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December 2017

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Grandmothers' Labor Supply*

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December 8, 2017
(First version: September 18, 2017)

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 childcare 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 third generation is not correlated with unobserved determinants of the grandmother's labor supply (first generation). Our respective instrumental variable estimations show 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 examine 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 ability to transfer 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 generations. 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

[1] See, for instance, Rosenzweig and Wolpin (1980*a*); Killingsworth and Heckman (1986); Bronars and Grogger (1994); Angrist and Evans (1998); Herr (2015); Lundborg et al. (2017).

[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* (henceforth 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 the age of one and five.

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 third 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* 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 childcare 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 childcare 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 (rather than substitutes).

Existing research taking into account the extended family, mostly concentrates on the effect of grandparent-provided childcare on parental labor supply. These papers consistently find that grandparent-provided childcare 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 correlations 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*. Reinkowski (2013) finds a negative correlation between grandchild care and the employment of elderly women in data from the SHARE and the *German Ageing Survey* (GAS). 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 childcare, triggers the fertility decision.[5]

The closest related works 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 an 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 the empirical evidence provided by Dahl and Moretti (2008) on the effect of child sex on parental behavior, this is an assumption, which may be questioned. Rupert and Zanella (2016) 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 were already working less than full-time, at the time they became grandmothers. The effect at the extensive margin is more important than the corresponding one at the intensive margin.

Our paper is based on high-quality administrative data covering all potential grandmothers in Austria. This allows us to examine labour supply responses at the extensive, as well as the intensive margin. We employ two different estimation strategies, resting on different identifying assumptions. We explore heterogeneity across different institutional settings, which make the occurrence of such intergenerational sharing more or less probable, e. g. the availability of formal

[5]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.

early childcare institutions. Our study and our findings cover several important policy areas, such as childcare and pensions regulations. Showing a clear connection between changes in fertility, childcare costs and costs of the pension system is a new way to bring these demographic issues together. A holistic discussion of these imminent demographic problems seems especially important in a pay-as-you-go pension system. While there may be more obvious interactions between reforms in childcare and — current — pension inflows, there may also be more dynamic interactions. For instance, 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 heterogeneous 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 childcare, and pension regulations. After this we briefly describe our data sources.

Maternity and parental leave After childbirth, 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.[6] While the exact regulations have varied over time, parental leave has always been almost universal (Danzer et al., 2017). Thus, during the first two years after childbirth, grandparental child caring is certainly appreciated by the parents; however, it is not as crucial given the generous leave regulations.

Formal childcare The Austrian system of formal childcare distinguishes between facilities for children below the age of three (nurseries, *Kinderkrippe/Krabbelstube*) and for those aged three to six (kindergarten, *Kindergarten*). While the vast majority of communities have a kindergarten 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 return to work after parental leave has elapsed, was (and is) often hampered by the lack of appropriate formal-care arrangement. This conjecture is clearly confirmed by survey data (Baierl and

[6] 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.

Kaindl, 2011). As expected, in such a situation the extended family is the main source of childcare, with a potentially important role for grandparents. Survey data show that this is in particular true for working-age grandparents (Kaindl and Wernhardt, 2012).

Pension regulation Compared to other OECD countries, Austria shows high replacement rates and a relatively low retirement age. Replacement rates reach up to 80 percent of the assessment basis (best 15 years of earnings), given the worker had 45 contribution years. While legal 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 in 2000 and 2003, leading to a full abolishment for men born in the cohort 1952 and women born in 1957 (Staubli and Zweimüller, 2013). However, there is still the possibility to enter early retirement via disability pension. Given these regulations, the average pension entry age was only 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. These data cover all Austrian workers and provide detailed information on labor market participation. 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.[7] The details on sample selection are summarized in Section 3.2 for the extensive margin 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

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

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 both challenges by applying the ToE approach proposed by Abbring and van den Berg (2003). Thus, we 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.[8]

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 suggestive 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.[9]

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

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

[9]For the unlikely case of anticipation in our setting, the argument by Richardson and van den Berg (2013) applies 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.

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 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 parameterized in the following fashion, which helps us to avoid the use of constrained maximization:

$$p_m = P(\nu_E = \nu_E^m, \nu_G = \nu_G^m) = \frac{exp(\alpha_m)}{\sum_{m=1}^{M} exp(\alpha_m)}. \tag{3}$$

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), the time until the conception of the

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

grandchild $D_{i,}$ (or censoring) for each of these individuals, the log-likelihood function for our empirical model is defined as

$$L = \sum_{i=1}^{N} \log \left\{ \sum_{m=1}^{M} p_m \; \theta_E(T_i|x_i, \nu_E^m, D_i)^{\Delta_{i,E}} exp \left(- \int_0^{T_i} \theta_E(T_i|x_i, \nu_E^m, D_i) \right) \right. \\ \left. \theta_G(D_i|x_i, \nu_G^m)^{\Delta_{i,G}} exp \left(- \int_0^{D_i} \theta_G(D_i|x_i, \nu_G^m) \right) \right\} . \tag{4}$$

$\Delta_{i,E}$ 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 by Gaure et al. (2007*a*,*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 potential 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 the cases were a grandchild is born, we use the 15th birthday of the offspring with the *first* grandchild as the reference date, from which on we measure all durations. In the cases without a grandchild (born until the end of 2013), we take the 15th birthday of the oldest offspring as the reference date. 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 exhibit a certain degree of labor market attachment, we require that potential grandmothers have accumulated at least 2.5 years of labor market experience within three 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 potential grandmother had not exited the labor market until December 31, 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

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

or after December 31, 2013, the individual is regarded as non-treated.

[Table 1]

Table 1 provides an overview over the sample and separate statistics by treatment status. In total, our sample comprises 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 December 31, 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 eventually are grandmothers tend to have slightly less experience in the labor market.

[Figure 1]

Figure 1 depicts estimated yearly transition rates into leaving the labor force (solid line) and treatment state (dashed line), respectively. The exit hazard does not change much during the first 12 years of our observation period, when the majority of women 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.* We provide further evidence for this in our analysis in Section 3.4.

3.3 Estimation results

Table 2 summarizes estimation output for two different specifications of our ToE model. 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 these 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.

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]

[Table 2]

The estimated duration dependence summarized in Panel C of Table 2 is essentially identical for the two 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 as 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

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

the son has become a parent. The labor market exit hazard is three percent higher in the case of the daughter's child (as compared to the son's child).

3.3.3 Main results: Effect of the first 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 $(= [e^{0.082} - 1] * 100)$ percent. This effect is highly statistically significant and indicates that the fertility decision of the extended 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 childcare on retirement.[13] 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) as in our case. 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.[14]

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.[15] 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 one and six months (see Panel A of Figure 2). In such a calculation, using the average daily pre-treatment wage rate of the individual, our counterfactual results imply an average individual income loss in the range of around $1,750$ Euros to $7,250$ Euros (see Panel B of Figure 2). This effect corresponds to a loss of 12 to 50 percent of annual income and is quite substantial. Note that these calculations constitute a likely lower bound, since our 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 analyze, whether a part of this loss is due to problems in finding suitable childcare.

[13]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 would be upward biased.

[14]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).

[15]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 21 years, close to the maximum duration we observe in our sample.

[Figure 2]

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 instance, they may start providing informal childcare, when parental 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 after cooonception. 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 would find 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.[16] We set the third and fourth knot at 45 and 87 months, respectively. Around age 3 children start enrol in kindergarten. At months 87 after the conception, the grandhcild reaches compulsory school age, which lies between ages 6 and 7 in Austria. Since the availability of full-time kindergarten 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 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 kindergarten.[17] Thereafter, the treatment effect decreases slightly, but it remain highly significant during the whole schooling period. 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, we can reject the null hypothesis of a constant treatment effect at the 7 percent level.[18] The rest of our estimates are similar to those

[16] 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.

