The Long-Term Effect of Non-standard Employment on Child Well-Being: Evidence from Three Generations in Japan

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Abstract: Utilizing nationally-representative data on adults and their children in Japan, a country characterized by a strong patriarchal culture and male breadwinner gender tradition, we examine the long-term effects of non-standard employment experiences of earlier generations – grandparents and parents – on children's cognitive and noncognitive outcomes. We pay particular attention to potential differences between the effects of paternal and maternal grandparents' non-standard employment, and between the effects of grandfathers' and grandmothers' non-standard employment on child outcomes in Japan's distinctive gender context. Marginal structural models (MSM) will be used to solve the problem of time-varying confounders, such as parents' income, working hours, and health. We expect 1) negative effects of non-standard employment of both grandparents and parents on children's outcomes; 2) stronger effects of paternal grandparents than those of maternal grandparents; 3) stronger effects of grandfathers than grandmothers; and 4) a multiplicative effect on children's outcomes in families where both grandparents and parents have experienced non-standard employment.

Background

Non-standard employment (NSE), also called atypical employment, contingent employment, or short-term employment, has expanded rapidly over the past several decades in both industrialized and developing countries (e.g., Kalleberg 2000; Kalleberg, Reskin, and Hudson 2000). As an emerging form of labor market insecurity, the rapid growth of NSE has been shown to be negatively associated with individuals' economic welfare, marriage prospects, health, and subjective well-being within their life course (Inanc 2018; Kalleberg 2018; Kim et al. 2006; Piotrowski, Kalleberg, and Rindfuss 2015). The negative implications of NSE for individuals' well-being are not limited to one generation, but could possibly have longer-term implications for individuals' offspring and future generations. To our knowledge, however, no previous research has investigated the influences of NSE in one generation on the well-being of future generation(s). To fill this gap, our study adopts a multigenerational framework (Mare 2011) to examine how experiences of NSE by parents and grandparents may affect children's cognitive and noncognitive well-being in Japan, a distinctive social setting characterized by a strong patriarchal culture and rapid growth of NSE during recent years.

Our study makes important contributions to three strands of literature. First, as stated above, previous research about the consequences of NSE mainly focuses on outcomes within individuals' own life course, while neglecting whether and how economic and social disadvantages associated with NSE can be transmitted across generations. Our multigenerational extension of previous research provides new evidence for understanding the intergenerational transmission of disadvantages associated with NSE. Second, following the multigenerational literature, our study examines the long-term effects of parents' and grandparents' NSE on children's outcomes across three generations. A limitation in this work has been insufficient attention to heterogeneity across groups and populations, such as minority groups, gender, and countries, or even geographic regions across different social contexts (Mare 2014; Pfeffer 2014). We therefore pay particular attention to the potential differences between the effects of paternal and maternal grandparents' NSE, and between the effects of grandfathers' and grandmothers' NSE on child outcomes in Japan. The *grandmother hypothesis* from evolutionary anthropology argues that grandmothers, maternal grandmothers in particular, played a key role in providing for children that may help to understand the evolution of human longevity (Hawkes 2004), and invest more and have more contact with their grandchildren than other grandparents (Coall and

Hertwig 2011). In the social mobility field, some studies suggest that it is important to consider the characteristics of mothers and grandmothers in the status attainment of both men and women (Beller, 2009; Kroeger and Thompson 2016), while others have found little variation in the grandparent effect in terms of educational mobility, possibly due to data limitations and homogeneous cultures (e.g., Song 2016). We focus on Japan, a social context with a strong patriarchal culture and male breadwinner and female-homemaker gender traditions, to examine under what circumstances the NSE of paternal grandparents, especially the grandfather, have stronger effects on child well-being than those of maternal grandparents, and under what circumstances the effects of NSE experiences of fathers are stronger than those of mothers. Finally, our study also contributes to the child well-being literature by incorporating the NSE experiences of previous generations as an important correlate of children's outcomes from a temporal perspective.

Research Questions

We address the following three research questions:

1) How do the long-term experiences of NSE of parents (G2) affect the well-being of their children (G3)?

Expectation: A negative effect of NSE in G2.

2) Does the NSE of grandparents (G1) - both paternal and maternal - during G2's childhood affect the well-being of G3, net of G2's characteristics? If so, which side has a stronger effect?

