. [15]

Due to our non-linear estimator, quantitative results are different according to the time of birth of the grandchild. We can use our estimates in a back-of-the-envelope exercise to investigate how the arrival of a grandchild at different durations $\bar{d}$ translates into losses of employment years for the grandmother.[16] Figure 2 shows the results of this exercise setting $\bar{d}$ to a range of values from 1 to 21 years.

Depending on the value of $\bar{d}$ our counterfactual analysis shows that the arrival of a grandchild shortens the duration until labor market exit between 2.4 and 3.6 month as one can see in Panel A of Figure 2. In such a calculation using the average daily pre-treatment wage rate of the individual our counterfactual results implies an average individual income loss in the range of $2,500$ Euros and 4,100 Euros as depicted in Panel B of Figure 2. This effect corresponds to a loss of 25 to 33 percent of annual income and is quite substantial. Note that these calculations constitute a likely lower bound since our

[13]Note, the correct calculation of the marginal effect is $exp^{0.082} - 1$.

[14]They treat the arrival of a grandchild as strictly exogenous and do not take potential correlations in unobserved heterogeneity into account. It is possible that grandmothers who are more likely to retire, for example to spend more time with family, are also more likely to have grandchildren. In this case, their results are upward biased.

[15]In their analysis, the significant labor supply adjustments take place by employed grandmothers at the lower quantiles of the hours distribution (i. e., among women, who are less attached to the labor market).

[16]We compute the residual labor market duration $Res(\bar{d}) = E\left[E[T|D=\bar{d}, X=x, T\geq\bar{d}] - E[T|D=\infty, X=x, T\geq\bar{d}]\right]$ for a given value of $\bar{d}$ using the observed covariate and estimated heterogeneity distributions. The expected duration $E[T|X=x, T\geq\bar{d}, D]$ can be calculated as $\bar{d} + \sum_{i=1}^{3} p_i \frac{1}{S\bar{d}|X=x, nu_E^i, D} \int_{\bar{d}}^{\infty} S(t|X=x, \nu_E^i, D)dt$, where $S(\cdot)$ is the conditional survival rate. In practice we set the upper limit of the integral to 55 years

effect refers to the extensive margin of labor supply and neglects the effect of a reduction in hours worked as response to a grandchild. In Section 5, we analyse whether a part of this loss is due to problems in providing suitable child care.

Model (I) imposes a constant treatment effect which does not depend on the age of the grandchild. Given the institutional settings in Austria, as discussed in Section 2, it is possible that some grandmothers only react at a certain point in time after the birth of the grandchild, for example, to provide informal child care when maternity leave is running out. Put differently, grandmothers may strategically time their labor market exit. To account for this possibility we now allow the treatment effect to depend on the elapsed time since the reception of the treatment. We model the time-varying effect by using a piece-wise constant function to characterize the treatment, where the knots are chosen to be at months 9, 33, 45, and 87. These points coincide with important events for the offspring and the grandmother.

The first knot at 9 months corresponds to the (approximate) end of the pregnancy. It allows us to determine how much of the total effect is due to an exit before the actual birth and serves as a test for the no anticipation assumption. If we found large and significant effects during the first 9 months after conception we might be concerned that the conception date might have been (partly) foreseen by the grandmother. The second knot corresponds to the end of the job protection period for the offspring. During this period the parent — typically the mother — has the possibility to return to the former employer.[17] We set the third and fourth knot at 45 and 87 months respectively. Around age 3 children attend kindergarden. At months 87 after the conception the child reaches compulsory school age which lies between ages 6 and 7 in Austria. Since the availability of full-time kindergarden and schools is still very restricted in Austria, parents have to reconsider care responsibilities and work at this point in time.

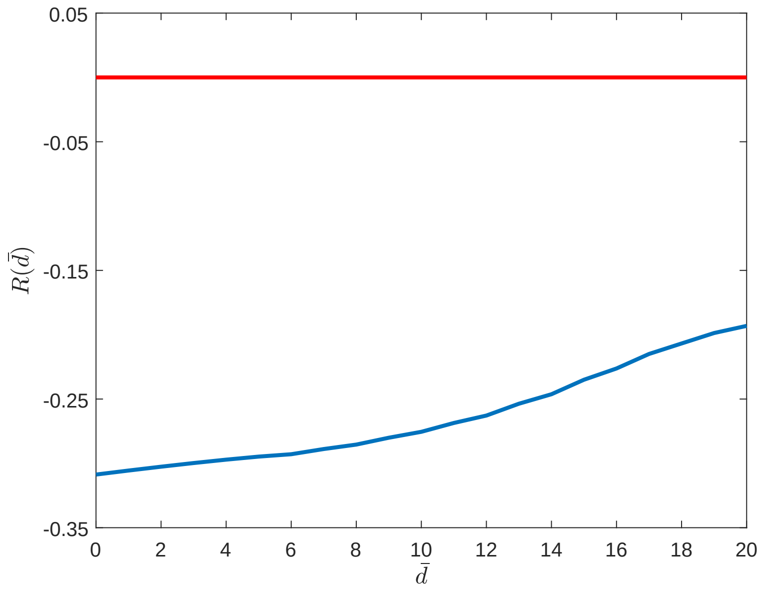
The results of our Model (II) are shown in the right two columns of Table 2. Each δ_t corresponds to the treatment effect for the specified time interval. The estimates confirm our conjecture of a strategically timed exit and provide furthermore support in favor of our no anticipation assumption. During the first 9 months of pregnancy we do not estimate a significant increase in the exit probability. After this point, the treatment effect almost quadruples to 11 percent which is also statistically significant at the 1 percent level and remains at a similar magnitude during the time the grandchild attends kindergarden.[18] It decreases afterwards slightly during the schooling period, but our estimates remain highly significant. In terms of model fit, our Model (II) seems to fit the data slightly better than assuming a homogenous treatment effect. Conducting a likelihood ratio test,

[17] Remember that we measure our duration from the conception date onward. Hence, 9 months of gestation together with 2 years of job protection is equal to 33 months.

