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Abstract

We study the impact of subsidizing home-based long-term care on recipients' health and the labor supply of their working-age children. We use administrative data from Israel on the universe of welfare benefit applications linked with tax records of applicants and their adult children. To address the endogeneity of benefit recipients' health status, we instrument for benefit receipt using the leniency of randomly assigned evaluators who assess the applicant's functional status and determine benefit eligibility. We find that for compliers — applicants who receive subsidies only from more lenient evaluators — subsidizing home-based care has large adverse effects on recipient health but no detectable effects on the labor market outcomes of their children. The results are consistent with the crowd-out of self-care for the marginal recipient, highlighting the need to assess the heterogeneous effects of home-care subsidies.

keywords: home-based long-term care; labor supply

JEL Codes: I13, I18, J22, H53

1 Introduction

The growing need for home-based care among the aging, particularly the disabled elderly, ranges from help with simple chores to extensive assistance with daily activities. This need is met through a mix of formal and informal care, with adult children often providing the latter. Subsidies for formal care can thus affect both the type of care elderly recipients get and the work availability of their adult children. Understanding these effects is key for evaluating the impacts of long-term care subsidies, which have implications for both elderly health and child labor market outcomes (Van Houtven et al., 2013). However, estimating the causal impact of formal care subsidies or programs is complicated by the endogeneity of the need for care and access to formal and informal assistance.

This study examines the effects of subsidizing home-based long-term care on recipient health and their working-age children's labor supply. We utilize comprehensive administrative data from Israel's Social Security Administration, encompassing welfare benefit applications from 2010 to 2015, matched with tax records of the applicants, their spouses, and adult children. These data allow us to consider the impacts of care subsidies on precisely measured health and labor outcomes in a large population.

The primary identification concern is the endogeneity of assistance, which is inherently targeted toward applicants with a greater need. Our empirical approach leverages Israel's approach to determining care subsidy eligibility. Unlike the near-universal systems in Nordic countries or the more limited ones in other countries, in Israel, subsidies are based on individual assessments of need (Van Houtven et al., 2013). This individualized assessment introduces arbitrary variation between evaluators, establishing a quasi-experimental framework for inferring the causal effects of subsidies. We exploit this variation through an instrumental variable strategy, focusing on the leniency of randomly assigned professional evaluators who assess applicants' functional status and eligibility for benefits (seminal uses of this strategy in domains such as evaluation of children's needs, criminal risk, include Gaudet et al., 1932; Imbens and Angrist, 1994; Kling, 2006). We follow best practices of evaluators design as laid out in (Chyn et al., 2024). After adjusting for variables reported on the application forms, including the applicant's income and city of residence, we find that the residualized assignment of evaluators is uncorrelated with other observable applicant characteristics, supporting our instrument exogeneity. We also show evidence supporting (average) instrument monotonicity (Frandsen et al., 2023). Furthermore, the residualized leniency is fairly dispersed: The evaluator in the 90th percentile of the leniency distribution approves 75% of the applications, whereas the 10th percentile approves only 51%. This evidence supports using the conditional assignment of evaluators for studying the impacts of home-based long-term care subsidies.

Using a flexible empirical specification, we find that the subsidization of long-term care in the home has notable adverse effects on the health of the recipient. Specifically, subsidy eligibility is associated with a 5.4 percentage point increase in one-year mortality rates, a considerable increase relative to baseline mortality of 8.5% of the applicant population. These findings were surprising to us, but not so surprising to practitioners, social security administrators, and physicians. The findings are further validated by a falsification analysis, which reveals no discernable impact on 60-day mortality rates—a horizon likely too short for care subsidies to have a meaningful effect on, thus further mitigating concerns of confounding effects in our estimations.

At the same time, we find inconclusive evidence on labor market outcomes for children of recipients. Our estimates do not permit us to reject the null hypothesis that there are no effects on labor market participation or income, although our estimates are not precise enough to reject substantive effects either. Moreover, we observe no meaningful impact on children's employment and wage trajectories up to 7 quarters post-initial care application. These results suggest a lack of crowd-out in informal care provision, at least to the extent that it would manifest in detectable labor market effects, particularly among compliers–children of those applicants whose functional statuses hover at the borderline of subsidy eligibility and are most susceptible to evaluator leniency. We interpret the findings as being consistent with a scenario in which formal caregivers primarily displace *self-care* rather than informal care.

This work adds to the literature that evaluates the impacts of home-based care on recipients' health, where findings are generally mixed, but the studies do not enjoy the same level of empirical design and data. For example, Løken et al. (2017) find that increased government support for home-based care had no impact on the health of older adult parents. Likewise, Hollingsworth et al. (2022), studying a policy reform in Scotland that introduced free formal home care, found no significant impact on hospital use and health outcomes. In contrast, Van Houtven and Norton (2004) found that informal care reduces home health care use and delays nursing home entry. Barnay and Juin (2016), using the number and gender of children as an instrument for informal care, find that such care reduces the risk of depression. Lei et al. (2022), examining long-term care insurance pilot programs in China, find improvements in self-reported health and one-year mortality. Massner and Wikström (2023), analyzing a Swedish policy reform aimed at reducing the fees for formal elderly care, found it was associated with decreased healthcare use. Our study contributes credible evidence using administrative data and a quasi-experimental leniency IV design.

Existing work also explores the impact of care for older adult parents on their children's labor supply. These studies find negative associations between informal and formal care (Bonsang, 2009; Hollingsworth et al., 2022; Lei et al., 2022), substitution between multiple children providing care (Fontaine et al., 2009), and between caring for parents and labor market opportunities (Bolin et al., 2008; Ettner, 1995; Johnson and Lo Sasso, 2006; Van Houtven et al., 2013; Shen, 2023; Massner and Wikström, 2023). However, results in this area are also mixed. For instance, Fu et al. (2017), examining policy changes in Japan's long-term care insurance, found that these initially significantly boosted caregivers' labor force participation, but a subsequent amendment had a negative effect on their employment. Coe et al. (2023), using changes in the state tax treatment of long-term care insurance policies as an instrument, finds no reduction in informal care usage over eight years but observed lower co-residence rates. The closest to this study is Løken et al. (2017), which studies a reform that expands government funding of formal home-based care for older adults using administrative data from Norway. It finds no impact on mobility or employment of children of formal care expansion, except for an increase in hours worked by only-child daughters. In related work, Fadlon and Nielsen (2021) estimate a large (positive) response of spousal labor supply in response to fatal or severe health shocks within households, though the trigger—a health shock—is quite different from subsidized care.

This paper continues as follows. Section 2 provides background on home-based long-term care in general and on the institutional details of its provision in Israel. Section 3 presents the data. Section 4 presents the empirical specification. Section 5 presents our results. Section 6 further discusses the results and concludes.

2 Background

2.1 Home-Based Long-Term Care

The older adult population is large and fast-growing, and their need for long-term care is increasing. By recent estimates, more than one-half of U.S. residents above the age of 65 develop disabilities that require long-term care (Johnson et al., 2021). According to the National Institute on Aging (2021), most people prefer to stay in their own homes for as long as possible, and most long-term care is provided at home. Home-based long-term care (henceforth, home care for short) includes health, personal, and support services to help people stay at home and live as independently as possible. The caregiving responsibilities span activities of daily living (ADLs) and instrumental activities of daily living (IADLs).[1] Home care can be provided either informally, by unpaid family members, or formally, by

[1] Caregivers assume many different responsibilities, including support with activities of daily living (ADLs, typically bathing, dressing, eating, toileting, and transferring; these activities are also used to assess physical functionality and formal care eligibility). Caregivers may also assist with instrumental activities of daily living (IADL, such as shopping, meal preparation, money management, light housework, and laundry), with health care management, and with monitoring of health status.

paid professional caregivers.

Traditionally, home-based care has largely been informal, often provided by family members who balance caregiving with other employment responsibilities (Institute of Medicine, 2008). However, demographic and economic factors, including increased life expectancy and greater female labor force participation, contribute to a growing reliance on formal, paid care (Spillman et al., 2021).

Given that formal home care is generally less expensive than professional institutional care, supporting formal home care is also a priority for funding agencies anticipating an increase in the number of people in need of care. For example, in Israel, where our study takes place, national expenditure on long-term care, recently estimated at 1.2% of GDP, is likely to grow as the country's relatively young population ages (Rosen et al., 2018). Due to its importance for working-age adults and the substantial financial burden of privately funding formal care, public funding of formal home-based care is also an increasingly central policy issue. Survey data reveal strong public support in the U.S. for budgetary increases aimed at expanding access to long-term home care (Nilsen, 2021).