Expectation: Net negative effect of NSE of G1; paternal > maternal; grandfather > grandmother

3) Is there an amplifying effect of NSE across generations? That is, do the combined NSE experiences of G1 and G2 have more than an additive effect on the well-being of G3?

Expectation: A negative interaction between the NSE experiences of G1 and G2.

Data and Measurement

Data

We use child data from the Japan Child Panel Survey (JCPS), and adult data from the Keio Household Panel Survey (KHPS) and the Japan Household Panel Survey (JHPS). Conducted every year from 2010, the JCPS is a child supplement to the JHPS and KHPS. The JCPS sample is comprised of children attending elementary or junior high school (aged 7-16) of participants in the JHPS or KHPS. The child surveys involve short tests of academic ability as well as a range of questions about time use, school, friends, and emotional well-being. The parents of children in

2010 and 2012 waves of JCPS are from the JHPS whereas the parents of children in the 2011 and 2013 waves of JCPS are KHPS respondents. In the 2014 JCPS, children have parents in both the KHPS and the JHPS.

Started in 2004, the KHPS is an on-going nationally-representative longitudinal survey of adult men and women aged between 20 and 69 years old. Started in 2009, The JHPS is another on-going nationally representative longitudinal survey of adult men and women aged 20 years and over.[1] The KHPS and the JHPS together cover a wide range of topics such as marriage and family behavior, education, employment, poverty trends, interhousehold transfers, and health/healthcare. These two surveys have been harmonized since 2014 using the same questionnaire.

Outcomes

Child cognitive outcomes include math test score, language test score, and reasoning test score, and noncognitive outcomes include self-rated health, emotional well-being, and self-esteem. For each child outcome, we take the average over survey years: For children of parents from the KHPS, we average outcomes over the 2011, 2013 and 2014 waves of the JCPS. For children of parents from the JHPS, we average outcomes over the 2012 and 2014 waves of the JHPS.[2]

Time-varying Treatment: Non-standard Employment of G2

Each wave of the KHPS and JHPS asked about G2's (the main respondents) and their spouses' employment status, which is a time-varying variable. We construct a four-category measure of employment status for each wave: full-time regular employment, NSE (part-time work, contract, sub-contract, and specialized contract work, self-employment, family business, piecework), not employed (taking leave, looking for work, homemaker), and "other/missing." Following previous studies that integrate information about time-varying treatment (Wodtke, Harding, and Elwert, 2011), we construct a *duration-weighted* measure, the proportion of years ever in NSE, to reflect the long-term NSE experiences of G2 (both father and mother) between the second wave (k = 1) and the year before G3's well-being was first measured. For the KHPS, this measure covers the period 2005-2010. For JHPS, this measure covers the period 2010-2011.

[1] Panel retention has been good, with between 83% and 94% of respondents in a given wave successfully interviewed in the subsequent wave.

[2] As explained below, the first wave of JHPS in 2009 is used as the baseline time period. We thus use JHPS 2010 and 2011 to derive parents' employment status and average child outcomes only over JCPS 2012 and 2014.

Non-standard Employment of G1

The KHPS and JHPS also asked respondents and their spouses about the employment status of their parents (G1) when they were 15 years old. We construct the same four-category measure of employment status of G1 when G2 were 15 years old, for both paternal and maternal grandfathers and grandmothers.

Covariates

The first waves of KHPS/JHPS define the baseline time period ($k = 0$) when G2's NSE and a rich set of covariates were first measured. A vector of time-varying covariates, L_k ($k = 1, 2, \ldots k$), include G2's occupation, family income, working hours, marital status, health, life satisfaction, and home ownership. Pretreatment, time-invariant covariates, V, include G1's level of education, G2's level of education, and G2's first job after finishing schooling (derived from respondents' employment history). Lastly, G3's sex and grade are categorized as C.