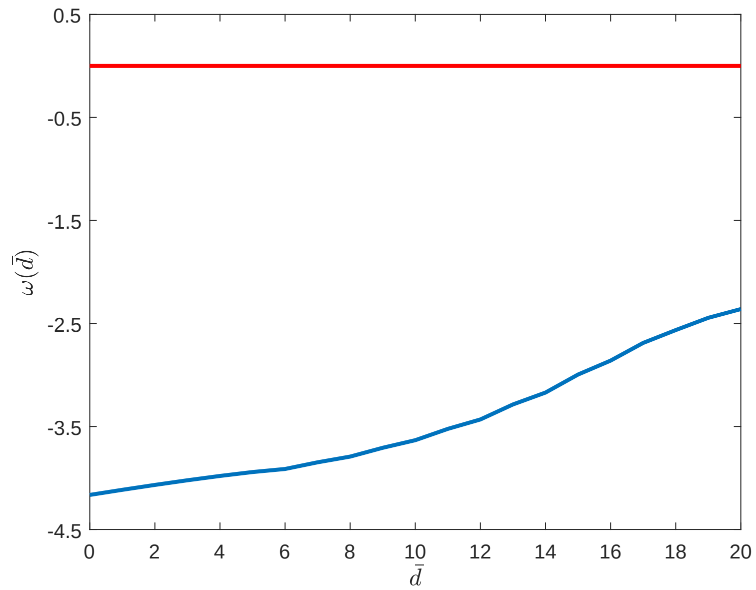
[18] We also conducted a set of estimations where we allowed the treatment effect to differ between the child-care leave and job protection period. The coefficients estimated for these periods were, however, virtually identical.

Figure 2: Average loss in employment years and income

Panel A: Loss in employment years



Panel B: Loss in income



Notes: This figure presents for different treatment durations the expected loss in employment years (see Panel A) and in income (see Panel B). The loss in employment years is defined as $Res(\bar{d}) = E\left[E[T|D = \bar{d}, X = x, T \geq \bar{d}] - E[T|D = \infty, X = x, T \geq \bar{d}]\right]$ where the outer expectation is taken over both the estimated distribution of the heterogeneity and the empirical distribution of the covariates. The loss in income is calculated by weighting $Res(\bar{d})$ with the individual income. Loss in employment years is expressed in years, losses in income are express in 1,000 Euros.

we can reject the Null of a constant treatment effect at the 7 percent level.[19] The rest of our estimates are similar to those obtained under a constant treatment effect.

Our results show that grandmothers react stronger during times where informal child care is the most valuable for their offspring. This finding is also supported by a robustness check, where we analyze the responsiveness of our results with respect to the minimum duration of labor market exit. Our main results are based on a minimum exit duration of 12 months, which goes beyond the maximum duration of receiving unemployment benefits. In Table A.1 in the Web appendix, we replicate our main results with a minimum exit duration of 6 months. We estimate very similar effects. The results show that grandmothers do not specifically support the offspring only for a short time after birth, but tend to leave the labor market for an extended time period. As a consequence, they effectively forgo income and pension-relevant insurance times which also leads to lower future pension payments.

3.4 Sensitivity analysis

One particular concern with our identification assumption is whether the timing of the conception of the grandchild is random. For example, it is possible that the birth of a grandchild lies in close distance to the official retirement date of the grandmother. In other words: Expected retirement of the potential grandmother might trigger fertility behavior of the offspring. In this case, our results could suffer from reverse causality. We investigate this potential problem by concentrating on individuals who are not eligible to retirement during our observation period.[20]

In our sensitivity analysis, we restrict the sample to potential grandmothers who are born between January, 1st 1955 and December, 31st 1960. Since all potential grandmothers in this sample are younger than 58 years by the end of our observation period (2013), we refer to them as our Age-58 Sample. In light of our discussion about pension regulations in Austria in Section 2 we also estimate our treatment effects concentrating on very young (potential) grandmothers born after the 1st of January 1958, our Age-55 Sample. For these cohorts, early retirement was not possible anymore, so the regular retirement age of 60 years applied. Retirement before the age of 60 was only possible through a disability pension. However, due to extensive medical screening processes, which will have an uncertain outcome unless a person is really very sick, the timing or even the availability of a disability pension is hard to predict. Thus, an adaptation of the timing behavior of the offspring to the granting of a disability pension is highly unlikely.

[19] The estimated log-likelihood for Model (I) is $-263,444.71$ and for Model (II) it is $-263,438.12$. The test statistic is 13.18 and under the Null it follows a χ^2-distribution with 7 degrees of freedom. We therefore obtain a P-value of 0.07.

[20] There is always the possibility that the offspring times the conception of the child with respect to other dates during the life-course of the grandmother. However, we would expect this effect to be the largest around retirement.

Table 3: Sample - Not Eligible for Retirement

	Age-58 Sample				Age-55 Sample			
	θ_E		θ_G		θ_E		θ_G	
Panel A: Treatment effects								
δ	0.18	(0.03)			0.21	(0.08)		
Panel B: Unobserved heterogeneity								
ν_1	-4.19	(0.08)	-9.57	(0.15)	-3.79	(0.12)	-4.51	(0.21)
ν_2	-1.40	(0.08)	-9.88	(0.17)	-0.89	(0.13)	-18.26	(164.54)
ν_3	-4.24	(0.11)	-4.75	(0.14)	-3.82	(0.19)	-0.92	(0.21)
ν_4	-1.67	(0.13)	-6.03	(0.17)	-1.34	(0.14)	-2.15	(0.21)
ν_5	-4.28	(0.20)	-2.39	(0.11)		(0.14)		
ν_6	-1.44	(0.18)	-3.61	(0.17)		(0.14)		
Pr_{ν_1}	0.80	(0.01)			0.78	(0.02)		
Pr_{ν_2}	0.06	(0.01)			0.04	(0.01)		
Pr_{ν_3}	0.07	(0.00)			0.13	(0.02)		
Pr_{ν_4}	0.01	(0.00)			0.05	(0.06)		
Pr_{ν_5}	0.06	(0.00)						
Pr_{ν_6}	0.02	(0.00)						
Panel C: Duration dependence								
$\lambda_{(0-6]}$	0		0		0		0	
$\lambda_{(6-8]}$	1.31	(0.03)	1.09	(0.05)	1.33	(0.05)	0.28	(0.07)
$\lambda_{(8-10]}$	1.63	(0.04)	1.83	(0.06)	1.52	(0.06)	0.44	(0.09)
$\lambda_{(10-12]}$	2.09	(0.04)	2.51	(0.08)	1.99	(0.06)	0.77	(0.10)
$\lambda_{(12-14]}$	2.43	(0.05)	3.35	(0.09)	2.35	(0.07)	0.99	(0.11)
$\lambda_{(14-16]}$	2.60	(0.05)	4.57	(0.09)	2.47	(0.08)	1.55	(0.12)
$\lambda_{(16-18]}$	2.41	(0.06)	5.62	(0.10)	2.17	(0.09)	2.07	(0.13)
$\lambda_{(18-\infty]}$	1.87	(0.09)	6.71	(0.10)	1.71	(0.16)	2.64	(0.15)

The sample consists of (potential) grandmothers with at least one child aged 15 in 1993-1998 and 2.5 years of labor market experience, who were younger than 58 (Age-58 Sample) and younger than 55 (Age-55 Sample) respectively by the end of 2013. The sample size of the Age-58 Sample is 40,617 observations and for the Age-55 Sample it is 14,645. Standard Errors are reported in parentheses. Standard errors for the probabilities were calculated using the delta method. All covariates as in Table 2 were included for estimation. The number of mass points for the Age-55 were restricted to 4 during the estimation. A higher number leads to defective risks.

