DEPARTMENT OF ECONOMICS
JOHANNES KEPLER UNIVERSITY OF LINZ

Grandmothers' Labor Supply

by

Wolfgang FRIMMEL
Martin HALLA
Bernhard SCHMIDPETER
Rudolf WINTER-EBMER

Working Paper No. 1720
This Version: June 2020
(Revised Version: March 2019)
(First Version: December 2017)

Johannes Kepler University of Linz
Department of Economics
Altenberger Strasse 69
A-4040 Linz - Auhof, Austria
www.econ.jku.at

martin.halla@jku.at

Grandmothers' Labor Supply*

Wolfgang Frimmel[a,b], Martin Halla[a,b,c,d], Bernhard Schmidpeter[e,c,d], Rudolf Winter-Ebmer[a,b,c,f,g]

[a] *Johannes Kepler University Linz*
[b] *Christian Doppler Laboratory Aging, Health and the Labor Market*
[c] *IZA, Institute for the Study of Labor, Bonn*
[d] *GÖG, Austrian Public Health Institute, Vienna*
[e] *RWI, Leibniz Institute for Economic Research, Essen*
[f] *IHS, Institute for Advanced Studies, Vienna*
[g] *CEPR, Centre for Economic Policy Research, London*

forthcoming in:
Journal of Human Resources

Last update: June 1, 2020

Abstract

The labor supply effects of becoming a grandmother are not well established in the empirical literature. We use high-quality administrative data from Austria to estimate the effect of grandmotherhood 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 the labor market by 9 percent. This effect is stronger when informal childcare is more valuable to the mother, and when grandmothers live close to the grandchild. To assess the effect of an additional grandchild (intensive margin), we estimate the reduced-form effect of a twin-birth among the first grandchild on grandmothers' labor supply. Our estimations show a significant effect of a further grandchild. Our results highlight the important influence of the extended family on the decisions of older workers and point to heterogeneity across institutional settings and families.

JEL Classification: J13, J14, J22.
Keywords: Grandchildren, female labor supply, timing of events, twin births.

* *Corresponding author*: Martin Halla, Johannes Kepler University of Linz, Department of Economics; email: martin.halla@jku.at. We thank the Editor Paul Devereux and three anonymous referees for excellent comments that significantly improved the paper. For helpful discussions and comments we would further like to thank seminar participants in Brno, Regensburg, Luxemburg, Vienna, Izmir, Bratislava, Augsburg, and Landeck. This research was funded by the Christian Doppler Society. Schmidpeter gratefully acknowledges funding from the ESRC Research Centre on Micro-social Change at the Institute for Social and Economic Research.

1 Introduction

Over the last decades, a substantial amount of evidence on the relationship between fertility and maternal labor supply has been 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 experience grandparenthood 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 a median 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 even expand their labor supply to increase their ability to transfer financial resources. Which type of transfer dominates, is unclear and not straightforward to quantify. The responses may also differ between the conception 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 estimate the extensive margin we make use of the *Timing-of-Events* (henceforth ToE) approach

[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 median effective age of retirement is about 64 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. These care-activities peak when the kids are between the age of one and five.

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 twin births among the first grandchild. In our reduced form, we relate the occurrence of twin births to grandmother's duration to labor market exit. Here, we only have to assume that unobserved determinants of twin births among the second generation have no impact on first generation's (i. e. the grandmother's) labor supply. In a second step, we use twin births as an instrumental variable for the total number of grandchildren.

We find a significant negative effect of grandmotherhood on labor supply at the extensive margin. A first grandchild increases the likelihood to leave the labor market by about 9 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 grandmothers time their exit to provide childcare when it is most valuable. Our estimated effects are also robust to an extension of our empirical model, which takes the maternal labor supply decision into account. On the intensive margin we find that further grandchildren decrease expected duration in the labor market for grandmothers even further with a comparable quantitative effect. Along both margins, we find interesting patterns of treatment effect heterogeneity. As expected, reductions in labor supply are larger in families with a shorter geographic distance between grandmother and grandchild.

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., 2018; Aassve, Arpino and Goisis, 2012). Unlike our focus on effects of fertility, Zamarro (2011) uses data from grandmothers in SHARE to investigate simultaneously the relation between the provision of child care by the grandmother and labor force participation of both the mother and the daughter. Reinkowski (2013) confirms findings from SHARE with data from the *German Ageing Survey* (GAS).

In contrast, very little is known about the effect of grandparenthood as such on grandparents' own labor supply. To the best of our knowledge there is only a handful of studies, which examine this link. Most of these do not provide a design-based approach and suggest to interpret their results as associations rather than causal. 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*. 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 studies to our research are Rupert and Zanella (2018) 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 (2018), on the other hand, exploit the sex of children of the grandparents as an exogenous source of variation in the timing of grandparenthood.[6] 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 (2018) 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 of grandchildren is more important than the corresponding one at the intensive margin.

Our paper complements the existing evidence in several dimensions. First, we can rely on high-quality administrative data covering all potential grandmothers in Austria. Second, we employ different estimation strategies, resting on different identifying assumptions. Third, we explore heterogeneity across different institutional settings and families. Our findings cover several important policy areas, such as fertility, childcare and pensions regulations. Showing a clear connection between changes in fertility and contemporaneous pension inflows 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.

[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, 2020).

[6]See Backhaus and Barslund (2019) for a similar analysis with European SHARE data.

The remainder of the paper is organized as follows. Section 2 outlines the relevant institutional background and describes our data sources. Section 3 focuses on the effect of the first grandchild (the extensive margin). Firstly, we discuss our ToE approach, explicate potential threats to identification and present a falsification check to support our identifying assumption. Secondly, we define our estimation sample and present some descriptive statistics. Thirdly, we present our estimation results along with several robustness checks and model extensions. For instance, we extend our model to provide evidence on grandmaternal labor market response if we take the daughter's re-employment probability and wages into account. Section 4 focuses on the effect of further grandchildren (the intensive margin). We first define our estimation sample for this analysis and present some descriptive statistics. Then we introduce our estimation approach using twin births among first grandchildren and discuss the respective estimation results. 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 introduce our data sources and discuss basic sample definitions.

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.[7] While the exact regulations have varied over time, parental leave take-up has always been almost universal (Danzer et al., 2017). Thus, during the first two years after childbirth, grandmaternal 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 Kaindl, 2011). As expected, in such a situation the extended family is the main source of

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

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. In case of early retirement, the replacement rates decrease by 4.2 percent per year of early retirement. 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 daily labor market activity. 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).

Sample definition We select all potential grandmothers born between 1950 and 1960 with at least one offspring, and grandmothers' first-born is of cohort 1973 or later, because (i) we do not have reliable information about first-born offsprings for earlier cohorts, and (ii) we would like to observe potential grandmothers' labor market behavior until they are at least close to their early retirement age of 55 years. 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. The limitations of the data are top-coded wages and no information on working hours (Zweimüller et al., 2009). The details on sample selection are summarized in Section 3.3 for the extensive margin analysis, and, correspondingly in Section 4.2 for the intensive margin analysis.

3 The effect of the first grandchild

3.1 Estimation strategy

We are interested in determining how the arrival of a first grandchild affects the labor supply of the grandmother. Let T be the observed duration until a long-term labor market exit of the (potential) grandmother and D be the duration until conception of the first grandchild.[8] The first grandchild can either be conceived by her daughter or daughter-in-law. The starting date (reference date) for durations D and T is the 15th birthday of the offspring (male or female) with the first grandchild. This ensures that potential grandmothers have completed their own fertility and are fully attached again to the labor market without own future maternity breaks. 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.[9] We assume that the transition rate from work to exit has a mixed proportional hazard specification (henceforth MPH). For a realized spell with duration T until exit and duration D until the first grandchild, the exit rate is defined as follows:

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

In equation (1), the baseline hazard $\lambda_E(T)$ represents individual duration dependence and the vector x consists of individual observable characteristics. The variable ν_E denotes unobserved and person-specific heterogeneity affecting the exit rate. The parameter of interests is $\delta(T-D)$, which captures the shift in the exit hazard due to the conception of the first grandchild. This shift represents our treatment effect, and we discuss its identification below. In a more general setting, we allow $\delta(T - D)$ to depend on the elapsed time since treatment by modeling it as a piecewise constant function $\delta(T - D) = \sum_k \delta_k \mathbb{1}_k(T - D)$, where k denotes the time intervals.[10] Likewise the rate at which the first grandchild is conceived (treatment hazard) is modeled as

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

Similar as above, the baseline hazard $\lambda_G(D)$ measures individual duration dependence and the vector x consists of possible confounding factors. ν_G captures the unobserved heterogeneity on the treatment hazard.

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 $\alpha_1 = 0$.

Identification requires that all selection effects are captured by related observed and unob-

[8]Note that we take the date of conception rather than birth as arrival of a first grandchild. Conceptions without a live birth later are not considered. We do not have information on miscarriages or abortions. In terms of abortion statistics, Austria is an outlier. There is no reliable source even on the aggregated number of abortions, since performing clinics do not report the number of cases to any national agency.

[9]In more than 70 percent of the cases, the offspring with the first child is also the oldest one. Concentrating only on the oldest offspring does not change our conclusions.

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

served covariates in the treatment and outcome processes (Abbring and van den Berg, 2003). Thus, in our model we allow for selectivity and do not impose any restrictions on the correlation between the unobserved components ν_E and ν_G. This means that selection into treatment can affect the exit transition and *vice versa*. For example, the probability of becoming a grandmother depends on her daughter(-in-law)'s attitude towards children and career. It is likely that career-oriented mothers also have more career-oriented children. If this holds true, then labor market outcomes of the potential grandmother and the probability of becoming a grandmother are negatively correlated and ignoring potential correlation would overstate the true effect.