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

[18] 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.

obtained by Model (I).

We conclude that grandmothers react stronger during times, where informal childcare 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. In Table A.1 in the Web Appendix, we replicate our main results with a minimum exit duration of 6 (instead of 12) months. This gives us very similar estimated effects. We conclude 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 remaining concern with respect to our identification is reversed causality. It is possible that children strategically decide to conceive a child, when the grandmother's retirement date approaches. Put differently, the expected retirement of the potential grandmother might trigger fertility behavior of the offspring (and not *vice versa*). To investigate this potential problem, we focus on potential grandmothers, who are not eligible to retirement during our observation period.[19]

In particular, we restrict the sample to potential grandmothers, who are born between January 1, 1955 and December 31, 1960. Since all potential grandmothers in this sample are younger than 58 years of age 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 (see Section 2), we also estimate our treatment effects concentrating on very young (potential) grandmothers, born after the 1st of January 1958. We refer to this group as 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.

[Table 3]

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

[19] 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.

duration dependence and unobserved heterogeneity. Looking at our treatment effect, we find that restricting the sample to younger individuals does increase our treatment effects. In the Age-58 Sample the arrival of a grandchild increases the exit probability by 20. In the Age-55 Sample the effect is even slightly higher and mounts to 23 percent. These effects are substantially larger compared to our baseline estimates reported in Table 2. In light of these findings, we are confident that our results capture the causal effect of a first grandchild on the labor supply of grandmothers (and not the reversed relationship). 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 nine months after conception (see Table 2).

4 The effect of further grandchildren

So far, we have concentrated on the effect of the first grandchild on grandmothers' labor market exit. In this section, we investigate the effect of additional grandchildren using two alternative IV estimations approaches. In either case, we exploit exogenous variation in the number of grandchildren due a twin birth among the first grandchild.

4.1 Estimation sample and descriptive statistics

To obtain our estimation sample for the analysis of the effect of further grandchildren, we consider all women born between 1950 and 1960, with at least one child born 1973 or later, with at least 2.5 years of labor market experience within 3 years before the reference date (i. e., 15th birthday of the offspring with the first grandchild), who became grandmother before 2014. Applying these criteria gives us an estimation sample of $106,820$ women. Figure 3 displays the distribution of these women's age at first grandparenthood (see Panel A) and their total number of grandchildren born by the end of 2013 (see Panel B). These women became on average grandmother at age 49.8, and by 2014 they had on average 2.5 grandchildren. About 64 percent of them had two or more grandchildren, and about 21 percent had 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. In our sample, 51 percent of women ($N = 54,270$) leave the labor market before 2014. In this sub-sample of uncensored observations, the average duration until the first long term exit is 6.1 years after grandparenthood. At this point in time, they are on average 55.4 years old. The distribution of these measures is depicted in Panels C and D of Figure 3. For the remaining 49 percent of women ($N = 52,550$), we do not observe the labor market exit.[20] These observations are censored. The average age at censoring is 56.2 years.

Below we will suggest now two alternative IV estimation approaches. The first strategy,

[20] Among these, $1,745$ women died before their labor market exit. All other women were still active in the labor market by the end of 2013 (based on our 12-month spell of non-employment criterion as used above).

a conventional *two-stage least squares* approach, focuses on the subset of women who have uncensored, i. e. complete, durations. The second method, a *censored quantile treatment effects estimator*, 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. The exit rates and the average age at censoring are the same for women with and without twin status.

[Figure 3 and Table 4]

Table 4 provides sample means for all variables. Column (1) refers to the overall sample. Column (2) to (6) refer to the sub-sample of uncensored observations. Column (2) is based on the overall uncensored sample, while columns (3) and (4) distinguish between grandmothers, whose first grandchild was a single birth and those with a twin birth (twin status). Columns (5) and (6) provide information on the difference between the sample means in the two respective sub-samples. Most importantly, we can see that the number of grandchildren (our endogenous treatment variable) has a significantly higher mean in the sample of grandmothers with a positive twin status. A twin birth significantly increases the total number of grandchildren by around 0.11. Among the latter group the share of women with two or more grandchildren is also significantly higher (0.82 versus 0.76). We will exploit these significant differences as first stages in our IV estimation approaches below to identify the causal effect of another grandchild on grandmothers' labor market exit.

The descriptive statistics in Table 4 suggest a significant difference in the duration to labor market exit between grandmothers with different twin status. A twin birth at the birth of the first grandchild decreases labor market exit on average by 1.36 years or 29 percent. In contrast, in terms of pre-treatment characteristics, grandmothers with and without a twin status are very comparable. All characteristics are measured 15 years after the birth of the reference child. Most importantly, we do not see any significant difference with respect to their year of birth or any labor market characteristic. The observable difference in their educational attainment distribution is quantitatively negligible. Notably, grandmothers with a positive twin status, have on average somewhat less own children (1.81 versus 1.93).

In the lowest panel of Table 4, we compare characteristics of the mothers (i. e., the daughters or daughters in law of our grandmothers). As expected, we see more pronounced differences here. Mothers of twins tend to be slightly older, had their first birth later and had higher pre-birth wages. This may reflect a correlation between fertility treatments (typically utilized by older and more career-oriented women) and the occurrence of twin births. Such a correlation does not invalidate our identification strategy (to be discussed in detail below), which assumes that twin status is not correlated with unobserved determinants of grandmother's labor supply, but does *not* refer to the unobserved determinants of mother's labor supply.

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]

4.2.1 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 *two-stage least squares* (2SLS) estimation approach, where the dependent variable in the first stage is equal to the total number of grandchildren by grandmother i:

$$grandchildren_i = \alpha + \beta \cdot twin1_i + \Gamma \cdot \mathbf{X}_i + u_i. \tag{5}$$

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 variables we include the sex of the child, the number of children the grandmother has, and some socio-economic 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:

$$labor\,market\,exit_i = \delta + \tau \cdot \widehat{grandchildren}_i + \Delta \cdot \mathbf{X}_i + v_i. \tag{6}$$

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.[22]. As an alternative endogenous treatment variable, we use a binary variable K_i. This variable is equal to one, if the grandmother i has two or more grandchildren, and zero otherwise.

The identifying assumption is that the occurrence of twins in the third generation is uncorrelated with v_i unobserved determinants of first generation's (i. e., the grandmother's) labor supply. This is a much weaker assumption as compared to the one used for previous papers using the twin-IV to study the labor supply of mothers. These papers have to assume that unobserved factors, which affect the occurrence of twins among a sample of mothers, do not have

[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).

[22]Estimation results based on the overall sample, which also includes women who are censored, are summarized in Table A.2 in the Web Appendix

an impact of the labor supply of these mothers. In contrast, we only have to assume that these unobserved factors do not have an impact on the labor supply of the respective grandmothers.

There are two known determinants affecting the occurrence of a twin birth; both of which refer to the biological mother (and not to the grandmother). A higher maternal age and fertility treatments (in particular, *in vitro* fertilization) are positively related to likelihood of a multiple birth. Beyond these two factors, the occurrence of multiple births is believed to be random. While there is no reason to assume that these two known factors have an impact on grandmother's labor supply, we follow a conservative strategy and try to explicitly control (or at least proxy) 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 fertility treatment is less straightforward, since we do not have information on this in our data. We know, however, that fertility treatments are mainly used by older and more career-oriented women. Thus, we control (besides mother's age at first birth) also for her pre-birth labor income. As expected, the exclusion of these two variables does not alter our results.