In total, 40,617 individuals are included in the analysis of the Age-58 sample and 14,645 individuals in the Age-55 sample. The estimation results are presented in Table 3. For expositional reasons the table contains only results for the treatment effect together with the parameters for duration dependence and unobserved heterogeneity.

Looking at our treatment effect, we find that restricting the sample to younger individuals does increase our treatment effects. For younger individuals the arrival of a grandchild increases the exit probability by 20 percent for the Age-58 Sample and 23 percent for the Age-55 Sample respectively. These effects are substantially larger compared to our baseline estimates reported in Table 2.

In light of our findings, we are confident that our results capture the causal effect of a first grandchild on the labor supply of grandmothers. We neither find any evidence for a strategic timing of conception from the side of the offspring, nor do we find significant effects during the first 9 months of pregnancy (see Table 2). Up until now we have concentrated on the extensive margin. In the next section, we will investigate the effect of additional grandchildren on the labor supply of grandmothers using an IV strategy.

4 The effect of further grandchildren

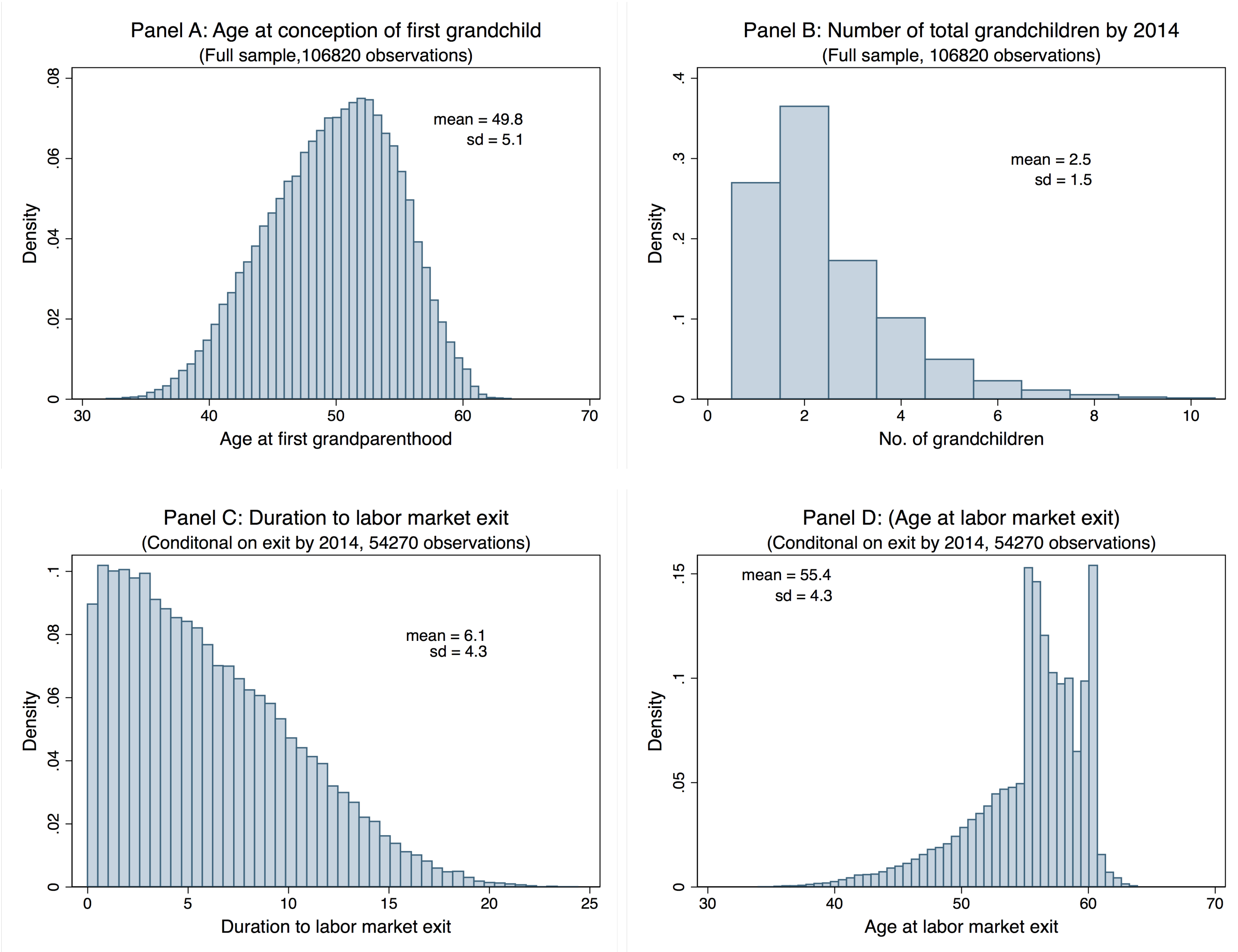
4.1 Estimation sample and descriptive statistics

To obtain our estimation sample for this analysis, we consider all women born between 1950 and 1960 with at least one child born 1973 or later, who became grandmother before 2014. Applying these criteria gives us an estimation sample of $121,264$ women. Figure 3 displays the distribution of these women's age at first grandparenthood (see Panel A) and the total number of grandchildren by 2014 (see Panel B). These women become on average grandmother at age 49 and by 2014 they had on average 2.52 grandchildren. About 77 percent of them have two or more grandchildren, and about 28 percent have three or more.

The outcome variable in this part of our analysis is the duration to labor market exit, measured from the conception of the first grandchild. About 52 percent (or 63,347) of the women in our sample leave the labor market before 2014 when we use the definition based on 12 consecutive months out of employment. The average duration until the first long term exit is 6.5 years after grandparenthood. At this point in time they are on average 55.2 years old. The distribution of these measures is depicted in Panels C and D of Figure 3 based on the sample of non-censored observations.

Table 4 provides variable means for the overall sample (column I), and by twin status (columns II and III). The latter is defined by distinguishing between grandmothers, whose first grandchild was a single birth from those with a multiple birth. A twin birth significantly increases the total number of grandchildren by around 0.11. This fact is

Figure 3: Distribution of the age at grandparenthood, the number of grandchildren, and the timing of labor market exit



Notes: The figures are based on 121,265 women born between 1950 and 1960, who become grandmother before 2014. Panel A displays the distribution of grandmothers' age at grandparenthood, Panel B the total number of grandchild by 2014, Panel C the duration to labor market exit of grandmothers, and Panel D grandmothers' age at labor market exit.

used in the first stage of the IV approach. Grandmothers with and without a twin status are very comparable. All characteristics are measured 15 years after the birth of her first child. Most importantly, we do not see any significant difference with respect to their year of birth or any labor market characteristics.

