Delaying Retirement Pays Off –
Singapore Retirement and Health Study

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NUS Research Team

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1. Introduction

According to the United Nations (2019), most countries are experiencing population ageing, and that one out of six people (16%) in the world will be over 65 by 2050. However, in 2017, Singapore has already 14.4% of its citizen population above the age of 65 (Department of Statistics, 2020a), making it one of the fastest ageing countries in the world. The speed of ageing is due in part to longer life expectancy resulting from accessibility to affordable health care as well as advancement in healthcare and medical technologies. Life expectancy at birth was 75.6 years in 1990 and has increased to 84.9 years in 2019, causing Singapore to lead with the world's longest life expectancy at birth. Singapore's healthy life expectancy (HALE) at birth is the highest in the world at 73.9 years up from 66.6 in 1990, surpassing Japan (73.3) and Switzerland (71.7). (Ministry of Health 2019, Global Burden of Diseases).

Singapore will be a super-aged society by 2030, with the number of persons above age 65 projected to reach 900,000 by then. (Population White Paper 2013). Increasing life expectancy together with lower birth-rates, the Population White Paper projected old-age support ratio to fall from 5.9 in 2012 to 2.1 by 2030. The increased number of retired people may place excessive burdens on healthcare resources and affect public finances in terms of social protection and tax productivity. The government also warns of a shrinking labour force due to the decline in the working-age share. Bloom and Finlay (2009) examine the sustainability of economic growth with a growing fraction of older-age population for a sample of Asian countries, including Singapore. Their analysis suggests that a decline in working-age share had a negative effect on economic growth for the sample period 1965 to 2005. However, as Herrman (2012) opines demography is not destiny; and can be shaped by policies to address population ageing to enhance human capital and productivity. To mitigate the effects of declining working-age share on economic growth, countries have introduced policies to increase total fertility rates, female labour force participation and in-migration to bolster the working-age population. Other older worker inclusive policies include legislating higher minimum retirement age, age discrimination legislation and providing incentives to work beyond average retirement age through part-time and flexible work arrangements.

Older workers can be a crucial resource to meet manpower needs in Singapore, especially since Singapore residents at age 65 are expected to live longer. In 1999, when Singapore was officially designated an ageing society, the government introduced statutory retirement age, pegged at 60. At that time, the life expectancy of Singapore residents at age 65 was 15.3 years for men and 17.9 years for women. In 2019, life expectancy at age 65 had increased by 4.2 more years for men and 5.1 more years for women. (Department of Statistics, 2020b). Whilst longevity imposes great cultural, economic and social challenges for individuals; it also provides a longevity dividend. Olshansky and his colleagues define the longevity dividend as the economic and health benefits that individuals and societies could reap if the processes of biological ageing could be slowed down to allow people to enjoy more years of good health. (Olshansky et al. 2006).

There is thus potential for older workers to work longer as health and longevity improve. To reap this potential, the Singapore Prime Minister announced the re-employment concept at the 2007 National Day Rally. The concept of re-employment was pioneered in Japan as longer work lives may help ease the crunch of population ageing. Other countries such as Denmark, Netherland, Sweden, UK and US passed retirement and age discrimination legislation to support older workers. In 1st January 2012, Singapore passed the Retirement and Re-employment Act (RRA). The RRA obliged employers to offer re-employment to eligible workers who turned 62 on or after 1st January 2012, until the employee turns 65. (Ministry of Manpower, 2011). The RRA assures older workers the option to continue working if they are able and willing to do so. In 2017, the re-employment age was raised to 67. The following year, a Tripartite Workgroup was set up to study how to strengthen support for older workers. In 2019, the Workgroup released their recommendation to increase the Retirement Age and Re-employment Age to 65 and 70 respectively in small steps by 2030, with the first increases to 63 and 68 on 1 July 2022. (Ministry of Manpower, 2019).

The RRA provides older workers with the option to delay their retirement, work partially or continue working fully. The choice made could very much depend on their health state and other considerations. Generally, people of poorer health status are more likely to retire due to health issues. It then appears that retirement is the cause of ill health when in fact, some other unobserved factors may be influencing retirement decision and health at the same time. When we observe people who remain working and have good health, it could be that delaying retirement leads to a better health state. The study on the relationship between work and health must account for such selection bias.

To tackle such endogeneity issues, existing literature utilizes approaches such as the instrumental variable estimation (Neuman, 2008; Coe, 2012; Silver et al. 2018) and regression discontinuity design (Johnson and Lee, 2009; Eibich, 2015). However, research findings on the impacts of retirement on various health outcomes have been mixed – some have found positive effects, others negative. For examples, Eibich (2015) using the German socio-economic panel data found that retirement was associated with improvements in mental and physical health, as well as a reduction in healthcare usage. Neuman (2008) used US Health and Retirement Study (HRS) data; his initial estimates using simple OLS models suggested retirement increases the likelihood of health declines. However, after controlling for endogeneity, using exogenous variation in public and private pensions as an instrument, retirement becomes significant and positive for both men and women in the subjective health model. However, Bonsang et al. (2012) using the same data set as Neuman, found a significant negative effect of retirement on cognitive thinking. The negative effect is not instantaneous, with most of the effect occurring at the beginning of the retirement period and stabilising afterwards. Furthermore, Rohwedder and Willis (2010) also found that retirement was associated with declines in memory recall. Similarly, Celidoni, *et al.* (2017) found that retirement has a long-term detrimental effect on cognition for individuals who retire at the statutory eligibility age, using longitudinal Survey of Health, Ageing and Retirement in Europe (SHARE) data. Behncke (2012) applying IV strategy on the English Longitudinal Study of Ageing (ELSA) data. His analysis showed that that retirement significantly increases the risk of being diagnosed with a chronic condition and raises the risk of severe cardiovascular disease and cancer. In addition, he also found that retirement increases risk factors (e.g., BMI, cholesterol, blood pressure) and increases problems in physical activities. Retirement worsens self-assessed health.