4.2.2 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.[23] 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.

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 2SLS estimation approach without censoring, the c2SLS estimator relies on minimal assumptions.[24] Second, by concentrating on quantiles we allow the treatment

[23]Ignoring the censoring and applying 'conventional' 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).

[24]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

to differ along the duration distribution. The downside of this method is its restriction to binary treatments. Therefore, we focus here on our alternative binary treatment variable, K, which indicates grandmothers with two or more grandchildren.

The estimation proceeds in two steps. In a first step, we estimate the IV probability $\pi(X) = P(twin1 = 1|X)$, where $twin1$ is our binary twin indicator as defined above, by means of logistic regressions. We then construct weights as proposed by Frölich and Melly (2013): $w = \frac{twin1-\pi(X)}{\pi(X)(1-\pi(X))}(2K-1)$, where K is the endogenous treatment indicator equal to one, 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:

$$F_{(1|\text{compliers})}(y) = \frac{E\left[K\mathbb{1}(Y \leq y)w|C > y\right]}{E\left[Kw|C > y\right]}, \tag{7}$$

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 $w^+ = E[w|Y, K]$, 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

$$\Delta(\tau) = Q_{Y(1|\text{compliers})(\tau)} - Q_{Y(0|\text{compliers})(\tau)}, \tag{8}$$

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. In this setting, the local quantile treatment effect can be interpreted as the quantile treatment effect on the non-treated. This parameter provides estimates of what would happen to the labor supply of grandmothers with only one grandchild, if we would increase the number of their grandchildren to at least two.

4.3 Estimation results: Effect of the further grandchildren on labor market exit

Two-stage least squares estimation Table 5 summarizes our 2SLS results for the effect of the number of grandchildren on the labor market exit of the grandmother. For comparison,

does not allow for heteroscedasticity which certainly is present in our data.

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 twin indicator (which is equal to one if the birth of the grandmother's first grandchild was a twin birth, and zero otherwise). 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 F-statistic of the IV is above 70. Thus, we do not face the problem of a weak instrument. 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).

[Table 5]

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 due to the twin birth as good as randomly. This provides us with a LATE 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 2SLS estimate is considerably higher than the OLS coefficient. This may either result from an omitted variables bias in the OLS estimate or from 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 grandmother's labor market exit.

Censored two-stage least squares estimation Figure 4 depicts our c2SLS estimates of having two or more grandchildren (as compared to having one) on the grandmother's duration to labor market exit. This estimation procedure exploits the same IV as our 2SLS estimation, but uses the overall sample (comprising censored and non-censored observations). Figure 4 shows $\Delta(\tau)$ for the full distribution together with a 95 percent significance interval. It reveals a strong and significant impact of further grandchildren on the duration to labor market exit of grandmothers: For the 5th percentile, we estimate a strong negative treatment effect of 3.9 years less. After the 4th quantile, this negative effect ceases to be existent. Integrating $\Delta(\tau)$ over all quantiles, we estimate an average loss in employment of around minus 0.43 years.

[Figure 4]

For comparison purposes, Column (5) of Table 5 lists the results of our 2SLS approach using the same binary treatment variable K. The estimated effect of minus 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. 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 resembles the pattern of the c2SLS estimation shown above: results are smaller for more attached women.

5 Heterogeneous effects

We now turn to the analysis of heterogeneous treatment effects. In the Table 6, we summarize our respective estimates for the first grandchild in Panel A, and those for further grandchildren in Panel B. To facilitate a comparison of estimates across panels/methods, we present in the case of Panel A the expected residual life time $Res(\bar{d})$ for the extensive margin. Here we set $\bar{d}$ as the mean duration until the first grandchild for the respective sub-population. Column (1) reiterates our baseline estimates for the overall sample. Here the estimated $Res(\bar{d})$ of minus 0.45 suggests that the first grandchild reduces grandmothers' average labor force participation by about half a year. In comparison, an additional grandchild (due to a twin birth among the first grandchild) reduces the duration to labor market exit by 0.63 years. This suggests that labor market responses of grandmothers to the first and further grandchildren are *on average* quite comparable.[25]

[Table 6]

In the remaining columns of Table 6, we explore patterns of potential treatment effect heterogeneity. We look at the availability of a nursery in grandchildren's home municipality (see columns 2a and 2b), geographic distance measured in driving minutes between grandmothers and grandchildren (see columns 3a and 3b), and grandmaternal earnings (see columns 4a and 4b).[26] The local availability of a nursery (i. e., the only formal childcare arrangement for

[25]This also holds for our c2SLS estimation, where we estimate an average loss in employment of around 0.43 years.

[26]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 5. This is the average age of women becoming a grandmother in our sample.

children below three years of age) is clearly an important dimension. On the one hand, the availability of a nursery might decrease the necessity of informal childcare. Hence, one would expect a negative or zero effect. On the other hand, most of the nurseries do not offer full-time care. Therefore, the availability and the use of formal childcare may trigger additional informal childcare by grandmothers. We re-estimate our models separately for the sample living in communities with and without nurseries, respectively. We find stronger effects of grandparenthood on labor supply if formal childcare is available, and smaller effects if there is no formal childcare in the community. This findings holds for both, the first and for an additional grandchild. Again, the results are fairly comparable with minus 0.6 and minus 1.2 years with formal childcare, and minus 0.3 and minus 0.4 years for communities without. This result suggests that formal institutions and grandparental time are complements in the provision of childcare.

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 or 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 childcare. 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 grandmother-grandchild 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 1.6 (extensive margin) and 0.9 years (intensive margin). The estimated effects for those with larger distances are consistently smaller.[27] 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 grandchildren, since 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 to provide more financial support instead 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.

[27] In the 2SLS model, the result for 30-90 minutes distance is numerically larger, but insignificant and also hampered by a very low F-test in the first stage.

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 (extensive margin) and the impact of further grandchildren (intensive margin). To estimate the extensive margin we make use of a ToE approach. We find that the arrival of a grandchild significantly reduces labor supply of grandmothers by approximately 0.5 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, decreases thereafter, but is still significant, when the child enrols in kindergarten and throughout school age. The estimated time pattern provides suggestive evidence that grandmothers partially time their labor market exit and provide childcare 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. Exploiting the occurrence of a twin birth at the birth of the first grandchild as a source of exogneous variation in the number of grandchildren, we find that a further grandchild reduces labor supply by approximately 0.4 years. The estimated effect exhibits pronounced non-linearities, with those at the bottom of the duration distribution being more affected by additional grandchildren as compared to those at the top.

While these labor supply effects are quite comparable at the extensive and the 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 childcare 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' (or daughters-in law) labor supply, allowing them a quicker return to the labor market after childbirth. Formal childcare for children under the age of three — in its current fairly restrictive form — does not resolve this tension. Most formal childcare settings are only part-time, and mothers, who rely on this form of childcare have to use complementary informal childcare, i. e. the grandmother. These patterns show that policy interventions to increase fertility or to change pre-kindergarten childcare may have unexpected side-effects on the labor supply of older women.

References

Aassve, Arnstein, Bruno Arpino and Alice Goisis (2012), 'Grandparenting and Mothers' Labour Force Participation: A Comparative Analysis Using the Generations and Gender Survey', *Demographic Research* **27**(3), 53–84.