Looking at the characteristics of the mother, one can see that parents who had a multiple birth tend to be slightly older, had their first birth later and had higher pre-birth wages. This may reflect the discussed correlation between IVF treatments and the occurance of twin births.

The exit rate in our total sample is around 50 percent and there does not seem to be any unconditional difference between the IV status. A majority of cases leaves the labor market three to five years after the conception of the grandchild. The density is decreasing afterwards with the upper part dominated by grandmothers who have not exited the labor market during our observations period.

Below we will suggest two alternative estimation strategies. The first strategy, a conventional 2SLS approach, focuses on the subset of women who have uncensored, i.e. complete, durations. In this sample, average duration until labor market exit is about 6.5 years. The second method, a censored quantile treatment effects estimator (c2SLS), includes all women in the analysis, and accounts for the potential censoring. In both cases, we aim to exploit exogenous variation in the number of grandchildren, by relying on the occurrence of a twin birth at the birth of the first grandchild.

4.2 Estimation strategies

To examine the effect of grandchildren on grandmothers' labor supply at the intensive margin we utilize an IV which originates from the literature studying the effect of family size on first borns' outcomes and maternal labor supply. We rely on the occurrence of a twin birth at the birth of the first grandchild.[21]

Two-stage least squares estimation The twin-IV strategy provides information on the effect of an unexpected additional grandchild in the sample of families with at least one grandchild. We implement this estimation strategy via a 2SLS estimation approach, where the dependent variable in the first stage is equal to the total number of grandchildren by grandmother i:

$$grandchildren_i = \alpha + \beta \cdot twin1_i + \Gamma \cdot \mathbf{X}_i + u_i. \tag{4}$$

The dependent variable of primary interest is $twin1_i$, which is equal to one if the birth of the grandmother's first grandchild was a twin birth, and zero otherwise. As control

[21] The idea to use twin births as a source of exogenous variation in the number of offspring was first proposed by Rosenzweig and Wolpin (1980*b*) and used in later studies to instrument for family size (e. g. Bronars and Grogger, 1994; Jacobsen et al., 1999).

Table 4: Mean of variables in the IV estimation sample, overall and by twin status

	(I)	(II)	(III)	(IV)	(V)
	Overall sample:	*By twin status:* Grandmother's first grandchild was a			
		single birth	twin birth	Diff.	P-value
Dependent variable					
Duration to labor market exit	6.12	6.14	4.78	1.36**	0.00
Endogenous treatment variables					
Number of grandchildren	2.57	2.57	2.68	−0.11*	0.03
Two or more grandchildren	0.76	0.76	0.82	−0.06**	0.00
Grandmother's characteristics					
First grandchild by son (vs. daughter)	0.39	0.39	0.40	−0.01	0.68
Year of birth	1954.20	1954.19	1954.16	0.03	0.75
Labor market characteristics:					
Wage (in Euro)	31.1	31.10	32.19	−1.09	0.24
Missing wage is imputed	0.24	0.24	0.22	0.02	0.17
Experience (in years)	11.18	11.18	11.50	−0.32	0.17
Educational attainment (shares):					
Level 1	0.11	0.11	0.09	0.02*	0.02
Level 2	0.11	0.11	0.10	0.01	0.22
Level 3	0.06	0.06	0.05	0.01	0.33
Level 4	0.02	0.02	0.02	−0.00	0.92
Level 5	0.01	0.01	0.01	0.00	0.28
Level 6	0.01	0.01	0.01	−0.00	0.28
Level 7	0.69	0.69	0.73	−0.04**	0.01
Number of children (shares):					
Has 1 child	0.36	0.36	0.41	−0.05**	0.00
Has 2 children	0.43	0.42	0.41	0.02	0.34
Has 3 children	0.16	0.16	0.14	0.02	0.17
Has 4 children or more	0.06	0.06	0.04	0.02**	0.01
Average number	1.93	1.93	1.81	0.12**	0.00
State of residence (shares):					
State 1	0.04	0.04	0.04	−0.00	0.56
State 2	0.07	0.07	0.08	−0.01	0.21
State 3	0.18	0.18	0.20	−0.02	0.27
State 4	0.17	0.18	0.14	0.03**	0.01
State 5	0.07	0.07	0.05	0.02*	0.04
State 6	0.17	0.17	0.17	0.00	0.80
State 7	0.07	0.07	0.06	0.00	0.82
State 8	0.04	0.04	0.05	−0.00	0.88
State 9	0.19	0.19	0.21	−0.02	0.13
Mother's characteristics					
First grandchild's birthyear	2004.16	2004.13	2005.92	−1.78**	0.00
Mother's income	12981.60	12936.86	16041.93	−3105.07**	0.00
Mother's age	25.12	25.09	27.16	−2.07**	0.00
Number of observations	54,270	53,488	782		

*,**,*** indicate a significance difference in the sample means defined by twin status at a 1%, 5% and 1% level. All variables on the grandmother level are measured at the 15th birthday of the reference child. All variables on the offspring level are measured at birth of first child.

variables we include the sex of the child, the number of children the grandmother has and additional information on the grandmother: her education, wage, work experience, state of residence within Austria, month and birth year of the grandmother and month and year of birth of the grandchild. In the second stage, we use the prediction from the first stage equation to explain the grandmother's duration to labor market exit,

$$labor\,market\,exit_i = \delta + \tau \cdot \widehat{grandchildren}_i + \Delta \cdot \mathbf{X}_i + v_i, \tag{5}$$

This duration is measured as the time from the first grandchild's conception to her labor market exit. As before we define a labor market exit if the grandmother is 12 consecutive months out of employment. We will carry out our main analysis only with women who exit the labor market within our observation period; results including women who are censored are in the Appendix (Table A.2).

The identifying assumption is that the occurrence of twins is uncorrelated with v_i and that censoring is independent of our outcome. There are two known determinants affecting the occurrence of a twin birth, a higher maternal age and an *in vitro* fertilization (IVF) treatment. Beyond these two factors, the occurrence of multiple births is believed to be random. Thus, the relevant question to ask is, whether these two factors are also determinants of grandmaternal labor market exit. Given that this question is hard to assess, we follow a conservative strategy and try to explicitly control for these two factors. In the case of maternal age, this approach is straightforward, since we observe this information in our data. Thus, we simply include the mother's age as a covariate. The case of the IVF treatment is less straightforward, since we do not have information on this in our data. We know, however, that IVF treatments are mainly used by older women with a higher socio-economic status. Thus, we control (besides mother's age at first birth) also for pre-birth labor income.