This paper explores if retirement is beneficial, neutral or detrimental for health using the data from the Singapore Retirement and Health Study (RHS). Having a good understanding of the impact of retirement on health outcomes and health utilisation is crucial in informing retirement policies in Singapore. To our knowledge, there is the first study in Singapore that explores the impacts of retirement on health using RHS data. There is a study published in MTI Feature Article, led by the Ministry of Manpower economists, that examines the impact of RRA on older workers' employment outcomes. (see Lee *et al.*, 2018). This MOM study also exploits the RRA age eligibility criterion but uses difference-in-differences analysis. The data used in the MOM study are panel administrative data spanning 2011 to 2015. The control group consisted of individuals aged 60-61, as they were not eligible for the RRA, and the treatment group consisted of individuals aged 62-64. They found that the RRA had a small but positive impact on the employment rate among eligible older workers, raising the employment rates by 1.6 percentage points. The presence of concurrent policy schemes violates the common trends assumption, especially since individuals are pooled over a wide age range to identify the effect of the RRA.

For this paper, besides employment outcomes, to gain better understanding of the consequences of retirement policies we also consider the impact of retirement on health and healthcare utilisation. If retirement affects health and increases healthcare utilisation, this will further add to the costs of retirement. We will investigate: (1) the impact of mandatory re-employment offers on retirement; (2) the impact of retirement on cognition, health and healthcare utilization; (3) pre-retirement occupational characteristics and post-retirement outcomes; (4) pre-retirement job satisfaction/ social connectedness and post-retirement outcomes and (5) the characteristics of respondents who rejoin the workforce. This report will provide important insight into the effectiveness of such policies on employment outcomes, as well as how individuals respond to these policies.

The remainder of this report is structured as follows: Section 2 describes the data and the research methodology employed in this analysis. Section 3 summarises several key summary statistics related to health and retirement observed in Singapore as well as presents the preliminary results. Section 4 concludes with a comparison of our findings with other countries and highlights some policy implications.

2. Data and Methodology

2.1 Data

The RHS is a longitudinal survey panel established by the Singapore government to understand the retirement and healthcare needs of Singapore residents over time. This dataset contains rich information on retirement, healthcare utilisation, health, income and expenditures, health insurance status, and demographic characteristics, from a nationally representative study of 15,103 individuals between ages 45-85. Individuals were interviewed once every two years. Currently, three waves have been completed in 2014, 2016 and 2018. This report will utilise data from the first wave survey in 2014. We restrict the sample to respondents aged 55 and above in 2014 (n=9,227) as it is the age when changes in retirement trends are observed. Setting the cut-off at age 55 will exclude those from ages 45-54 who are in their prime working lives, defined as people aged 25 to 54, from the study. Next, we further exclude respondents in the samples who: (1) has never worked before as they are not part of the workforce, (2) are disabled, permanently ill or in poor health as chances of them returning to work is very low and (3) are studying as they do not belong to the workforce. This reduces our sample to 7,903 individuals.

<u>Retirement</u>
For our study, we identified two working categories for the respondents. Respondents' working statuses were defined as: (1) *non-retired*, if their economic status was working, or if their economic status was not working but actively looking for a job or were temporarily laid off, retrenched or wish to start a business (2) *retired*, if they were not working, not actively looking for a job and reported that they are not working due to non-economic related reasons, for example, being caregiver/ homemaker and preferring to spend time on other personal interests. In our main analysis, we primarily compared the respondents in categories *non-retired and retired*. We also performed two sensitivity analyses: (i) excluded individuals near the cut-off (ages 63 and 64 years old) and (ii) excluded caregivers in the retired category.

<u>Normalised age</u>

Fig. 1 shows the "retirement rate" (the sample fraction of individuals in partial or full retirement) by age and gender. We observe a steady trend of increasing retirement rates over time. We define the normalised age *a* as the actual age minus 64, which is the corresponding age for the age-eligibility cut-off of the RRA in 2014: *a* = age – 64. This variable acts as the assignment variable in our main analysis for the fuzzy RDD.

<u>Outcome variables</u>

This report considers various health outcomes pertaining to mental and physical health, as well as healthcare utilisation from various healthcare services. The health indexes which we culled from the RHS include the following:

(1) *Cognitive score:* The RHS administers the *Mini-Mental State Exam (MMSE) score*, which is a continuous variable ranging from 0 to 30 to evaluate the cognition functions of a respondent, where a higher score indicates higher cognition capabilities. As MMSE was administered only to respondents age 60 and above (n=6,100), when analysing this outcome, we included only respondents age 60 and above who completed all questions in the MMSE (n=4,424). We used the MMSE score to proxy cognitive impairment. Respondents scoring lower than an education-adjusted cut-off MMSE score will be categorised as cognitively impaired. The education-adjusted cut-off scores are as follows: a) respondents who attained only Primary School Leaving Examination (PSLE) and has MMSE score of 22 or lower, b) respondents who attained secondary school education and has MMSE score of 24 or lower, c) respondents who attained post-secondary education and has MMSE score of 25 and lower, and d) respondents who attained diploma or university education and has MMSE of 26 and lower.