We assume the distribution of heterogeneity to be unknown and approximate it by means of a discrete distribution (Heckman and Singer, 1984). Our estimation strategy accounts only for time-constant unobserved heterogeneity. 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:

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

We make use of the ToE approach proposed by Abbring and van den Berg (2003) to identify $\delta(T - D)$. This approach requires that the duration until treatment and labor market exit are modeled as MPHs and that the so-called 'no anticipation' assumption holds.[11] This untestable assumption requires that grandmothers do not anticipate the *exact* date of conception. We assume that grandmothers do not systematically react with their labor supply prior to the exact date of conception, so the hazard rate should not change before this date. This framework, however, allows that grandmothers may react between conception and the birth of their grandchildren or any other later event in life, i.e. date of school start. Thus, it does not rule out potential bargaining over how the grandmother will adjust her labor supply once the grandchild is conceived.

This "no-anticipation assumption" can be more formally expressed as

$$\theta_E(T|x, \nu_E, D_1) = \theta_E(T|x, \nu_E, D_2) \quad \text{for all } \; T < min\{D_1, D_2\}.$$

Notably, this framework also allows the (potential) grandmother to hold certain believes about the treatment probability as long as she does not react on those beliefs before conception date D.

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

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

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

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

Here, $\Delta_{i,E}$ 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 Potential threats to identification

There are two main potential threats to the validity of the "no-anticipation assumption". First, older female workers might adjust their labor supply in anticipation of a first grandchild before conception. However, the costs of such a behavioral response are high. These women would forgo any direct potential income flow until time D, as well as indirect benefits such as contributions to pensions. Depending on the time span between anticipation and the actual treatment these indirect monetary benefits can be substantial. Future pension payments depend on both, the income during the "best" 30 years and the total number of employment years. For example, consider a grandmother born in 1952 who anticipates the birth of the first grandchild one year in advance and forgoes potential income of 24,000 Euros during this year. Assuming that at retirement this grandmother has worked a total of 29 years and, for simplicity, that each month during her employment the income was 2,000 Euros. Then the yearly gross pension amounts to 11,976 Euros compared to 12,816 Euros if the grandmother had not acted on her believes.[12]

Besides the loss in income, a premature labor supply adjustment is complicated by the high variance in 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 impor-

[12]These figures are based on the legislation in 2018 for individuals born before the 1st of January 1955 which calculates the total pension amount as $P = BM$ x 0.0178 x V with BM the average of the 'best' 360 monthly incomes and V the number of total employment years.

tant role (Heckman and Walker, 1990; Larsen and Vaupel, 1993). Besides the evidence from the literature that conception is not exactly predictable 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.[13]

A second threat to our identification strategy is reverse causality. In this case, the exit from the labor force (or retirement) of the grandmother affects the likelihood of a grandchild (and not *vice versa*). A possible scenario would be that the daughters(-in-law) strategically decide when to conceive a child. For instance, she may try to plan pregnancy, when the grandmother's retirement date approaches. In a robustness check, we restrain our analysis to cases, where potential grandmothers are not eligible to an old-age pension payments during our observation period (see Section 3.4.4). In this subsample, where strategic timing is not feasible, we obtain the same results.

3.2.1 Falsification check

Our data allow us to observe the conception of a grandchild even before a (potential) grandmother has exited the labor market. If grandmothers anticipate the conception of the first grandchild, or if daughters(-in-law) strategically time the conception of their child, we would expect to see sudden changes in the exit hazard of the grandmother shortly before or around the conception date.

[Figure 1]

In Figure 1, we plot the daily exit hazard together with a smoothed version for grandmothers in a window of 900 days around the conception date of the first grandchild. (Using the birth date gives very similar results.) Two features of the hazard are striking. First, we can observe an upward sloping pattern, indicating an increasing risk of becoming a grandmother as the own offspring grows older. This pattern will be captured by the flexible specification of our baseline hazard. Second, the estimated hazards do not suggest the presence of sudden changes in the transition rate around the conception date of the child, but varies smoothly around it. The same holds true for raw (un-smoothed) daily exit rates (see Appendix Figure A.1) The hazard also does not show any sudden changes around the conception date.

Thus, grandmothers do not abruptly adjust their labor supply decision as a response to the conception of a first grandchild. We interpret this as support of our identification assumptions.

[13] 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.

3.3 Estimation sample and descriptive statistics

To allow for sufficient time between treatment and a possible exit, we restrict our sample to potential grandmothers with a reference date for durations T and D between 1993 and 1998. This ensures that we can observe grandmothers' labor market behavior for at least 15 years, and we can perfectly detect first-born grandchildren in the data. 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.[14] 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 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 grandmothers. 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. Furthermore, we observe $D = min\{D_{grandchild}, T\}$, where $D_{grandchild}$ is the conception date of the grandchild. A woman is considered as treated if $T > D$.

Our summary statistics show that 56 percent of the sample has at least one long-term labor market exit during our observation period. In the majority of these cases, we do not observe a return to the labor market before December 31, 2013, the end of our observation period. We consider these exits as permanent. Of those women who become grandmothers before December 31, 2013 and therefore considered treated, for about 48 percent we also observe a long-term exit from the labor market before that date. In comparison, around 63 percent of women who did not have a grandchild until the end of our observation period have a long-term exit before December 31, 2013. While treated women are in general less likely to exit the labor market compared to women in our control group, if they do so they leave permanently. For around 98 percent of women in our treatment group who have a long-term exit we do not observe a return to the labor market within our observation period compared to only 90 percent of women in our control group. Treated women are also more likely to transit into retirement and

[14] The conception date is inferred from the birth date of the first grandchild using gestational length information from the birth register.

are less likely to be out-of-labor force.[15] We do not see any differences in terms of the labor market state before the exit. The majority of non-permanent exits are into out-of-labor force. The share of non-permanent transitions into out-of-labor force is slightly higher for women in our control group (75 percent) as compared to women in our treatment group (68 percent). Those women who get treated tend to be younger, have slightly lower education, and tend to have more children. Moreover, our summary statistics show that those, who eventually become grandmothers within our observation period tend to have slightly less experience in the labor market.

[Figure 2]

Figure 2 depicts the Kaplan-Meier estimates for leaving the labor force (solid line) and treatment state (dashed line), respectively. The exit probability 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 probability over the same time period, which reaches a maximum around 20 years after the start of our observation period. At this time, the relevant offspring is around 29 years of age. The treatment probability remains fairly constant after this date, while the exit probability increases sharply.

3.4 Estimation results: First grandchild

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 conception 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 grandmotherhood on female labor supply.

[Table 2]

3.4.1 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

[15] We define an individual transiting out-of-labor force if she did not return to the labor market until December 31, 2013 and we do not observe the beginning of a retirement spell in our data.

(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 grandmotherhood 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.[16]

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 2. 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.

3.4.2 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 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).

3.4.3 Main results: Effect of the first grandchild

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

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

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 shows 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.[17] Relating our results to the ones reported in Rupert and Zanella (2018) 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.[18]

Due to our non-linear estimator, quantitative results are different according to the conception of the grandchild. We can use our estimates in a back-of-the-envelope exercise to investigate how the conception of a grandchild at different durations $\bar{d}$ translates into losses of employment years for the grandmother.[19] When calculating the effect, we assume that labor market exits are permanent. This assumption seems reasonable, given that 98 percent of all treated and 90 percent of untreated women do not return to the labor market after the first long term exit. Figure 3 depicts the results 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 conception of a grandchild shortens the duration until labor market exit between one and six months (see Panel A of Figure 3). 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 3). 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.

[Figure 3]

Model (I) imposes a constant treatment effect, which does not depend on the age of the grandchild. Given the institutional settings in Austria (see Section 2), it is possible that some grandmothers only react at a certain point in time, after the conception of the grandchild. For

[17] 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.

[18] 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).

[19] 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.

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 conception. 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. 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.[20] We set the third and fourth knot at 45 and 87 months, respectively. Around age 3 children start enrolling in kindergarten. At months 87 after the conception, the grandchild 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 provide no evidence for anticipation and confirm our conjecture of a strategically timed post-birth exit. 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 is at kindergarten age.[21] Thereafter, the treatment effect decreases slightly, but remains 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.[22] The rest of our estimates are similar to those 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 Appendix Table A.1, we replicate our main results with a minimum exit duration of 6 (instead of 12) months. This gives us very similar estimated effects. Thus,

[20] 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.

[21] 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.

[22] 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.

grandmothers not only support their offspring for a limited time after birth, but they 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.

3.4.4 Addressing reverse causality

A remaining concern with respect to our identification is reverse causality. We have discussed the possibility that children strategically decide to conceive a child, when the grandmother is able to claim a retirement pension. In this scenario, the expected retirement of the potential grandmother triggers fertility behavior of the offspring (and not *vice versa*). Another scenario of reverse causality is informal talks and coordination between daughter and mother before conception. To evaluate the importance of the first mechanism, we focus on potential grandmothers, who are not eligible to receive an old-age pension payments during our observation period.[23] To address the second mechanism, we extend our estimation model with a coordination period.

Non-eligible women To focus on potential grandmothers, who are not eligible to receive an old-age pension payments, we restrict our sample to women 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. These cohorts could leave the work force anytime before the regular retirement age of 60 years, but they would not receive any pension payments. Receiving retirement benefits before the age of 60 is 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. Given the substantial income loss when retiring before the age of 60, reverse causality such that daughters adjust their fertility behavior to a possible upcoming retirement is of less concern here. Around 85% of women with a permanent labor market exit in our Age<55 Sample transit into out of labor force compared to 38% overall.[24]

[Table 3]

[23]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.

[24]The chosen exit state does not substantially differ by having a grandchild or not. Around 87% of all women with a grandchild and a permanent labor market exit transit into out of labor force. For women with a permanent exit but without a grandchild, the figure is 84%.