Censored two-stage least squares estimation One potential complication arises in our setting as our outcome variable, the duration until the first labor market exit, is subject to censoring.[22] To account for this potential problem, we present results combining the estimators proposed by Frandsen (2015) and Frölich and Melly (2013). Frandsen (2015) shows that the local quantile treatment effect can be non-parametrically identified under the presence of endogeneity if the outcome is subject to censoring. His setting is similar to the one used in Imbens and Angrist (1994) with the exception that the assumptions imposed are conditional on the censoring point and it is assumed that latent outcomes are jointly independent from the censoring mechanism among compliers. As we use administrative data without selective drop-out, this assumption is very likely to hold in our setting.

[22] Ignoring the censoring and applying "usual" IV methods to estimate the effect, such as the ones proposed by Imbens and Angrist (1994) and Abadie (2003), can lead to biased results. This is also confirmed in the Monte Carlo simulations by Frandsen (2015).

Frandsen (2015) does not incorporate covariates in his model. To account for the fact that our IV is likely to fulfill the imposed restrictions once we condition on observed covariates, we combine the censored two-stage least squares estimator (c2SLS) of Frandsen (2015) with the weighting approach proposed by Frölich and Melly (2013). Combining these two methods allows us to estimate the local average quantile treatment effect under censoring and, at the same time, to account for possible confounding factors. The advantage of this procedure is twofold: first, similar to the two stage least squares approach without censoring the censored two stage least squares estimator relies on minimal assumptions.[23] Second, by concentrating on quantiles we allow the treatment to differ along the duration distribution.

The estimation proceeds in two steps. In a first step, we estimate the instrument probability $\pi(X) = P(Z = 1|X)$, where Z is a binary indicator if the first birth was a multiple birth, by means of logistic regressions. We then construct weights as proposed by Frölich and Melly (2013): $w = \frac{Z-\pi(X)}{\pi(X)(1-\pi(X))}(2K-1)$, where K is the endogenous treatment indicator. Here, K is a binary variable which takes a value of 1 if the grandmother has at least two grandchildren.

In the second step, we use the weights, w, to estimate the c2SLS. The counterfactual distribution under treatment among compliers is estimated as:

$$F_{(1|\text{compliers}}(y) = \frac{E\left[K\mathbb{1}(Y \leq y)w|C > y\right]}{E\left[Kw|C > y\right]}$$

where C denotes the censoring point. The counterfactual distribution under the control can be obtained by exchanging K with $1 - K$. We deal with the possibility that w can be negative by using $w^+ = E[w|Y, D]$ in practice where the conditional expectation is obtained using local linear regressions. .

The c2SLS estimates the counterfactual distribution of leaving the labor market before time y by assigning each individual the appropriate weights and then taking the average over the uncensored population, standardized by the probability of belonging to the (uncensored) complier group. Using the estimated distribution functions, we can calculate the quantile treatment effect among the compliers for a given percentile τ as

$$\Delta(\tau) = Q_{Y(1|\text{compliers})(\tau)} - Q_{Y(0|\text{compliers})(\tau)}$$

where $Q_{Y(j|\text{compliers}(\tau))} \equiv inf\left\{y : F_{j|\text{compliers}}(y) \leq \tau\right\}$ for $j \in \{0, 1\}$. The inference is based on 500 bootstrap replications.

[23] Estimating mean impacts under censoring and endogeneity is in general difficult when dealing with duration outcomes. An alternative estimator would be the IV Tobit proposed by Newey (1987). However, this estimator does not allow for heteroscedasticity which certainly is present in our data.

Notice that in our case there are no never-takers. In this setting, the local quantile treatment effect can be interpreted as the quantile treatment effect on the non-treated. This parameter gives estimates of what would happen to the labor supply of grandparents with only one grandchild if we did increase the number of grandchildren to at least two.

4.3 Estimation results

Two-stage least squares estimation Table 5 summarizes our 2SLS results for the impact of the number of grandchildren on labor market exit of the grandmother. For comparison, column (1) reports a simple OLS estimation, which shows a negative association between the number of grandchildren and the duration until labor market exit. Column (2) shows the reduced form estimates where duration on the labor market of the grandmother is regressed on the incidence of a twin birth. Column (3) summarizes the first stage of our 2SLS estimation. It turns out that if the first grandchild is a twin birth, the ultimate number of grandchildren will increase by 0.37 additional children. Given the average number of about 2.57 grandchildren, this effect is substantial and equivalent to an increase by 14.4 percent. The results on the covariates show some interesting patterns (full estimation output is available upon request). As expected, the higher the number of the grandmother's children, the higher the number of her grandchildren. Interestingly, the number of total grandchildren is higher, if the first grandchild is from her son (as compared to from her daughter).

Column (4) summarizes the second stage of our 2SLS estimation. Here, we exploit only exogenous variation in the number of children, caused by the twin birth. We argue that the estimate can be interpreted causally, since the number of grandchildren a grandmother has, increases as good as randomly. This provides us with a local average treatment effect suggesting that an increase in the number of grandchildren by one — due to a twin birth — leads to an early labor market exit by the grandmother of 0.63 years. This corresponds to a 10.3 percent shorter spell. This figure corresponds nicely with the ToE effect, which is a 8.2 percent higher exit rate.

This 2SLS estimate is considerably higher than the OLS coefficient. This may either result from an omitted variables bias in the OLS estimate or measurement error. Omitted variables bias could arise from variables which are unobserved but correlated with the number of grandchildren and labor market exit. One example may be a high career orientation of the grandmother which will be negatively correlated with the number of grandchildren – in particular if there is some intergenerational persistence – and will be positively correlated with the length of the career of the grandmother. Leaving out this variable may lead to a substantial underestimation of the effect of grandchildren on the length of the labor market career of the grandmother. Measurement error could arise as well, as we do observe the births of both children and grandchildren from a combination

Table 5: The effect of the no. of grandchildren on the duration to labor market exit