Identification Problems and Method

Figure 1 is a simplified two-wave example of the possible direct and indirect causal pathways linking NSE and child well-being. This figure contains a directed acyclic graph (DAG) that shows the hypothesized causal relationships between NSE, time-varying confounders, time-invariant covariates, child well-being, and unobserved factors. All arrows between the temporally ordered variables represent direct causal effects, whereas the absence of an arrow indicates there is no causal effect. As shown in Figure 1, L_k is affected by G2's NSE and at the same time affects G2's future NSE. To correctly estimate the causal effect of NSE on Y, we must control for L_k, as it is a confounder of future *NSE* and Y. However, simply conditioning on L_k in a conventional regression model will create two endogeneity problems that result in biased estimates for the effect of NSE_k on Y. First, since L_k is on the causal pathway from NSE_k to Y, controlling for L_k may thus control away part of the effect of G2's NSE on Y. Second, as L_k is a collider variable, conditioning on L_k will induce a noncausal association between NSE_k and U, and thus between NSE_k and Y, creating endogenous selection bias (Elwert and Winship 2014).

[Figure 1 About Here]

We utilize marginal structural models (MSM) with inverse-probability-of-treatment weights (IPTW) to estimate the effect of NSE of G1 and G2 on G3's well-being. The IPTW estimators make MSM more suitable than conventional regression models for observational data when estimating the causal effect of a time-dependent exposure in the presence of time-dependent covariates that may be simultaneously confounders and intermediate variables (Robins, Hernán, and Brumback, 2000). The MSM is a two-step process. First, we generate the IPTW to reweight the data to generate a pseudo-population in which NSE_k is no longer confounded by time-varying covariates L_k, that is, all arrows from L to NSE are removed, as shown in Figure 2. In practice, we use the stability weights to improve efficiency and stabilize the estimate, which is expressed as follows:

$$SW_i(t) = \prod_{k=0}^{t} \frac{\Pr[T_i(t)|\bar{T}_i(k-1), V]}{\Pr[T_i(t)|\bar{T}_i(k-1), \bar{L}_i(t), V]} \tag{1}$$

where T indicates time-varying treatment, NSE of G2. The denominator is the probability estimated from the multinomial logistic regression of being in NSE in each wave as a function of previous employment status, time-varying covariates, pretreatment covariates, and time-dependent covariates measured at the baseline. The numerator is the probability estimated from a constrained version of the denominator model that excludes time-varying covariates.

[Figure 2 About Here]

Second, for the weighted pseudo-population, we estimate a standard OLS model which includes the duration-weighted NSE experiences of G2, NSE of G1 when G2 was 15, other time-invariant covariates V, time-dependent covariates L_0 measured at $k = 0$, and G3's sex and grade, C. This model can be expressed as follows:

$$Y_i = \beta_0 + \beta_1 NSE_{G2} + \beta_2 NSE_{G1} + \gamma_1 V + \gamma_2 L_0 + \gamma_3 C + \varepsilon_i \tag{2}$$

We are interested in β_1, the effect of long-term NSE experiences of G2 on Y, and β_2, the effect of G1's NSE on Y net of G2's employment status.

We further add the interaction between G2's and G1's NSE to Eq. 2:

$$Y_i = \beta_0 + \beta_1 NSE_{G2} + \beta_2 NSE_{G1} + \beta_3 NSE_{G1} * NSE_{G2} + \gamma_1 V + \gamma_2 L_0 + \gamma_3 C + \varepsilon_i \tag{3}$$

A negative sign β_3 indicates that the (negative) effect of NSE of G2 and G1 have a multiplicative negative effect on on G3's well-being.

In both models, we distinguish between paternal and maternal grandparents and between grandfathers and grandmothers. In Japan's distinctive social context, we expect a stronger effect of paternal grandparents than maternal grandparents, and a stronger effect of grandfathers than grandmothers.

Descriptive Results and Next Step

Table 1 shows the unweighted descriptive statistics for outcomes and the key independent variables. When G2 were 15 years old, for both paternal and maternal grandparents, more than half of grandfathers were employed as regular, full-time workers, and around 30% of them were working in non-standard jobs. Nearly 50% of paternal grandmothers were not employed and more than 20% of them were in non-standard work. The situations of maternal grandmothers were similar, with slightly lower percentages not employed. The average duration of fathers' employment in non-standard work (proportion of years during 2005-2010) was 0.176, while mothers nearly spent half of their time in non-standard jobs during the same period.

[Table 1 About Here]

Figure 3 and Figure 4 show differences in child well-being by tertiles of parents' duration in NSE. The basic pattern is that longer NSE duration for parents is associated with worse child outcomes. But this relationship appears to be nonlinear, with children faring worse on all indicators if their fathers' duration of NSE is in the middle tertile.