In total, 40,617 individuals are included in the analysis of the Age<58 sample and 14,645 individuals in the Age<55 sample. The estimation results are presented in Table 3. For expositional reasons the table contains only results for the treatment effect together with the parameters for duration dependence and unobserved heterogeneity. We find that restricting the sample to younger individuals, who cannot claim an old-age pension, does increase our treatment effects. In the Age<58 Sample the conception of a grandchild increases the exit probability by 20 percent. In the Age<55 Sample the effect is even slightly higher and amounts to 23 percent. These effects are larger compared to our baseline estimates reported in Table 2.

While these results are reassuring, there are other scenarios of reverse causality, not addressed by this check. Even in the absence of a fixed retirement date, grandmothers and daughters might coordinate over time in a less strategic way.

Coordination before conception To address the scenario of informal talks and coordination before conception, we assume that coordination takes place y months before conception D. We consider all grandmothers as treated for whom $\mathbb{1}(T > D - y)$. Under this assumption, all grandmothers who exit the labor market between time $D - y$ and D are considered as additionally treated compared to the baseline of our model. We consider the time between y and actual conception date D as coordination time and the effect as a coordination effect δ^{Coord}. Allowing the treatment effect to change at time D, similar as in Model (II), and setting y to a wide range of values allows us to gauge how sensitive our results are to this pre-conception coordination. If we find that δ^{Coord} is large and significant, this would point towards reverse causality in our model.

[Table 4]

The results are summarized in Table 4. Column (1) re-states the results from our baseline model. The estimates summarized in Column (2) to (7) allow for a coordination effect, with a wide range of alternative values for y. Our conclusions are unaltered. The estimates of the coordination effect are rather small — in particular, compared to the main treatment effect — and not significant at any conventional level. In contrast, our estimates for δ are very close to the obtained baseline estimates of 0.082 across the different specifications.

While these arguments against reverse causality are no formal proof, we are confident that our results capture a causal effect of a first grandchild on the labor supply of grandmothers (and not the reversed relationship).

3.4.5 Including an effect on daughter's labor supply and wages

So far, we analysed the employment decision of the grandmother disregarding decisions of other family members. A full bargaining model analysing decisions of both generations, as in Honoré and Áurelo de Paula (2016), is beyond the scope of this paper. However, we extend now our previous estimation model and take mothers' labor supply decisions into account.

In our main specification, we concentrate on daughters who were on the labor market at the conception date and disregard labor supply adjustments of sons and daughters-in-law, when calculating the contribution to the overall likelihood. This simplification can be justified by two reasons: The first one is related to the dominant division of labor. In the vast majority of Austrian families, the mother is the primary care-taker and also goes on parental leave. Hence, fathers are typically not affected by the labor market decision of their mother. The reason for concentrating on employed daughters and excluding daughters-in-law is more technical: While the estimated coefficients are virtually identical when including them, one of our mass points converges to a large negative number implying a defective risk.

We extend now our previous ToE model with a duration until the return to the labor market (or censoring) of the daughter. Using similar notation as before, the individual likelihood contributions of the daughter for an observed duration until return to the labor market (or censoring) L and the duration $E = T - D$ (the duration between conception and labor market exit of the grandmother) is then given by

$$\mathscr{L}_i = \theta_R(L_i|x_i^d, \nu_R^m, E_i)^{\Delta_{i,R}} exp\left(-\int_0^{L_i} \theta_R(L_i|x_i^d, \nu_R^m, E_i)\right),$$

where $\Delta_{i,R}$ is a censoring indicator, with value one if the daughter returns to the labor market. The vector of covariates x^d includes binary variables for daughter's education and age at conception, as well as age of the grandmother at conception and her previous labor market experience. The other parameters are defined analogously as described in Section 3.

To obtain an estimate of the effect of grandmaternal exit on daughter's labor market return, $\delta_{Daughter}$, we maximize the joint likelihood of the grandmother and daughter allowing for correlation in the unobservable heterogeneity between grandmother's and daughter's labor market decision. In a similar way, we can also use a MPH structure when including the re-employment wages of the daughter. This approach provides a more flexible way than assuming a specific distribution, such as a Probit model (Donald et al., 2000).[25] The wage hazard has the same interpretation as our exit hazard: the probability of earning a wage ω conditional of earning a wage of at least ω. Hence, the effect of grandmaternal labor market exit on mean wages and all other quantiles has the *opposite* sign as the effect on the wage hazard (Cockx and Picchio, 2013).

The individual likelihood contribution in this model is similar as before. For an observed wage ω (or censoring) of the daughter and the time from conception until exit from the labor

[25]The estimator requires censoring, so we follow Donald et al. (2000) and censor the 99th percentile of the observed wage distribution.

market (or censoring) E of the grandmother, it is given by

$$\mathscr{L}_i^{\omega} = \left[\theta_W(\omega_i|x_i^d, \nu_\omega^m, E_i)^{\Delta_{i,\omega}} exp\left(-\int_0^{\omega_i} \theta_W(\omega_i|x_i^d, \nu_\omega^m, E_i)\right)\right]^{\Delta_{i,R}},$$

where $\Delta_{i,\omega}$ is a censoring indicator taking a value of one, if the re-employment wage is below the 99th percentile. The remaining parameters are defined as before. To obtain our estimates, we maximize the joint likelihood over all unknown parameters. Notice that when estimating the impact of grandmaternal labor supply on daughters' labor market outcomes, only daughters, who are on the labor market at the time of the conception and for whom $E > 0$ contribute to the joint likelihood.

Before we discuss our estimates, we want to emphasize that the results relating grandmaternal labor supply to employment of the daughter should be interpreted as suggestive rather than causal. Although we allow for correlation in the unobserved heterogeneity between the grandmother and the daughter, it is possible that both parties engage in bargaining during the course of the pregnancy and the "no-anticipation assumption" is (partially) violated in this setting.[26] This exercise serves primarily as a robustness check on grandmaternal labor supply, and less so for a direct test of interrelations between grandmother and daughter.

[Table 5]

Panel A of Table 5 summarizes the estimation results for the effect of a first grandchild on grandmaternal labor supply denoted by δ. These estimates can be compared to our previous results (see Table 2). The estimated treatment effect on grandmother's labor supply is 0.081, when considering the re-employment hazard, and 0.082, when considering re-employment wages of the daughter. The results are very similar when considering all daughters, regardless their labor market status at the conception date (Columns (3) and Columns(4)) or when considering both daughters and daughters-in-law (Columns (5) and Columns(6)). Thus, the results are virtually identical to our original estimates of 0.08.

In Panel B we show results for the impact of grandmother's labor market exit on the return and wage hazard of the daughter, $\delta_{daughter}$, together with the expected residual working time and residual wages which are calculated as described in Section 3. For the sake of brevity, we refrain from reporting detailed results on our control variables and unobserved heterogeneity. Column (1) shows that a grandmaternal labor market exit increases the return probability to the labor market of the daughter significantly by around 29 percent. This corresponds to an earlier entry of around 0.5 years, as compared to the case if the grandmother had not exited the labor market. The estimated loss in employment years for the grandmother, reported in Section 3, is almost entirely off-set by the employment gain of the daughter. Our results

[26] This is different to the no-anticipation assumed previously, which was build around the conception of the grandchild.

support the hypothesis that grandmothers do indeed trade their own career for the career of their daughters.

Looking at the effect on re-employment job quality reported in Column (2), we also find that a grandmaternal labor market exit has a positive effect on the re-employment wage of her daughter. An early exit decreases the wage hazard by around 13 percent, which translates into an increase in the daily wage by 4.33 Euros compared to the situation if the grandmother had not left the labor market. This effect is quite substantial and corresponds to around 9 percent compared to the baseline results (not reported). These results provide evidence that daughters do not only benefit in terms of time until re-employment, but also in terms of job quality. With an additional potential care-giver at home, daughters are more flexible in their job search, and can also be more restrictive in what type of employment to accept.

To show that our results are robust to a less restrictive sample selection, we also report estimates on the effect of grandmother's labor market exit on labor market outcomes of the daughter for all daughters and the overall sample, including daughters-in-law, in Columns (3) to (6). In general, we find very similar results to those obtained from our more restrictive sample. A labor market exit of the grandmother leads to a higher re-employment probability and wages for the daughter. Our estimates are, however, smaller in magnitude and in the case of the overall sample and re-employment wages not statistically significant. This is not surprising given our discussion above.

4 The effect of a further grandchild

So far, we have concentrated on the effect of the first grandchild on grandmothers' labor market exit. We now investigate the effect of an additional grandchild (intensive margin). Clearly, the number of grandchildren should not be treated as exogenous. To identify causal effects, we focus on twin births among the first grandchild.[27] In this analysis, the outcome variable is the duration to labor market exit, which is measured from the conception of the first grandchild. We present reduced form and instrumental variable (hereafter IV) estimates.

4.1 Estimation strategy

The dependent variable is now the duration until labor market exit. This duration is measured from the first grandchild's conception to the grandmother's labor market exit. As before, we define a labor market exit if the grandmother is 12 consecutive months out of employment. Since not every grandmother leaves the labor market before the end of our observation period, this variable is censored for many grandmothers and we estimate Tobit models. We mainly focus on the reduced-form effect of a twin-birth among the first grandchild, $twin1_i$, and estimate

[27] The idea to use twin births as a source of exogenous variation in the number of offspring originates from the literature studying the effect of family size on first-borns' outcomes and maternal labor supply (e. g. Rosenzweig and Wolpin, 1980*b*; Bronars and Grogger, 1994; Jacobsen et al., 1999).

the following Tobit model

$$labor\, market\, exit_i^* = \iota + \kappa \cdot twin1_i + \Delta \cdot \mathbf{X}_i + \upsilon_i, \quad \upsilon_i \sim N\left(0, \sigma^2\right), \tag{5}$$

where $labor\, market\, exit_i^*$ is a latent variable. The parameter of interest is κ. It informs us about the effect a twin birth event has on the duration to grandmothers' labor market exit. A twin birth is certainly an event that calls for more care. First, it captures an increase in the number of children by one, albeit with a specific timing, since the additional child is born at the same time.[28] Second, in comparison to the birth of a second, non-twin grandchild, the event further involves a particularly busy and stressed-out daughter(-in-law).