(2) *Self-reported health*: In the RHS, there is a variable that indicates self-reported health condition. Respondents rated their overall health on a scale of 1 ("Poor") to 5 ("Excellent"), with categories "Poor", "Fair", "Good", "Very good", and "Excellent" in increasing scale.

(3) *Disability and ADLs*: The variable Activities of Daily Living (ADL) includes activities concerning mobility, bathing, dressing, eating, toileting and transferring. Respondents with limitations in at least three out of six ADLs will be categorized as being severely disabled. We also count the total number of ADL limitations a respondent has.

(4) *Chronic conditions*: The six identified chronic conditions are high blood pressure or hypertension, high blood cholesterol or lipids, diabetes, arthritis, depression and dementia. The presence of these chronic conditions in the survey is self-reported by the respondent based on any past doctor diagnosis.

(5) *Healthcare utilization*: The RHS reports on healthcare utilization by respondents in the last 12 months of the survey. *Total healthcare visits*: the total number of healthcare visits in the last 12 months, inclusive of polyclinic visits and hospital visits. *Polyclinic visits*: the number of times respondents visited the polyclinics in the last 12 months. *Hospital admission*: the number of local hospital admissions respondents had in the last 12 months. *Emergency visits*: the number of local hospital emergency visits respondents had in the last 12 months. *Surgery or procedures*: the number of local day surgery or procedures (excluding dental) respondents had in the last 12 months.

(6) *Total healthcare cost*: The total cost for all healthcare utilisation in the last 12 months, inclusive of, polyclinic cost, hospital admission cost, hospital emergency cost and surgery or procedure cost. *Total polyclinic cost*: the total cost for polyclinic visits in the last 12 months. *Inpatient cost*: the total cost for local hospital admissions in the last 12 months. *Emergency cost*:

the total cost for local hospital emergency department visits in the last 12 months. *Surgery or procedure cost*: the total cost for local day surgery or procedures (excluding dental) in the last 12 months. Due to the positive skewness of healthcare utilization data, logarithmic transformation was performed with ordinary least squares regression on cost and visit data.

(7) Lifestyle Behaviors and Social Engagements: *Sports*: the inclusion of sports activities in the last 12 months.

Control variables

The analysis was adjusted for variables such as education levels, marital status, housing assets, household expenditures and gender. Education levels are categorised to four main categories, Primary School Leaving Examination (PSLE) and below, secondary, post-secondary and diploma together with the university. Marital status is categorised to single, married or cohabitating, separated or divorced and widowed. Housing assets are defined as the total apportioned housing asset by the local residential property to respondents while household expenditure is represented by the average monthly non-healthcare household consumption expenditure.

2.2 Econometric Strategy: Regression Discontinuity Design

In order to tease out the impacts of retirement on health, we utilised the the introduction of the Retirement and Re-employment Act (RRA) in 2012. RRA provides option to mature workers the flexibility to work beyond the age of 62, up to 65. Since the RRA utilises the age of an individual as a key determinant for his/her eligibility for mandatory re-employment offers, this legislation naturally generates an age cut-off for retirement. Regression Discontinuity Design is an econometric strategy to estimate the treatment effects in a non-experimental setting when treatment is determined by whether an observed assignment variable exceeds a known cut-off. In this instance, the RDD framework searches for discontinuities in health outcomes of individuals close to the RRA age-eligibility cut-off (if any), as these individuals are likely to be similar to each other after controlling for age. In this context, the treatment group is the pool of individuals whose age lies below the RRA cut-off.

The key assumption for the regression discontinuity design is that all other unobservable factors are continuously related to the assignment variable (Lee and Lemieux, 2010). This assumption automatically holds if respondents do not have control over the assignment variable and are thus unable to manipulate their treatment status. In this instance, as individuals cannot easily manipulate their age on official records, there is good reason to believe that the assumption holds and hence the RD design is valid. The variation in treatment (i.e.re-employment) near the threshold (at age 62) is randomised as though it is from a randomised experiment. By construction, the assignment of treatment is independent of the baseline covariates.

The authors have checked that the assumption holds by performing density tests on the distribution of observed baseline individual characteristics, such as educational attainment and marital status. We did not find any statistically significant density differences across the discontinuity.

Given the significant impact of the RRA on retirement decisions, the RRA provides an opportunity to determine the impact of retirement on health. In order to do so, we need to further assume that the RRA has no direct effect on health, other than via its effect on the retirement decision. This is a reasonable assumption as there is no reason to believe that receiving re-employment offers has a direct impact on health.

Given these assumptions, we can tease out the effects of retirement on these health outcomes using the regression discontinuity framework. Formally, we start off with a linear model for our outcome variables of interest.

$$Y_{i,2014} = \tau R_{i,2014} + X'_{i,2014}\beta + \varepsilon_i \qquad (1)$$

Where $Y_{i,2014}$ represents the outcome variables of interest (as stated in Section 2.1) for each individual i. τ represents the treatment effect of retirement on each outcome, while $R_{i,2014}$ is a binary indicator for retirement at 2014. $X'_{i,2014}$ are the control variables such as education levels, marital status, housing assets, household expenditures and gender and ε_i represents individual-level error terms that are correlated with retirement.