In addition to its direct economic implications, the transition from informal to formal care may introduce a change in the quality and scope of care, with uncertain effects on the health and well-being of older adults. On the one hand, formal caregivers are available for longer hours and may provide more continuous support. On the other hand, formal caregivers often have limited geriatric training sourced from agencies providing minimal screening and basic training. As such, a subset of formal caregivers consists of migrant workers, who may not share the applicant's native language. Further, Institute of Medicine (2008) suggests that informal caregiving yields benefits like shorter hospital stays and fewer problematic discharges. Another downside of more services by a formal caregiver is reducing the recipient's independence by crowding out activities they could perform themselves.[2]

[2]Gitlin et al. (2009) find that increasing the independence of the elderly contributed to elders' health. In conversations with Geriatric specialists at the Israeli Ministry of Health, concerns were raised that formal care may reduce elderly independence by prioritizing task efficiency over engagement

Hence, the net effect of replacing informal care with formal care on the health of the elderly remains ambiguous.

2.2 Institutional Context

Our study takes place in Israel, which offers government subsidies to support long-term home care. The subsidies are mandated by law and provided on a per-need basis, but are not universal. The eligibility test facilitates our identification of subsidies impact by exploiting arbitrary variations in need assessments. Legislation in Israel has responded to trends, paralleling those in other developing countries, of an increasing reliance on formal care. Enacted in 1988, the Long-Term Care Law extended home care subsidies, primarily used to hire formal caregivers.[3] Eligibility for a subsidy also reduces the fixed cost of applying for a foreign caregiver by automatically granting an employment authorization, thereby reducing the administrative burden for applicants. The eligibility is determined by a combination of age, income, and need. Age thresholds are set at 62 for women and 67 for men. Financial eligibility is defined by an income cap that varies based on household size and is linked to the Israeli average monthly wage. Need is based on ADL assessment of functional performance in the areas of personal self-care and general activities in and around the home. Administered by the Israeli National Social Security, the application process involves submission to central district offices using a standardized form (Appendix B lists the fields on this form). Upon submission, financial eligibility is ascertained through administrative data, and those failing to meet the criteria are rejected. Applicants who are older than 80 years at the time of application may be approved without further review (therefore, we exclude them from our sample). The functional status of applicants younger than 80 is evaluated by a professional evaluator—a nurse, occupational therapist, or physical therapist—employed by the Social Security Administration.

[3] During the study period, 98.2% of subsidies were used for home care. In addition to subsidized home care, the subsidy may also be used for other services, including medical alert systems, laundry services, and transportation services. https://www.btl.gov.il/Publications/Skira_shnatit/2012/Pages/default.aspx

Evaluators are randomly assigned to applicants within geographical units, taking into consideration geographic proximity and language concordance between the evaluator and the applicant. During home visits, evaluators assess ADL capabilities using a standardized questionnaire, scoring applicants on a four-level need scale. The level of subsidy (measured in caregiver hours) is increasing in the approved level of need.[4] Typically processed within weeks, subsidies facilitate hiring caregivers through private agencies, which are subsequently reimbursed by the government. Applicants are permitted to select the agency of their choice, but they are not permitted to employ family members. Additional care hours beyond those subsidized may be financed out-of-pocket by the applicant or their family. These same agencies also serve applicants who do not qualify for financial support.

3 Data

3.1 Sample

We combine data from two administrative sources: applications and approvals for home care subsidies from the Social Security Administration, including the date of death where applicable, and income records panel (for children of applicants) from the Israeli Tax Authority.

The population from which we draw our sample consists of the universe of all non-Arab applications from 2010 to 2015. To construct the main sample, we restrict attention to first-time applications by applicants who applied for a permanent LTC subsidy aimed at custodial care (rather than temporary assistance for post-acute care) and are under the age of 80 at the time of application. For these applicants, an evaluator review is required. To reduce noise in the measurement of evaluator leniency, we restrict attention to applications reviewed by one of 303 evaluators who performed at least 100 evaluations over the six-year study period. These evaluators reviewed 73.2% of the total applications. The resulting sample contains

[4]Subsidies for need levels 1, 2, and 3 cover 9.75, 19, and 22 weekly hours of home care, respectively. In practice, the vast majority of approved applications are eligible for the basic level of support. Applicants with above-median income qualify for half the number of hours.

51,111 applications. Appendix A provides additional details on the sample construction.

Panel A of Table 1 describes the characteristics of applicants in our sample. The average applicant is 72.2 years old and 96.4% of applicants are married or were married in the past. 71% of applicants have children.[5] Like many older Israelis, most applicants are foreign-born. About 60% of the applicants list Hebrew as their main language; Russian, common among immigrants from the former Soviet Union, is the second most common language. Table 1 also provides the distribution of approval rates for all applications, with 64% being approved. Notably, 78% of approved applications meet the basic need definition, with only small fractions falling into other need levels. Therefore, we consider all need levels combined.

When studying labor market outcomes of adult children, we narrow our focus to applicants with children, linking the application records with child monthly income data from tax records. We further restrict attention to a balanced panel spanning seven quarters before and seven quarters after the application time. We include all children, including those who did no work during the study period or any subset thereof. The resulting sample comprises 76,589 Applicant-child combinations of 24,004 applicants. Appendix Table A1 describes this sample. Appendix Table A2 describes the household characteristics of these applicants. The average applicant with children has three children. Most children are in their prime working age. The average child is 42 years old at the time of their parent's application.

3.2 Main Variables

Applicant Health Our only universally available measure of applicant health is all-cause mortality. We observe the date of death from administrative sources for all applicants in our sample, regardless of their subsidy eligibility status. We measure mortality one, two, and three years from the date of application. Panel B of Table 1 describes the mortality of

[5]Children who are born in Israel are registered on their parents file at birth. Even though 84% of applicants were not born in Israel themselves, 78% of linked children were born in Israel. Data on children might be missing for people who immigrated with already-adult children, but unlikely missing for people who immigrated with children under 18 since there are significant tax benefits for having children. See Table 1 for the distribution of the number of children.

applicants in our sample. Reflecting the frailty of long-term care applicants, this mortality rate is, unsurprisingly, fairly high: 8.5% die within a year and 18.3% die within three years from the initial application. It is even higher among approved applicants, for which the respective one- and three-year mortality rates are 12% and 23%. The unsurprising higher mortality rates of approved applicants highlight the need to account for the endogeneity of subsidy approval, as we do later.

Labor Market Outcomes We observe the applicants' children labor market participation and their labor income. Based on their national ID number, the Social Security Administration exactly matches the applicant's children with their income data from tax records. Our dataset includes encrypted IDs, which protect privacy but allow us to track individuals over time. These records include both wage income and income from self-employment, reported on an annual basis. For every calendar year, we observe total earnings and indicators for months with any income reported from either employment or self-employment. We calculate the monthly income by averaging the total annual income across all months with reported earnings. Appendix Table A2 describes these measures in our sample. During the study period, 85% of children were ever employed and 9.2% were ever self-employed. The average child in our sample is observed to be employed 73% of the months, which is consistent with prior work showing that informal family caregivers often work while providing assistance to those in need.

Control Variables The benefits application form (Form number 2600, "Claim for Long-term Care Benefits"; see Appendix B for a detailed translation) is the sole source of information on applicants for the Social Security field office. The form includes information on the following: application date, city, language, gender, birth date, number of people living in the household, number of children, income, marital status, and whether they are Israeli-born. We use all these variables as control variables. This allows us to compare applicants within narrowly defined cells that could potentially influence evaluator assignment. We further use these variables to conduct heterogeneity analyses of the impacts of home-care subsidies on applicant health by several applicant characteristics.

We augmented data sourced from the application forms with additional administratively sourced demographic information on applicant children. These additional data are not available to field offices and were provided to us by the Social Security Administration research center. For children of applicants, we observe age, gender, city, marital status, and whether they are Israeli-born.

4 Empirical Specification

The main challenge with identifying the impacts of subsidized care is that subsidies are, obviously, endogenous: they are given to sicker applicants. To address this challenge, we use a leniency instrumental-variable (IV) design (Kling, 2006) that exploits the random assignment of evaluators to first-time applicants. That is, because conditional on information observed on the initial application form, evaluators are randomly assigned to applicants, differences in evaluator leniency generate random variation in the provision of subsidies. We use this variation to estimate the effects of elder's eligibility for subsidy on outcomes, by using the evaluator's (leave-one-out) approval rate of first-time applicants, conditional on all observed characteristics as an instrument for the actual approval of a subsidy. The rest of this section discusses the empirical specifications in detail.