As an alternative estimation approach, we will also consider using $twin1_i$ as an IV for the total number of grandchildren. While this estimation requires additional assumptions, it allows us to scale the reduced-form estimate with a first-stage estimate and to obtain a more informative *local average treatment effect* (hereafter LATE) interpretation, which is closer to a true effect at the intensive margin (i.e., additional grandchild).

4.2 Estimation sample

We consider now 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 15$^{\text{th}}$ birthday of the offspring with the first grandchild, who became grandmother before 2014. Grandchildren from both biological daughters and biological sons are considered.Applying these criteria gives us an estimation sample of $106,800$ women.

[Figure 4 and Table 6]

Figure 4 displays the distribution of these women's age at first grandmotherhood (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 they had on average 2.3 grandchildren. About 70 percent of them had two or more grandchildren, and about 21 percent had three or more. The outcome variable, duration to labor market exit, is measured from the conception of the first grandchild. In our sample, 51 percent of women ($N = 54,263$) 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 grandmotherhood. 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 4. For the remaining 49 percent of women, we do not observe the labor market exit. These observations are censored.[29] The average age at censoring is 56.2 years.

[28]That said, in the case of grandchildren (as compared to own children) a short spacing is also possible in the case of single births, since they can happen across different daughters(-in-law).

[29]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).

Table 6 provides sample means for all variables. Columns (1), and (3) to (6) refer to the overall sample. Column (2) refers to the sub-sample of uncensored observations. 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 0.33. Among the latter group the share of women with two or more grandchildren is also significantly higher (1.00 versus 0.69). The descriptive statistics also 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 1.59 years or 23.3 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 age 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 (1.90 versus 2.02).

In the lowest panel of Table 6, 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, as long as twin status is not correlated with unobserved determinants of grandmother's labor supply, and does *not* refer to the unobserved determinants of mother's labor supply (see below).

Identifying assumption In order to identify κ free of bias, we have to assume that the occurrence of twins in the third generation is uncorrelated with v_i, the unobserved determinants of first generation's (i. e., the grandmother's) labor supply. Notably, this is a much weaker assumption as compared to the one imposed by papers using twins to study the effect of the number of own children on 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 an impact on 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. Moreover, for a reduced form estimate we do not need to impose an exclusion restriction assumption — i.e., the twin births may affect grandmothers' labor market exit not only via their effect on the total number of grandchildren.

To evaluate the plausibility of our identifying assumption it is instructive to review the determinants of twin births. There are three well-documented risk factors for multiple births. First, fertility treatments (in particular, certain types of *in vitro* fertilization) are positively related to the likelihood of a multiple birth. The other two best-defined factors are a higher maternal age and a hereditary component (Bortolus et al., 1999). While there is no reason to assume that these 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 factors. In the cases of maternal age and heritability, this approach is straightforward. We simply control for mother's age and include also a binary variable capturing whether the grandmother herself had a multiple birth. The case of the fertility treatment is less straightforward, since we do not have information on this in our data. Fertility treatments are mainly used by older and more career-oriented women. Thus, we control for mother's age at first birth. Ideally, we would also like to capture to mother's career orientation; since this and fertility treatments could be correlated via intergenerational transmission with grandmother's career orientation. Due to a lack of data, we have to rely on earnings (measured at conception of the first grandchild) as proxy for career orientation.

The other covariates included in $\mathbf{X}_i$ cover a range of socio-economic characteristics of the grandmother: the number of her own children, her education, wage, work experience, state of residence within Austria, and year and month of her birth. Finally, we control also for the sex of the grandchild and its year and month of birth.

4.3 Estimation results: Further grandchildren

Table 7 summarizes our estimations results. Columns (2) to (5) list our reduced form Tobit estimates with varying covariates. For reference, column (1) includes a Tobit estimation relating the total number of grandchildren by 2014 to the duration to labor market exit. The remaining columns summarize our IV approach. In column (6), an OLS first stage estimation relates the twin-status to the total number of grandchildren, and in columns (7) and (8) two variants of a possible IV estimate are presented.

The naïve estimate in column (1) shows a negative correlation between the number of grandchildren and the duration of labor market exit of the grandmother, where each additional grandchild is associated with a small reduction of about 0.06 years. The first stage shows that if the first grandchild is a twin birth, the ultimate number of grandchildren will increase by 0.64 additional children. Given the average number of about 2.34 grandchildren, this effect is substantial and equivalent to an increase by 27.4 percent.

The unconditional reduced-form effect in column (2) provides a substantial negative effect, which shrinks considerably once we control for birth year dummies in column (3). In contrast, the additional covariates added stepwise in columns (4) and (5), have little impact. We see that a twin-birth among the first grandchild reduces the grandmothers' duration on the labor market by about 0.40 years or 5.9 percent. The advantage of this reduced-form estimate is that it allows us to identify a causal effect under quite weak assumptions. The disadvantage is its limited interpretability. While the strong first stage indicates that the most likely mechanism reflected in this reduced-form is the increased number of grandchildren, our estimate also allows for other mechanisms, and is not scaled by the first stage parameter.

[Table 7]

If we are willing to assume that the twin status affects grandmothers' labor supply decisions only via its impact on the total number of grandchildren (and not through any other channels, such as the specific timing), then we can scale the reduced-form estimate with the first-stage estimate and obtain an IV estimate. We estimate this (second stage) as control function with a Tobit model, which controls for the residual from the first stage. This provides us with a more informative LATE interpretation closer to the effect of an additional grandchild (intensive margin). According to our estimate summarized in column (7), we find that an increase in the total number of grandchildren by one — caused by a twin birth — reduces labor supply of the grandmother by 0.63 years or 9.3 percent.[30] A remaining shortcoming of this IV set-up is that the endogenous treatment variable (i.e., the total number of grandchildren) is measured at the end of 2013, while labor market exit happens some time before. To solve this discrepancy, we use in column (8) an alternative endogenous treatment variable. We define a binary variable equal to one, if the grandmother i has two or more grandchildren, and zero otherwise. This IV estimate suggests that grandmothers with at least two grandchildren leave the labor market about one year before grandmothers with only one grandchild. This effect is equivalent to a reduction of 14.9 percent.

Finally, in Appendix Table A.2 we repeat our estimations based on the sub-sample of all uncensored observations (i.e., grandmothers who exit the labor market within our observation period) using OLS/2SLS. This sample is about half in size. We obtain qualitatively equivalent results, but the reduced form and second stage estimates are now somewhat smaller in absolute terms.

5 Heterogeneous effects

We now turn to the analysis of heterogeneous treatment effects. In Table 8, we examine several sub-samples.[31] We summarize our respective estimates for the first grandchild in Panel A,

[30] This IV estimate is considerably higher than the naïve Tobit estimate. This may either result from an omitted variables bias in the naïve estimation 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.

[31] Note, that the number of observations in the sub-samples does not always add up to the number of observations in our baseline analysis; this is due to missing information on the stratification criteria.

reduced form results for further grandchildren in Panel B, and finally IV estimation results in Panel C. 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 of grandchildren. 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. The IV estimate for one additional grandchild is equal to a reduction of about 0.6 years. This comparison suggests that labor market responses of grandmothers to the first and a further grandchild are *on average* quite comparable.

[Table 8]

In the remaining columns of Table 8, we compare estimates across different sub-samples. We look at the geographic distance measured in driving minutes between grandmothers and grandchildren (see columns (2a) to (2c)), and grandmaternal earnings (see columns (3a) and (3b)).[32]

Geographic distance is a potentially important factor. 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 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 (first grandchild) and 0.64 years (further grandchild). The estimated effects for those with larger distances are smaller (and also less statistically significant). In the case of the first grandchild, we find a consistent pattern across sub-samples with precisely estimated effects. Grandmothers with driving distances of more than 90 minutes are even less likely to leave the labor market once a grandchild arrives. This result can be explained by the desire to provide monetary transfers (instead of time), since the distance to care directly is too large. In the case of a further grandchild, estimates in the two higher distance samples are quite imprecise.

Next, we split our sample according to the grandmothers' annual earnings in two-equally sized samples. On the one hand, grandmothers with lower earnings and worse job prospects might choose to provide informal care, as the opportunity cost is relatively low, while grandmothers with higher earnings might expand their labor supply to provide more financial support

[32] 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, variables are measured at women's 50th birthday. This is the average age of women becoming a grandmother in our sample.

instead of time transfer. It turns out that we do not find major differences across these two samples.

Finally, the local availability of a nursery (i. e., the only formal childcare arrangement for children below three years of age) is another 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 for (potential) grandmothers in this sample. On the other hand, most of the nurseries do not provide full-time care. Therefore, the availability and the use of formal childcare may also trigger additional informal childcare by grandmothers. To shed some light on this, we examine the labor supply effects in sub-samples based on the combination of availability of formal childcare in the community and of proximity of grandmothers (within driving distance of 60 minutes). Results are summarized in the Appendix Table A.3. Columns (1) and (2) show results from the ToE-estimation, column (3) presents Tobit reduced form estimates for the effect of further grandchildren. At the extensive margin, the proximity of the grandmother increases grandmothers' labor supply exit in all communities, but we find stronger effects of grandparenthood if there is no formal childcare in the community. The latter finding holds for both, the first and further grandchildren. This suggests that formal institutions and grandmaternal time are weak substitutes in the provision of childcare.

6 Conclusions

We use administrative data from Austria to estimate the impact of grandmotherhood on the labor supply of older workers. We distinguish between the effect of the arrival of a first grandchild (extensive margin) and the impact of a further grandchild (intensive margin). To estimate the extensive margin we make use of a timing-of-events approach. We find that the first grandchild increases the probability of leaving the labor market by 9 percent. This translates on average to a reduction in the labor market participation of 0.5 years. Investigating the time dependence of this 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 enrolls 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.

