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Partial basic income has positive and no heterogenous effects on mental health – An analysis of the Finnish basic income randomized experiment among people in unemployment

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Data availability

The data is available after registration in the Finnish Social Science Data Archive (dataset id FSD3488). Our codes are saved in the repository:
https://github.com/MoritzOberndorfer/Finnish_Basic_Income_Heterogeneous_Effects

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Abstract AJE

A randomized trial of a partial basic income scheme for the population in unemployment in Finland was conducted in 2017–2018. No studies to date that we are aware of have investigated to what extent the effects of the trial on self-reported mental health were heterogeneous. This is an important question for understanding the implications of basic income schemes for the distribution of mental health in a population. We studied effect heterogeneity using data from a survey conducted at the end of the two-year experiment with a response rate of 20% (intervention n=569, control n=1028). Mental health was measured by the MHI-5 five-item instrument. We considered effect heterogeneity across potential indicators of labor market disadvantages, including age, gender, education, prior employment status, household size, and family type. Participants in the intervention group had moderately better mental health compared with those in the control group (adjusted risk difference for poor mental health -0.08 [95%CI: -0.12; -0.03]). Multilevel modelling and causal forest showed no evidence for heterogenous effects on mental health. Our results suggest that basic incomes schemes have no harmful effects on mental health across multiple potential axes of labor market disadvantage, and are unlikely to increase mental health inequalities among people in unemployment.

Introduction

Basic income programs are social policies providing unconditional income payments, i.e., without means testing or requirements for job seeking efforts. In an era of increasing job automation and rapidly improving artificial intelligence applications, basic income programs are among the social policy programs that have been proposed to support standards of living; promote incentives to accept job offers and economic freedom; reduce poverty and financial stress; improve youth mental health (1,2); and improve well-being across the entire population, and particularly among people in precarious employment situations (3,4). It has even been suggested that basic income programs could reduce persistent social inequalities in population health (5,6). While few large-scale randomized trials of basic income schemes exist, a systematic review of seven pilot studies has provided some suggestive evidence of improvements in mental health following participation in these schemes (4). In Finland, a randomized trial of a partial basic income scheme with payments of €560 (US$750 in 2025) per month targeted at people in unemployment was conducted in 2017–2018. Similar to studies carried out in other countries (4), a previous study of this Finnish randomized experiment found small to moderate improvements in average mental health outcomes and employment (7). Another study on the experiment's effect on mental health based on register data found a 5% to 12% reduction in the quarterly use of defined daily doses of psychotropic medication (mainly driven by a reduction in the defined daily dose of antidepressants) in the intervention group, but no difference in the probability of psychotropic use between the intervention group and the control group (8).

Previous studies on basic income programs have focused on average treatment effects on mental health. However, studies systematically investigating if, and to what extent, the mental health effects of basic income programs are heterogeneous across population groups are rare. Studying such potential effect heterogeneity is important, not least because it is possible that while a basic income program improves average mental health, the mental health of some groups may be harmed by such a scheme. For example, it has been speculated that basic income provision may reinforce traditional gender roles regarding unpaid labor (6,9), which could have negative consequences for mental health among women (10). The presence of harmful effects would suggest the need for targeted or adjusted programs. Moreover, even if no population groups are harmed by a basic income program, some groups may benefit from it more than others. For example, compared to people in full-time employment, people in precarious employment situations and students may benefit more from a basic income scheme because for them receiving a basic income would reduce the administrative burden associated with reporting income to social insurance institutions.

Effect heterogeneity of social policy programs can have implications for the distribution of health in a population, and therefore for health inequalities (11–13). If beneficial effects are concentrated among groups with better baseline health outcomes, the program will lead to increased differences in health across population groups, even if average mental health has improved. Thus, given the observed association between social disadvantage and worse mental health (14) among people in unemployment, such a scenario could increase social inequalities in mental health (albeit on an improved average). However, heterogeneous effects of basic income programs on mental health may also reduce social inequalities in mental health in a scenario in which the beneficial effects are concentrated among socially disadvantaged groups. Such effects on health inequalities have been anticipated in the previous literature (5,6).

Differences in levels of support for basic income schemes suggest that effect heterogeneity may be relevant. In a survey unrelated to the Finnish basic income experiment, 72% of Finnish adolescents and young adults aged 14-24 supported partial basic income, compared to 42% of Finnish people aged 65 and older (15). At the European level, previous surveys found that support for basic income was higher among people in unemployment and people with lower levels of formal education than among more socioeconomically advantaged groups (16,17). Importantly, if socioeconomic disadvantage is associated with larger beneficial effects on mental health, we would expect basic income programs to not only improve average mental health, but also to reduce mental health inequalities related to socioeconomic position, which is an important axis of social inequalities in population health (5,6).

An exploratory subgroup analysis of the effect of the Finnish basic income experiment on the defined daily doses of psychotropic medication using register-based data indicated that there was no effect among the 25–34-year-old participants but a decrease among those aged 35–44 and 45–59. The study also found a stronger effect among women, no effect heterogeneity across levels of educational attainment, and no effect among couples, but a decrease among singles, couples with children, and especially adults with children, as well as a larger decrease among people with a history of psychotropic medication use (8).
However, people may experience labor market disadvantages across multiple dimensions simultaneously, such as low educational attainment, lack of past employment experience (due to young age), and care

responsibilities. Where these potential labor market disadvantages intersect, individuals may be under a higher stress burden caused by the need to meet job seeking requirements while juggling unpaid labor, care responsibilities, efforts to obtain further qualifications, and other responsibilities. It is thus plausible that as multiple potential labor market disadvantages and other (possibly unexpected) individual pre-treatment characteristics coincide, a basic income may have a more beneficial effect on mental health than the average treatment effect. Therefore, it is important to study effect heterogeneity across combinations of multiple effect modifiers to obtain a more detailed view on the heterogenous effects of basic income programs on mental health and their potential implications for the distribution of mental health in a population.