Under the assumptions stated earlier, the change in retirement rates generated by the RRA across the discontinuity is not due to selection bias. We can then determine the effects of retirement on the outcomes of interest via two-stage-least-squares (TSLS). TSLS is necessary here as some individuals choose to retire even before hitting the discontinuity. Similarly, some individuals do not retire even after crossing the age cut-off. When there is imperfect compliance, the discontinuity is a fuzzy discontinuity, and thus TSLS is needed to uncover the effect of retirement on health.

Under TSLS, we first estimate the following equation:

$$R_{i,2014} = \pi_0 Z_i + X'_i\pi + v_i \qquad (2)$$

Where Z_i is the instrument used - a binary variable that takes the value of 1 if the individual was aged 64 or above in Wave 1 of the RHS, and thus was likely not covered by the RRA in 2012. As part of two-stage-least-squares, we then rerun equation 1 (the reduced form equation) using the predicted values for retirement from the first stage. Note that for both equations, we cluster the error terms by age to account for the possibility of cohort-specific shocks to the outcome variables.

We assume that individuals do not have control over the re-employment eligibility cut-off age (instrument), and that the cut-off age has no impact on health outcomes except by influencing retirement decision. The treatment effect identified through fuzzy RD procedure is then effectively dividing the jump in the outcome variable at the discontinuity, by the jump in retirement status at the discontinuity. (Lee and Lemieux, 2010, p, 300). As part of our robustness checks, we also rerun gender-specific versions of these regressions in our results. Doing so allows us to account for the fact that the effect of the RRA on the retirement decision is strongly influenced by the gender of the individual, as will be detailed in the next section.

3. Key Results and Findings

Table 1 presents the summary statistics for the first wave of RHS conducted in 2014. All sample means, standard deviations and categorical percentages reported are survey weighted while categorical numbers are unweighted. After implementing our sample selection criteria, the RHS Wave 1 sample consists of 7,903 respondents, of which 48.5% of respondents were male. The average age of the sample in 2014 is 64.3 years old. Only 17.7% of respondents obtained post-secondary, and higher education and most of the respondents were either married or cohabitate (73.6%). The average monthly non-healthcare household consumption expenditure was $3,150 (SD=$2,900), with the males having a higher average consumption expenditure compared to the females (mean=$3,231; SD=$3,343 and mean=$2,743; SD=$2,585 respectively). In terms of healthcare utilization, males and females reported similar polyclinic visits and polyclinic cost, the sample average is 2.74 and $289 respectively. However, males have higher total number of healthcare visits and incurred higher healthcare costs compared to females. Most respondents (67.3%) rated their health status to be “Good”, “Very good” or “Excellent”. Respondents have an average of 1.5 chronic conditions amongst the six listed above and 71.1% have at least one. A minority (0.5%) of the respondents have at least three or more ADLs which is an indication of their disability severity. Since MMSE score was only collected from respondents who are 60 years old or above, the overall average MMSE score for respondents above 60 was 25.3 (SD=5.4) with the males having a higher score (mean=26.6; SD=4.4) compared to females (mean=25.2; SD=5.1).

We found that the majority of retired respondents were females (67.4%), compared to only 40.5% of females in the non-retired category. In comparison to respondents who were non-retired, the retired respondents also tend to be older (mean=69.1; SD==7.5 vs. mean=62.7; SD=6.0, $p<0.001$), have lower educational attainment (% with only PSLE, 59% vs. 45%, $p<0.001$), lower non-healthcare expenditure (mean=$2,737; SD=$2,500 vs. mean= $3,436; SD=3,116, $p<0.001$), higher total healthcare visit (mean=3.7; SD=5.1 vs. mean=2.9; SD=4.4, $p<0.001$), higher total healthcare cost (mean=$2,133; SD=$6,490 vs. mean=$1,418; SD=$5,569, $p<0.001$), poorer self-reported health (% reported good and above, 62.7 % vs. 70.4%), greater disease burden for hypertension, diabetes, and high blood cholesterol, higher proportion with at least three or more ADLs (1.0% vs 0.2%), and more likely to have cognitive impairment (19.9% vs. 11.6%).

3.1 Impact of RRA on Retirement

In the sample, 54.7% of the respondents were categorised in the working group, 24.8% in the partially retired group and 20.5% in the retired group. A majority of male respondents (67.2%) fall into the working category, while the females were mostly either partially retired or retired (57%). **Fig. 1** illustrates the impact of the RRA on retirement using the RHS dataset. As expected, the proportion of retired individuals increases with age. After adjusting for education, marital status, housing asset and expenditure, the impact of RRA on both full/partial retirement for the entire population was 8.7% ($p<0.01$), with a larger impact among males of 9.1% ($p<0.01$) compared to the females of 7.3% ($p<0.05$) (**Table 2, Fig 2**).

Fig. 1: Proportion of retired and non-retired respondents (weighted)