For the estimation of the intensive margin, we exploit twin-births among the first grandchild. Using rather weak assumptions, we identify a significant reduced-form effect suggesting further labor supply reductions due to twins. Under the additional assumption that this twin status affects grandmothers' labor supply decisions only via its impact on the total number of grandchildren (and not through any other channel), we also provide IV estimates. These suggest that an additional grandchild (or more than one grandchild) reduces the labor supply by 0.6 (or one) years.

While the labor supply adjustments are quite comparable at the extensive and the intensive margin, there is ample heterogeneity across institutional settings and families. As expected, reductions in labor supply happen mostly in cases, when geographic distance between grandmother and grandchild is low. We also find that grandmothers tend to reduce their labor supply a bit stronger in communities without nurseries, as compared to other communities. However, the geographic proximity of a grandmother reduces her labor supply significantly also in the presence of nurseries. This reaction could be due to fairly restricted time-schedules of such facilities in the Austrian setting, which would suggest that formal care and informal care by grandmothers are relatively weak substitutes.

Our results show 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 — only partially resolves this tension. 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. Currently, many older Austrian women forgo earnings (and accept a lower future retirement pay) in order to provide child-care.

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.

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.

Backhaus, Andreas and Mikkel Barslund (2019), The Effect of Grandchildren on Grandparental Labour Supply: Evidence from Europe, EconPol Working Paper 31, ifo Institute - Leibniz Institute for Economic Research at the University of Munich.

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.

Bortolus, Renata, Fabio Parazzini, Liliane Chatenoud, Guido Benzi, Massimiliano M. Bianchi and Alberto Marini (1999), 'The Epidemiology of Multiple Births', *Human Reproduction Update* **5**(2), 179–187.

Bratti, Massimiliano, Tommaso Frattini and Francesco Scervini (2018), 'Grandparental Availability for Child Care and Maternal Employment: Pension Reform Evidence from Italy', *Journal of Population Economics* **31**, 1239–1277.

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.

Cockx, Bart and Matteo Picchio (2013), 'Scarring Effects of Remaining Unemployed for Lon-Term Unemployed School Leavers', *Journal of the Royal Statistical Society: Series A* **176**(4), 951–980.

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.

Donald, Stephen G., David A. Green and Harry J. Paarsch (2000), 'Between Canada and the United Sates: An Application of a Flexible Estimator of Distribution Functions in the Presence of Covariates', *Review of Economic Studies* **67**(4), 609–633.

Eibich, Peter and Thomas Siedler (2020), 'Retirement, Intergenerational Time Transfers, and Fertility', *European Economic Review* (124).

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

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.

Honoré, Bo E. and Áurelo de Paula (2016), 'A New Model for Interdependent Durations', *forthcoming Quantitative Economics* .

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.

Muller, Hans-Georg and Jane-Ling Wang (1994), 'Hazard Rate Estimation under Random Censoring with Varying Kernel and Bandwidths', *Biometrics* **50**(1), 61–76.

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 (2018), 'Grandchildren and their Grandparents' Labor Supply', *Journal of Public Economics* **159**, 89–103.

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.

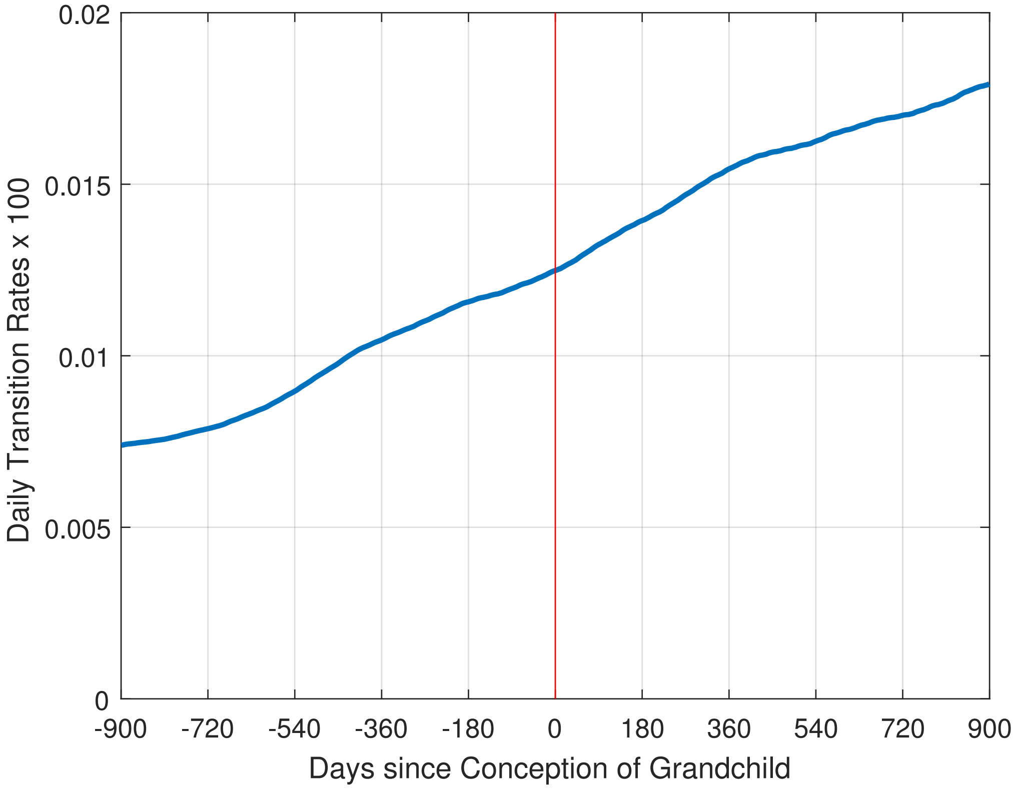
Zamarro, Gema (2011), 'Family Labor Participation and Child Care Decisions - The Role of Grannies', *RAND WR-833* .

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.

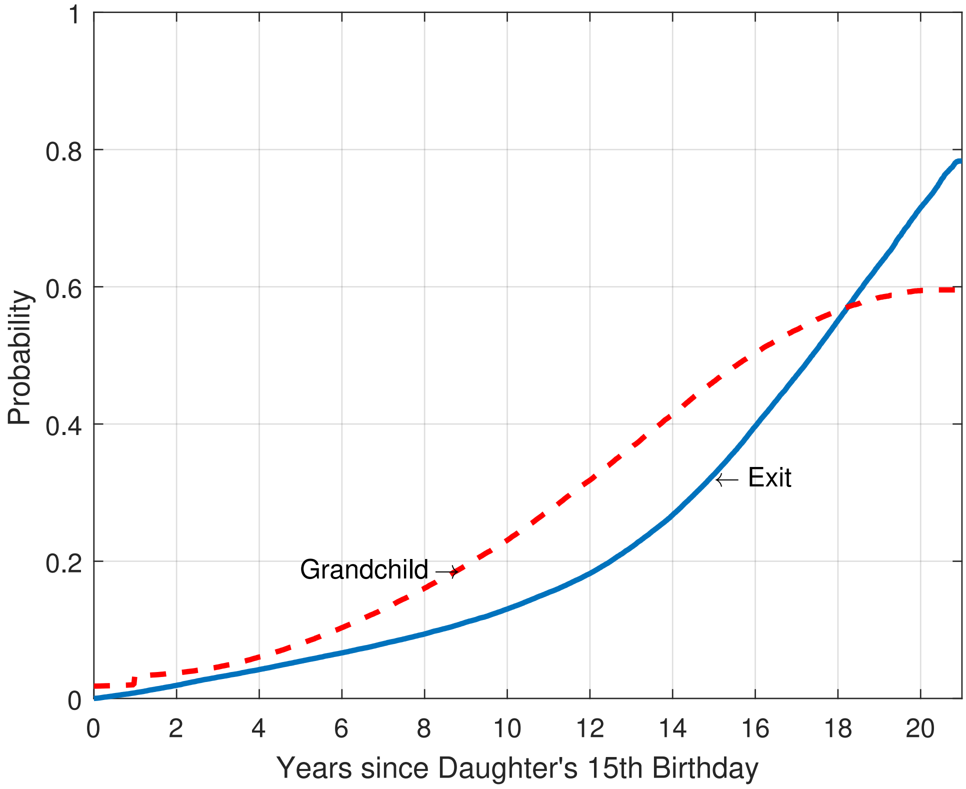
7 Figures (to be placed in the article)

Figure 1: Transition rates of grandmothers around conception date



Notes: This figure presents daily transition rates of grandmothers around the conception date of the first grandchild using the method of Muller and Wang (1994). The sample consists of all 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 (15$^{\text{th}}$ birthday of the reference child).