	(1) OLS	(2) Reduced form	(3) First stage	(4) Second stage –v1	(5) Second stage –v2
No. of grandchildren	-0.040***			-0.633**	
	(0.012)			(0.275)	
Two or more grandchildren					-2.071**
					(0.889)
Twin birth (first grandchild)		-0.232**	0.367***		
		(0.096)	(0.044)		
First grandchild by son (vs. daughter)	0.078***	0.072***	0.159***	0.172***	0.167***
	(0.027)	(0.027)	(0.011)	(0.052)	(0.050)
Grandmother characteristics					
Has 2 children	0.189***	0.154***	0.872***	0.706***	0.479***
	(0.032)	(0.030)	(0.011)	(0.241)	(0.143)
Has 3 children	0.169***	0.101**	1.677***	1.163**	0.592***
	(0.050)	(0.048)	(0.022)	(0.463)	(0.216)
Has 4 children or more	-0.153*	-0.262***	2.682***	1.436*	0.336
	(0.084)	(0.080)	(0.040)	(0.741)	(0.269)
Educ. attainmnet (base group: low)					
Level 2	0.044	0.053	-0.230***	-0.092	-0.016
	(0.061)	(0.061)	(0.027)	(0.089)	(0.069)
Level 3	0.304***	0.317***	-0.326***	0.110	0.250***
	(0.069)	(0.069)	(0.031)	(0.114)	(0.077)
Level 4	0.520***	0.537***	-0.412***	0.276*	0.443***
	(0.105)	(0.105)	(0.050)	(0.157)	(0.117)
Level 5	1.063***	1.080***	-0.451***	0.794***	1.015***
	(0.110)	(0.110)	(0.058)	(0.171)	(0.119)
Level 6	0.408***	0.421***	-0.297***	0.233	0.417***
	(0.145)	(0.145)	(0.073)	(0.172)	(0.150)
Level 7	0.279***	0.268***	0.282***	0.446***	0.378***
	(0.052)	(0.052)	(0.022)	(0.094)	(0.071)
Wage rate (daily):					
Wage (in Euro)	0.000	0.000	0.001***	0.001	0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Missing wage is imputed	-0.434***	-0.436***	0.032*	-0.415***	-0.429***
	(0.046)	(0.046)	(0.018)	(0.048)	(0.047)
Labor market experience:					
Experience (in years)	0.016***	0.016***	-0.006***	0.012***	0.012***
	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)
Grandmother's year of birth FE	Yes	Yes	Yes	Yes	Yes
Grandmother's month of birth FE	Yes	Yes	Yes	Yes	Yes
Grandmother's state of residence FE	Yes	Yes	Yes	Yes	Yes
Grandchild's year of birth FE	Yes	Yes	Yes	Yes	Yes
Grandchild's month of birth FE	Yes	Yes	Yes	Yes	Yes
Mother's age and income	Yes	Yes	Yes	Yes	Yes
Number of obs.	54,270	54,270	54,270	54,270	54,270
R-squared	0.50	0.50	0.32	0.47	0.46
Mean of dependent variable	6.12	6.12	2.57	6.12	6.12
S.d. of dependent variable	4.33	4.33	1.51	4.33	4.33
Mean of treatment				2.57	0.76
Mean of twin		0.0144	0.0144	0.0144	0.0144
F-test of weak instrument				70.82	78.29

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of administrative data, where, e.g. children out-of-wedlock may be underrepresented.

Censored two-stage least squares estimation Figure 4 presents the estimation results for $\Delta(\tau)$ for the full distribution together with a 5 percent significance interval. Our estimation results reveal a strong and significant impact of the birth of a grandchild on the length of labor force participation of grandmothers: For the 5th percentile, we estimate a strong negative treatment effect of 3.9 years less. After quantile 4, this negative effect ceases to be existent.

For comparison purposes, Column 5 of Table 5 contains the results of our 2SLS approach using a binary treatment variable – either to have two or more children or less than two. The estimated effect of -2.07 is similar to the c2SLS results at the lower quantiles. In general, our results show that reductions of labor supply only arise in cases where the attachment to the labor market is rather low. Finally, in the Table A.2 in the Web appendix we repeat the 2SLS analysis using all grandmothers, regardless whether their labor supply is censored or not. This sample is now almost twice as large; we still get comparable 2SLS results, though. These results are now somewhat smaller in size, which is due to the inclusion of many uncensored spells of grandmothers which are better attached to the labor market. This result copies the pattern of the censored two-stage least squares estimation shown above: results are smaller for more attached women.

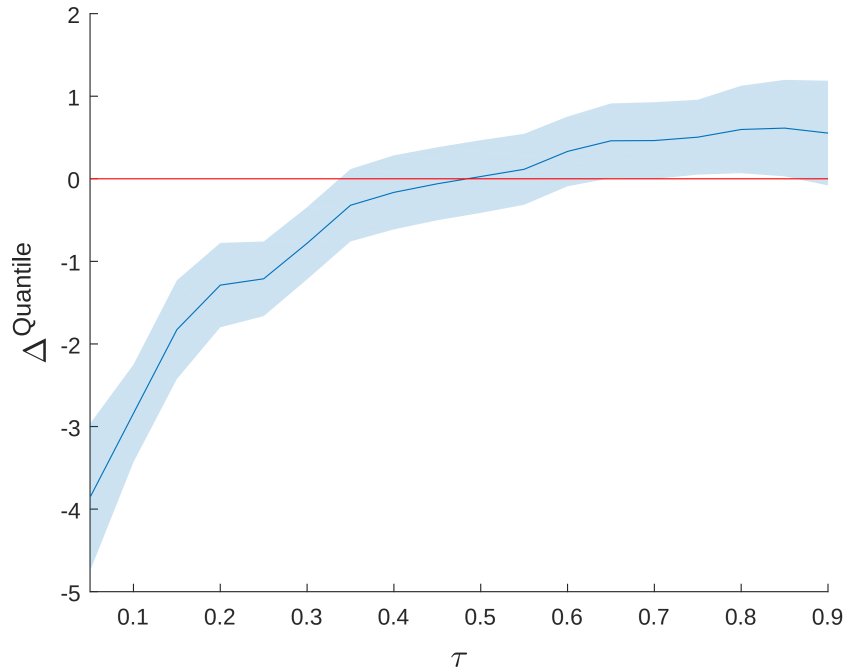
5 Heterogeneous effects

The birth of the first grandchild increases the likelihood to leave the labor market by around 8 percent. Table 6 compares this main effect for the extensive margin with the one for the intensive margin; i.e. the comparison between having one or two grandchildren. To make the comparison easier, we also present the expected residual life time $Res(\bar{d})$ for our ToE samples for which we set $\bar{d}$ as the mean duration until the first grandchild for the respective sub-population. This comparison shows remarkably close estimates: while at the extensive margin one grandchild reduces average working time by -0.68 years, this effect is -0.63 for the birth of an additional grandchild — using a completely different estimation strategy. Note, that these estimates may also accidentally be the same, because they do measure different decisions — after the first vs. after the second grandchild.

In this section, we examine patterns of potential treatment effect heterogeneity. In particular, we look at the existence of formal child care facilities in children's home municipality, geographic distance measured in driving minutes between grandmothers and children, and grandmaternal earnings.[24] The results for the extensive margin are

[24]All dimensions of heterogeneity are assessed at the time of the grandchildren's conception, or - if information at this point in time is not available - at the closest available time. In case of no grandchildren, the assessment year is the year when women reach the age of 50, which is the average age of women

Figure 4: Quantile treatment effects for intensive margin



Notes: The graph shows estimates of $\Delta(\tau)$ measured in Years with $\tau \in [.05, ..90]$ at 0.05 unit intervals together with a 95 percent confidence interval. The estimation is based on the procedure following Frandsen (2015) and Frölich and Melly (2013), and is described in Section 4. Inference is based on 500 bootstrap replications of the whole estimation process. The sample consists of all individuals with at least one grandchild; in total $107,133$ observations. Lifetime fertility of the offspring is instrumented using the occurrence of a multiple birth at first birth.

reported in the upper panel of Table 6, the corresponding results for the intensive margin are shown in the lower panel.