[Figure 3 and 4 About Here]

Figure 5 shows child well-being by employment status of paternal and maternal grandparents. The general pattern is that non-standard work of grandparents is associated with worse child outcomes (the pattern is weaker for maternal grandmothers). Non-standard work of both the paternal grandfather and grandmother is related to lower cognitive and noncognitive outcomes, and the paternal grandmother's duration in NSE has a similar relationship with child well-being compared with paternal grandfather. The relationship of maternal grandfathers' duration in NSE with children's outcomes is weaker than paternal grandparents, but is still stronger than that of maternal grandmother. These bivariate descriptive statistics suggest that the negative association of NSE of paternal grandparents with children's outcomes is stronger than that of maternal grandparents. However, the gender of grandparents only matters among maternal grandparents, and NSE of both the paternal grandfather and grandmother are important for child well-being. For the next step, we will conduct multivariate analyses using MSM to test whether these descriptive patterns still hold after removing time-varying confounders.

[Figure 5 About Here]

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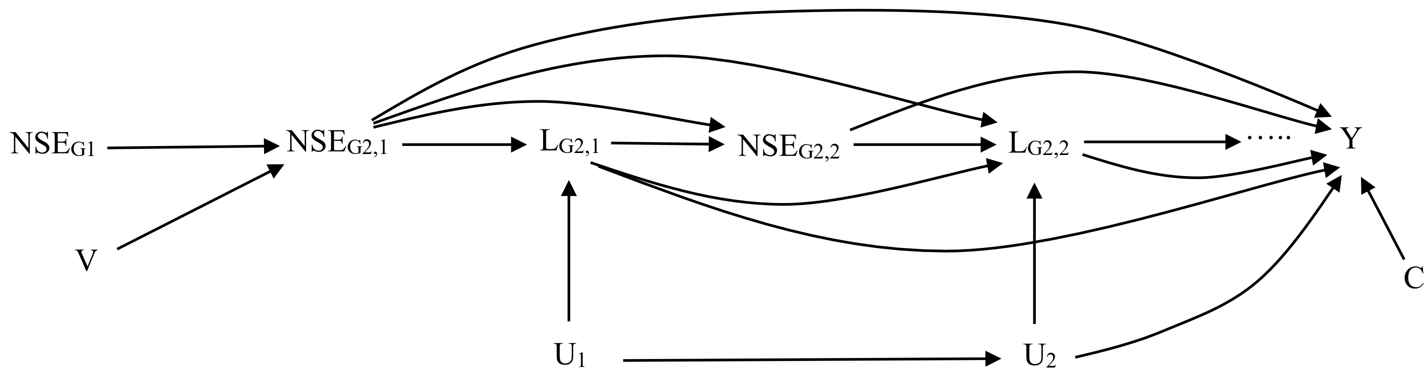


Figure 1: Directed acyclic graph (DAG) displaying possible direct and indirect causal pathways linking Non-standard employment (NSE) and Child Well-Being using two waves of data.

Note: $NSE_{G2,k}$ = Parents' (G2) non-standard employment in wave k; $L_{G2,k}$ = Time-varying variables of G2 in wave k that are affected by history of NSE and will also affect future NSE, such as earnings, family income, marital status, health, life satisfaction, homeownership; NSE_{G1} = Grandparents' (G1) non-standard employment when G2 were 15 years old; V = Other pretreatment covariates including G1's level of education, G2's level of education, G2's first job after finishing education. U = unmeasured variables. Y = Children's (G3) cognitive and emotional well-being. C = exogenous variables of G3 that influence Y, such as gender and age group. For simplicity, the arrows pointing from NSE_{GP} and V to Y are omitted.