Define the leniency of the evaluation of applicant i, who is evaluated by evaluator j, as the evaluator's leave-one-out application approval rate:

$$Leniency_{ij} = \frac{\sum_{i' \neq i} Approved_{i'j}}{\sum_{i' \neq i} Evaluated_{i'j}} \tag{1}$$

where *Approved* is an indicator that equals zero for rejected applications and one for approved applications of any level of need; $Evaluated_{i'j}$ is an indicator that equals one for any applicant i' evaluated by j, regardless of approval status. Because the evaluator and their associated leave-one-out leniency score are unique to i, we use the subscript notation $Leniency_{i,j(i)}$.

Using this definition, we estimate two-stage least squares specifications. For mortality, we estimate:

$$
\begin{aligned}
Eligible_i &= \alpha Leniency_{i,j(i)} + \eta_i' \gamma + \nu_i \\
Y_i &= \beta \widehat{Eligible}_i + \eta_i' \delta + \epsilon_i,
\end{aligned}
\tag{2}
$$

$Eligible$ is an indicator for the applicant eligibility; $Leniency_{i,j(i)}$ is the evaluator leave-one-out approval rate defined above; and η_i is a vector of individual controls (which include the following applicant characteristics: gender, age, city, language, calendar year and month-of-year of application, income decile, immigrant status, marital status, household size). Y is one of several measures for applicant mortality (all-cause mortality within two months and one, two, or three years). The parameter of interest is β, the impact of home-based long-term care subsidy on outcomes.[6]

To estimate the effects of subsidies on child labor-market outcomes, we conduct a series of second-stage regressions for each quarter relative to the time of application. We use the following specification:

$$
\Delta Y_{kt} = \tau_t \widehat{Eligible}_{i(k)} + \eta_{i(k)}' \delta + \epsilon_{kt}, \tag{3}
$$

Where k indexes children of first-time applicants and $i(k)$ is used to index the applicant associated with child k; the index t refers to the time (in quarters) relative to the time of application, with quarter zero being the quarter beginning with the month of application; ΔY_{kt} stands for one of two labor market outcomes: either participation, defined as an indicator for any work during the quarter, or the log of the average monthly wage. Outcomes are calculated as the difference from their value in the reference period, which we designate

[6]We use robust standard errors (Chyn et al., 2024).

as one quarter prior to the application (i.e., $\Delta Y_{kt} = Y_{kt} - Y_{k,-1}$). Since some applicants have more than one child, we weight this regression so that each applicant's children's weights sum to one. The parameters of interest here are τ_t, for $t > 0$ which capture how home-care subsidy impacts the labor market trajectory of the recipient's children upon its receipt.

We build on the recent innovations in judge and examiner IV designs and require the following identification assumptions: average exclusion, independence, and average monotonicity (Frandsen et al., 2023; Chyn et al., 2024). The exclusion restriction is that evaluator assignment only affects applicant outcomes through its impact on the treatment (in our case, the eligibility for subsidy), not directly. This seems plausible in our context, since most evaluators only meet the applicants once for a structured assessment based on the ADL questionnaire.

Independence means that, conditional on observed applicant characteristics (namely, within cells defined by a combination of the controls for these characteristics), the assignment of evaluators is independent of the potential outcomes of the applicant. In interviews with current administrators and evaluators, we learned that the assignment of evaluators is indeed conditionally random. The assignment is done at the local level, with a pool of evaluators responsible for each area. A new application is assigned an evaluator in that area that matches their spoken language. Formally, no other factors should underlie the match. However, as excess caution, to mitigate the possibility that other factors that are observed on the application forms (such as the applicant's age, gender, ethnicity, or even income) do, in fact, influence the match, we also include specifications that condition on all these observed factors.

We provide evidence from falsification tests in support of the independence and exclusion assumptions (Danieli et al., 2023). These tests are based on the idea that leniency-driven benefits receipt status, to the extent that it is quasi-randomly assigned, should not be associated with outcomes that were determined prior to the application. First, we evaluate the (conditional) independence of assignment with child income and number of children—observed predetermined covariates that are not available to field offices at the time of assignment. Second, we estimate a version of (2) using as pseudo-outcome the applicant mortality in the immediate period following the application, which is unlikely to be affected by benefit subsidy. Finally, the parameters τ_t for $t < 0$ in (3) also serve as a falsification test, as benefit receipt should not impact child labor market outcomes prior to the application.

The last requirement is average monotonicity (Frandsen et al., 2023), a weaker identification condition than the standard strict monotonicity. Strict monotonicity (Imbens and Angrist, 1994), which is not testable, was commonly assumed in similar studies (Kling, 2006; Doyle Jr, 2007; Anwar et al., 2012; Dahl et al., 2014; Aizer and Doyle Jr, 2015; Dobbie et al., 2018; Bhuller et al., 2020; Bakx et al., 2020), but Frandsen et al. (2023) show that a weaker assumption suffices for a causal interpretation of the estimates. Within our context, average monotonicity requires that for every applicant, a more lenient nurse is on average more likely to approve a subsidy. This means that while some individuals may encounter violations of strict monotonicity (i.e., a more lenient nurse might reject benefits that a stricter one would approve), across all nurses, greater leniency predicts a higher likelihood of treatment. Following the suggested approach by Frandsen et al. (2023), we provide two types of evidence for average monotonicity. The more formal approach is estimating the first stage for different applicant groups defined by observed characteristics. If average monotonicity holds, the first stage coefficient should be positive and significant within each subgroup. As Appendix Table Appendix Table A3 shows, this condition holds for all subgroups. We also provide an informal test that is similar in nature and gained some popularity in applied work (Bhuller et al., 2018; Dobbie et al., 2018). Namely, measure for each evaluator their average leniency separately for different subgroups and see if these measures are strongly and positively correlated across nurses. E.g., is an evaluator lenient toward men also lenient toward women? This is indeed the case in our setting across all subgroups, as shown in Appendix Figure Appendix Figure A4.

These tests support the underlying identifying assumptions, making us more confident in the validity of the results as causal estimates of the average effects on the compliers.

5 Results

Variation in Leniency and IV Validity

Before discussing our main results, we review evidence related to the key identifying variation: the approval rates of different evaluators. The histogram in Figure 1 shows the distribution of our leniency measure among evaluators in our sample, after residualizing by all fixed-effects included in our specification, which account for information available through the application form. Residualized approval rates are fairly symmetric, ranging between 0.51 and 0.75 on the 10^{th}–90^{th} percentiles. Important for our design, approval rates exhibit a fair amount of dispersion, even conditional on applicant characteristics (Appendix Figure A1 shows the raw rates, which are slightly more dispersed, as expected). Since we focus on first-time applicants, it is unlikely that any additional information that could have affected the match was available before the first encounter with the applicant. This dispersion, therefore, most likely reflects between-evaluator noise (Kahneman et al., 2021). In further support of the independence assumption, Appendix Figure A2 shows that conditional on observables, evaluator leniency does not depend on the number of children applicants have or their children's income—two variables that are unavailable to the field offices and therefore should not have impacted evaluator assignment. Figure 1 further shows evidence for a strong first stage: application acceptance rate is highly correlated with the leave-one-out rate.

The Impacts of Home-Care Subsidies

Recipient Health. Table 2 shows estimates for the impact of receiving a subsidy for home-based long-term care on recipient one-year mortality. OLS estimates show that applicants approved for subsidized home care are 8.6 percentage points more likely to die within a year compared to applicants who were declined. Naturally, subsidy recipients are sicker, so this estimate may purely reflect this. However, IV estimates from equation (2) also suggest that subsidy-eligibility for home care negatively impacts applicant health. For the marginal recipient, subsidy approval is associated with a 5.4 percentage-point increase in mortality within a year from application. These estimates instrument for subsidy eligibility using evaluator leniency, conditional on the applicant's city, language, and time of application. Further supporting the independence assumption is the fact that estimates (presented in Column 2), are unchanged when we saturate (in Column 3) the set of fixed-effects to include all applicant characteristics observed on the application form.

To gain more insight into timing of the effect of home-care subsidy on mortality, Appendix Table A4 shows additional estimates of the impact of a subsidy on mortality measured at different horizons. Two key findings emerge. First, consider mortality during the short term—the first two months after the application. While subsidy recipients have higher baseline mortality risk than non-recipients (the OLS estimate is 3.1 percentage points and highly significant), our leniency-IV estimate detects no significant impact of the subsidy on short-term mortality. This (null) result in what is akin to a falsification test suggests that there is no correlation between evaluator leniency and case severity, further supporting the independence assumption. Appendix Figure A3 further supports this by showing negligible effects over short horizons and growing and significant effects for longer horizons. Second, consider the impact of the subsidy on mortality over the longer term. We find that IV estimates for the impacts of a subsidy on two- and three-year mortality are very similar to its impact on one-year mortality: we estimate a 4.3 percentage point increase in two-year mortality and 4.4 percentage point increase in three-year mortality. Together, these results indicate that most of the (adverse) health effects of the subsidy accrue during the first year.