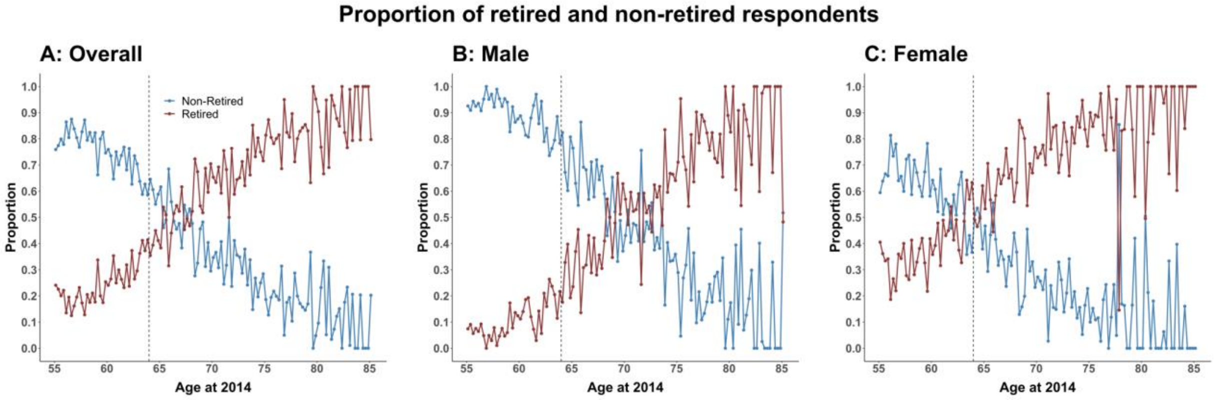


Fig. 2: Average proportion of retired individuals by age and gender

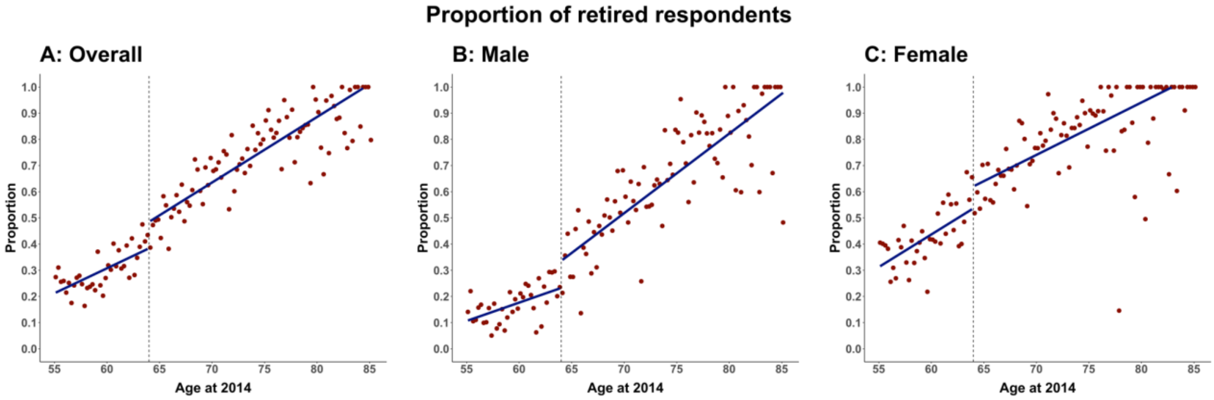


Table 1. Summary statistics

		Gender			Working categories		
Variables	**Overall**	**Male**	**Female**	**p-value**	**Non-retired**	**Retired**	**p-value**
N	7903	3959	3944		4338	3565	
Demographics							
Age, mean (SD)	64.34 (7.20)	64.20 (7.12)	64.48 (7.27)	<0.001	62.68 (6.02)	69.13 (7.48)	<0.001
Gender, N (%)							<0.001
Female	3944 (51.5%)				1654 (40.5%)	2290 (67.4%)	
Male	3959 (48.5%)				2684 (59.5%)	1275 (32.6%)	
Working categories, N (%)				<0.001			
Non-retired	3565 (59.1%)	2684 (72.5%)	1654 (46.5%)				
Retired	4338 (40.9%)	1275 (27.5%)	2290 (53.5%)				
Education levels, N (%)				<0.001			<0.001
PSLE	4056 (50.6%)	1783 (44.2%)	2273 (56.7%)		1949 (44.9%)	2107 (59.0%)	
Sec	2519 (31.7%)	1320 (33.0%)	1199 (30.4%)		1546 (35.5%)	973 (26.3%)	
Post-sec	361 (4.8%)	204 (5.3%)	157 (4.3%)		207 (4.8%)	154 (4.7%)	
Diploma and University	961 (12.9%)	649 (17.4%)	312 (8.6%)		633 (14.8%)	328 (10.0%)	
Marital status, N (%)				<0.001			<0.001
Single	534 (7.8%)	203 (84.9%)	331 (9.5%)		348 (9.2%)	186 (5.9%)	
Married or Cohabitate	5741 (73.6%)	3368 (4.4%)	2373 (63.0%)		3299 (76.3%)	2442 (69.8%)	
Separated or Divorced	437 (5.7%)	162 (4.6%)	275 (6.8%)		304 (7.0%)	133 (3.8%)	
Widowed	1191 (12.9%)	226 (4.6%)	965 (20.6%)		387 (7.6%)	804 (20.5%)	
Non-healthcare expenditure ($), mean (SD)	3150 (2900)	3231 (3343)	2743 (2585)	<0.001	3436 (3116)	2737 (2500)	<0.001
Total housing asset (in thousands), mean (SD)	376 (776)	392 (845)	362 (705)	<0.001	368 (726)	388 (843)	<0.001
Healthcare utilisation and health outcomes							
Total healthcare visits, mean (SD)	3.23 (4.71)	3.28 (5.40)	3.19 (3.94)	<0.001	2.88 (4.36)	3.73 (5.13)	<0.001