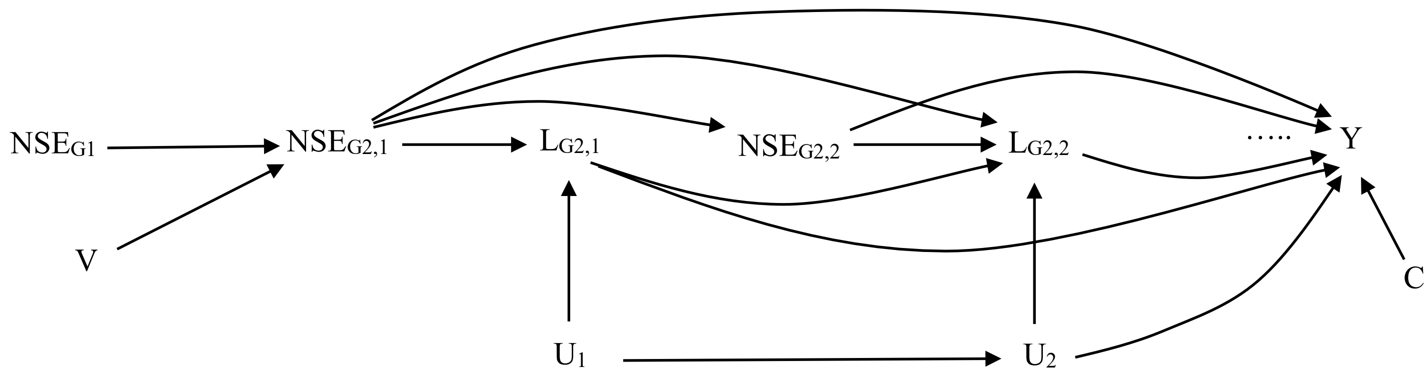


Figure 2: Directed acyclic graph (DAG) representing the same data structure as figure 1 reweighted with inverse probability of treatment weights to remove the confounding by time-variant causes of treatments.

Note: $NSE_{G2,k}$ = Parents' (G2) non-standard employment in wave *k*; $L_{G2,k}$ = Time-varying variables of G2 in wave *k* that are affected by history of NSE and will also affect future NSE, such as earnings, family income, marital status, health, life satisfaction, homeownership; NSE_{G1} = Grandparents' (G1) non-standard employment when G2 were 15 years old; V = Other pretreatment covariates including G1's level of education, G2's level of education, G2's first job after finishing education. U = unmeasured variables. Y = Children's (G3) cognitive and emotional well-being. C = exogenous variables of G3 that influence Y, such as gender and age group. For simplicity, the arrows pointing from NSE_{GP} and V to Y are omitted.

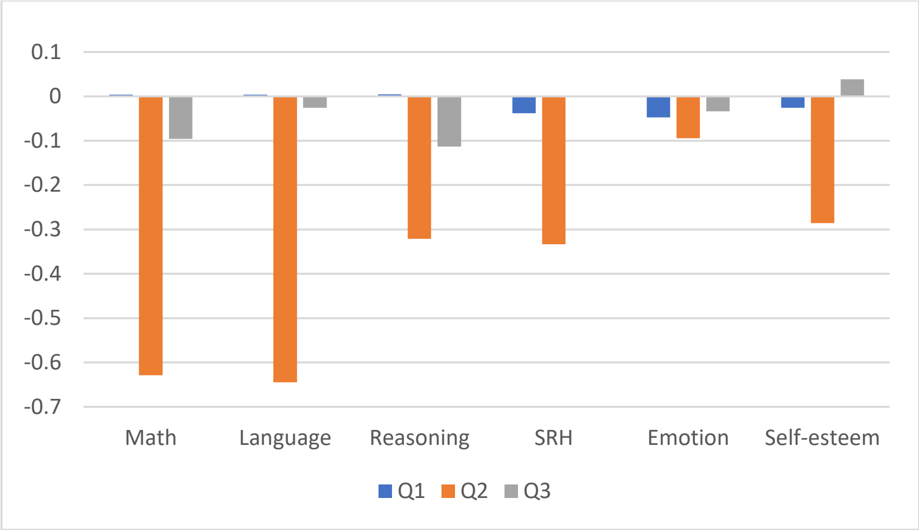


Figure 3: Child well-being by lower tertile (Q1), middle tertile (Q2), and upper tertile (Q3) of father's duration of non-standard employment.