However, using traditional methods like stratified subgroup analysis and interaction terms in regression analysis to estimate population group-specific treatment effects – also called conditional treatment effects (CATEs) – for such purposes can run into problems. These methods are insufficient when researchers want to estimate treatment effects across a larger number of groups but a limited number of observations, or when there are unexpected sources of effect heterogeneity. For example, as the number of observations per group decreases and the number of groups increases, statistical power to reliably estimate group-specific treatment effects decreases and multiple testing concerns start to arise (18–22). To overcome these issues, new methodological approaches to estimate group-specific treatment effects have been proposed. However, while proponents praise these methods for advancing goals of precision medicine (18) and precision public health (23), they are often data-driven and exploratory (16,17), and are rarely used to analyze the health effects of social policy programs.

In this study, we use secondary survey data from the Finnish basic income experiment to investigate if, and to what extent, the effects of the partial basic income program on mental health were heterogenous across population groups while applying these new methodological approaches. To this end, we compare the results of using conventional subgroup analysis, multilevel modelling, and a machine learning method. Based on evidence of differential support for basic income and the previous literature, we hypothesized that the beneficial effects on mental health would be stronger in younger groups and those potentially exposed to more labor market disadvantages.

Methods

Data

The Finnish partial basic income experiment focused on the population in unemployment. The target population were people aged 25 to 58 who were receiving a basic unemployment benefit from the national social insurance institution in November 2016. The basic unemployment benefit is a form of benefit for people who either have no past earned income or have been unemployed for a prolonged period. From this target population, 2,000 persons were randomly assigned to the intervention group. The rest of the target population of 173,222 persons served as their control group.

The intervention period was from January 1, 2017 to December 31, 2018, during which the intervention group received a basic benefit of €560 (US$750 in 2025) per month, a sum equal to the basic unemployment benefit, regardless of their income. The control group, by contrast, would lose some of their unemployment benefits if they gained additional income through employment. Thus, while the intervention group did not necessarily receive more money, their administrative burden was lower as they received the €560 partial basic income without any conditionality. A recent analysis found that during the experiment in 2017 and 2018, the intervention group had €131 and €172 more total average monthly income than the control group (8). A detailed description of the experiment is provided in a government report (24).

The study design was mainly built around administrative registers through which the participants' income and employment outcomes were followed. However, a survey was conducted at the end of the study period from October 15 to December 14, 2018, which is openly available via the Finnish Social Science Data Archive (25). The computer-assisted telephone surveys (CATI) were conducted by the private firm Taloustutkimus Oy. The target group for this survey were all 2,000 people in the intervention group and 5,600 people in the control group (of whom 600 were part of a supplemental sample recruited later due to difficulties in obtaining a sufficient number of responses). People who died during the experiment period (n=51), people who had a non-disclosure of personal information for personal safety reasons (n=35), people without a phone number in the register of the social insurance institution (n=432), and people who were left out of the supplemental sample (n=58) were not contacted. The remaining sample of 7,049 people were contacted, resulting in 1,633 successful interviews and a response rate of 23.2%. The response rate was substantially higher in the intervention group (31.3%) than in the control group (20.2%).

The data holder provided weights that adjusted for non-response based on key variables drawn from the administrative registers (sex, age group, marital status, foreign language, previous unemployment benefits, and geographical area). After excluding cases with missing outcomes and covariates, the analyzed sample consisted of 981 people in the comparison group and 546 people in the intervention group.

Variables

The outcome of this study was the mental health of the participants measured using the Mental Health Inventory (MHI-5), a validated five-item mental health screening instrument (26,27). MHI-5 asked the participants about their experience of five items related to anxiety, depression, and general positive affect in the past four weeks, with six response options ranging from never to all the time. To follow the procedure in the official assessment of the experiment and the Finnish use of the MHI-5 scale, we rescaled the sum of the items to 100. The respondents with a total score of 52 or less were considered to be at risk of mood and anxiety disorder. MHI-5 has been shown to be a robust tool to identify people at high risk of mood disorders in the general population (27,28).

For our analyses, we considered individual-level variables that we conceptualized to appear before the experiment, although these variables were asked in the survey at the end of the experiment. These variables included the following: gender, age group (four groups of less than 30, 30-34,35-44,45-54, and 55 years or more), urbanicity (city, densely populated municipality, rural municipality) past employment status (unemployed, entrepreneur, student, salaried, homemaker/retired/other), educational attainment (low: primary, lower secondary, upper secondary in vocational track; medium: upper secondary in general track, college-level vocational, polytechnic/university of applied sciences; high: university undergraduate degree or higher), partnership status (single, having a partner), and having children in the household. All of these variables were derived from the survey except for those for urbanicity, which were taken from the administrative registers.

Data analysis

Our estimands of interest were the conditional average treatment effects on mental health of receiving the partial basic income for two years versus receiving basic unemployment benefits across different socioeconomic and demographic population groups. The conditional average treatment effect (CATE) is the average treatment effect on the outcome conditional on the value of a (pre-treatment) third variable (29). As participants in the intervention group received the partial basic income during the two-year follow-up period without an option to drop out and the control group had no option to receive the partial basic income, our effect estimates were by default per-protocol effects and our effect measure of interest was the risk difference.

We used three different methods – analysis stratified by population groups, multilevel modelling, and a machine learning approach (causal forest) – to estimate CATEs of partial basic income on mental health. These methods are complementary because they rely on different assumptions and balance bias with signal, as discussed previously in, for example, (30).

First, in the conventional approach, we estimated interactions between the binary treatment indicator variable and the values of our categorical covariates for each covariate separately using logistic regression models while adjusting for the other covariates. This led to CATEs by gender (female, male), age group (four groups of less than 30, 30-34, 35-44, 45-54, and 55 years or more), urbanicity (city, densely populated municipality, rural municipality) past employment status (unemployed, entrepreneur, student, salaried, homemaker/retired/other), education (low, medium, high), partnership status (single, not single), and having children in the household.

In the second approach, we used multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA) to estimate the treatment effect by combinations of gender (female, male), age group (younger than 30, 30-54, 55 or older), past employment status before unemployment (entrepreneur, salaried, student, unemployed, homemaker/retired/other), and educational attainment (compulsory, secondary or tertiary) and their respective interactions. These participant characteristics were chosen because of their potential to indicate labor market disadvantages and the constraints of the available data. After collapsing groups with too small cell sizes (see details in the supplementary material page 2), our data had a two-level structure in which 1,527 individuals were nested within 43 groups. We estimated the risk difference in the outcome for each group by estimating a Bayesian multilevel linear probability model with a fixed and random intercept for the outcome, and a fixed and random effect for the treatment indicator. As using survey weights in Bayesian multilevel modelling is not supported by current software, we included the survey weights as covariates in the models, as suggested previously (31).