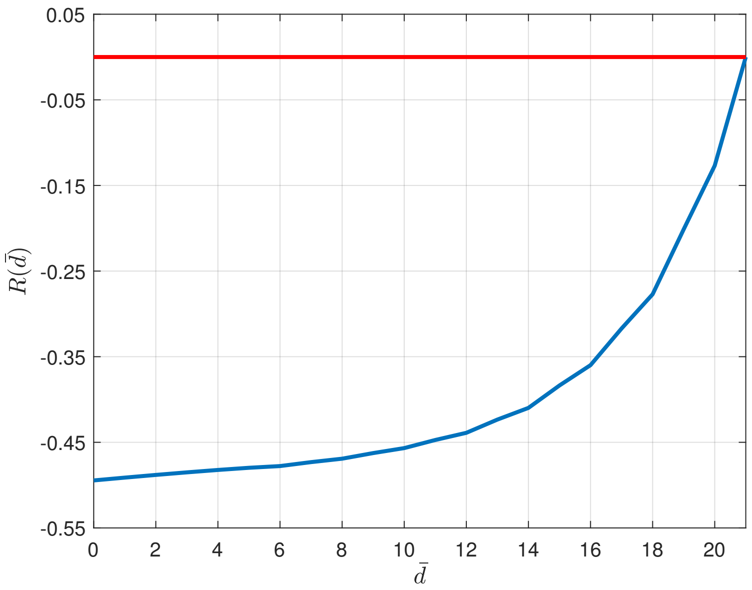
Figure 2: Kaplan-Meier estimates



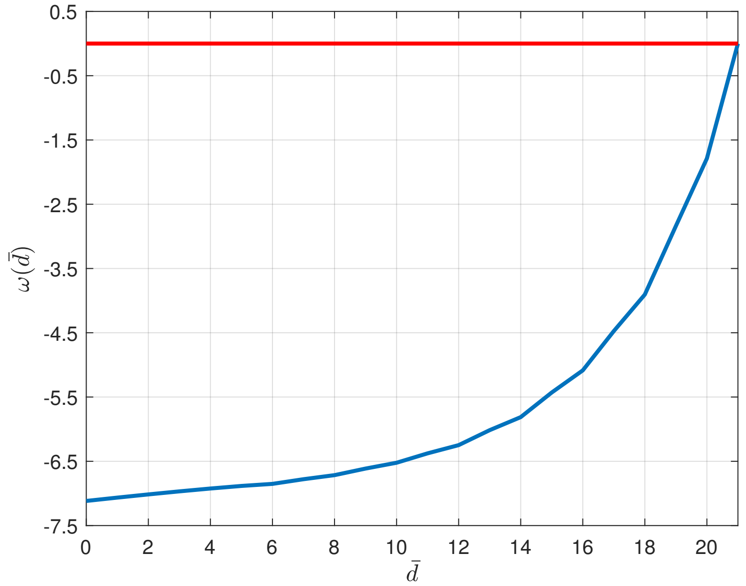
Notes: The solid line represents the Kaplan-Meier estimates for out of labor force (outcome: labor market exit), the dashed line the estimates into grandmotherhood (treatment: conception of first grandchild). The sample consists of all (potential) grandmothers with at least one child aged 15 in 1993-1998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

Figure 3: Average loss in employment years and income due to first grandchild

Panel A: Loss in employment years

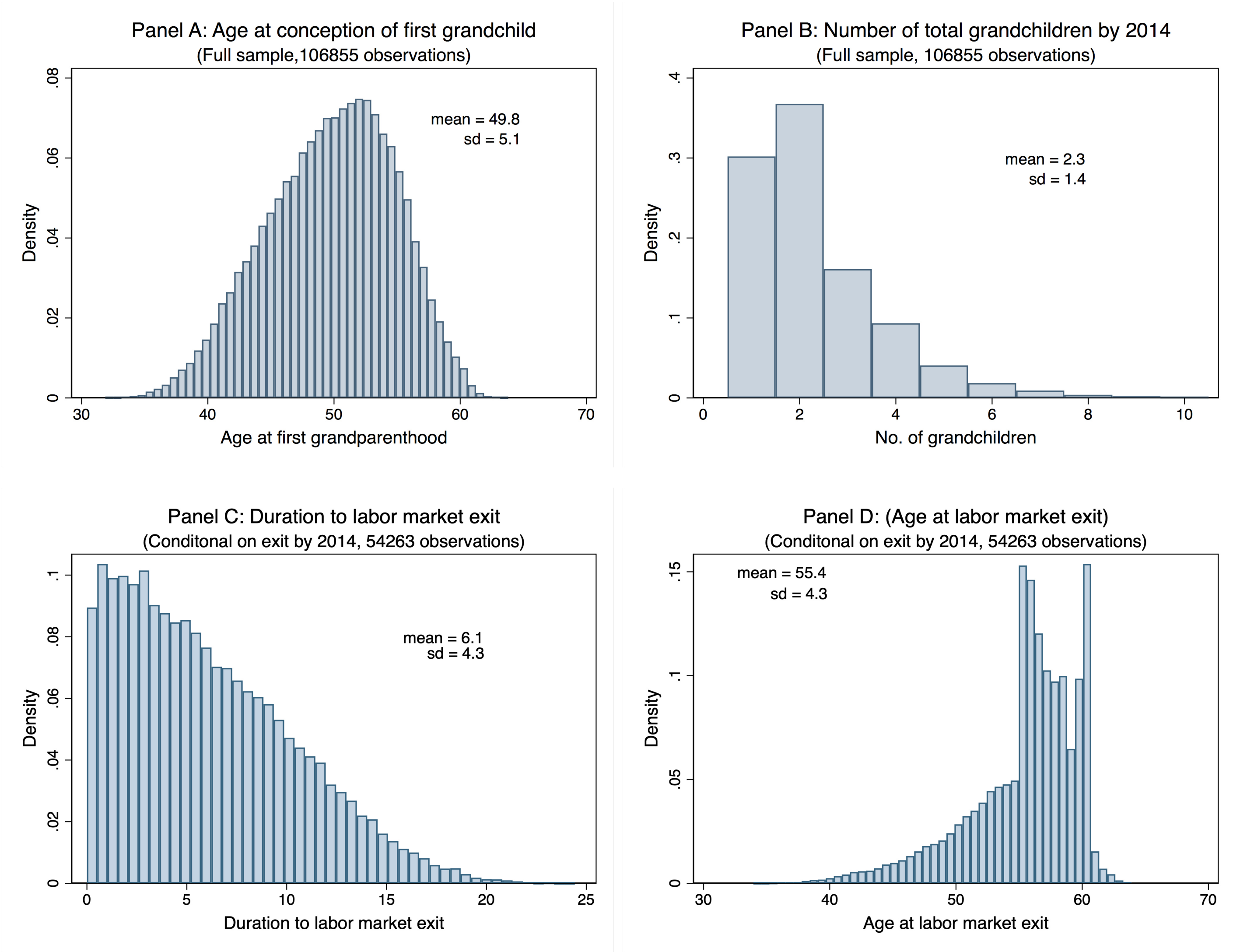


Panel B: Loss in income



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 4: Distribution of the age at grandmotherhood, number of grandchildren, and timing of labor market exit



Notes: Panels A and B are based on the total sample of 106,855 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 (54,263 women). Panel C shows the duration to labor market exit of grandmothers, and Panel D grandmothers' age at labor market exit.

8 Tables (to be placed in the article)

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

	(1) *Overall sample:*	(2) *By Treatment status* $\mathbb{1}(T > D)$: 1	(3) 0	(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
Permanence of labor market exits & distribution of exit states (shares)					
Permanent exit‡	0.93	0.98	0.90	0.08***	0.00
to retirement	0.62	0.65	0.60	0.05***	0.00
to out-of-labor force	0.38	0.35	0.40	−0.05***	0.00
Non-permanent exit	0.07	0.02	0.10	0.08***	0.00
to unemployment	0.26	0.32	0.25	0.06**	
to out-of-labor force	0.74	0.68	0.75	−0.06**	
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):					
Burgenland	0.04	0.04	0.04	0.00	0.63
Carinthia	0.06	0.06	0.07	−0.01***	0.00
Lower Austria	0.20	0.22	0.20	0.02***	0.00
Upper Austria	0.16	0.17	0.15	0.02***	0.00
Salzburg	0.06	0.07	0.06	0.01	0.24
Styria	0.15	0.15	0.15	−0.00	0.31
Tyrol	0.06	0.05	0.06	−0.01***	0.00
Vorarlberg	0.04	0.03	0.04	−0.01**	0.02
Vienna	0.22	0.21	0.23	−0.02***	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. Column (1) refers to the overall sample. Column (2) refers to treated women, i.e, those who became grandmothers D before their first long term exit from the labor market (or censoring) T: $\mathbb{1}(T > D)$. Column (3) refers to untreated women, i.e, those who became grandmothers after their first long term exit from the labor market; or non-grandmothers. 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. † A labor market exit is defined as any state of non-employment, with a minimum duration of 12 months. ‡ A permanent labor market exit is defined as any state of non-employment, which lasts until the end of our observation period. ¶ Grandmother's characteristics 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)		
$\delta_{(87-\infty]\ months}$					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_{ν_1}	0.90***	(0.00)			0.90***	(0.00)		
Pr_{ν_2}	0.03***	(0.00)			0.03***	(0.00)		
Pr_{ν_3}	0.07***	(0.00)			0.04**	(0.02)		
Pr_{ν_4}					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***	(0.00)
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 conception of the first grandchild. *, ** and *** indicate statistical significance at the 10 percent level, 5 percent level and 1 percent level, respectively. Standard errors are reported in parentheses.

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)				
ν_6	−1.44 ***	(0.18)	−3.61 ***	(0.17)				
$\Pr_{\nu_1}$	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. *, ** and *** indicate statistical significance at the 10 percent level, 5 percent level and 1 percent level, respectively. Standard errors are reported in parentheses.

Table 4: Impact of Pre-Conception Coordination on Exit Behavior

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Months of Coordination before actual conception date					
	Baseline	3	6	9	18	21	24
δ^{Coord}	–	0.044	0.045	0.024	-0.008	-0.033	0.032
		(0.032)	(0.039)	(0.029)	(0.061)	(0.063)	(0.023)
δ	0.082***	0.093***	0.085***	0.091***	0.087***	0.084***	0.087***
	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.014)
Grandmother's characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grandmother's unobserved heterogeneity	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations for grandmother	72,935	72,935	72,935	72,935	72,935	72,935	72,935
Number of treated grandmothers	31,373	31,765	32,078	32,416	33,359	33,620	33,868
Additionally treated over baseline		392	706	1,043	1,986	2,247	2,495

Notes: This table summarizes ToE estimation results from our extended model allowing for coordination prior to the conception date; see Section 3.4.4. The sample to estimate the effect of a first grandchild on grandmaternal labor supply 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) and has 72,935 observations; see Section 2. Column (1) replicates the baseline estimates from Table 2. For the estimates in Columns (2) to (7) the conception date used for estimation was chosen to lie y months before the actual conception date with $y \in \{3, 6, 9, 18, 21, 24\}$. The treatment effect is allowed to vary with the distance to the actual conception date D. The number of support points in each model is chosen to be 3. *, ** and *** indicate statistical significance at the 10 percent level, 5 percent level and 1 percent level, respectively. Standard errors are reported in parentheses.