Total hospital visits, mean (SD)	0.49 (1.20)	0.53 (1.32)	0.44 (1.06)	<0.001	0.41 (1.05)	0.59 (1.37)	<0.001
Total polyclinic visits, mean (SD)	2.74 (4.31)	2.74 (4.96)	2.74 (3.60)	0.96	2.47 (4.03)	3.14 (4.65)	<0.001
Total healthcare cost ($), mean (SD)	1710 (5973)	1762 (5878)	1661 (6061)	<0.001	1418 (5569)	2133 (6490)	<0.001
Total hospital cost ($), mean (SD)	1421 (5938)	1475 (5836)	1371 (6033)	<0.001	1174 (5548)	1780 (6444)	<0.001
Total polyclinic cost , mean (SD)	289(466)	288 (484)	290 (449)	0.041	244 (419)	353 (521)	<0.001
Self-reported health, N (%)				<0.001			<0.001
Poor	270 (3.3%)	134 (3.3%)	136 (3.3%)		112 (2.5%)	158 (4.5%)	
Fair	2229 (29.4%)	1061 (27.8%)	1168 (30.9%)		1118 (27.1%)	1111 (32.7%)	
Good	4120 (52.9%)	2036 (52.9%)	2084 (52.9%)		2324 (54.3%)	1796 (50.9%)	
Very good	926 (11.4%)	514 (12.1%)	412 (10.8%)		590 (12.5%)	336 (9.9%)	
Excellent	266 (2.9%)	173 (3.9%)	93 (2.1%)		179 (3.6%)	87 (1.9%)	
Total number of chronic conditions[a], mean (SD)	1.50 (1.19)	1.35 (1.18)	1.44 (1.19)	<0.001	1.23 (1.14)	1.64 (1.21)	<0.001
High blood pressure, N (%)				<0.001			<0.001
No	3746 (50.1%)	1884 (49.2%)	1862 (51.0%)		2352 (56.2%)	1394 (41.3%)	
Yes	4157 (49.9%)	2075 (50.8%)	2082 (49.0%)		1986 (43.8%)	2171 (58.7%)	
High blood cholesterol, N (%)				<0.001			<0.001
No	3763 (50.0%)	1980 (52.5%)	1783 (47.7%)		2290 (54.5%)	1473 (43.5%)	
Yes	4140 (50.0%)	1979 (47.5%)	2161 (52.3%)		2048 (45.5%)	2092 (56.5%)	
Diabetes, N (%)				<0.001			<0.001
No	5913 (78.7%)	2907 (76.6%)	3006 (80.6%)		3360 (80.7%)	2553 (75.8%)	
Yes	1990 (21.3%)	1052 (23.4%)	938 (19.4%)		978 (19.3%)	1012 (24.2%)	
Number of ADLs[b] , N (%)				<0.001			<0.001
0	7768 (98.6%)	3908 (99.0%)	3860 (98.3%)		4307 (99.4%)	3461 (97.5%)	
1	72 (0.7%)	26 (0.5%)	46 (1.0%)		20 (0.3%)	52 (1.3%)	
2	15 (0.2%)	9 (0.2%)	6 (0.1%)		3 (0.1%)	12 (0.2%)	

3 or more	48 (0.5%)	16 (0.3%)	32 (0.7%)		8 (0.2%)	40 (1.0%)	
MMSE, mean (SD)	25.85 (4.84)	26.59 (4.36)	25.17 (5.14)	<0.001	26.67 (3.83)	25.10 (5.49)	<0.001
Cognitive impairment, N (%)				<0.001			<0.001
No	4429 (84.1%)	2396 (88.5%)	2033 (80.0%)		2162 (88.4%)	2267 (80.1%)	
Yes	1062 (15.9%)	406 (11.5%)	656 (20.0%)		362 (11.6%)	700 (19.9%)	
Lifestyle behaviours and social engagements							
Drinking status, N (%)				<0.001			<0.001
Non-drinkers	7459 (93.9%)	3576 (89.3%)	3883 (98.2%)		4020 (92.4%)	3439 (96.0%)	
Current drinkers	444 (6.1%)	383 (10.7%)	61 (1.8%)		318 (7.6%)	126 (4.0%)	
Smoking status, N (%)				<0.001			<0.001
Non-smokers	7056 (89.5%)	3177 (80.3%)	3879 (98.3%)		3689 (86.0%)	3367 (94.7%)	
Current smokers	847 (10.5%)	782 (19.7%)	65 (1.7%)		649 (14.0%)	198 (5.3%)	
Sports, N (%)				<0.001			<0.001
No	5058 (60.8%)	2343 (57.0%)	2715 (64.4%)		2791 (61.7%)	2267 (59.5%)	
Yes	2845 (39.2%)	1616 (43.0%)	1229 (35.6%)		1547 (38.3%)	1298 (40.5%)	

Note: N given are sample size and mean, SD and percentage proportions given are weighted.
Sample size may not sum to column total, and percentage may not sum to 100% due to missing data.
a: Sum of hypertension, high cholesterol, diabetes, dementia, depression and arthritis
b: Sum of mobility, bathing, dressing, eating, toileting and transferring

Table 2. Multiple Regression Discontinuity of RRA on retirement

Outcome: retirement	Overall	Male	Female
Threshold (age at 64)	**0.087******	**0.091******	**0.073*****
	(0.025)	**(0.030)**	**(0.036)**
Age	0.021***	0.017***	0.025***
	(0.004)	(0.003)	(0.006)
Age*Threshold indicator	0.005	0.016***	-0.004
	(0.004)	(0.004)	(0.006)
Education (ref: PSLE)			
Secondary	-0.010	0.034**	-0.043**
	(0.013)	(0.015)	(0.020)
Post-secondary	0.049**	0.110***	-0.007
	(0.024)	(0.031)	(0.046)
Diploma/University	0.041**	0.122***	-0.055
	(0.020)	(0.020)	(0.034)
Log(1+housing asset)	-0.002*	-0.001	-0.002
	(0.001)	(0.002)	(0.002)
Log(1+housing expenditure)	-0.019**	-0.029**	-0.004
	(0.008)	(0.011)	(0.011)
Male	-0.265***		
	(0.012)		
Observations	844,495	409,482	435,013
R-squared	0.272	0.290	0.184