We estimated the models using the R package “brms” (32), and visualization was done in Stata v18 (33). Estimation was performed by Markov Chain Monte Carlo (MCMC) methods estimating 12 chains with 4,000 iterations (2,000 burn-in iterations). We used the posterior distribution to obtain point estimates (means) and 95% credible intervals for the CATEs. For comparison, we estimated the same CATEs using a more conventional single-level linear probability model in which we included interaction terms between the treatment indicator variable and each group indicator (leaving one group indicator out as a reference category).

Third, we used a machine learning approach to explore unexpected and more complex effect modification by the combination of multiple potential pre-treatment participant characteristics that could act as effect modifiers. We used causal forest, which is a data-driven approach to estimating CATEs (34). A causal forest consisted of combinations of causal trees that iteratively divided the sample based on any covariate value into leaves in order to maximize differences in estimated treatment effects across leaves. These trees were then combined, and forest-weighted CATE estimates were calculated for each observation given their covariate values. Our aim was to identify population groups for which the partial basic income had the most beneficial, the least beneficial, or the most harmful effects. To avoid overfitting, we ran five causal forests. We first divided the sample into five equally sized random sets, and then ran a causal forest using data from four sets while assigning the fifth unseen dataset along quarters in terms of the effect sizes of the estimated CATE (35). This process was repeated four times until all sets were assigned to quarters. That is, we assigned participants to the treatment effect groups based on the model to which these observations did not contribute. We labelled the first quarter the weakest effect group and the last quarter the strongest effect group. We then compared the average effects in these quarters to determine whether there was any evidence of effect heterogeneity. We included gender, age group, urbanicity, past employment status, education, singlehood, and the binary variable of having children as covariates in the causal forest and used the default tuning parameters. We used the R package “grf” version 2.4 for this analysis (34). For a more detailed and accessible explanation of how the causal forest approach was used to estimate heterogenous treatment effects, readers are referred to (19–21).

Results

Descriptive statistics of the analytical sample are shown in Table 1. The intervention and the control group were similar in terms of their background characteristics, before and after weighting, except for household composition and employment status. The intervention group was larger and had a higher proportion of participants with children in the household. The prevalence of poor mental health was 24% in the control group and 16% in the intervention group. Adjusting for survey weights and background variables changed this difference only negligibly. The adjusted OR comparing the treatment and the control group was 0.62 (95%CI: 0.47; 0.82) and the risk difference was 8 percentage points (95%CI: -012; -0.03).

Results from a series of logistic regression models with interaction terms included separately and with survey weights, shown in Figure 1, indicated that, across all groups, participants receiving the partial basic income had lower odds and a lower probability of the outcome than the comparison groups. This association was not directly moderated by background characteristics with the exception of age. The likelihood of poor mental health was 20 percentage points lower (95%CI:-0.32; -0.07) in the intervention group than in the control group among people aged 30-34, while it was 3 percentage points lower (95%CI: -0.12; 0.06) in the intervention group than in the control group among people aged 55+. However, a joint Wald test of differences in (multiplicative) effects across age groups was insignificant (p= 0.24).

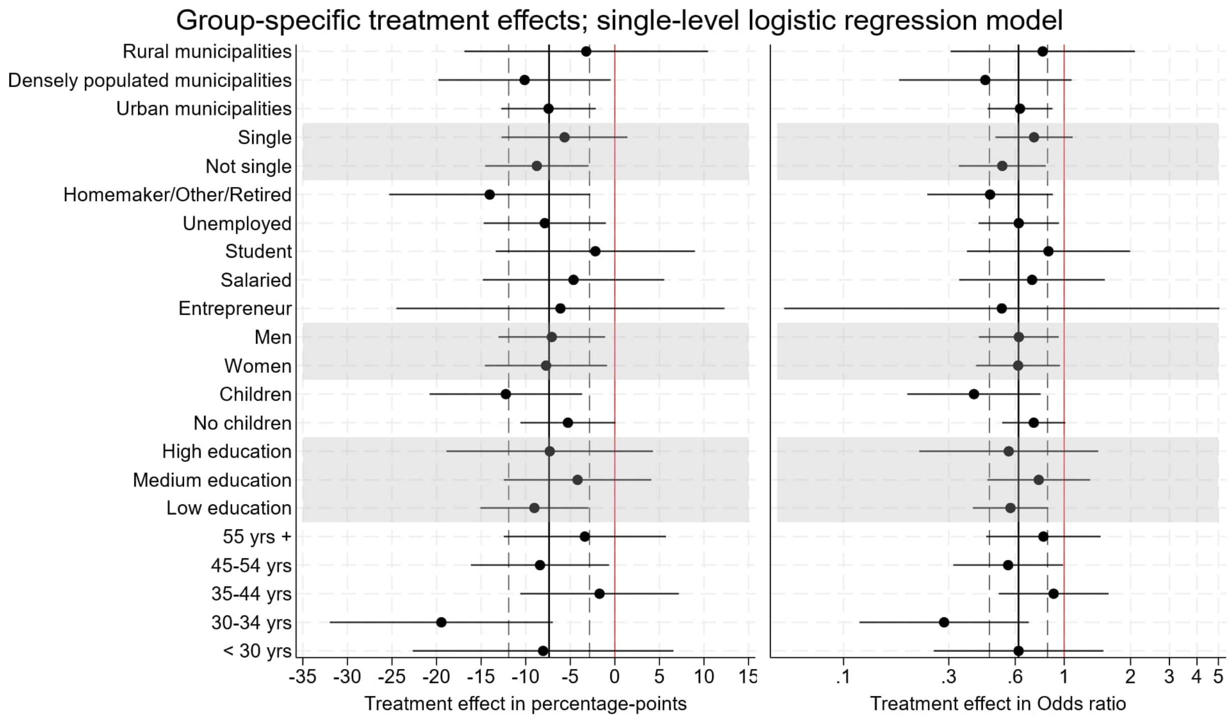

Figure 1. Results from logistic regression models with interaction terms based on data from survey participants (n=1,527) at the end of the Finnish basic income experiment (2017-2018). We estimated separate models for each covariate including the interaction with this covariate and the intervention indicator. All other covariates were adjusted for. Data were weighted by survey weights that adjusted for non-response based on key variables drawn from the administrative registers (sex, age group, marital status, foreign language, previous unemployment benefits, and geographical area).