Aassve, Arnstein, Elena Meroni and Chiara Pronzato (2012), 'Grandparenting and Childbearing in the Extended Family', *European Journal of Population* **28**(4), 499–518.

Abadie, Alberto (2003), 'Semiparametric Instrumental Variable Estimation of Treatment Response Models', *Journal of Econometrics* **113**(2), 231–263.

Abbring, Jaap H. and Gerard J. van den Berg (2003), 'The Nonparametric Identification of Treatment Effects in Duration Models', *Econometrica* **71**(5), 1491–1517.

Angrist, Joshua D. and William N. Evans (1998), 'Children and Their Parents' Labor Supply: Evidence from Exogenous Variation in Family Size', *American Economic Review* **88**(3), 450–477.

Aparicio-Fenoll, Ainhoa and Marian Vidal-Fernandez (2014), 'Working Women and Fertility: The Role of Grandmothers Labor Force Participation', *CESifo Economic Studies* **61**(1), 123–147.

Arpino, Bruno, Chiara D. Pronzato and Lara P. Tavares (2014), 'The Effect of Grandparental Support on Mothers Labour Market Participation: An Instrumental Variable Approach', *European Journal of Population* **30**(4), 369–390.

Baierl, Andreas and Markus Kaindl (2011), Kinderbetreuung in Österreich - Rechtliche Bestimmungen und die reale Betreuungssituation, Working Paper 77, Austrian Institute of Family Studies, Vienna, Austria.

Battistin, Erich, Michele DeNardi and Mario Padula (2014), Roadblocks on the Road to Grandma's House: Fertility Consequences of Delayed Retirement, IZA Discussion Paper 8071, Institute for the Study of Labor, Bonn, Germany.

Bratti, Massimiliano, Tommaso Frattini and Francesco Scervini (2016), Grandparental Availability for Child Care and Maternal Employment: Pension Reform Evidence from Italy, IZA Discussion Paper 9979, Institute for the Study of Labor, Bonn, Germany.

Bronars, Stepehn G. and Jeff Grogger (1994), 'The Economic Consequences of Unwed Motherhood: Using Twin Birth as Natural Experiment', *American Economic Review* **84**(5), 1141–1156.

Cardia, Emanuela and Serena Ng (2003), 'Intergenerational Time Transfer and Childcare', *Review of Economic Dynamics* **6**(2), 431–454.

Colombo, Bernardo and Guido Masarotto (2000), 'Daily Fecundability: First Results from a New Data Base', *Demographic Research* **3**(5).

Compton, Janice and Robert A. Pollak (2014), 'Family Proximity, Childcare, and Women's Labor Force Attachment', *Journal of Urban Economics* **79**, 72–90.

Dahl, Gordon B. and Enrico Moretti (2008), 'The Demand for Sons', *The Review of Economic Studies* **75**(4), 1085–1120.

Danzer, Natalia, Martin Halla, Nicole Schneeweis and Martina Zweimüller (2017), Parental Leave, (In)formal Childcare and Long-term Child Outcomes , IZA Discussion Paper 10812, Institute for the Study of Labor, Bonn, Germany.

Dimova, Ralitza and François-Charles Wolff (2011), 'Do Downward Private Transfers Enhance Maternal Labor Supply? Evidence from around Europe', *Journal of Population Economics* **24**(3), 911–933.

Eibich, Peter and Thomas Siedler (2016), Retirement, Intergenerational Time Transfers, and Fertility, Unpublished manuscript, University of Oxford and University of Hamburg.

Ellis, Renee R. and Tavia Simmons (2014), 'Coresiding Grandparents and Their Grandchildren: 2012', *report October* .

Frandsen, Brigham R. (2015), 'Treatment Effects With Censoring and Endogeneity', *Journal of the American Statistical Association* **110**(512), 1745–1752.

Frölich, Markus and Blaise Melly (2013), 'Unconditional Quantile Treatment Effects Under Endogeneity', *Journal of Business & Economics Statistics* **31**(3), 346–357.

Gaure, Simen, Knut Røed and Tao Zhang (2007*a*), 'Time and Causality: A Monte Carlo Assessment of the Timing-of-Events Approach', *Journal of Econometrics* **141**(2), 1159–1195.

Gaure, Simen, Knut Røed and Thao Zhang (2007*b*), Details of Estimation - Elaborating on Time and Causality. Unpublished manuscript.

Glaser, Karen, Debora Price, Giorgio DiGessa, Eloi Ribe, Rachel Stuchbury and Anthea Tinker (2013), 'Grandparenting in Europe: Family Policy and Grandparens' Role in Providing Childcare', *report March* .

Hank, Karsten and Isabella Buber (2009), 'Grandparents Caring for their Grandchildren Findings from the 2004 Survey of Health, Ageing, and Retirement in Europe', *Journal of Family Issues* **30**(1), 53–73.

Heckman, James J. and Burton Singer (1984), 'A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data', *Econometrica* **52**(2), 271–320.

Heckman, James J. and James R. Walker (1990), 'Estimating Fecundability From Data on Waiting Times to First Conception', *Journal of the American Statistical Association* **85**(410), 283–294.

Herr, Jane Leber (2015), 'The Labor Supply Effects of Delayed First Birth', *American Economic Review Papers & Proceedings* **105**(5), 630–637.

Ho, Christine (2015), 'Grandchild Care, Intergenerational Transfers, and Grandparents Labor Supply', *Review of Economics of the Household* **13**(2), 359–384.

Hochman, Oshrat and Noah Lewin-Epstein (2013), 'Determinants of Early Retirement Preferences in Europe: The Role of Grandparenthood', *International Journal of Comparative Sociology* **54**(1), 29–47.

Imbens, Guido W. and Joshua D. Angrist (1994), 'Identification and Estimation of Local Average Treatment Effects', *Econometrica* **62**(2), 467–475.

Jacobsen, Joyce P., James Wishart Pearce III and Joshua L. Rosenbloom (1999), 'The Effects of Childbearing on Married Women's Labor Supply and Earnings: Using Twin Births as a Natural Experiment', *Journal of Human Resources* **34**(3), 449–474.

Kaindl, Markus and Georg Wernhardt (2012), Wie Großeltern ihre Kinder und Enkelkinder unterstützen - Persönliche und finanzielle Hilfe von Großeltern aus Sicht der Großeltern und der erwachsenen Kindern, Working Paper 78, Austrian Institute for Family Studies, University of Vienna.

Kaptijn, Ralf, Fleur Thomese, Theo G. van Tilburg and Aart C. Liefbroer (2010), 'How Grandparents Matter', *Human Nature* **21**(4), 393–405.

Killingsworth, Mark R. and James J. Heckman (1986), Female Labor Supply: A Survey, *in* O.Ashenfelter and R.Layard, eds, 'Handbook of Labor Economics', Vol. 1, Elsevier.

Larsen, Ulla and James W. Vaupel (1993), 'Hutterite Fecundability by Age and Parity: Strategies for Frailty Modeling of Event Histories', *Demography* **30**(1), 81–102.

Lehrer, Evelyn L. and Seiichi Kawasaki (1985), 'Child Care Arrangements and Fertility: An Analysis of Two-earner Households', *Demography* **22**(4), 499–513.

Leopold, Thomas and Jan Skopek (2015), 'The Demography of Grandparenthood: An International Profile', *Social Forces* **94**(2), 801–832.

Loughran, David S. and Julie M. Zissimopoulos (2009), 'Why Wait? The Effect of Marriage and Childbearing on the Wages of Men and Women', *Journal of Human Resources* **44**(2), 326–349.