Table 5: Including an effect on daughter's employment and wages

Sample definition:	*Daughters employed at conception*		*All daughters*		*All daughters & daughters-in-law*	
Panel A: Effect of first grandchild	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)
	Exit hazard	Exit hazard	Exit hazard	Exit hazard	Exit hazard	Exit hazard
δ	0.081***	0.082***	0.081***	0.084***	0.081***	0.083***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Panel B: Effect of exit on daughters	(B1)	(B2)	(B3)	(B4)	(B5)	(B6)
	Re-employment hazard	Wage hazard	Re-employment hazard	Wage hazard	Re-employment hazard	Wage hazard
$\delta_{daughter}$	0.256***	-0.131**	0.228***	-0.108**	0.198***	-0.055
	(0.032)	(0.059)	(0.030)	(0.054)	(0.024)	(0.047)
$R(0)$	-0.423	4.335	-0.371	3.22	-0.322	1.66
Grandmother's characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Grandmother's unobserved heterogeneity	Yes	Yes	Yes	Yes	Yes	Yes
Mother's age and education	Yes	Yes	Yes	Yes	Yes	Yes
Mother's unobserved heterogeneity	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations for grandmother	72,935	72,935	72,935	72,935	72,935	72,935
Number of daughters with first child	22,512	22,512	23,933	23,933	38,965	38,965
Number of daughters who return to work	16,534	16,534	17,619	17,619	28,399	28,399

Notes: This table summarizes ToE estimation results from our extended model presented in Section 3.4.5 of the paper, and provide sensitivity checks of the results presented in Table 2 of the paper. The sample to estimate the effect of grandmaternal labor market exit on daughter's labor market outcomes varies across columns. Results summarized in columns (1) and (2) re-state our baseline estimations (presented in Table 4 in the paper) using the sample daughters, who were employed on the date of conception. Results summarized in columns (3) and (4) are based on a sample, which includes *all* daughters, regardless of their labor market status at conception. Results summarized in columns (5) and (6) are based on a sample, which further includes daughters-in-law. Panel A shows the estimated effect of the first grandchild on the employment of grandmothers (exit hazard). Panel B shows in uneven columns the estimated effect of grandmother's labor market exit on daughters'(-in-law) duration until re-employment, and in even columns the re-employment wages (wage hazard). It also reports the expected residual life time expressed in years for time until labor market return and residual wages expressed in Euros for re-employment wages. The number of support points in each model is chosen to be 3. One mass point in the daughters as well as in the daughters & daughters-in-law sample converged to a large negative number and where fixed during estimation. 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: 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	6.82	5.23	1.59**	0.00
Endogenous treatment variables						
Number of grandchildren	2.34	2.47	2.33	2.66	−0.33**	0.00
Two or more grandchildren	0.70	0.75	0.69	1.00	−0.31**	0.00
Grandmother's characteristics						
First grandchild by son	0.38	0.39	0.38	0.38	0.01	0.52
Year of birth	1955.69	1954.20	1955.69	1955.67	0.02	0.77
Labor market characteristics:						
Wage (in Euro)	30.66	31.12	30.66	30.66	−0.00	1.00
Missing wage is imputed	0.25	0.24	0.25	0.26	−0.01	0.50
Experience (in years)	11.01	11.18	11.01	11.15	−0.14	0.37
Educational attainment (shares):						
Level 1	0.12	0.11	0.12	0.10	0.02**	0.00
Level 2	0.14	0.11	0.14	0.15	−0.00	0.78
Level 3	0.08	0.06	0.08	0.07	0.01*	0.05
Level 4	0.03	0.02	0.03	0.03	0.00	0.83
Level 5	0.02	0.01	0.02	0.03	−0.00	0.55
Level 6	0.01	0.01	0.01	0.02	−0.00	0.34
Level 7	0.59	0.69	0.59	0.61	−0.03*	0.03
Number of children (shares):						
Has 1 child	0.30	0.36	0.30	0.36	−0.06**	0.00
Has 2 children	0.46	0.42	0.46	0.44	0.02	0.10
Has 3 children	0.18	0.16	0.18	0.16	0.02*	0.03
Has 4 children or more	0.06	0.06	0.06	0.04	0.02**	0.00
Average number	2.02	1.93	2.02	1.90	0.12**	0.00
State of residence (shares):						
Burgenland	0.04	0.04	0.04	0.04	−0.00	0.70
Carinthia	0.07	0.07	0.07	0.07	−0.01	0.40
Lower Austria	0.18	0.18	0.18	0.20	−0.01	0.27
Upper Austria	0.18	0.17	0.18	0.17	0.01	0.34
Salzburg	0.07	0.07	0.07	0.05	0.02**	0.01
Styria	0.17	0.17	0.17	0.15	0.02	0.06
Tyrol	0.07	0.07	0.07	0.07	0.00	0.93
Vorarlberg	0.04	0.04	0.04	0.04	0.00	0.74
Vienna	0.18	0.19	0.18	0.20	−0.03*	0.01
Mother's characteristics						
First grandchild's birthyear	2005.41	2004.16	2005.38	2007.19	−1.81**	0.00
Mother's income	13,796.75	12,999.86	13,745.26	17,274.76	−3,529.49**	0.00
Mother's age	25.43	25.12	25.40	27.44	−2.04**	0.00
Number of observations	106,800	54,263	105,242	1,558		

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. Columns (1), (3) to (6) refer to the overall sample. Column (2) refers to the sample of non-censored observations. Column (3) focuses on the sub-sample of grandmothers, whose first grandchild was a single birth. Column (4) focuses on the sub-sample of 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 7: The effect of the no. of grandchildren and twin-births on the duration to labor market exit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Tobit	Reduced forms (Tobit)				1st stage†	2nd stages‡	
		Spec. 1	Spec. 2	Spec. 3	Spec. 4		Spec. 1	Spec. 2
Treatment variable								
No. of grandchildren	-0.064***						-0.630***	
	(0.013)						(0.197)	
Twin birth (first grandchild)		-1.531***	-0.597***	-0.443***	-0.401***	0.642***		
		(0.173)	(0.136)	(0.136)	(0.126)	(0.028)		
Two or more grandchildren								-1.011***
								(0.321)
First grandchild by son (vs. daughter)	0.061**				0.061**	-0.006	0.058*	0.051
	(0.031)				(0.031)	(0.007)	(0.031)	(0.031)
Grandmother characteristics								
Had twins	0.116			-0.003	0.119	-0.034	0.097	0.108
	(0.114)			(0.122)	(0.114)	(0.026)	(0.114)	(0.114)
Has 2 children	0.440***				0.390***	0.727***	0.850***	0.553***
	(0.038)				(0.037)	(0.009)	(0.147)	(0.063)
Has 3 children	0.354***				0.258***	1.361***	1.122***	0.499***
	(0.056)				(0.053)	(0.012)	(0.272)	(0.093)
Has 4 children or more	-0.293***				-0.447***	2.172***	0.933**	-0.145
	(0.082)				(0.076)	(0.017)	(0.433)	(0.122)
Educational attainment	Yes	No	No	No	Yes	Yes	Yes	Yes
Labor market characteristics	Yes	No	No	No	Yes	Yes	Yes	Yes
State of residence FE	Yes	No	No	No	Yes	Yes	Yes	Yes
Year and month of birth FE	Yes	No	No	No	Yes	Yes	Yes	Yes
Mother characteristics								
Mother's age	0.003			-0.165***	0.005	-0.022***	-0.009	-0.001
	(0.005)			(0.005)	(0.005)	(0.001)	(0.007)	(0.006)
Mother's income	0.024			0.023	0.022	0.041***	0.048**	0.051**
	(0.018)			(0.019)	(0.018)	(0.004)	(0.020)	(0.020)
Grandchild characteristics								
Year of birth FE	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Month of birth FE	Yes	No	No	No	Yes	Yes	Yes	Yes
Mean of dependent variable	6.80	6.80	6.80	6.80	6.80	2.34	6.80	6.80
F-test of weak instrument							507.62	1504.42

Notes: The table summarizes estimates of the effect of i.) the number of grandchildren, and ii.) twin-births among the first grandchild on grandmother's duration to labor market exit. The number of observations is in each case equal 106,800. Since the labor market exit is censored for 52,537 (or 49 percent) of all women, estimations are (if not indicated otherwise) based on a Tobit model. Standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10 percent level, 5 percent level and 1 percent level, respectively. † The first stage is estimated with OLS. ‡ The second stage is estimated as control function with a Tobit model, which controls for the residual from the first stage.