In Figure 2, we show the results of the multilevel modelling approach to heterogenous treatment effects and how they compare to the results obtained through a "naïve" single-level model (Panel A). Uncertainty around group-specific treatment effects estimated by the single-level model is high due to small sample sizes for some groups (see Supplementary Table S1) and even includes values below -100 percentage points (Panel A, Figure 2)). When using the multilevel modelling approach, group-specific treatment effects cluster closely around the average effect (-7.19 percentage points [95% credible interval: -11.63; -2.74]) because effect estimates are precision-weighted (Panel B, Figure 2).

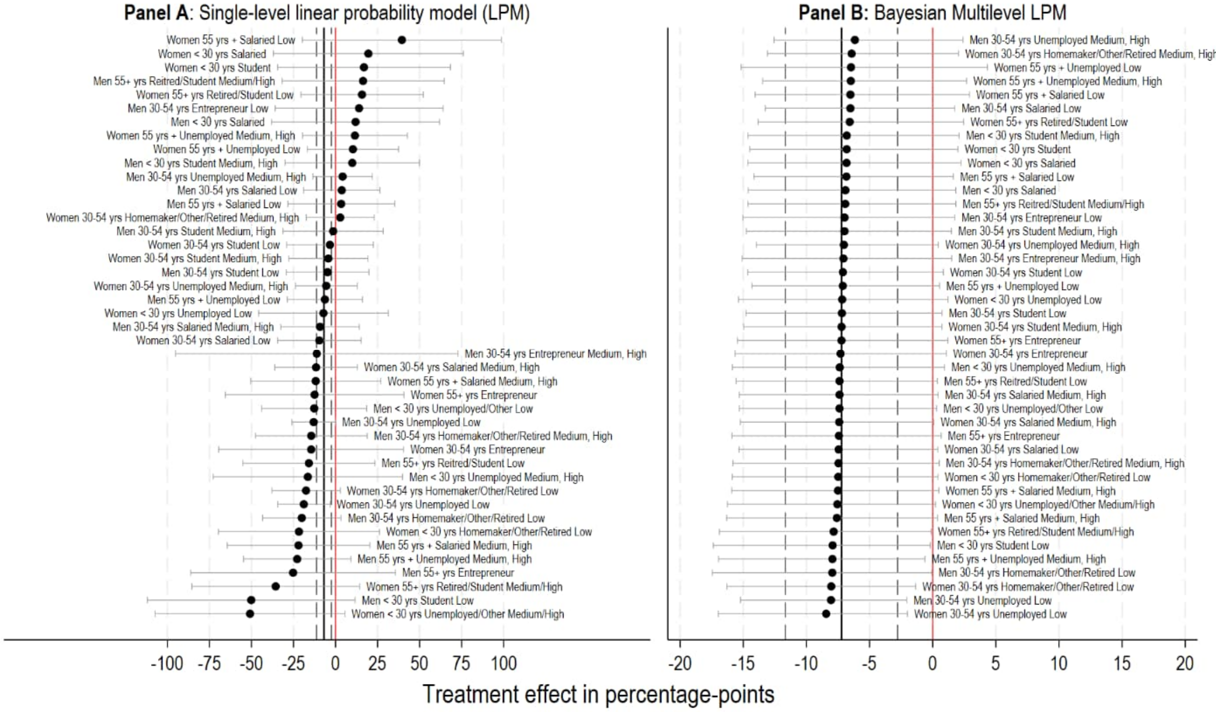

Figure 2: Group-specific treatment effects on mental health based on data from survey participants (n=1,527) at the end of the Finnish basic income experiment (2017-2018) estimated by the single-level linear probability model (Panel A) and by the Bayesian multilevel linear probability model (Panel B). The solid red vertical line indicates a 0 percentage point difference in mental health between the treatment group and the control group in Panels A and B. The solid black vertical lines in Panels A and B indicate the population average treatment effect. The dashed vertical lines in Panels A and B indicate the limits of the 95% confidence interval (A) and the 95% credible interval (B) around the average treatment effects. The labels beside the estimates indicate the group. Survey weights that adjust for non-response based on key variables drawn from the administrative registers (sex, age group, marital status, foreign language, previous unemployment benefits and geographical area) were included as covariates in all models. Effects shown in Panels A and B are presented numerically in Supplementary Tables S2 and S3, respectively.