Lumsdaine, Robin L. and Stephanie J.C. Vermeer (2015), 'Retirement Timing of Women and the Role of Care Responsibilities for Grandchildren', *Demography* **52**(2), 433–454.

Lundberg, Shelly and Elaina Rose (2000), 'Parenthood and the Earnings of Married Men and Women', *Labour Economics* **7**(689–710).

Lundberg, Shelly and Elaina Rose (2002), 'The Effects of Sons and Daughters on Men's Labor Supply and Wages', *Review of Economics and Statistics* **84**, 251–268.

Lundborg, Petter, Erik Plug and Astrid Würtz Rasmussen (2017), 'Can Women Have Children and a Career? IV Evidence from IVF Treatments', *American Economic Review* **107**(6), 1611–1637.

Newey, Whitney K. (1987), 'Efficient Estimation of Limited Dependent Variable Models with Endogenous Explanatory Variables', *Journal of Econometrics* **36**(3), 231–250.

Posadas, Josefina and Marian Vidal-Fernandez (2013), 'Grandparents Childcare and Female Labor Force Participation', *IZA Journal of Labor Policy* **2**(1), 14.

Reinkowski, Janina (2013), Does Grandchild Care Conflict with Grandparents' Employment, Technical report, Ifo Institute, Munich.

Richardson, Katarina and Gerard J. van den Berg (2013), 'Duration Dependence versus Unobserved Heterogeneity in Treatment Effects: Swedish Labor Market Training and the Transition Rate to Employment', *Journal of Applied Econometrics* **28**(2), 325–351.

Rosenzweig, Mark R. and Kenneth I. Wolpin (1980*a*), 'Life-Cycle Labor Supply and Fertility: Causal Inference from Household Models', *Journal of Political Economy* **88**(2), 328–348.

Rosenzweig, Mark R. and Kenneth I. Wolpin (1980*b*), 'Testing the Quantity-Quality Fertility Model: The Use of Twins as a Natural Experiment', *Econometrica* **48**(1), 227–240.

Rupert, Peter and Giulio Zanella (2016), 'Grandchildren and Their Grandparents Labor Supply', *mimeo March* .

Slama, R., O.K.H. Hansen, B. Ducot, A. Bohet, D. Sorensen, L. Giorgis Allemand, M.J.C. Eijkemans, L. Rosetta, J.C. Thalabard, N. Keiding and J. Bouyer (2012), 'Estimation of the Frequency of Involuntary Infertility on a Nation-Wide Basis', *Human Reproduction* **27**(5), 1489–1498.

Staubli, Stefan and Josef Zweimüller (2013), 'Does Raising the Early Retirement Age Increase Employment of Older Workers?', *Journal of Public Economics* **108**, 17–32.

Stiglbauer, Alfred (2013), 'Effective Retirement Age in Austria – A Review of Changes since 2000', *Monetary Policy & the Economy* **1**, 29–49.

Van Bavel, Jan and Tom De Winter (2013), 'Becoming a Grandparent and Early Retirement in Europe', *European Sociological Review* **29**(6), 1295–1308.

Vere, James P. (2011), 'Fertility and Parents' Labour Supply: New Evidence from US Census Data', *Oxford Economic Papers* **63**(2), 211–231.

Wang, Ying and Dave E. Marcotte (2007), 'Golden Years? The Labor Market Effects of Caring for Grandchildren', *Journal of Marriage and Family* **69**(5), 1283–1296.

Wilcox, Allen J., Clarice R. Weinberg and Donna D. Baird (1995), 'Timing of Sexual Intercourse in Relation to Ovulation', *The New England Journal of Medicine* **333**(23), 1517–1521.

Wulff Pabilonia, Sabrina and Jennifer Ward-Batts (2007), 'The Effect of Child Gender on Parents' Labor Supply: An Examination of Natives, Immigrants, and their Children', *American Economic Review Papers and Proceedings* **97**(2), 402–406.

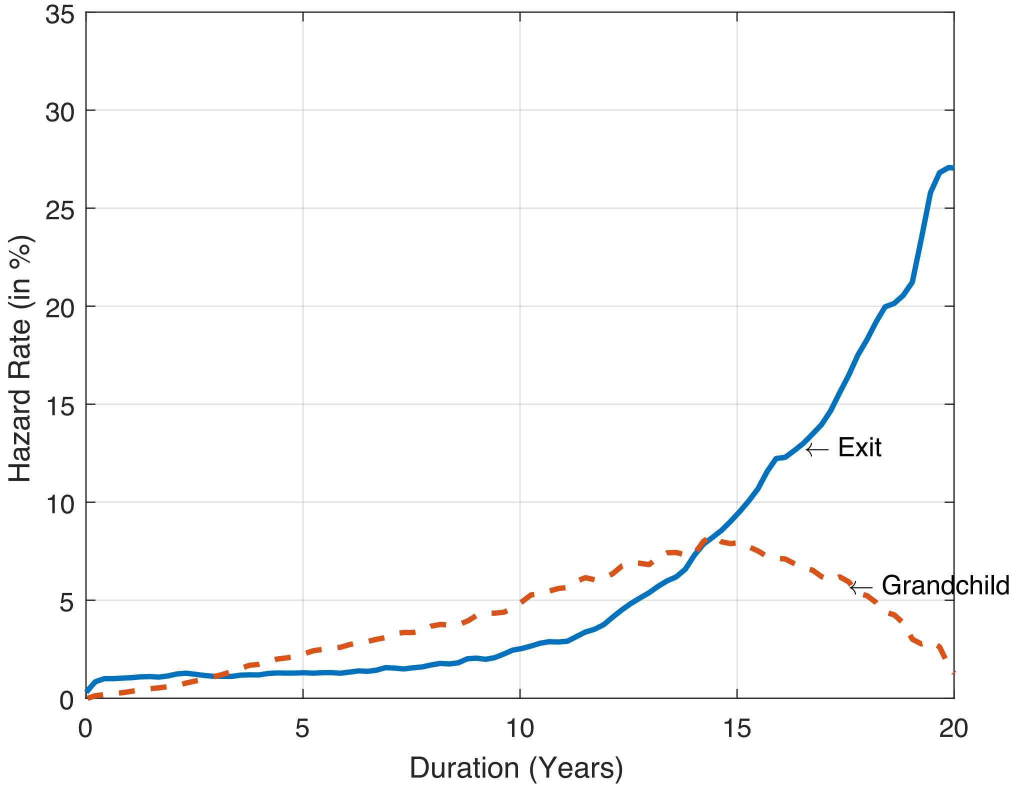
Zamarro, Gema (2011), 'Family Labor Participation and Child Care Decisions - The Role of Grannies', *RAND WR-833* .

Zanella, Giulio (2017), 'How Does Grandparent Childcare Affect Labor Supply?', *IZA World of Labor* **337**.

Zweimüller, Josef, Rudolf Winter-Ebmer, Rafael Lalive, Andreas Kuhn, Jean-Philippe Wuellrich, Oliver Ruf and Simon Büchi (2009), The Austrian Social Security Database (ASSD), Working Paper 0901, The Austrian Center for Labor Economics and the Analysis of the Welfare State, University of Linz.