The finding that subsidizing formal home care adversely affects elderly health may seem counterintuitive. However, as discussed in Section 2, formal care may substitute for both self-care and informal care by family members of the recipient. Therefore, it is possible that subsidizing formal care changes the nature and quality of care received, including crowding out of essential aspects present only in other forms of care, such as emotional support and encouragement of recipient independence, with detrimental impacts. While we do not have granular outcome data that would be required for a detailed examination of such mechanisms, we return to this discussion in Section 6.

Figure 2 shows additional heterogeneity analyses by all observed covariates (the underlying subsamples are described in Appendix Table A5). We could not reject the null of no differences between subgroups in mortality effects, though these estimates are obviously less powered due to the restriction of sample sizes. We observe a statistically significant effect only for women or for individuals who are married or do not live alone in their households. This hints at crowding out of informal care by co-residents as another possible mechanism, but should be interpreted with care.

Child Labor Market Outcomes. Figure 3 shows estimates for the impact of home-care subsidy on labor market outcomes of children, obtained from estimating the event-study model specified in equation (3) using the sample of adult children of applicants. Figure 3a shows the impact on participation and Figure 3b shows the impact on income. In both cases, the parallel-trends assumption seems to hold: in the year and a half leading to the application, there is no discernible difference between the labor market outcomes of children of applicants whose (later) evaluators have high and low leniency. Neither do we find any significant impact on either outcome for the seven quarters after applications. Admittedly, these null estimates are also fairly noisy. For example, we cannot rule out a several percentage-points increase (or decrease) in labor market participation and income within a year of applications. Accordingly, we interpret these estimates with caution.

6 Discussion and Conclusion

We study the impact of subsidizing home-case long-term care on recipient mortality and the labor market outcomes of their adult children. Our design exploits the variation in subsidy eligibility induced by the quasi-random assignment of evaluators. We focus on first-time applications, for which both administration and evaluators lack prior information unavailable to us, and provide falsification test evidence supporting the conditional independence of evaluator assignment.

Using this IV design, we find that subsidizing home care seems to worsen recipients' health: we estimate that subsidizing home care leads to a greater one-year mortality risk. The impact appears to occur only within several months to a year—we find no mortality impacts immediately following the application. Further, we fail to reject the null of no impact of home-care subsidies on the participation and earnings of applicant children, though our estimates, which contrast with some existing evidence (c.f., Løken et al., 2017), are admittedly noisy.

This result was surprising to us. Why might a subsidy for formal home care result in greater mortality risk? One possible explanation is that formal care may crowd out self-care, particularly among compliers—marginal recipients who exhibit sufficient functional capability for some evaluators to consider them ineligible for home care subsidy. For such (relatively) high-functioning individuals, a formal caregiver may reduce the level of independence and physical exercise, leading to lower physical fitness and health over time.[7] An alternative mechanism, which should be consistent with increased participation of children in the labor market, is that home care by a hired caregiver substitutes for higher quality care by informal child caregivers. Finally, formal home care may also delay moving to a long-term care facility that might be better at extending life.

We stress that our results should be interpreted with caution and warn against unwarranted extrapolation from these findings. Our estimates are localized, being identified

[7]This is a very real possibility in the eyes of geriatric specialists we consulted. For example, Gitlin et al. (2009) find that randomized intervention aimed at increasing the independence of elderly at home reduced mortality after two years by 7.6 percentage points. The largest effect—11.5 percentage points—was for participants defined ex-ante as moderate mortality risk. This group might be similar to our borderline recipients. In our context, the key concern is that formal workers may not take into account the value of engaging disabled individuals. It may seem simpler and safer to substitute for the elderly, even in tasks they are able to do, with the result being a deterioration of fitness by the subsidized elderly.

through evaluator-induced variation, specifically among borderline cases which may not generalize to more severe instances. Moreover, we do not observe detailed applicant health records, which limits our ability to explore the mechanisms underlying the adverse health impacts of subsidies. This calls for further research.

While we do not view the current evidence as compelling enough to have direct policy implications, these results illuminate potential tradeoffs inherent to subsidizing home care. They highlight the need to further study the impact and substitution patterns related to subsidized formal home care and to acknowledge that, at least in some cases, subsidies may adversely impact recipients, as the induced substitution from self or informal care to formal care may alter both the nature and quality of care received. Therefore, results call for heightened scrutiny concerning the unintended consequences of substituting formal for informal care.

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Table 1: Descriptive Statistics for the Sample of Applicants

	Sample, by Application Approval Status		
	Approved (1)	Not Approved (2)	All (3)
A. Applicant Characteristics			
Age	72.2	72.3	72.2
Female (%)	64.7	71.6	67.2
Living Alone (%)	42.0	53.4	46.1
Marital Status (%)			
Single	3.2	4.1	3.6
Married	57.7	49.0	54.6
Divorced	14.5	18.8	16.0
Widowed	24.6	28.0	25.8
Number of Children (%)			
0	25.5	34.9	28.9
1	13.5	14.8	14.0
2	15.6	12.7	14.5
3	18.3	13.3	16.5
4	12.4	9.8	11.4
5 or more	14.8	14.5	14.7
Income (NIS)	5,776	3,660	5,010
Native Hebrew Speaker (%)	63.5	51.0	59.0
Israeli Born (%)	16.9	11.4	14.9
B. Mortality (%)			
Within 1 year of application	11.6	3.1	8.5
Within 2 years	18.2	6.3	13.9
Within 3 years	23.1	9.7	18.4
Observations	32,601	18,510	51,111
Percent of total	63.8	36.2	100

Notes: The table shows descriptive statistics for applicants in our sample. Different columns show different subsamples, by application approval status. For detailed sample and variable definitions, see Section 3.

Table 2: The Impact of Subsidized Home-Based Long-Term Care on Applicant Mortality

	OLS (1)	*IV* (2)	*IV* (3)
A. IV First Stage			
		Dependent Variable: Subsidy Approved	
Evaluator Leave-One-Out Leniency		0.764	0.702
		(0.022)	(0.022)
F Statistic [d.f.]		1227.38	1059.67
		[1,50176]	[1,50123]
B. OLS and IV Second Stage			
		Dependent Variable: 1-Year Mortality	
Subsidy Approved	0.086	0.054	0.052
	(0.002)	(0.017)	(0.019)
Included Fixed Effects:			
Applicant City		V	V
Applicant Language		V	V
Application Year		V	V
Application Month			V
Applicant Martial Status			V
Applicant Gender			V
Applicant Age			V
Applicant Income Percentile			V
Applicant Is Israeli Born			V
Applicant Is Living Alone			V
N Obs (Applicants)	51,111	50,802	50,802

Notes: The table shows estimates of the impact of subsidized home care on applicant one-year all-cause mortality with robust standard errors. The sample consists of all first-time applications. Column 1 shows OLS estimates (which do not adjust for selection). Columns 2 and 3 show IV estimates that use evaluator leave-one-out leniency as an instrument for subsidy approval, obtained by estimating equation (2) with different sets of controls. For details of the sample and variable definitions, see Section 3. The slight reduction in sample size in Columns 2 and 3 is due to a small number of missing control variables.