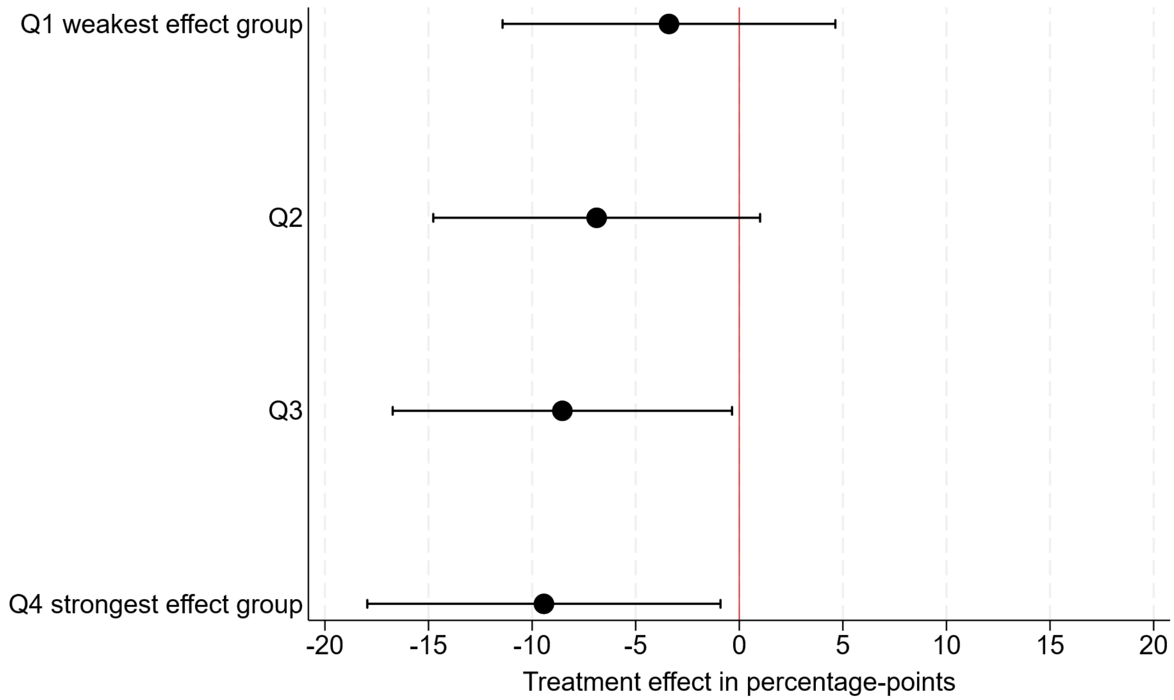

Figure 3: Conditional treatment effects in effect size groups identified using causal forest based on data from survey participants (n=1,527) at the end of the Finnish basic income experiment (2017-2018). The effects are the effects of the intervention on the dichotomous mental health outcome. Four groups of different effect strengths were identified in cross fitting fashion. Key sociodemographic variables were included in the models.

Causal forest did not identify any subgroups with differential effects. The high and the low effect groups were identified via covariate splitting, and did not differ in the conditional average treatment effects (CATEs -9 percentage points (95% confidence interval: -0.17; -0.00) versus -3 percentage points (95%CI: -0.11, 0.05)). The characteristics of the low and the high effect groups are presented in Supplementary Table S2.

Discussion

In this study, we used secondary survey data from the Finnish partial basic income experiment and investigated if, and to what extent, the effects of a partial basic income on mental health varied across several individual characteristics associated with potential labor market advantages or disadvantages. Answering these questions is crucial to identifying groups for whom a basic income may be harmful or especially beneficial, and to anticipate the potential distributional effects of a basic income policy on population mental health. In line with previous findings from the same experiment (24), we found a moderately (about 7 percentage point) lower risk of mood and anxiety disorders in the treatment group compared to in the control group. However, contrary to our expectations, we found no evidence of heterogeneity in the effects across individual socioeconomic and demographic characteristics associated with labor market advantages and disadvantages. This finding also contradicts results based on a recent evaluation of the Finnish basic income experiment's effect on the defined daily doses of psychotropic medication using register-based data (8). Based on their exploratory subgroup analysis, the authors found differences by age, family type, gender, and history of psychotropic medication use. The differences between these findings and our results may be caused by the different outcomes used (defined daily dose of psychotropic medication purchases versus self-reported mental health based on the MHI-5 instrument) and/or the differences between the methodological approaches used (exploratory subgroup versus multilevel modelling and machine learning).

The Finnish basic income experiment implies that a partial basic income program, if rolled out, may improve average mental health among people in unemployment. This finding is consistent with experimental (36) and natural experimental studies from other countries (3). While we did not study potential mechanisms, we speculate that receiving basic income may improve people's perceived autonomy due to the reduced administrative burden, and provide them with more time for social relationships as there are no activation (job application) requirements. Mental health could also be improved through better job incentives. A randomized trial in Germany in which participants received monthly payments of €1,200 for three years led to improvements in mental health, more time spent with friends, and improvements in perceived autonomy (37). A UK microsimulation study estimated that the positive mental health effects of receiving a basic income would translate into substantial health care cost savings (38).

Additionally, our results indicate that a partial basic income may neither harm specific groups nor impact the social distribution of mental health among the population in unemployment. These results suggest that even a partial low to moderate basic income (instead of the pre-existing basic conditional unemployment benefits) moderately improves mental health among people in unemployment regardless of age, gender, educational attainment, former employment, urbanicity of residential location, partnership status, and household composition. While this potential property of basic income programs seems desirable, the policy's ability to reduce social inequalities in mental health remains unclear. If it is only rolled out among the population in unemployment, who are at higher risk of adverse mental health outcomes than people in employment (39), inequalities in mental health between people in employment and people in unemployment may indeed decrease. If the effect homogeneity observed for the population in unemployment holds for the general population when a partial basic income policy is rolled out, mental health inequalities related to social and demographic characteristics could remain unchanged. To address these questions, a trial targeting the general working-age population would be necessary.

Strengths and limitations

The strengths of this study are i) the assignment of the intervention to 2,000 individuals randomly drawn from the full target population via population registers; ii) no attrition of participants during the experiment; iii) a clear separation between the intervention and the control group, that is, participants were not able to switch between the intervention and the control group during the experiment; and iv) the application and comparison of three complementary methodological approaches to reach a more robust conclusion.

However, our study also has limitations. The effects we found may have alternative explanations due to baseline differences in mental health between the intervention and the control group or selection into survey response associated with mental health. The data used for this study was collected at the end of the experiment. Thus, we cannot control for a potential difference in baseline mental health between the treatment and the control group, and we need to assume that randomization was successful in balancing baseline mental health and the distribution of baseline characteristics that act as effect modifiers between the intervention and the control group. Similarly, even if randomization achieved the likely sufficient baseline similarity between the groups, differences in the response rate to the survey associated with the interaction of baseline mental health and intervention group assignment may provide an alternative explanation for our results. For example, people in the intervention group may have been more likely to respond to the survey if the partial basic income had a positive effect on their mental health (or if they already had better mental health at baseline), or disappointed participants in the control group with worse mental health may have been more likely to reply to the survey. We tried to mitigate this potential bias by using weights adjusting for non-response provided by the data holder. Previous evidence on this experiment suggests that this bias is unlikely. A register-based analysis of the same experiment, which does not suffer from this potential bias, showed significant differences in psychotropic medication purchase and psychiatric primary care use between the intervention and the control group (24). Another limitation is that during the study period, the Finnish government implemented an unemployment benefit reform in 2018 in which a person's unemployment benefits were cut if they did not participate activation measures (41). This also affected the intervention group if they received some other higher earnings-related unemployment benefits, but it affected the control group more. Part of the observed effect may thus be attributable to the negative mental health effects of this additional reform among the control group.