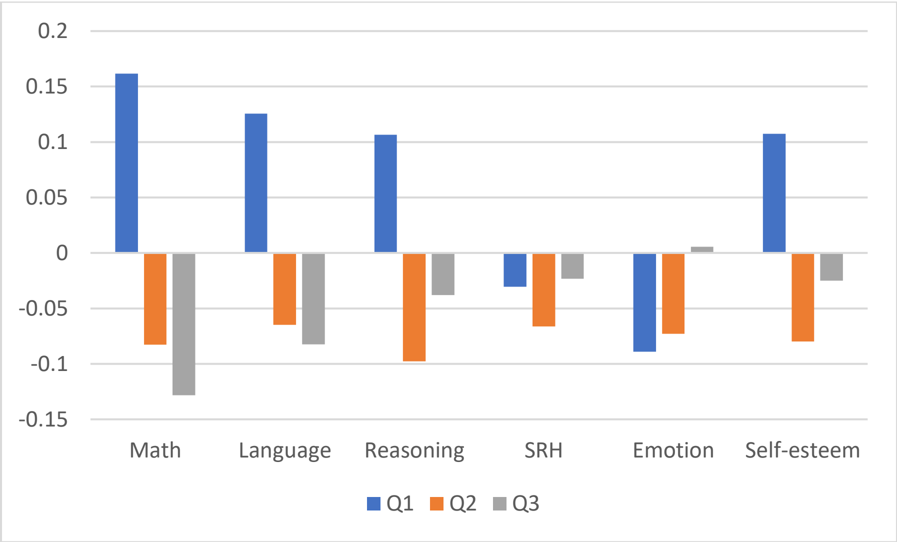
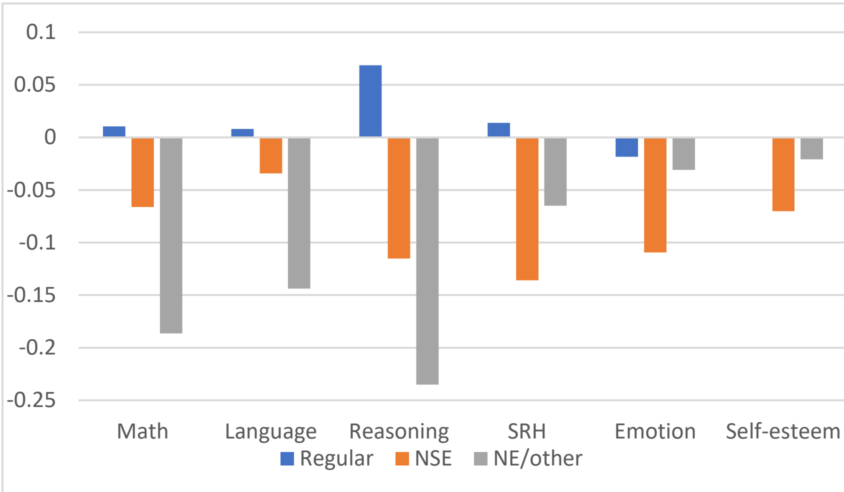
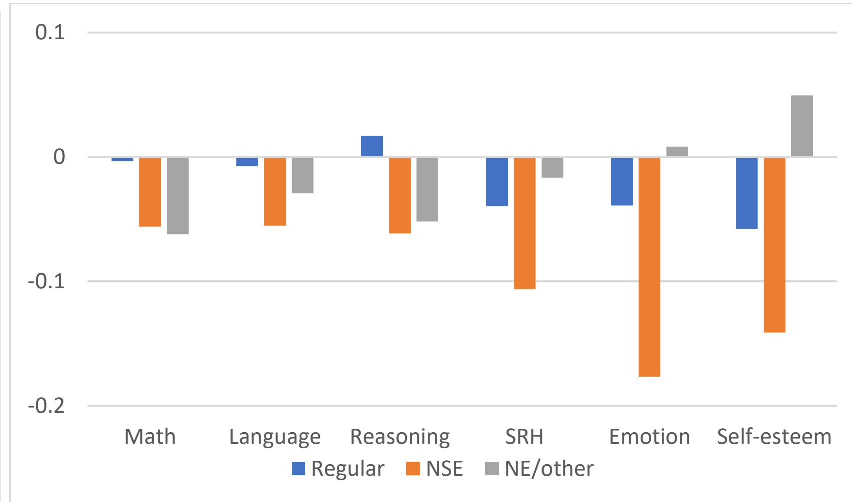