Standard errors in parentheses, models adjusted for marital status. *** p<0.01, ** p<0.05, * p<0.1

This difference in effect size of RRA on retirement is likely because females are more marginally attached to the workforce compared to males, and are thus more likely to consider early retirement, even in the face of reemployment offers. This is reflected in the age-sex specific labour force participation rates, as seen in **Table 3**. While male labour force participation rates among those aged 55-64 were 12.4 percentage points lower than prime-age males aged 25-54; labour force participation rates among those aged 55-64 females were 23.4 percentage point lower than prime-age females.

Table 3. Age-sex specific labour force participation rates in 2020

Age Category	Males	Females
25 to 54	95.1	82.4
55 to 64	82.7	59.0
65 & Over	40.1	21.7

Source: Department of Statistics

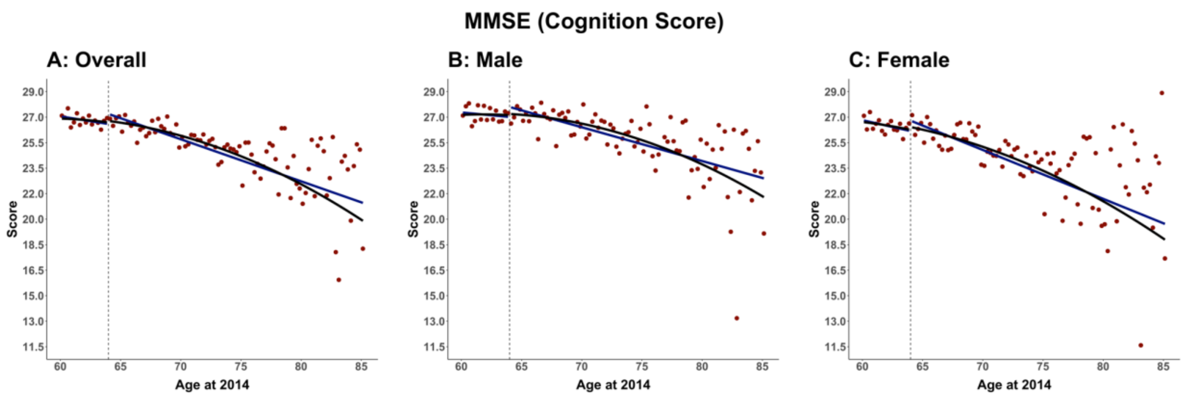
A possible explanation for why females are more likely to be marginally attached to the workforce is that females are often involved in caregiving for others. For example, Frimmel (2021) shows that there is a difference in gender responses to policies that reintegrate elderly unemployed workers in Austria. This is due to greater family obligations for women such as parental care for children/grandchildren or informal care for sick relatives. (Frimmel, p. 6) This is also evidence in the Singapore RHS data. In the RHS questionnaire, economically inactive respondents were asked why they were economically inactive. A majority of female respondents (52.16%) cited that they were involved in caregiving. This contrasts with merely 3.09% of economically inactive males who cited caregiving. These greater caregiving obligations mean that females are more likely to leave the workforce to manage their obligations. Furthermore, the coefficients of our marital status controls in the RD regressions showed opposing significant and large effects. A married/cohabitating female tends to be retired more often than singles (0.214, p<0.01) in contrast to males (-0.132, p<0.01). Taken together, this suggests that gender roles are an important factor that determines the likelihood of accepting a reemployment offer.

3.2 Impact of retirement on cognition, health and healthcare utilisation

We observe a slight increase in MMSE scores around the age cut-off, however it is not statistically significant (**Fig. 3**). This indicates that delaying retirement via the implementation of mandatory re-employment offers may not have a noticeable impact on cognitive function. While we found RRA has no impact on cognition, this could be because mild cognitive impairment is more prevalent in older age groups (Gao, 2018) and that cognitive decline happens over time. Also, environmental changes are unlikely to affect cognition instantaneously, and the "honeymoon" effect of retirement may attenuate the negative effect. Atchley (1976, 1982) suggested that retirees may experience a "honeymoon' phase following retirement, where retirees engaged in different activities that were put off for years due to work constraints. This engagement in desired activities may have attenuate the negative effect of retirement on cognitive function. However, overtime, Rennemark and Berglund (2014) using Swedish data found that cognitive ability decreased over a period of 6 years, among participants who retired before 60 years old. At the age of 60, cognition of those who had retired did not differ from those still working.

Additionally, since the MMSE was only conducted on respondents aged 60 and above, the number of surveyed individuals that were covered by the RRA is much smaller (n=1906) than the number of surveyed individuals that were not covered by the RRA (n=3721). This large disparity in sample size between the treatment and control groups limits the statistical power of our study in estimating the causal impact of retirement on cognition within the Wave 1 sample.

Fig. 3: Average MMSE scores over age, with the age-eligibility cut-off



Note: A linear fit as well as a quadratic fit are shown in the plots.