The local availability of formal child care for children below three years of age is an important dimension. On the one hand, the existence of such an opportunity might decrease the necessity for informal child care. Hence, one would expect a negative or zero effect. On the other hand, most of the facilities do not offer full-time care. Therefore, the availability and the use of formal child care may trigger additional informal child care by the grandmother. We re-estimate our model separately for the sample living in areas/communities with and without formal child-care institutions, respectively. We find stronger effects of grandparenthood on labor supply if formal child care is available, but smaller effects if there is no formal child care in the community — this is true for both the first and an additional grandchild. Again, the results are fairly comparable with minus 0.8 and minus 1.2 years with child care and minus 0.4 and minus 0.4 years for communities without. This result suggests that formal institutions and grandparental time are complements in the provision of child care.

Geographic distance is another important indicator. Compton and Pollak (2014) show that married women with young children have a higher labor supply, if either their mother of their mother-in-law is in close geographical proximity. They argue that the mechanism through which proximity increases maternal labor supply is the availability of grandmaternal child care. Consequently, we expect that grandmothers in very close proximity to the grandchild to be less likely employed as compared to those who live further apart. To test this hypothesis, we divide grandparent-mother pairs into three groups: distance less than 30 minutes driving time, between 30 and 90 minutes and more than that. According to our expectations, we find that the lower the driving distance between the two households, the more likely grandmothers reduce their labor supply. Those living very close by reduce their labor supply by 2.2 (extensive margin) or 0.9 years (intensive), the effects for those with larger distances are consistently smaller.[25] At the extensive margin, grandmothers with driving distances of more than 90 minutes are even less likely to leave the labor market once a grandchild arrives. This result is not unexpected and can be explained by a desire to provide monetary transfers to the children/grandchildren because the distance for personal help is just too large. Labor supply might thus increase.

Finally, we split our sample of grandmothers along median annual earnings. On the one hand, grandmothers with lower earnings and worse job prospects might choose to provide informal care, as the cost of substitution is relatively low, while grandmothers with higher earnings might expand their labor supply, providing monetary support instead

becoming a grandmother in our sample.

[25] In the IV model, the result for 30-90 minutes distance is numerically larger, but insignificant and also hampered by a very low F-test for weak IVs problem.

Table 6: Treatment Effect Heterogeneity

	(I)	(IIa)	(IIb)	(IIIa)	(IIIb)	(IIIc)	(IVa)	(IVb)
		Formal child care		Distance to grandchild (in min.)			Earnings	
	Baseline	available	not available	$d < 30$	$30 \leq d < 90$	$90 \leq d$	e <median	e >median
Timing-of-Events:								
δ	0.082***	0.100***	0.054**	0.271***	0.140***	-0.074***	0.078***	0.094***
$Res(\bar{d})$	-0.678	-0.826	-0.443	-2.188	-1.139	0.690	-0.657	-0.841
Number of observations	72,935	35,283	25,191	18,657	12,604	27,743	30,563	30,563
2SLS :								
No. of grandchildren	-0.633**	-1.163**	-0.435	-0.882*	-1.750	-0.222	-0.537	-0.571*
	(0.275)	(0.549)	(0.372)	(0.479)	(1.587)	(0.362)	(0.404)	(0.329)
Number of observations	54,270	25,203	25,953	16,633	10,563	22,800	28,986	25,284
Mean of dependent variable	6.12	5.81	6.87	5.88	5.90	6.87	6.50	5.68
S.d. of dependent. variable	4.33	4.17	4.40	4.35	4.29	4.32	4.58	3.98
Mean of grandchildren	2.57	2.45	2.77	2.48	2.52	2.74	2.78	2.33
Mean of twin	0.0144	0.0148	0.0130	0.0163	0.0142	0.0118	0.0135	0.0155
F-test of weak instrument	70.82	21.47	40.54	23.78	3.49	45.37	41.86	29.77

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The Number of Support Points are 3 in all specifications. δ is the coefficient in the Timing of Events Analysis. It can be interpreted as follows: the arrival of a first grandchild increases the exit probability by $exp(\delta) - 1\%$. The estimates in the second panel are based on the 2SLS approach outlined in Section 4. For comparison purpose, we also present the expected residual life time $Res(\bar{d})$ expressed in years for our Timing-of-Events samples for which we set $\bar{d}$ as the mean duration until the first grandchild for the respective sub-population. Details how the residual life time is calculated can be found in Section 3.

of time transfer. On the other hand, grandmothers with higher earnings might cope with a labor market exit more easily. Our results show that grandmothers at the upper half of the wage distribution react somewhat stronger to a grandchild – and in particular to an additional grandchild. These results might be due to an easier allocation of time and working time for this group of elderly women.

6 Conclusions

In this paper, we estimate the impact of grandparenthood on the labor supply of older female workers. We are distinguishing between the effect of the arrival of a first grandchild (intensive margin) and the impact of further grandchildren (extensive margin). To estimate the intensive margin we make use of a Timing-of-Events approach. We find that the arrival of a grandchild significantly reduces labor supply of grandmothers by approximately 0.68 years. Investigating the time dependence of the treatment effect, we find an interesting pattern: there is no effect during pregnancy, the effect is largest during the first three years of the child and gets lower, but still significant, when the child gets into kindergarden and school age. The estimated time pattern provides suggestive evidence that grandmothers partially time their labor market exit and provide child care when it is most needed.

Our estimation approach for the intensive margin is based on an IV approach, which also takes the censoring in our data into account. Applying a 2SLS estimation using a twin-birth as IV for the increase in the number of grandchildren, we find that a second grandchild reduces labor supply by approximately 0.63 years. The effect exhibits pronounced non-linearities with those at the bottom of the duration distribution being more affected by additional grandchildren compared to those at the top.

While these labor supply effects are quite homogenous regarding the extensive vs. intensive margin, there is ample heterogeneity across types of potential grandmothers. As expected, reductions in labor supply happen mostly in cases, when geographic distance between grandmother and grandchild is low. Somewhat unexpectedly, we find that grandmothers tend to reduce their labor supply more in communities with formal child-care institutions, as compared to communities without. This reaction could be due to fairly restricted time-schedules of such facilities, which make formal care and grandparental informal care complements.