Further, although the sample size for the experiment was large compared to those in previous studies (36), this study may have been underpowered to detect group-specific treatment effects. While group-specific effects estimated by conventional subgroup analysis are particularly affected by statistical power concerns (42) and are prone to chance findings, estimates obtained by multilevel modelling and causal forests may be more reliable. Estimates for group-specific effects from multilevel modelling are less likely to be chance findings due to multiple testing because group-specific random effects are shrunk toward the group-average effect if uncertainty is high (due to small group size, low between-group variance, or high within-group variance) (43–45). The causal forest method, on the other hand, may need a larger sample size and a larger number of pretreatment variables to separate the signal from the noise.
Lastly, the beneficial effect on average mental health among people in unemployment and the reduction in mental health inequalities would only have occurred under two conditions: first, if the rolled out basic income policy had no (or smaller) beneficial effects on the mental health of the (untreated) population in employment (46); and, second, if we could assume that a randomized experiment on a basic income program (even if carried out perfectly) can provide a real-world causal intervention effect of such a social policy (46,47). Our study cannot answer whether these two conditions were met.

Conclusion

In line with a previous analysis (24), we found that people in unemployment had better average mental health after receiving a partial basic income for two years compared to people in unemployment who received the pre-existing basic unemployment benefits. Moreover, comparing the results of three complementary methodological approaches – conventional subgroup analysis, multilevel modelling, and machine learning – we found that the effect of receiving partial basic income on mental health did not vary by (combinations of) individual characteristics associated with potential labor market advantages and disadvantages. Importantly, this result suggests not only that a partial basic income has a beneficial effect on the mental health of recipients in unemployment, but also that it is unlikely that a partial basic income program would harm the mental health of specific population groups. Because the beneficial effect did not vary by social and demographic characteristics, our results additionally indicate that a partial basic income program is unlikely to affect the social distribution of mental health among the population in unemployment. However, if a partial basic income program has no effects on the population in employment when it is rolled out only among the population in unemployment, inequalities in mental health between the population in unemployment and the population in employment may decrease.

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Table 1: Unweighted descriptive statistics of survey participants at the end of the Finnish two-year basic income experiment (2017-2018)

	Control	Intervention
Total sample	981	546
Male N (%)	501 (51.1)	281 (51.5)
Age N (%)		
<30 yrs	92 (9.4)	49 (9.0)
30-34 yrs	128 (13.0)	92 (16.8)
35-44 yrs	256 (26.1)	151 (27.7)
45-54 yrs	276 (28.1)	148 (27.1)
55 yrs +	229 (23.3)	106 (19.4)
Household size (mean (SD))	2.08 (1.34)	2.25 (1.40)
Urbanicity N (%)		
Urban municipality	715 (72.9)	419 (76.7)
Densely populated municipality	151 (15.4)	73 (13.4)
Rural municipality	115 (11.7)	54 (9.9)
Past employment status N (%)		
Entrepreneur	41 (4.2)	16 (2.9)
Salaried	227 (23.1)	96 (17.6)
Student	142 (14.5)	77 (14.1)
Unemployed	386 (39.3)	250 (45.8)
Homemaker, Other, Retired	185 (18.9)	107 (19.6)
Educational attainment N (%)		
Low	558 (56.9)	316 (57.9)
Medium	304 (31.0)	148 (27.1)

	Control	Intervention
High	119 (12.1)	82 (15.0)
Single household N (%)	447 (45.6)	221 (40.5)
Children in household N (%)	279 (28.4)	185 (33.9)
Poor mental health N (%)	231 (23.5)	89 (16.3)

Supplementary material for:

Partial basic income has positive and no heterogenous effects on mental health – An analysis of the Finnish basic income randomized experiment among people in unemployment

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Supplementary information on methods

Multilevel modelling to estimate treatment heterogeneity

We created 60 groups made up by each unique combination of the individual-level characteristics above. Five groups contained no observations in our data: female + <30 years + entrepreneur + compulsory education; female + <30 years + entrepreneur + secondary or tertiary education; male + <30 years + entrepreneur + compulsory education; male + <30 years + entrepreneur + secondary or tertiary education. Where necessary, we further combined similar groups with less than seven observations to obtain observations from both treatment and control group in each group:

The group female, <30 years, salaried, low educational attainment (n=5) was combined with the group female, <30 years, salaried, medium/high educational attainment (n=4). The group female, <30 years, student, low educational attainment (n=6) was combined with the group female, <30 years, student, medium/high educational attainment (n=9). The group female, <30 years, unemployed, medium/high educational attainment (n=4) was combined with the group female, <30 years, homemaker/other/retired, medium/high educational attainment (n=5). The group female, <30 years, entrepreneur, low educational attainment (n=4) was combined with the group female, <30 years, entrepreneur, medium/high educational attainment (n=6). The group female, >55 years, entrepreneur, low educational attainment (n=5) was combined with the group female, >55 years, entrepreneur, medium/high educational attainment (n=7). The group female, >55 years, student, low educational attainment (n=3) was combined with the group female, >55 years, homemaker/other/retired, low educational attainment (n=17). The group female, >55 years, student, medium/high educational attainment (n=4) was combined with the group female, >55 years, homemaker/other/retired, medium/high educational attainment (n=16).

The group male, <30 years, salaried, low educational attainment (n=4) was combined with the group male, <30 years, salaried, medium/high educational attainment (n=7). The group male, <30 years, homemaker/other/retired, low educational attainment (n=7) was combined with the group male, <30 years, unemployed, low educational attainment (n=20). The group male, >55 years, entrepreneur, low educational attainment (n=10) was combined with the group male, >55 years, entrepreneur, medium/high educational attainment (n=4). The group male, >55 years, student, low educational attainment (n=1) was combined with the group male, >55 years, homemaker/other/retired, low educational attainment (n=16). The group male, >55 years, student, medium/high educational attainment (n=1) was combined with the group male, >55 years, homemaker/other/retired, medium/high educational attainment (n=10).