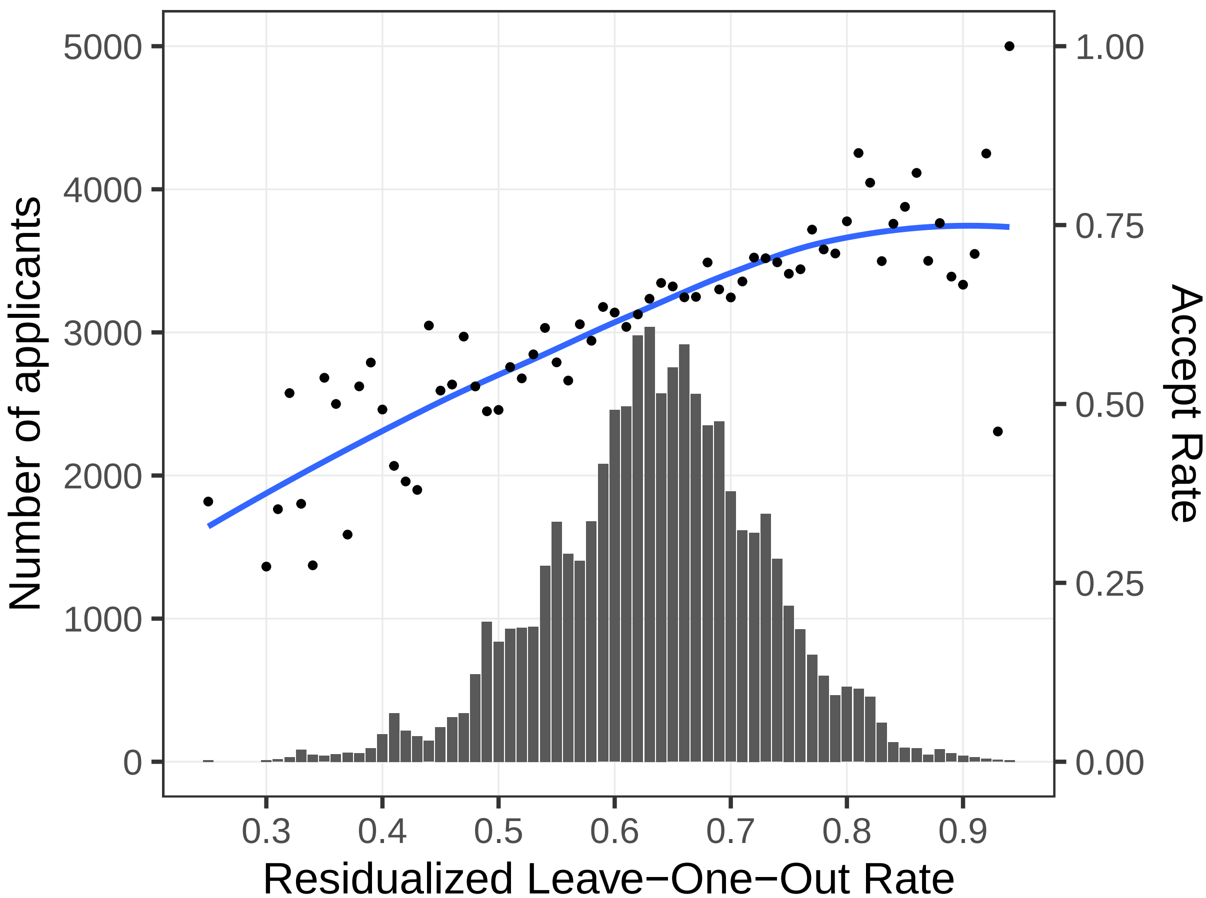


Figure 1: Distribution of Evaluator Leniency and approval rates

Notes: The figure shows the distribution of evaluator application approval rates—our measure of evaluator leniency defined in equation (1). Leniency shown is residualized by applicant characteristics that appeared on the application form and, therefore, may have affected the assignment of evaluators. Each dot represents the average acceptance rate for each bin. The blue line represents the smoothed local mean. Raw rates are shown in Appendix Figure A1.

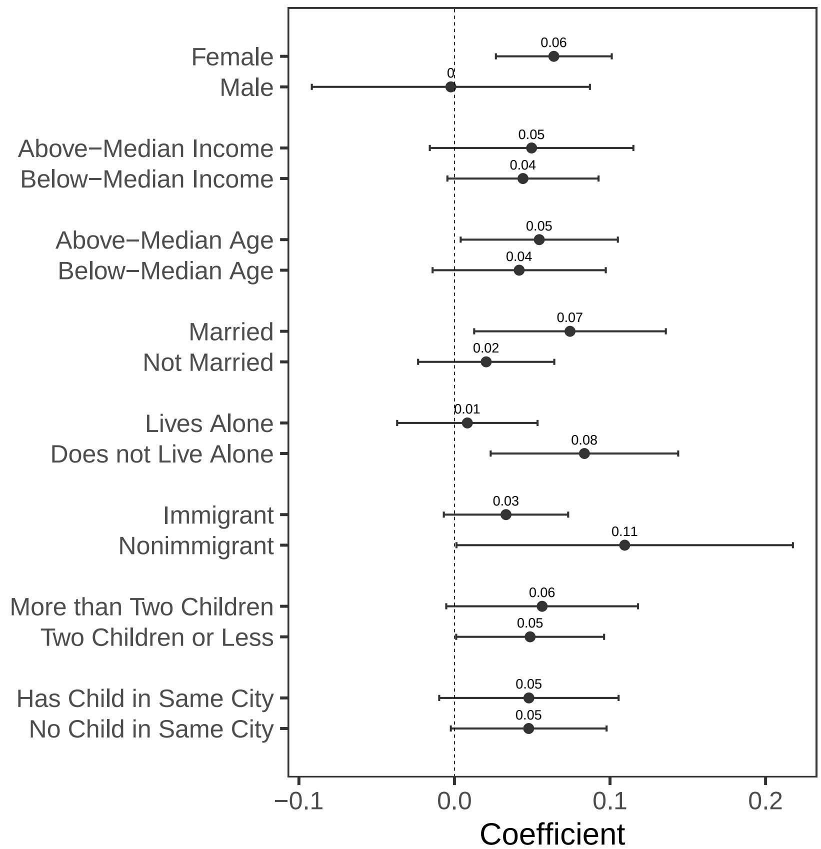


Figure 2: Analyses of Heterogeneity in Estimated Impact of Subsidized Home-Based Long-Term Care on One-Year Mortality

Notes: The figure summarizes the results of multiple heterogeneity analysis in which we reestimated equation 3 using subsamples defined based on observed applicant covariates. Point values represent the point estimate. The analysis uses our main sample of 50,111 applicants, each subgroup is then restricted to evaluators with at least 50 observations in the subgroup.

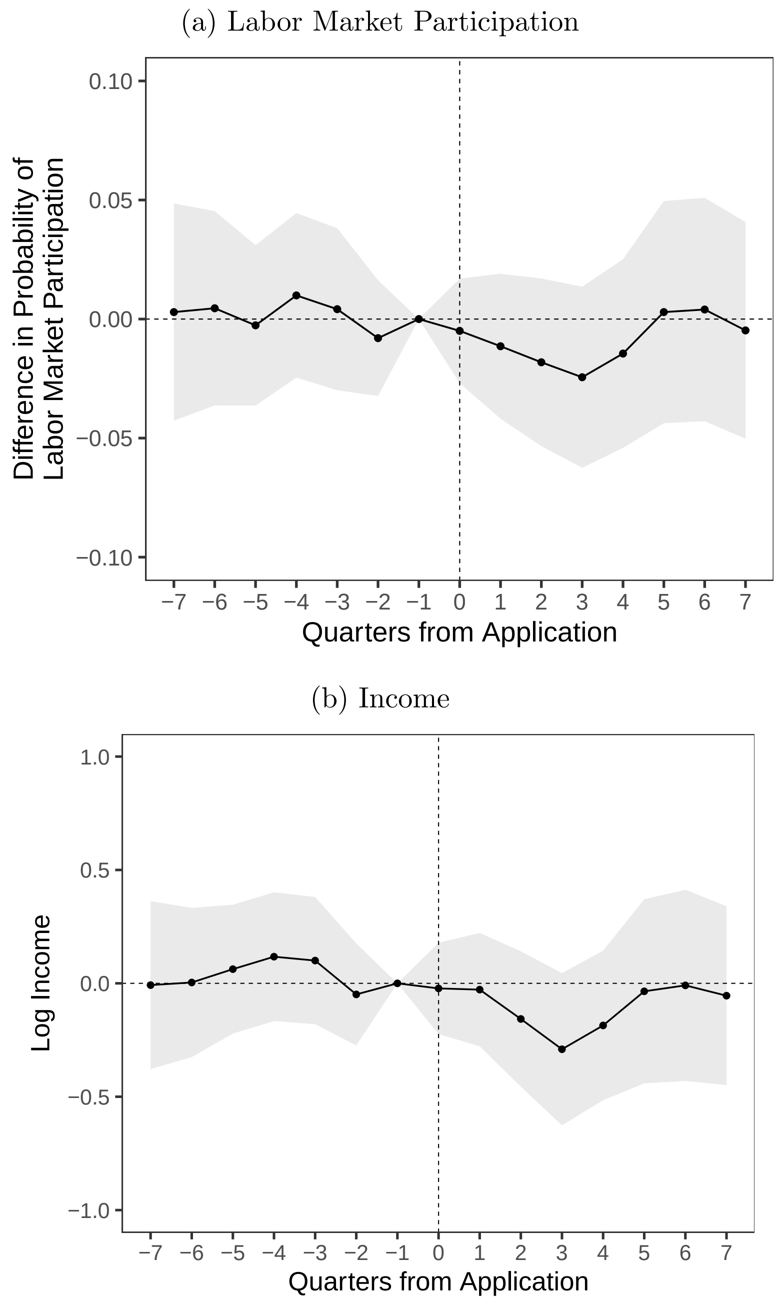


Figure 3: The Impact of Subsidized Home-Based Long-Term Care on Labor Market Outcomes of Applicants' Children

Notes: The figure shows estimates from equation (3) for the impact of subsidizing home-based long-term care on the labor market outcomes of children of subsidy recipients. Panel (a) shows results for labor market participation, where the outcome variable is an indicator for any income from employment or self-employment during the quarter. Panel (b) shows results for income, where the outcome is the log of the income from employment or self-employment. Each point represents one quarter. Both measures are estimated as a difference from the quarter prior to the application date. Error bars show 95% confidence intervals for the point estimates. The sample consists of 76,589 combinations of child-parent.