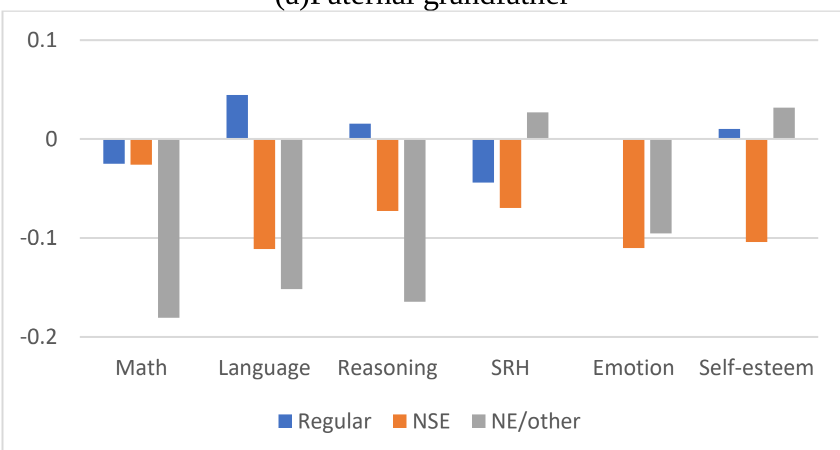
Figure 4: Child well-being by lower tertile (Q1), middle tertile (Q2), and upper tertile (Q3) of mother's duration of non-standard employment.



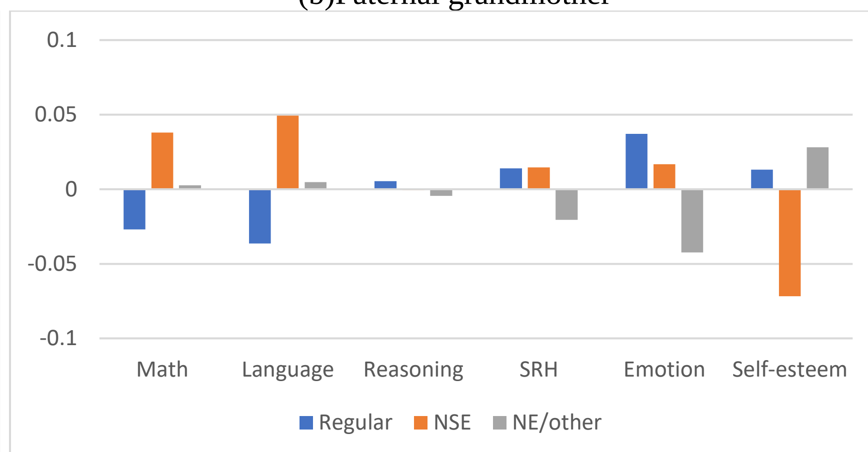
(a)Paternal grandfather



(b)Paternal grandmother



(a)Maternal grandfather



(d)Maternal grandmother

Figure 5: Child well-being by employment status of grandparents.

Table 1: Unweighted descriptive statistics for key independent variables, KHPS and JCPS sample

Variable	Cognitive		Noncognitive	
	Mean (%)	S.D.	Mean (%)	S.D.
Math[a]	-0.044	0.957		
Language[a]	-0.029	0.936		
Reasoning[a]	-0.034	0.906		
Self-rated health[a]			-0.048	0.963
Emotions[a]			-0.033	0.947
Self-esteem[a]			-0.044	0.915
Paternal grandfather's employment (%)				
Regular	54.61		53.36	
Non-standard	29.19		28.81	
Not employed/deceased/other/NA	16.20		17.83	
Paternal grandmother's employment (%)				
Regular	28.61		27.57	
Non-standard	22.60		22.77	
Not employed/deceased/other/NA	48.79		49.66	
Maternal grandfather's employment (%)				
Regular	55.97		55.83	
Non-standard	32.01		31.82	
Not employed/deceased/other/NA	12.03		12.35	
Maternal grandmother's employment (%)				
Regular	35.11		34.98	
Non-standard	23.86		24.14	
Not employed/deceased/other/NA	41.03		40.88	
Father's duration of NSE (0-1)	0.176	0.346	0.179	0.349
Mother's duration of NSE (0-1)	0.461	0.357	0.502	0.361
N of children	1031		729	

Note: [a] We first standardized children's cognitive and noncognitive outcomes within each grade of children, and then take the average over survey waves.