7 Figures (to be placed in the article)

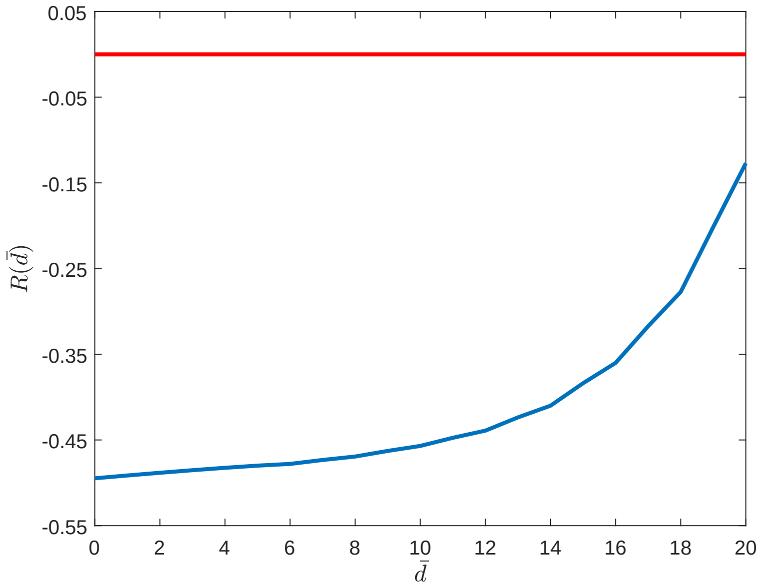
Figure 1: Kaplan-Meier transition rate



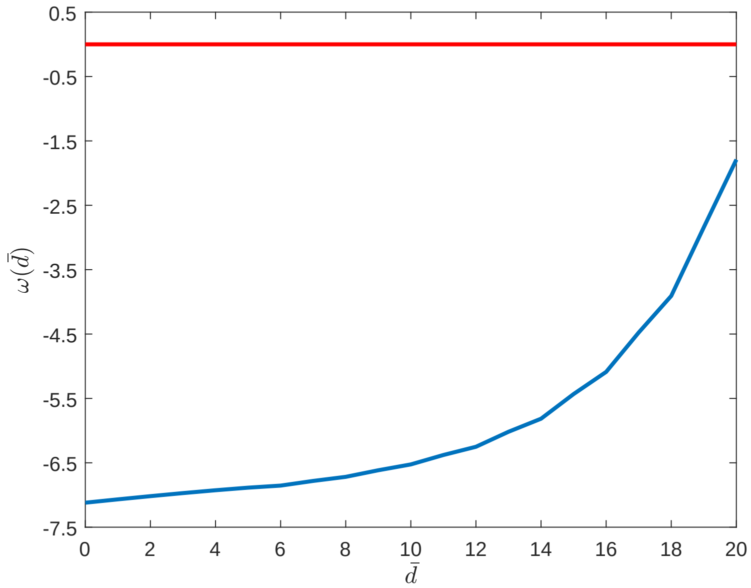
Notes: The solid line represents the estimated yearly transition rate out of labor force (outcome: labor market exit), the dashed line the yearly transition rate into grandparenthood (treatment: conception of first grandchild). The sample consists of all (potential) grandmothers with at least one child aged 15 in 1993-1998 and at least 2.5 years of labor market experience within 3 years before the reference date (15th birthday of the reference child).