Online Appendix Material

Appendix A Construction of the Main Sample

Applicants Our study population consists of all non-Arab elders aged 67–79 who applied for LTC subsidy between 2010 and 2015. We restrict attention to the first application of each applicant, to avoid any endogeneity of the sample selection. We include only applicants who, at the time of application, were living in a household of one or two members. We also exclude applicants who were not eligible according to their income and those who could be evaluated based on documents only, because they did not meet an evaluator which is our main identification instrument. This leaves us with 69,843 applicants. We choose to use only applications evaluated by evaluators that conducted more than 100 evaluations, so their measure of leniency is more reliable (on average, at least 1.4 evaluations per month). This is leaves us with 51,111 applicants, the sample described in Table 1. 187 observations were removed in the main specification for reasons of collinearity.

Applicant children Of the 51,111 applicants in our main sample, 71% had children according to the records of the Ministry of Interior Affairs. For the event study design, we need 7 quarters before and after the application date. To keep a balanced sample, we included only applicants who applied until the first quarter of 2014, leaving 24,004 applicants, 73,344 children and 76,589 child-parent combinations. This is our main children sample described in Appendix Table A2. We excluded additional 81 applicants due to collinearity when evaluating the residualized leave-one-out leniency rate for each applicant.

Appendix B Application Form

To initiate the process, applicants submit a form to any branch of the Israeli National Insurance. The fields in the application form include:

1. Applicant's details: name, ID number, birth-date, sex, and martial status.
2. Applicant's current location: home, hospital or other, address and contact details.
3. Address for mail (if different from home address).
4. Details of a family member or a guardian: name, connection to the applicant, contact details, checkbox for "interested to be present during evaluation visit."
5. Additional information: spoken languages, checkbox for "interest in advice of a volunteer," details of spouse (name and ID), checkbox for "the spouse applied for or eligible to long-term care subsidy."
6. Details of people living with the applicant: ID, name, relation, year of birth, eligibility for long-term care or other special subsidy.
7. Applicant and spouse's income details.
8. Constant expenses: payment for stay in an institution, alimony, and rent (rent is included only if the applicant has income from another apartment).
9. Activities of daily living: clothing, washing, eating, treatment of excretions. For each of the four, the applicant can mention if done independently or needs help. If checked "need help," there is place for a short explanation (this field is not mandatory and is rarely answered).
10. Checkbox for eligibility for veteran assistance from the ministry of defense.
11. Details of the nursing home or other institution where the applicant is staying in case the applicant is not staying at home, filled by the institution: approval of stay; date of entrance; type of license of the institution (Ministry of Welfare, Ministry of Health, no license); type of unit/department in the institution; services provided in the institution: food, cleaning, laundry; and whether the stay is subsidized.

12. Was the reason for the elder's dependency caused by an accident? If so, what type of accident? (car or other, date, place and circumstances); Was the police notified? was there a tort claim filed (details of representing lawyer, details of any compensation received).

13. Bank account details.

14. Signature and declaration that the content of the form is truth.

Appendix Table A1: Descriptive Statistics of Applicants with Children

	Sample, by Application Approval Status		
	Approved (1)	Not Approved (2)	All (3)
A. Applicant Characteristics			
Age	71.9	71.6	71.8
Female (%)	63.5%	71.9%	66.2%
Living Alone (%)	37.6%	48.3%	41.1%
Marital Status (%)			
Single	0.5%	0.8%	0.6%
Married	61.7%	54.1%	59.2%
Divorced	12.7%	16.7%	14.0%
Widowed	25.0%	28.3%	26.1%
Number of Children (%)			
1	18.3%	23.2%	19.9%
2	21.1%	19.3%	20.5%
3	24.2%	20.5%	23.0%
4	16.2%	14.4%	15.6%
5 or more	20.2%	22.6%	20.1%
Income (NIS)	6750	4744	6107
Native Hebrew Speaker (%)	72.7%	64.1%	70.0%
Israeli Born (%)	19.7%	13.9%	17.8%
B. Mortality (%)			
Within 1 year of application	11.0%	3.0%	8.5%
Within 2 years	17.7%	6.1%	14.0%
Within 3 years	23.0%	9.6%	18.7%
Observations	16,315	7,689	24,004
Percent of total	68.0%	32.0%	100.0%

Notes: The table shows descriptive statistics for the sample of applicants with children, which we used to analyze the impacts of subsidies on child outcomes. Different columns show different subsamples, by application approval status. For detailed sample and variable definitions, see Section 3.

Appendix Table A2: Characteristics of Applicant Households with Children

	Sample, by Application Approval Status		
Household Characteristics	Approved (1)	Not Approved (2)	All (3)
Applicant Number of Children	3.26	3.26	3.26
Percent of Female Children	49.0	47.5	48.5
Percent of Children in Same City as Applicant	53.3	55.5	54.0
Percent of Children born in Israel	74.9	65.0	71.7
Children Age	42.8	42.1	42.6
Children Marital Status			
Single	16.3	18.8	17.1
Married	70.8	67.1	69.6
Divorced	12.1	13.2	12.4
Widowed	0.8	0.8	0.8
Percent of Children Self-Employed	9.6	8.4	9.2
Percent of Children Ever Employed	85.3	84.7	85.1
Percent of Months Child Employed	73.4	71.8	72.9
Child Mean Monthly Income (NIS) at the Time of Application	9,068	7,790	8,659
Percent of Applicants/Households	68.0	32.0	100
Number of Applicants/Households	16,315	7,689	24,004
Observations (Applicant-Child)	52,019	24,570	76,589

Notes: The table shows descriptive statistics for children of applicants, for the sample of applicants with children with at least two years of labor outcomes under observations. Different columns show different subsamples, by application approval status. Measures are weighted so that all families (namely, sets of children of one applicant) receive equal weights, regardless of the family size. For detailed sample and variable definitions, see Section 3.

Appendix Table A3: Average Monotonicity Test

Applicant Characteristic	Coefficient	Standard Error
Age Below Median	0.64	0.03
Age Above Median	0.72	0.03
Income Below Median	0.69	0.03
Income Above Median	0.61	0.03
No Coresidents	0.75	0.03
Coresidents	0.63	0.03
Female	0.70	0.03
Male	0.65	0.04
Nonimmigrant	0.71	0.06
Immigrant	0.68	0.02
Not Married	0.77	0.03
Married	0.61	0.03
Applicants with Children:		
1 or 2 Children	0.71	0.03
2 or More Children	0.66	0.03
No Child Living in Same City	0.74	0.03
Any Child Living in Same City	0.62	0.03

Notes: The table shows evidence supporting average monotonicity. Each row presents estimates and their robust standard errors for the first-stage coefficient from equation (2). For a discussion of the test rationale, see Section 4. The sample includes all evaluators who performed at least 75 evaluations during the study period.

Appendix Table A4: The Impact of Subsidized Home Care on Alternative Mortality Measures

	OLS (1)	*IV* (2)	*OLS* (3)	*IV* (4)	*OLS* (5)	*IV* (6)
A. IV First Stage						
	Dependent Variable: Subsidy Approved					
Evaluator Leave-One-Out Leniency	—	0.702	—	0.716	—	0.740
	—	(0.022)	—	(0.024)	—	(0.027)
F Statistic [d.f.]	—	1059.67	—	913.04	—	768.26
	—	[1,50123]	—	[1,40948]	—	[1,31697]
B. OLS and IV Second Stage						
	Dependent Variable: Two-Month Mortality		Two-Year Mortality		Three-Year Mortality	
Subsidy Approved	0.031	0.016	0.120	0.043	0.134	0.044
	(0.001)	(0.010)	(0.003)	(0.025)	(0.004)	(0.031)
Included Fixed Effects:						
Applicant City		V		V		V
Applicant Language		V		V		V
Application Year		V		V		V
Application Month		V		V		V
Applicant Martial Status		V		V		V
Applicant Gender		V		V		V
Applicant Age		V		V		V
Applicant Income Percentile		V		V		V
Applicant Is Israeli Born		V		V		V
Applicant Is Living Alone		V		V		V
N Obs (Applicants)	51,111	50,802	41,903	41,551	32,581	32,200

Notes: The table shows estimates of the impact of subsidized home care on all-cause mortality of applicants at various time horizons. The sample consists of all first-time applications. Columns 1, 3, and 5 show OLS estimates (which do not adjust for selection). Columns 2, 4, and 6 show IV estimates that use evaluator leave-one-out leniency as an instrument for subsidy approval, obtained by estimating equation (2) with different time horizons. Standard errors are robust. For details of the sample and variable definitions, see Section 3. The reduction in sample size is because our data is restricted to 2010-2016, so we have a two (three) years mortality horizon only for applications before 2015 (2014). The slight reduction in sample size between the OLS and IV columns is due to a small number of missing control variables.