These results give a clear indication that demographic trends in fertility and labor market exit for retirement are strongly related. Grandmothers play a substituting role for their daughters' labor supply allowing the daughter a quicker return to the labor market after childbirth. Formal child care for children under the age of three — in its current fairly restrictive form — does not resolve this tension. Most formal child-care settings are only part-time, and mothers who rely on this form of child care have to use complementary informal child care, i.e. the grandmother. These patterns show that policy interventions to increase fertility or to change pre-kindergarden child care may have unexpected side-effects as well.

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Web Appendix

This Web Appendix (not for publication) provides additional material discussed in the unpublished manuscript 'Grandmothers' Labor Supply' by Wolfgang Frimmel, Martin Halla, Bernhard Schmidpeter, and Rudolf Winter-Ebmer.

Table A.1: Results for Full Sample - 6 month Exit

	Model (I)			
	Exit hazard θ_E		Treatment hazard θ_G	
Panel A: Treatment effects				
δ	0.09	(0.01)		
Panel B: Unobserved heterogeneity				
ν_1	−5.49	(0.06)	−4.09	(0.05)
ν_2	0.74	(0.07)	−4.63	(0.27)
ν_3	−1.02	(0.07)	−3.74	(0.07)
$\Pr_{\nu_1}$	0.89	(0.00)		
$\Pr_{\nu_2}$	0.04	(0.00)		
$\Pr_{\nu_3}$	0.07	(0.00)		
Panel C: Duration dependence				
$\lambda_{(0-6]}$	ref.			
$\lambda_{(6-8]}$	1.19	(0.04)	1.01	(0.02)
$\lambda_{(8-10]}$	1.93	(0.04)	1.33	(0.02)
$\lambda_{(10-12]}$	2.67	(0.05)	1.73	(0.02)
$\lambda_{(12-14]}$	3.54	(0.05)	2.05(0.02)	
$\lambda_{(14-16]}$	4.40	(0.05)	2.27	(0.02)
$\lambda_{(16-18]}$	5.12	(0.05)	2.15	(0.03)
$\lambda_{(18-20]}$	5.85	(0.05)	1.71	(0.06)
$\lambda_{(20-\infty)}$	6.45	(0.07)	−0.30	(0.58)
Panel D: Covariate effects				
First grandchild by son	−0.04	(0.01)	1.29	(0.01)
Age $<$ 40 Years	−3.03	(0.03)	0.33	(0.03))
40 $\geq$Age $<$ 45 Years	−1.55	(0.02)	0.12	(0.03)
45$\geq$Age	ref.			
Wage (in Euro)	0.00	(0.00)	0.00	(0.00)
Missing wage is imputed	−0.33	(0.02)	−0.29	(0.02)
Experience (in years)	0.10	(0.00)	0.00	(0.00)
Has 1 Child	−0.53	(0.03)	−1.13	(0.03)
Has 2 Children	−0.47	(0.03)	−0.70	(0.03)
Has 3 Children	−0.26	(0.03)	−0.36	(0.03)
Has 4 Children or more	ref.			

The sample consists of (potential) grandmothers with at least one child aged 15 in 1993-1998 and 2.5 years of labor market experience with a total of 72,935 observations. The duration is measured until exit from the labor market for at least 6 month. Standard Errors are reported in parentheses. Standard errors for the probabilities are calculated using the delta method. In addition to the listed covariates, education, residential, and time dummies are included in the estimation.

Table A.2: The effect of the no. of grandchildren on the duration to labor market exit, including censored observations

	(1) OLS	(2) Reduced form	(3) First stage	(4) Second stage –v1	(5) Second stage –v2
No. of grandchildren	-0.021***			-0.293**	
	(0.007)			(0.128)	
Two or more grandchildren					-1.579***
					(0.461)
Twin birth (first grandchild)		-0.125**	0.427***		
		(0.053)	(0.032)		
First grandchild by son (vs. daughter)	0.049***	0.045***	0.228***	0.112***	0.181***
	(0.015)	(0.015)	(0.008)	(0.033)	(0.043)
Grandmother characteristics					
Has 2 children	0.115***	0.098***	0.792***	0.330***	0.443***
	(0.019)	(0.018)	(0.008)	(0.102)	(0.074)
Has 3 children	0.135***	0.105***	1.470***	0.536***	0.527***
	(0.027)	(0.026)	(0.014)	(0.189)	(0.109)
Has 4 children or more	-0.023	-0.071*	2.302***	0.605**	0.283**
	(0.043)	(0.042)	(0.026)	(0.297)	(0.141)
Educ. attainmnet (base group: low)					
Level 2	0.013	0.017	-0.199***	-0.041	0.140***
	(0.029)	(0.029)	(0.016)	(0.039)	(0.037)
Level 3	0.081***	0.086***	-0.279***	0.004	0.360***
	(0.030)	(0.030)	(0.018)	(0.047)	(0.039)
Level 4	0.079**	0.086**	-0.352***	-0.018	0.463***
	(0.040)	(0.040)	(0.025)	(0.061)	(0.052)
Level 5	0.235***	0.242***	-0.373***	0.133**	0.912***
	(0.037)	(0.037)	(0.027)	(0.061)	(0.048)
Level 6	0.078	0.086	-0.382***	-0.026	0.713***
	(0.054)	(0.054)	(0.035)	(0.074)	(0.069)
Level 7	0.164***	0.158***	0.244***	0.230***	0.414***
	(0.027)	(0.027)	(0.015)	(0.042)	(0.042)
Wage rate (daily):					
Wage (in Euro)	0.001**	0.001**	0.001***	0.001***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Missing wage is imputed	-0.213***	-0.214***	0.028**	-0.206***	-0.317***
	(0.025)	(0.025)	(0.012)	(0.026)	(0.030)
Labor market experience:					
Experience (in years)	0.013***	0.013***	-0.005***	0.012***	-0.025***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Grandmother's year of birth FE	Yes	Yes	Yes	Yes	Yes
Grandmother's month of birth FE	Yes	Yes	Yes	Yes	Yes
Grandmother's state of residence FE	Yes	Yes	Yes	Yes	Yes
Grandchild's year of birth FE	Yes	Yes	Yes	Yes	Yes
Grandchild's month of birth FE	Yes	Yes	Yes	Yes	Yes
Mother's age and income	Yes	Yes	Yes	Yes	Yes
Number of obs.	106,820	106,820	106,820	106,820	106,820
R-squared	0.72	0.72	0.31	0.72	0.61
Mean of dependent variable	6.80	6.80	2.46	6.80	6.80
S.d. of dependent variable	4.49	4.49	1.46	4.49	4.49
Exit rate	0.51	0.51	0.51	0.51	0.51
Mean of treatment				2.46	0.73
Mean of twin		0.0146	0.0146	0.0146	0.0146
F-test of weak instrument				181.63	176.50

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$