Figure 2: Average loss in employment years and income due to first grandchild

Panel A: Loss in employment years

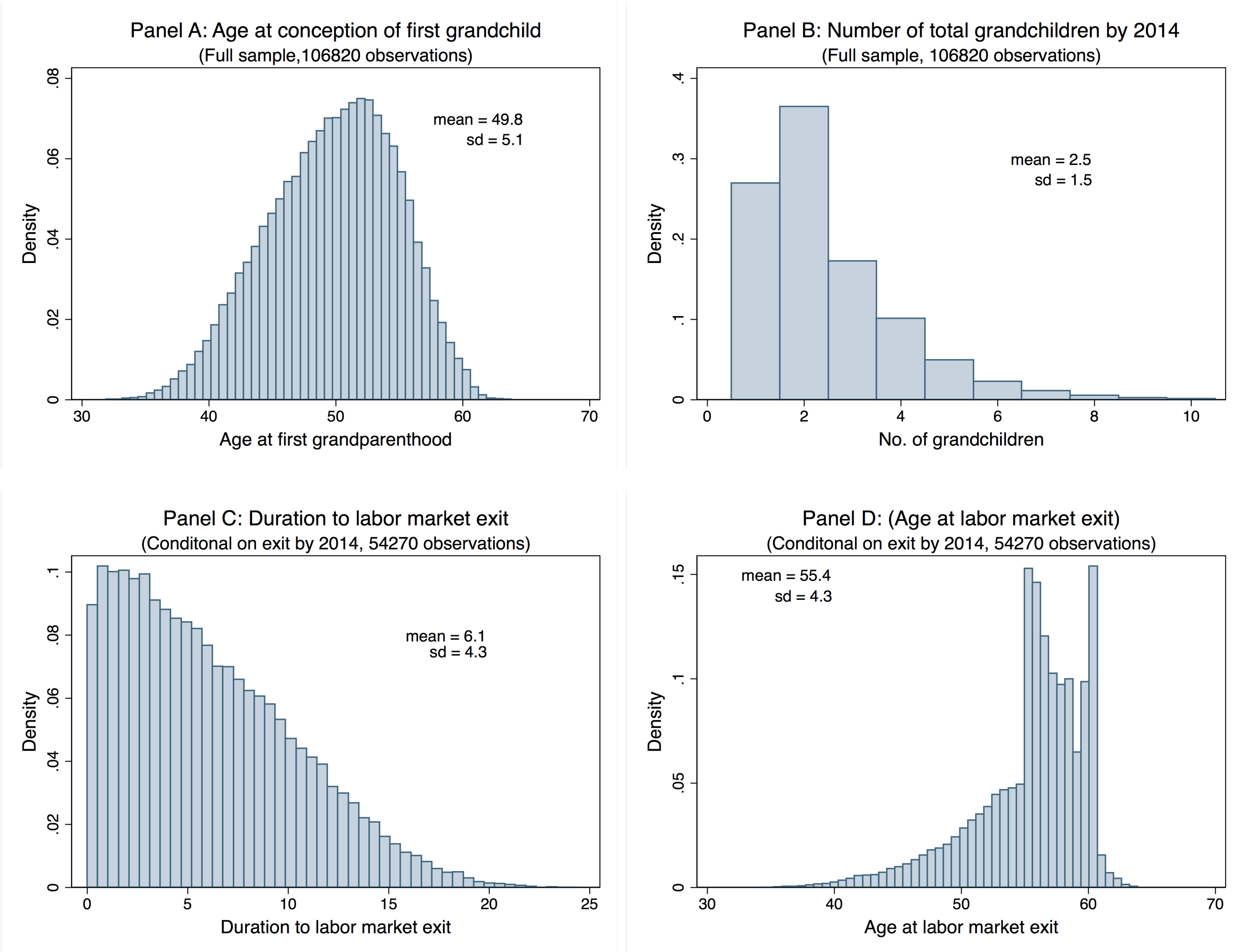


Panel B: Loss in income



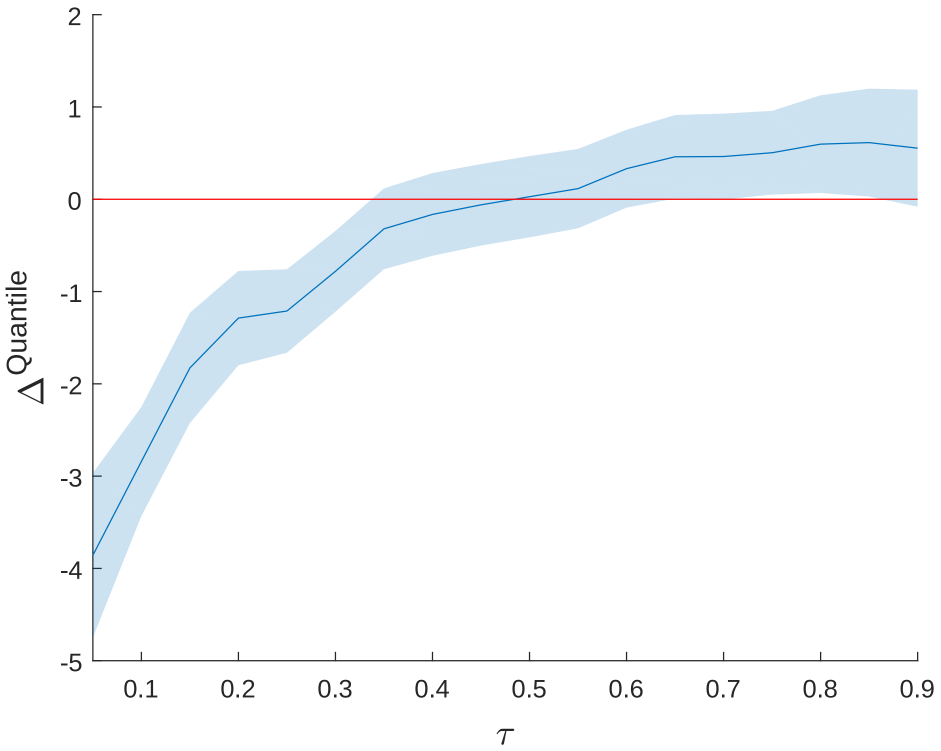
Notes: Based on our ToE estimation results, this figure presents the expected loss in employment years (see Panel A) and in income (see Panel B) for different treatment durations. The loss in employment years is defined as $Res(\bar{d}) = E\left[E[T|D=\bar{d}, X=x, T \geq \bar{d}] - E[T|D=\infty, X=x, T \geq \bar{d}]\right]$ 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 individual income. Loss in employment years is expressed in years, losses in income are express in 1,000 Euros.

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



Notes: Panels A and B are based on the total sample of 106,820 women born between 1950 and 1960 with at least 2.5 years of labor market experience within 3 years before the reference date (15th birthday of the offspring with the first grandchild), 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 and D are based on the sub-sample of uncensored observations (54,270 women). Panel C shows the duration to labor market exit of grandmothers, and Panel D grandmothers' age at labor market exit.

Figure 4: Censored IV estimation: Quantile treatment effects for intensive margin



Notes: This graph depictes the estimates of a censored two-stage least squares estimation of having two or more grandchildren (as compared to having one) on the grandmother's duration to labor market exit. The endogenous binary variable K is instrumented with a binary indicator for a twin birth at the birth of the first grandchild. The graph shows $\Delta(\tau)$ 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.

8 Tables (to be placed in the article)

Table 1: Mean of all variables in the ToE estimation sample

	(1) *Overall sample:*	(2) *By Grandmother status:* Yes	(3) No	(4) Diff.	(5) 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					
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		

Notes: This table summarizes descriptive statistics for all variables used in the ToE estimations. The ToE estimation sample comprises all Austrian women, with i. at least one child aged 15 in 1993-1998, and ii. a minimum of 2.5 years of labor market experience within 3 years before the reference date. Column (1) refers to the overall sample. Column (2) focuses on the sub-sample of women with a grandchild. Column (3) focuses on the sub-sample of women without a grandchild. Column (4) lists the difference between columns (2) and (3). *, ** and *** indicate a significance difference in the sample means (defined by treatment status) at the 10 percent level, 5 percent level, and 1 percent level, respectively. Column (5) provides the respective P-values. All variables on the grandmother level are measured at the 15th birthday of the reference child.

Table 2: **ToE estimation of the first grandchild on grandmothers' labor market exit**

	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.							

Notes: This table summarizes ToE estimation results of the effect of the first grandchild on labor market exit. The ToE estimation sample comprises all Austrian women with at least one child aged 15 in 1993-1998, and at least 2.5 years of labor market experience within 3 years before the reference date (15th birthday of the offspring with the first grandchild). This sample has 72,935 observations (see Table 1). 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.

Table 3: ToE estimation of the first grandchild on grandmothers' labor market exit, using the sub-sample of women not eligible for retirement

	Age-58 Sample Time-Dependent Effect				**Age-55 Sample** Time-Dependent Effect			
	Exit hazard θ_E		Treatment hazard θ_G		Exit hazard θ_E		Treatment hazard θ_G	
Panel A: Treatment effects								
δ	0.18	(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)		
$\Pr_{\nu_1}$	0.80	(0.01)			0.78	(0.02)		
$\Pr_{\nu_2}$	0.06	(0.01)			0.04	(0.01)		
$\Pr_{\nu_3}$	0.07	(0.00)			0.13	(0.02)		
$\Pr_{\nu_4}$	0.01	(0.00)			0.05	(0.06)		
$\Pr_{\nu_5}$	0.06	(0.00)						
$\Pr_{\nu_6}$	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)

Notes: This table summarizes ToE estimation results of the effect of the first grandchild on labor market exit using two different sub-samples. The focus is on women, who are not eligible for retirement. The 'Age-58 Sample' comprises only women, who were younger than 58 by the end of 2013 ($N = 40,617$). The 'Age-55 Sample' focuses on women, who were younger than 55 by the end of 2013 ($N = 14,645$). 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.

Table 4: Mean of all variables in the IV estimation sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Overall sample:	*Non censored obs.:*	*By twin status:* Grandmother's first grandchild was a			
			single birth	twin birth	Diff.	P-value
Dependent variable						
Duration to labor market exit	6.80	6.12	6.14	4.78	1.36**	0.00
Endogenous treatment variables						
Number of grandchildren	2.46	2.57	2.57	2.68	−0.11*	0.03
Two or more grandchildren	0.73	0.76	0.76	0.82	−0.06**	0.00
Grandmother's characteristics						
First grandchild by son (vs. daughter)	0.38	0.39	0.39	0.40	−0.01	0.68
Year of birth	1955.69	1954.20	1954.19	1954.16	0.03	0.75
Labor market characteristics:						
Wage (in Euro)	30.66	31.1	31.10	32.19	−1.09	0.24
Missing wage is imputed	0.25	0.24	0.24	0.22	0.02	0.17
Experience (in years)	11.01	11.18	11.18	11.50	−0.32	0.17
Educational attainment (shares):						
Level 1	0.12	0.11	0.11	0.09	0.02*	0.02
Level 2	0.14	0.11	0.11	0.10	0.01	0.22
Level 3	0.08	0.06	0.06	0.05	0.01	0.33
Level 4	0.03	0.02	0.02	0.02	−0.00	0.92
Level 5	0.02	0.01	0.01	0.01	0.00	0.28
Level 6	0.01	0.01	0.01	0.01	−0.00	0.28
Level 7	0.59	0.69	0.69	0.73	−0.04**	0.01
Number of children (shares):						
Has 1 child	0.30	0.36	0.36	0.41	−0.05**	0.00
Has 2 children	0.46	0.43	0.42	0.41	0.02	0.34
Has 3 children	0.18	0.16	0.16	0.14	0.02	0.17
Has 4 children or more	0.06	0.06	0.06	0.04	0.02**	0.01
Average number	2.02	1.93	1.93	1.81	0.12**	0.00
State of residence (shares):						
State 1	0.04	0.04	0.04	0.04	−0.00	0.56
State 2	0.07	0.07	0.07	0.08	−0.01	0.21
State 3	0.18	0.18	0.18	0.20	−0.02	0.27
State 4	0.18	0.17	0.18	0.14	0.03**	0.01
State 5	0.07	0.07	0.07	0.05	0.02*	0.04
State 6	0.17	0.17	0.17	0.17	0.00	0.80
State 7	0.07	0.07	0.07	0.06	0.00	0.82
State 8	0.04	0.04	0.04	0.05	−0.00	0.88
State 9	0.18	0.19	0.19	0.21	−0.02	0.13
Mother's characteristics						
First grandchild's birthyear	2005.40	2004.16	2004.13	2005.92	−1.78**	0.00
Mother's income	13798.6	12981.6	12936.9	16041.9	−3105.1**	0.00
Mother's age	25.43	25.12	25.09	27.16	−2.07**	0.00
Number of observations	106,820	54,270	53,488	782		