Appendix Table A5: Descriptive Statistics for Subgroups of Applicants Used in Heterogeneity Analyses

(a)

	Female	Male	Above 2 Kids	2 Kids or Below	Above Median Inc.	Median Inc. or Below
N	39,374	19,354	25,280	33,448	29,356	29,372
Mean Age	71.86	74.16	72.14	72.97	72.46	72.77
Mean HH Members	1.47	1.69	1.65	1.46	1.72	1.36
Married	0.46	0.72	0.65	0.47	0.70	0.39
Widow	0.32	0.12	0.24	0.27	0.20	0.31
Divorced	0.18	0.13	0.12	0.20	0.08	0.25
Single	0.04	0.03	0.00	0.06	0.02	0.05
Number of Kids	2.23	2.57	4.44	0.76	3.13	1.56
Income	4,820	5,680	7,249	3,482	9,280	929
Approved Subsidy	0.61	0.68	0.68	0.61	0.73	0.54
Mortality in 2 months	0.02	0.04	0.02	0.02	0.03	0.02
Mortality in 1	0.06	0.14	0.08	0.09	0.10	0.08
Mortality in 2	0.10	0.22	0.14	0.14	0.16	0.12
Mortality in 3	0.13	0.29	0.18	0.18	0.20	0.17
Share of Applicants	0.67	0.33	0.43	0.57	0.50	0.50

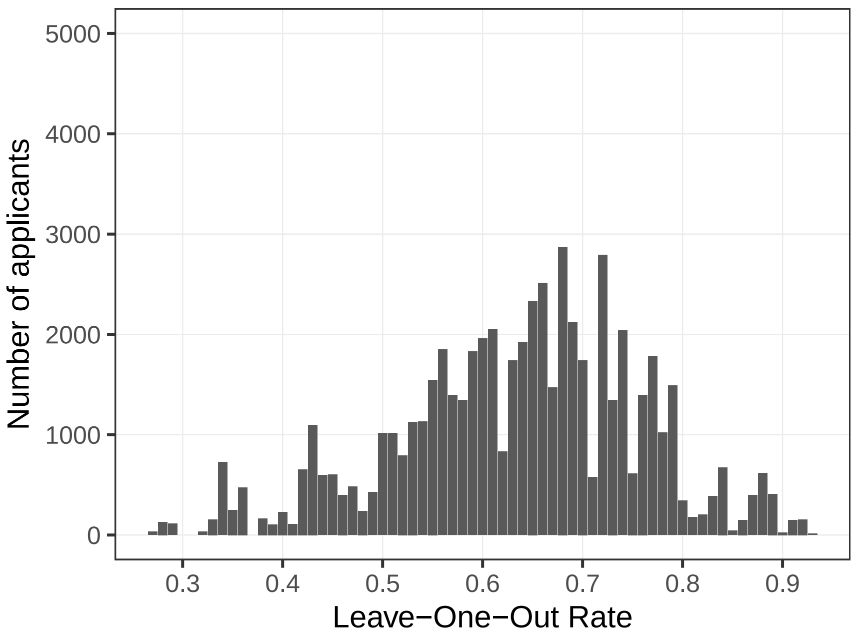
(b)

	Above Median Age	Median Age or Below	Same City	Diff. City	Married	Not Married
N	29,168	29,560	31,910	26,818	32,089	26,638
Mean Age	76.77	68.51	71.92	73.44	72.64	72.58
Mean HH Members	1.53	1.55	1.62	1.45	1.92	1.08
Married	0.54	0.55	0.61	0.47	1.00	0.00
Widow	0.31	0.20	0.25	0.26	0.00	0.56
Divorced	0.12	0.20	0.13	0.20	0.00	0.36
Single	0.02	0.05	0.01	0.07	0.00	0.08
Number of Kids	2.11	2.57	3.58	0.88	2.69	1.92
Income	4,857	5,346	6,450	3,501	6,808	3,050
Approved Subsidy	0.63	0.64	0.67	0.60	0.67	0.59
Mortality in 2 months	0.02	0.02	0.02	0.02	0.03	0.02
Mortality in 1	0.09	0.08	0.08	0.09	0.10	0.07
Mortality in 2	0.14	0.13	0.14	0.14	0.16	0.11
Mortality in 3	0.19	0.17	0.18	0.19	0.21	0.15
Share of Applicants	0.50	0.50	0.54	0.46	0.55	0.45

(c)

	One Person HH	Mult. People HH	Immigrant	Non-Immigrant
N	26,948	31,780	49,709	9,019
Mean Age	72.63	72.60	72.81	71.55
Mean HH Members	1.00	2.00	1.53	1.58
Married	0.09	0.93	0.54	0.57
Widow	0.51	0.04	0.26	0.21
Divorced	0.32	0.03	0.16	0.17
Single	0.07	0.00	0.03	0.05
Number of Kids	1.88	2.74	2.22	3.02
Income	2,826	7,035	4,639	7,666
Approved Subsidy	0.58	0.68	0.62	0.72
Mortality in 2 months	0.02	0.03	0.02	0.03
Mortality in 1	0.07	0.10	0.08	0.10
Mortality in 2	0.11	0.16	0.13	0.17
Mortality in 3	0.15	0.21	0.18	0.22
Share of Applicants	0.46	0.54	0.85	0.15

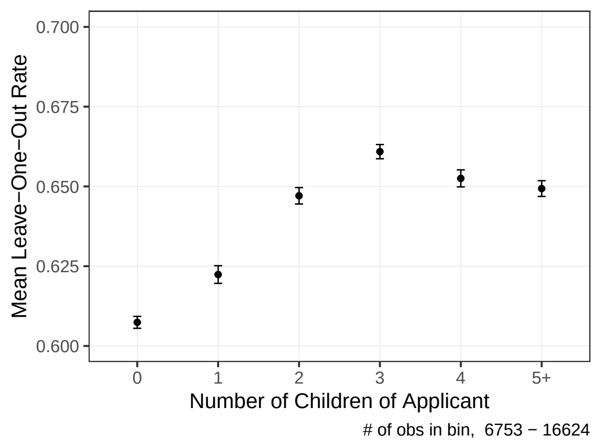
Notes: This table presents the main sample divided into subsamples defined based on observed applicat covariates. The analysis uses our main sample of 50,111 applicants. Each subgroup is then restricted to evaluators with at least 50 observations in the subgroup. Figure 2 shows the estimated impact of subsidized home-based long-term care on one-year mortality for each subgroup.



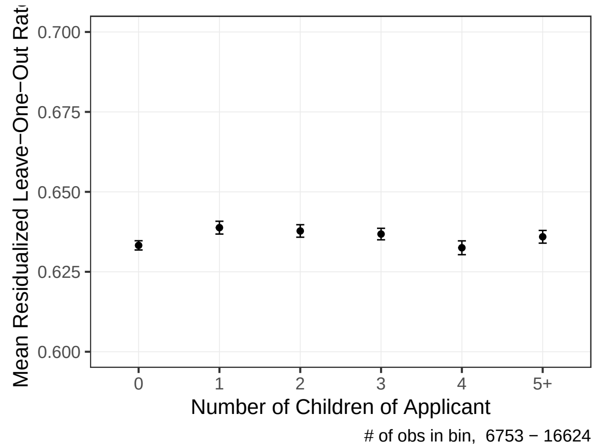
Appendix Figure A1: Distribution of Unadjusted Leave-One-Out Leniency

Notes: The figure shows the distribution of evaluator application approval rates—our measure of evaluator leniency defined in equation (1). Residualized rates are shown in Figure 1.