Table 8: Treatment effect heterogeneity of the first and further grandchildren

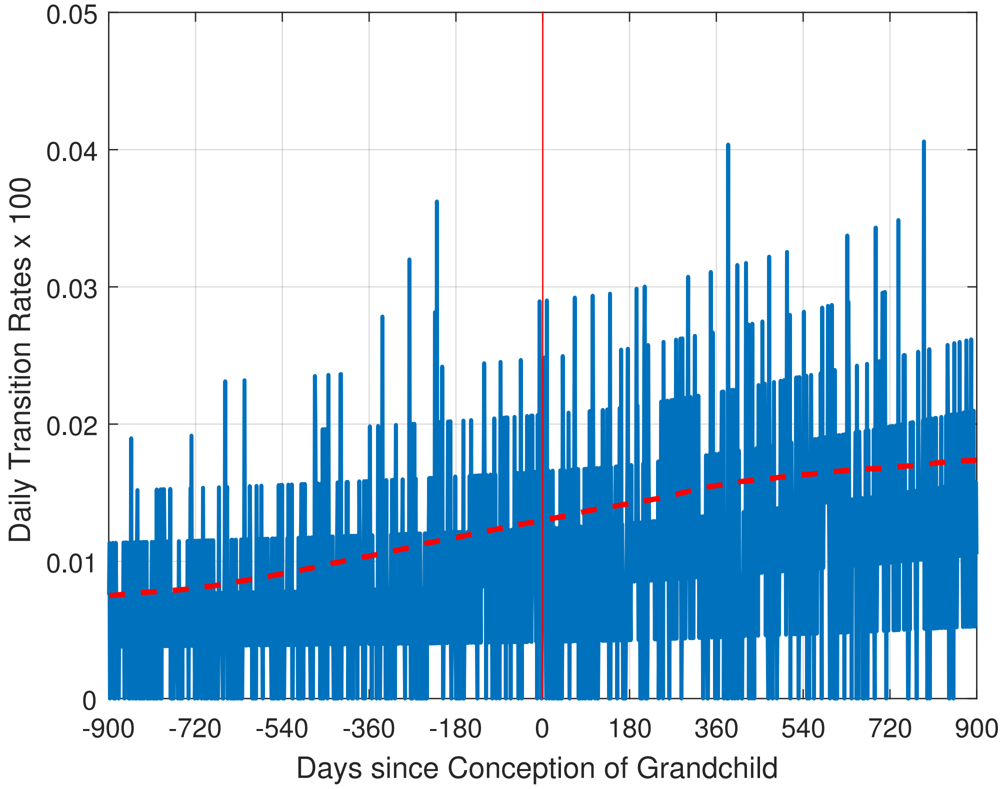
	(1)	(2a)	(2b)	(2c)	(3a)	(3b)
		Distance to grandchild (in min.)			Earnings	
	Baseline	d< 30	30≤d< 90	0≤d	e<median	e>median
Panel A: First grandchild (ToE estimation)						
δ	0.082***	0.271***	0.140***	−0.074***	0.078***	0.094***
$Res(\bar{d})$	−0.453	−1.612	−0.803	0.451	−0.453	−0.494
Number of observations	72,935	18,657	12,604	27,743	30,563	30,563
Panel B: Further grandchildren (Tobit reduced form estimation)						
Twin birth (first grandchild)	−0.401***	−0.418**	−0.242	−0.381	−0.665***	−0.145
	(0.126)	(0.206)	(0.271)	(0.240)	(0.215)	(0.125)
Number of observations	106,800	33,575	21,488	40,079	53,374	53,426
Exit rate	0.41	0.41	0.40	0.44	0.38	0.44
Mean of dependent variable	6.80	6.49	6.58	7.95	7.57	6.02
S.d. of dependent variable	4.49	4.42	4.39	4.58	4.80	4.01
Mean of twin birth	0.0146	0.0158	0.0154	0.0119	0.0131	0.0160
Panel C: Further grandchildren (IV estimations)						
Number of grandchildren	−0.630***	−0.641**	−0.400	−0.638	−1.133***	−0.211
	(0.197)	(0.315)	(0.446)	(0.400)	(0.364)	(0.183)
Two or more grandchildren	−1.011***	−1.019**	−0.593	−1.214	−1.989***	−0.318
	(0.321)	(0.503)	(0.687)	(0.771)	(0.645)	(0.284)
Number of observations	106,800	33,575	21,488	40,079	53,374	53,426
Mean of dependent variable	6.80	6.49	6.58	7.95	7.57	6.02
S.d. of dependent variable	4.49	4.42	4.39	4.58	4.80	4.01
Mean no. of grandchildren	2.34	2.24	2.29	2.58	2.58	2.09
Share with two or more	0.70	0.67	0.70	0.76	0.75	0.64

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 middle panel presents reduced form Tobit estimates outlined in Section 4. The estimates in the lower panel are IV estimations. These are estimated as control function with a Tobit model, which controls for the residual from a OLS first stage. 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 "Grandmothers' Labor Supply" by Wolfgang Frimmel, Martin Halla, Bernhard Schmidpeter, and Rudolf Winter-Ebmer, which is forthcoming in the *Journal of Human Resources*.

Figure A.1: Transition rates of grandmothers around conception date with raw data



Notes: This figure presents daily transition rates of grandmothers around the conception date of the first grandchild. The solide lines are (raw) daily transition rates. The dashed line are smoothed daily transition rates using the method of Muller and Wang (1994). The sample consists of all 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).

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)
$\Pr_{\nu_1}$	0.89***	(0.00)		
$\Pr_{\nu_2}$	0.04***	(0.00)		
$\Pr_{\nu_3}$	0.07***	(0.00)		
Panel C: Duration dependence				
$\lambda_{(0-6]}$	ref.			
$\lambda_{(6-8]}$	1.19***	(0.04)	1.01***	(0.02)
$\lambda_{(8-10]}$	1.93***	(0.04)	1.33***	(0.02)
$\lambda_{(10-12]}$	2.67***	(0.05)	1.73***	(0.02)
$\lambda_{(12-14]}$	3.54***	(0.05)	2.05***	(0.02)
$\lambda_{(14-16]}$	4.40***	(0.05)	2.27***	(0.02)
$\lambda_{(16-18]}$	5.12***	(0.05)	2.15***	(0.03)
$\lambda_{(18-20]}$	5.85***	(0.05)	1.71***	(0.06)
$\lambda_{(20-\infty)}$	6.45***	(0.07)	−0.30	(0.58)
Panel D: Covariate effects				
First grandchild by son	−0.04 ***	(0.01)	1.29***	(0.01)
Age < 40 Years	−3.03 ***	(0.03)	0.33***	(0.03))
40 ≥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. *, ** and *** indicate statistical significance at the 10 percent level, 5 percent level and 1 percent level, respectively. Standard errors are reported in parentheses.

Table A.2: The effect of grandchildren on the duration to labor market exit with uncensored observations using OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Reduced forms				1st stage	2nd stages	
		Spec. 1	Spec. 2	Spec. 3	Spec. 4		Spec. 1	Spec. 2
Treatment variable								
Number of grandchildren	-0.048***						-0.398**	
	(0.014)						(0.173)	
Twin birth (first grandchild)		-1.367***	-0.195**	-0.218**	-0.224**	0.563***		
		(0.140)	(0.099)	(0.099)	(0.096)	(0.034)		
Two or more grandchildren								-0.683**
								(0.292)
First grandchild by son (vs. daughter)	0.072***				0.072***	-0.006	0.070***	0.067**
	(0.027)				(0.027)	(0.010)	(0.027)	(0.027)
Grandmother characteristics								
Had twins	-0.043			-0.164	-0.041	-0.031	-0.053	-0.055
	(0.105)			(0.107)	(0.105)	(0.052)	(0.107)	(0.106)
Has 2 children	0.193***				0.155***	0.807***	0.476***	0.267***
	(0.032)				(0.030)	(0.010)	(0.142)	(0.056)
Has 3 children	0.181***				0.106**	1.565***	0.730***	0.275***
	(0.051)				(0.048)	(0.021)	(0.274)	(0.086)
Has 4 children or more	-0.142*				-0.264***	2.549***	0.752*	-0.059
	(0.085)				(0.080)	(0.039)	(0.447)	(0.119)
Educational attainment	Yes	No	No	No	Yes	Yes	Yes	Yes
Labor market characteristics	Yes	No	No	No	Yes	Yes	Yes	Yes
State of residence FE	Yes	No	No	No	Yes	Yes	Yes	Yes
Year and month of birth FE	Yes	No	No	No	Yes	Yes	Yes	Yes
Mother characteristics								
Mother's age	0.031***			0.021***	0.032***	-0.025***	0.023***	0.028***
	(0.004)			(0.004)	(0.004)	(0.002)	(0.006)	(0.005)
Mother's income	0.012			0.029**	0.010	0.044***	0.028**	0.032**
	(0.012)			(0.012)	(0.011)	(0.005)	(0.014)	(0.015)
Grandchild characteristics								
Year of birth FE	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Month of birth FE	Yes	No	No	No	Yes	Yes	Yes	Yes
Mean of dependent variable	6.12	6.12	6.12	6.12	6.12	2.47	6.12	6.12
Mean of treatment	2.471	0.014	0.014	0.014	0.014	2.471		0.746
F-test of weak instrument							280.87	1725.09

Notes: The estimations summarized in this table are comparable to those presented in Table 7 in the paper, but exclude those women, who have *not* left the labor market before 2014 (censored observations). The number of observations is 54,263. The method of estimation is in columns (1) to (6) OLS, and in columns (7) and (8) 2SLS. Robust standard errors in parentheses. *, ** and *** indicate statistical significance at the 10 percent level, 5 percent level and 1 percent level, respectively.

Table A.3: Treatment effect heterogeneity of the first and further grandchildren: child-care availability

	(1)	(2)	(3)
	First grandchild		**Further grandchildren**
	ToE Estimation		**Tobit reduced form**
	Grandmother	Daughter	Grandmother
Distance > 60 min, Formal-child care	-0.048^{*}	0.170^{***}	-0.205
	(0.029)	(0.075)	(0.298)
Distance > 60 min, No formal-child care	-0.033	0.147^{*}	-0.472
	(0.039)	(0.079)	(0.330)
Distance $\leq$ 60 min, Formal-child care.	0.199^{***}	0.217^{***}	-0.278
	(0.028)	(0.058)	(0.224)
Distance $\leq$ 60 min, No formal-child care	0.236^{***}	0.392^{***}	-0.633^{***}
	(0.038)	(0.074)	(0.293)

Notes: Columns (1) and (2) present estimates from the ToE approach outlined in Section 3. The estimated coefficients measure the effect of the arrival of a first grandchild on the exit probability of grandmothers (column (1)) and mothers (column(2)) by $[exp(\delta) - 1]$ percent. The estimates column (3) are based on Tobit reduced form estimates outlined in Section 4. *, ** and *** indicate statistical significance at the 10 percent level, 5 percent level and 1 percent level, respectively. The availability of grandmothers and formal-child care 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.