Software code to reproduce our results are openly available at https://github.com/MoritzOberndorfer along with instructions on how to obtain the openly available data.

Supplementary Table S2: Sample size for each stratum by treatment group at the end of the Finnish two-year basic income experiment (2017-2018)

Group Gender | age | past employment | educational attainment	control	intervention	total
female <30 years Salaried	6	3	9
female <30 years Student	12	3	15
female <30 years Unemployed Low	11	7	18
female <30 years Homemaker/Other/Retired Low	9	4	13
female <30 years Unemployed/Other Medium/High	3	6	9
female 30-54 years Entrepreneur	7	3	10
female 30-54 years Salaried Low	26	17	43
female 30-54 years Salaried Medium/High	43	14	57
female 30-54 years Student Low	24	16	40
female 30-54 years Student Medium/High	27	20	47
female 30-54 years Unemployed Low	63	45	108
female 30-54 years Unemployed Medium/High	46	32	78
female 30-54 years Homemaker/Other/Retired Low	43	24	67
female 30-54 years Homemaker/Other/Retired Medium/High	39	26	65
female 55+ years Entrepreneur	9	3	12
female 55+ years Salaried Low	19	2	21
female 55+ years Salaried Medium/High	9	8	17
female 55+ years Unemployed Low	31	12	43
female 55+ years Unemployed Medium/High	24	9	33
female 55+ years Retired/Student Low	12	8	20
female 55+ years Retired/Student Medium/High	17	3	20
male <30 years Salaried	7	4	11
male <30 years Student Low	10	2	12
male <30 years Student Medium/High	12	6	18
male <30 years Unemployed/Other Low	16	11	27
male <30 years Unemployed Medium/High	6	3	9
male 30-54 years Entrepreneur Low	4	7	11
male 30-54 years Entrepreneur Medium/High	9	1	10
male 30-54 years Salaried Low	46	17	63
male 30-54 years Salaried Medium/High	38	17	55
male 30-54 years Student Low	25	18	43
male 30-54 years Student Medium/High	25	10	35
male 30-54 years Unemployed Low	95	63	158
male 30-54 years Unemployed Medium/High	51	34	85
male 30-54 years Homemaker/Other/Retired Low	33	18	51
male 30-54 years Homemaker/Other/Retired Medium/High	16	9	25
male 55+ years Entrepreneur	12	2	14
male 55+ years Salaried Low	21	9	30
male 55+ years Salaried Medium/High	12	5	17
male 55+ years Unemployed Low	35	20	55
male 55+ years Unemployed Medium/High	13	12	25
male 55+ years Retired/Student Low	10	7	17
male 55+ years Retired/Student Medium/High	5	6	11
	981	546	1527

Supplementary Table S3: Group-specific treatment effects on mental health estimated by single-level linear probability model visualized in Figure 2, Panel A. Ordered by estimated effect size.

Group Gender | age | past employment | educational attainment	**% point difference intervention vs. control**
Women <30 yrs Unemployed/Other Medium/High	-50.9 [-107.2; 5.5]
Men <30 yrs Student Low	-50.1 [-111.9; 11.6]
Women 55+ yrs Retired/Student Medium/High	-35.6 [-85.5; 14.3]
Men 55+ yrs Entrepreneur	-25.3 [-86.1; 35.6]
Men 55+ yrs Unemployed Medium/High	-22.8 [-54.7; 9.1]
Men 55+ yrs Salaried Medium/High	-22.0 [-64.4; 20.4]
Women <30 yrs Homemaker/Other/Retired Low	-21.8 [-69.7; 26.1]
Men 30-54 yrs Homemaker/Other/Retired Low	-20.1 [-43.4; 3.3]
Women 30-54 yrs Unemployed Low	-18.9 [-34.4; -3.3]
Women 30-54 yrs Homemaker/Other/Retired Low	-17.5 [-37.8; 2.8]
Men <30 yrs Unemployed Medium/High	-16.5 [-72.8; 39.9]
Men 55+ yrs Retired/Student Low	-15.9 [-55.1; 23.4]
Women 30-54 yrs Entrepreneur	-14.5 [-69.5; 40.5]
Men 30-54 yrs Homemaker/Other/Retired Medium/High	-14.4 [-47.7; 18.8]
Men 30-54 yrs Unemployed Low	-13.0 [-26.0; -0.1]
Men <30 yrs Unemployed/Other Low	-12.7 [-43.9; 18.5]
Women 55+ yrs Entrepreneur	-12.5 [-65.6; 40.7]
Women 55+ yrs Salaried Medium/High	-11.8 [-50.5; 26.9]
Women 30-54 yrs Salaried Medium/High	-11.6 [-36.1; 12.9]
Men 30-54 yrs Entrepreneur Medium/High	-11.2 [-95.2; 72.8]
Women 30-54 yrs Salaried Low	-9.7 [-34.5; 15.2]
Men 30-54 yrs Salaried Medium/High	-9.2 [-32.5; 14.1]
Women <30 yrs Unemployed Low	-7.2 [-45.8; 31.3]
Men 55+ yrs Unemployed Low	-6.3 [-28.7; 16.0]
Women 30-54 yrs Unemployed Medium/High	-5.5 [-23.9; 12.8]
Men 30-54 yrs Student Low	-4.8 [-29.4; 19.9]
Women 30-54 yrs Student Medium/High	-4.3 [-27.8; 19.2]
Women 30-54 yrs Student Low	-3.3 [-29.1; 22.4]
Men 30-54 yrs Student Medium/High	-1.4 [-31.2; 28.4]
Women 30-54 yrs Homemaker/Other/Retired Medium/High	2.8 [-17.4; 22.9]
Men 55+ yrs Salaried Low	3.4 [-28.4; 35.1]
Men 30-54 yrs Salaried Low	3.7 [-18.9; 26.3]
Men 30-54 yrs Unemployed Medium/High	4.2 [-13.4; 21.8]
Men <30 yrs Student Medium/High	10.0 [-30.0; 49.9]
Women 55+ yrs Unemployed Low	10.3 [-16.8; 37.5]
Women 55+ yrs Unemployed Medium/High	11.5 [-19.7; 42.7]
Men <30 yrs Salaried	11.9 [-38.1; 61.9]
Men 30-54 yrs Entrepreneur Low	14.0 [-35.9; 63.9]
Women 55+ yrs Retired/Student Low	15.8 [-20.6; 52.1]
Men 55+ yrs Retired/Student Medium/High	16.3 [-31.9; 64.6]
Women <-30 yrs Student	16.9 [-34.5; 68.3]
Women <30 yrs Salaried	19.5 [-37.0; 76.0]
Women 55+ yrs Salaried Low	39.5 [-19.8; 98.7]

Supplementary Table S4: Group-specific treatment effects on mental health estimated by Bayesian multilevel-level linear probability model visualized in Figure 2, Panel B. Ordered by estimated effect size.