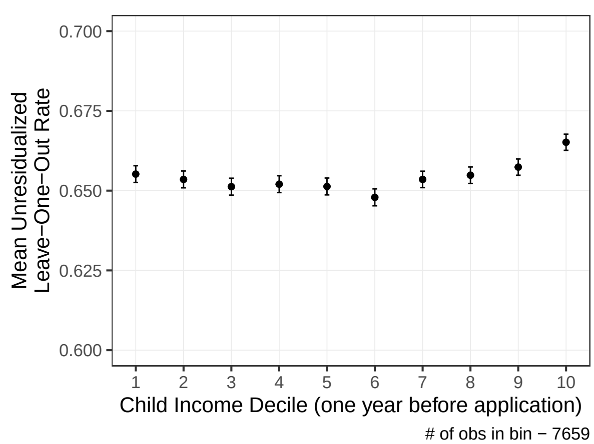
(a) Number of Children (Unadjusted)



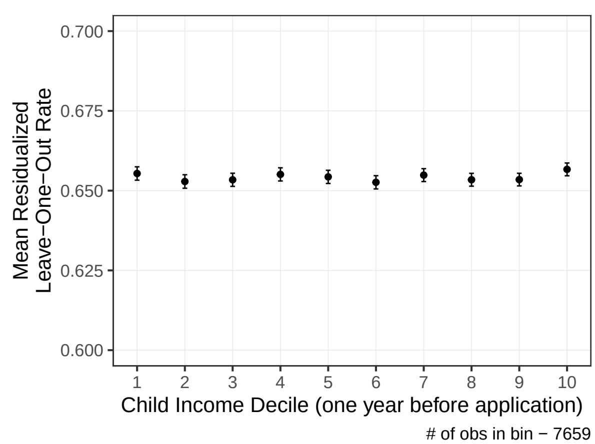
(b) Number of Children (Residualized)



(c) Child Income (Unadjusted)

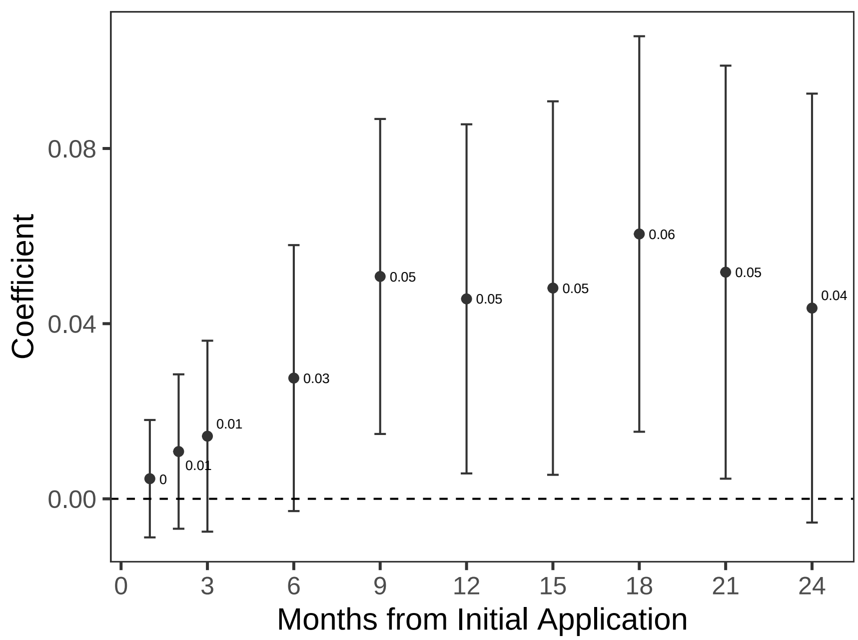


(d) Child Income (Residualized)



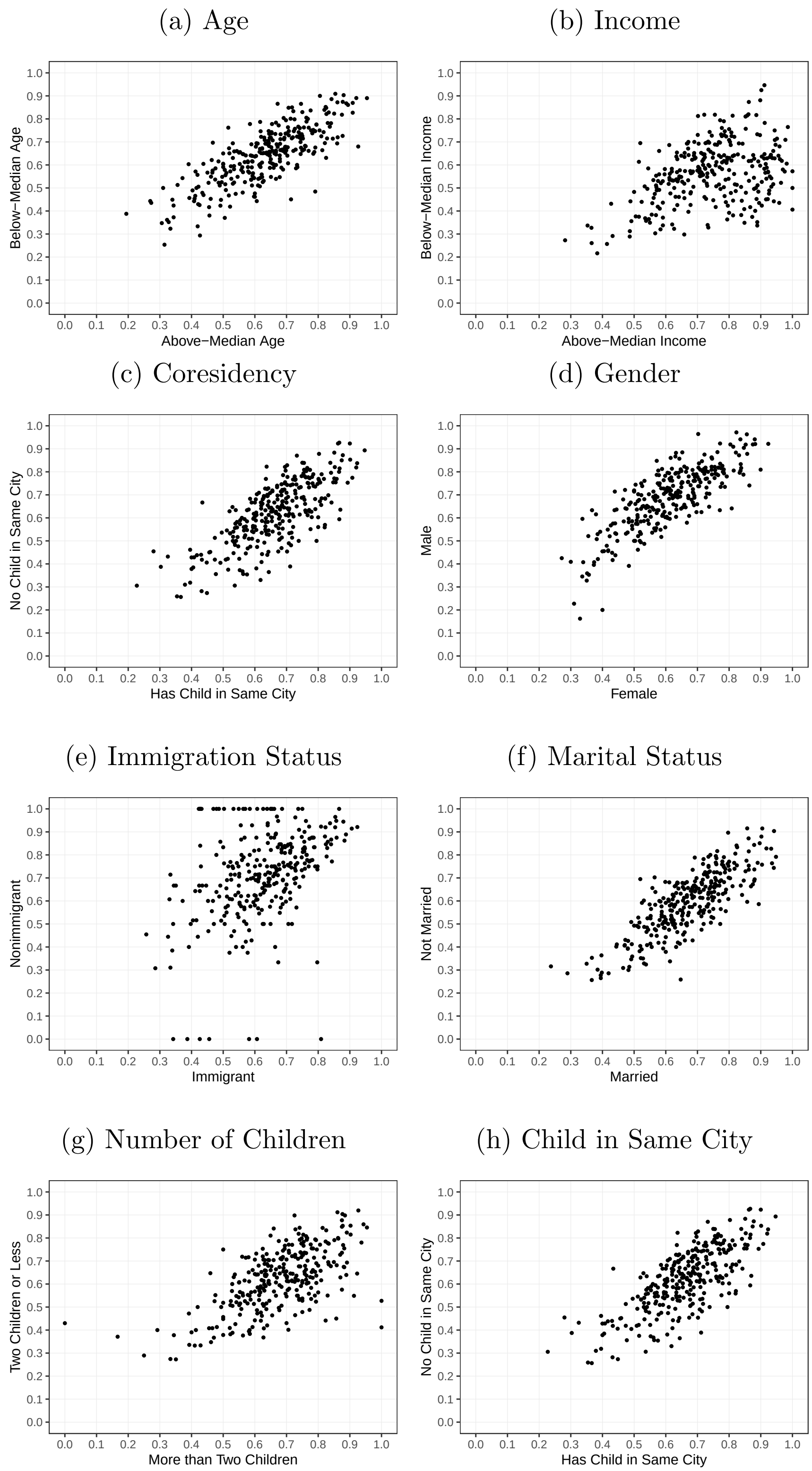
Appendix Figure A2: Evaluator Leniency by Applicant's Characteristics

Notes: The figure shows the average leniency (leave-one-out average application approval rate) as a function of two applicant characteristics: number of children and average child income. These characteristics are not observed by the Administration before the evaluation is made, and thus serve as a way to evaluate the independence assumption. In Panels (a) and (c), we estimate non-parametrically the association between leniency and each of the two characteristics by showing the average leniency for each value separately, adjusting for observables that may have affected the evaluator assignment. In Panels (b) and (d) we repeat this, but this time residualizing leniency by observed characteristics. For details of the sample and variable definitions, see Section 3.



Appendix Figure A3: Analyis of Mortality Impacts Over Different Horizons

Notes: The figure summarizes the results of multiple separate regression analyses in which we reestimated equation 3 for mortality measured over different horizons. Point estimates and 95% confidence intervals are shown. The sample includes all 41,551 applicants, which we observe for two years after the initial application (or until death).



Appendix Figure A4: Evaluator Leniency by Applicant's Characteristics

Notes: The figure illustrates the correlation in evaluator leniency across different partitions of the sample into subgroups. Each point represents one evaluator. In each facet, the scatterplot displays evaluators' average leniency for two subgroups corresponding to one characteristic, plotted on the horizontal and vertical axes.