Notes: This table summarizes descriptive statistics for all variables used in the IV estimations. The IV estimation sample comprises all Austrian women, i. born between 1950 and 1960 with a minimum of 2.5 years of labor market experience within 3 years before the reference date (15th birthday of the offspring with the first grand child), ii. who become grandmother before 2014, and iii. who left the labor market before 2014. Column (1) refers to the overall sample. Column (2) refers to the sample of non-censored observations. Column (3) focuses on the sub-sample of non-censored grandmothers, whose first grandchild was a single birth. Column (4) focuses on the sub-sample of non-censored grandmothers, whose first grandchild was a twin birth. Column (5) lists the difference between columns (3) and (4). *, ** and *** indicate a significance difference in the sample means (defined by twin status) at the 10 percent level, 5 percent level, and 1 percent level, respectively. Column (6) provides the respective P-values. 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.

Table 5: IV estimation of the number of grandchildren on labor market exit

	(1) OLS	(2) Reduced form	(3) First stage	(4) Second stage	(5) Alternative second stage
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's number of own children (base group: one child):					
Two children	0.189***	0.154***	0.872***	0.706***	0.479***
	(0.032)	(0.030)	(0.011)	(0.241)	(0.143)
Three children	0.169***	0.101**	1.677***	1.163**	0.592***
	(0.050)	(0.048)	(0.022)	(0.463)	(0.216)
Four children or more	-0.153*	-0.262***	2.682***	1.436*	0.336
	(0.084)	(0.080)	(0.040)	(0.741)	(0.269)
Grandmother's educational attainment (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)
Grandmother's labour market characteristics:					
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)
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 and moth of birth FE	Yes	Yes	Yes	Yes	Yes
Grandmother's state of residence FE	Yes	Yes	Yes	Yes	Yes
Grandchild's year and month of birth FE	Yes	Yes	Yes	Yes	Yes
Mother's age and income	Yes	Yes	Yes	Yes	Yes
Number of observations	54,270	54,270	54,270	54,270	54,270
Mean of dependent variable	6.12	6.12	2.57	6.12	6.12
Mean of endogenous treatment				2.57	0.76
F-test of weak instrument				70.82	78.29

Notes: This table summarizes estimation results of the effect of the number of grandchildren on the grandmother's duration to labor market exit. The estimation sample comprises all Austrian women born between 1950 and 1960 with at least 2.5 years of labor market experience within 3 years before the reference date (15th birthday of the offspring with the first grandchild), who become grandmother before 2014, and who left the labor market before 2014. This sample has 54,270 observations (see Table 4). (The latter restriction is relaxed in the estimations summarized in Table A.2 in the Web appendix.) In columns (1), (2), (4), and (5) the dependent variable is the duration to labor market exit, which is measured as the time from the first grandchild's conception to the first spell of non-employment with a minimum duration of 12 months. In columns (3), the dependent variable is the total number of grandchildren. The estimations in columns (2) to (3) summarize a 2SLS approach, where the endogenous treatment is defined as the total number of grandchildren, which is instrumented with a binary variable equal to one, if the birth of the grandmother's first grandchild was a twin birth, and zero otherwise. Column (1) provides estimates from a simple OLS approach. Column (5) provides an alternative specification of the 2SLS approach, where the endogenous treatment K is defined as having two or more grandchildren. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10 percent level, 5 percent level, and 1 percent level, respectively.

Table 6: Treatment effect heterogeneity of the first and further grandchildren

	(1)	(2a)	(2b)	(3a)	(3b)	(3c)	(4a)	(4b)
		Formal childcare		Distance to grandchild (in min.)			Earnings	
	Baseline	available	not available	$d < 30$	$30 \leq d < 90$	$90 \leq d$	e <median	e >median
Panel A: First grandchild (ToE estimation)								
δ	0.082***	0.100***	0.054**	0.271***	0.140***	-0.074***	0.078***	0.094***
$Res(\bar{d})$	-0.453	-0.587	-0.306	-1.612	-0.803	0.451	-0.453	-0.494
Number of observations	72,935	35,283	25,191	18,657	12,604	27,743	30,563	30,563
Panel B: Further grandchildren (2SLS estimation)								
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

Notes: The upper panel presents estimates from the ToE approach outlined in Section 3. The treatment coefficient δ measures the effect of the arrival of a first grandchild on the exit probability by $[exp(\delta) - 1]$ percent. In all specifications, the number of support points is 3. The estimates in the lower panel are based on the 2SLS approach outlined in Section 4. For a better comparison of the estimates from the two estimation approaches, we also present the expected residual life time $Res(\bar{d})$ expressed in years for our ToE 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.*, ** and *** indicate statistical significance at the 10 percent level, 5 percent level and 1 percent level, respectively. 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 becoming a grandmother in our sample.

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: ToE estimation of the first grandchild on grandmothers' labor market exit, using an alternative exit duration of 6 months

	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_{ν_1}	0.89	(0.00)		
Pr_{ν_2}	0.04	(0.00)		
Pr_{ν_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 ≥Age < 45 Years	−1.55	(0.02)	0.12	(0.03)
45≥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.			

Notes: 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: IV estimation of the number of grandchildren on labor market exit, including censored observations

	(1) OLS	(2) Reduced form	(3) First stage	(4) Second stage	(5) Alternative second stage
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's number of own children (base group: one child):					
Two children	0.115***	0.098***	0.792***	0.330***	0.443***
	(0.019)	(0.018)	(0.008)	(0.102)	(0.074)
Three children	0.135***	0.105***	1.470***	0.536***	0.527***
	(0.027)	(0.026)	(0.014)	(0.189)	(0.109)
Four children or more	-0.023	-0.071*	2.302***	0.605**	0.283**
	(0.043)	(0.042)	(0.026)	(0.297)	(0.141)
Grandmother's educational attainment (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)
Grandmother's labour market characteristics:					
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)
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 and month of birth FE	Yes	Yes	Yes	Yes	Yes
Grandmother's state of residence FE	Yes	Yes	Yes	Yes	Yes
Grandchild's year and moth of birth FE	Yes	Yes	Yes	Yes	Yes
Mother's age and income	Yes	Yes	Yes	Yes	Yes
Number of observations	106,820	106,820	106,820	106,820	106,820
Share of non-censored observatons	0.51	0.51	0.51	0.51	0.51
Mean of dependent variable	6.80	6.80	2.46	6.80	6.80
Mean of endogenous treatment				2.46	0.73
F-test of weak instrument				181.63	176.50

Notes: The estimations summarized in this table are equivalent to those presented in Table 5 in the paper, but use also those women, who have *not* left the labor market before 2014. These observations can be considered as censored. For further details see the notes to Table 5 in the paper.