Group Gender | age | past employment | educational attainment	**% point difference intervention vs. control**
Women 30-54 yrs Unemployed Low	-8.4 [-17.0; -2.0]
Men 30-54 yrs Unemployed Low	-8.0 [-15.2; -2.1]
Women 30-54 yrs Homemaker/Other/Retired Low	-8.0 [-16.3; -1.3]
Men 30-54 yrs Homemaker/Other/Retired Low	-7.9 [-17.5; -0.1]
Men 55 yrs + Unemployed Medium/High	-7.9 [-17.0; -0.6]
Men <30 yrs Student Low	-7.9 [-17.4; -0.2]
Women 55+ yrs Retired/Student Medium/High	-7.8 [-16.9; -0.1]
Men 55+ yrs Salaried Medium/High	-7.6 [-16.3; 0.4]
Women <30 yrs Unemployed/Other Medium/High	-7.5 [-16.2; 0.2]
Women 55+ yrs Salaried Medium/High	-7.5 [-15.9; 0.5]
Women < 30 yrs Homemaker/Other/Retired Low	-7.5 [-15.9; 0.4]
Men 30-54 yrs Homemaker/Other/Retired Medium/High	-7.5 [-15.8; 0.5]
Women 30-54 yrs Salaried Low	-7.4 [-15.3; 0.4]
Men 55+ yrs Entrepreneur	-7.4 [-15.9; 0.7]
Women 30-54 yrs Salaried Medium/High	-7.4 [-15.2; 0.1]
Men <30 yrs Unemployed/Other Low	-7.4 [-15.3; 0.3]
Men 30-54 yrs Salaried Medium/High	-7.4 [-15.3; 0.4]
Men 55+ yrs Retired/Student Low	-7.4 [-15.6; 0.4]
Men <30 yrs Unemployed Medium/High	-7.4 [-15.9; 0.9]
Women 30-54 yrs Entrepreneur	-7.3 [-15.6; 1.1]
Women 55+ yrs Entrepreneur	-7.2 [-15.5; 1.2]
Women 30-54 yrs Student Medium/High	-7.2 [-15.0; 0.7]
Men 30-54 yrs Student Low	-7.2 [-14.8; 0.7]
Women <30 yrs Unemployed Low	-7.2 [-15.4; 1.2]
Men 55+ yrs Unemployed Low	-7.1 [-14.3; 0.5]
Women 30-54 yrs Student Low	-7.1 [-14.7; 0.8]
Men 30-54 yrs Entrepreneur Medium/High	-7.1 [-15.1; 1.5]
Women 30-54 yrs Unemployed Medium/ High	-7.0 [-14.0; 0.5]
Men 30-54 yrs Student Medium/High	-7.0 [-14.8; 1.5]
Men 30-54 yrs Entrepreneur Low	-7.0 [-15.0; 1.7]
Men 55+ yrs Retired/Student Medium/High	-6.9 [-14.6; 1.8]
Men <30 yrs Salaried	-6.9 [-14.6; 1.8]
Men 55+ yrs Salaried Low	-6.8 [-14.2; 1.6]
Women <30 yrs Salaried	-6.8 [-14.6; 2.2]
Women <30 yrs Student	-6.8 [-14.5; 2.0]
Men <30 yrs Student Medium/High	-6.8 [-14.6; 2.1]
Women 55+ yrs Retired/Student Low	-6.6 [-13.8; 2.5]
Men 30-54 yrs Salaried Low	-6.5 [-13.2; 1.7]
Women 55 yrs Salaried Low	-6.5 [-14.1; 2.9]
Women 55+ yrs Unemployed Medium/High	-6.5 [-13.5; 2.7]
Women 55+ yrs Unemployed Low	-6.5 [-15.2; 4.3]
Women 30-54 yrs Homemaker/Other/Retired Medium/High	-6.4 [-13.1; 2.0]
Men 30-54 yrs Unemployed Medium/High	-6.2 [-12.6; 2.4]

Supplementary Table S5: Characteristics of the effect groups identified via causal forest

Characteristic	**1** N = 377	**2** N = 381	**3** N = 390	**4** N = 371	**p-value**
Gender					0.11
Women	52%	45%	52%	47%	
Male	48%	55%	48%	53%	
Age group					<0.001
<30 years	6.6%	17%	8.2%	5.7%	
30-34 years	39%	13%	3.8%	0.5%	
35-44 years	0.8%	13%	28%	67%	
45-54 years	44%	38%	22%	6.7%	
55+ years	9.5%	19%	38%	20%	
Urbanicity					0.5
Urban municipality	75%	70%	75%	78%	
Densely populated municipality	14%	17%	15%	12%	
Rural municipality	11%	13%	11%	10.0%	
Past employment status					<0.001
Entrepreneur	1.6%	3.4%	6.7%	3.2%	
Salaried	8.2%	24%	20%	34%	
Student	13%	14%	12%	19%	
Unemployed	48%	35%	50%	33%	
Homemaker/Other/Retired	29%	24%	12%	10%	
Educational attainment					<0.001
Low	68%	60%	56%	43%	
Medium	19%	30%	28%	43%	
High	13%	10.0%	16%	14%	
Singlehood					<0.001
Not single	70%	59%	48%	47%	
Single	30%	41%	52%	53%	
Children in household					<0.001
No children	53%	71%	78%	77%	
Children	47%	29%	22%	23%	