Retirement was found to lead to an increase in polyclinic costs (**Table 4, Figure 4a**). Retirement causes respondents to pay an average of 2.09% (p<0.10) more per annum, or equivalently an increase in $426 (p<0.10) more per annum for total healthcare cost compared to non-retirees. This effect was concentrated among males (4.72%, p<0.05), no statistically significant impact was observed among females. Similarly, it is observed that there was a corresponding increase in healthcare visits among males upon retirement (1.57%, p<0.05), with no significant impacts on females as well as the overall population (**Table 4, Figure 4b**). The results indicate that there is a causal effect of retirement on polyclinic utilization among males, with no statistically significant impact on other healthcare metrics.

Fig. 4a: Total polyclinic cost (log) over age, with the age-eligibility cut-off

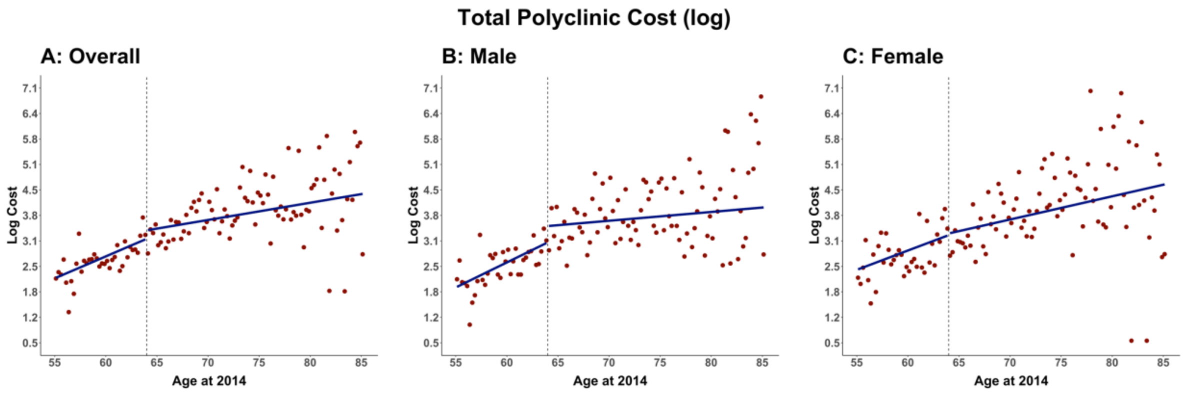


Fig. 4b: Total healthcare visits (log) over age, with the age-eligibility cut-off

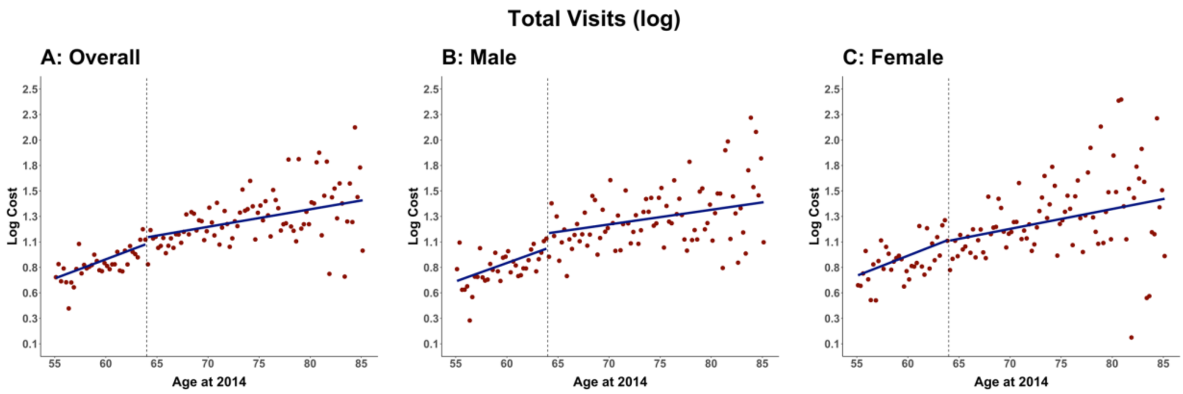


Table 4. RD-IV regression estimates for selected variables

	Total polyclinic cost (log)			Total healthcare visits (log)		
VARIABLES	**Overall**	**Male**	**Female**	**Overall**	**Male**	**Female**
Retirement (with IV)	**2.087***	**4.724****	-0.676	0.575	**1.566****	-0.519
	(1.208)	**(2.152)**	(2.846)	(0.390)	**(0.739)**	(0.950)
Age	0.057	0.025	0.110	0.021	0.002	0.048
	(0.040)	(0.060)	(0.097)	(0.013)	(0.022)	(0.032)
Age*Threshold indicator	-0.061***	-0.153***	-0.026	-0.018***	-0.041***	-0.016
	(0.020)	(0.038)	(0.043)	(0.006)	(0.013)	(0.014)
Education (ref: Primary school)						
Secondary	0.303***	0.188	0.158	0.107***	0.065	0.057
	(0.094)	(0.141)	(0.178)	(0.029)	(0.044)	(0.058)
Post-secondary	0.154	-0.015	-0.066	0.051	-0.011	-0.025
	(0.205)	(0.3774)	(0.285)	(0.062)	(0.123)	(0.091)
Diploma/University	-0.317*	-0.830**	-0.251	-0.054	-0.220**	-0.055
	(0.173)	(0.362)	(0.246)	(0.049)	(0.112)	(0.084)
Log(1+Housing asset)	0.009	0.007	0.001	0.000	0.001	-0.003
	(0.008)	(0.013)	(0.011)	(0.002)	(0.004)	(0.004)
Log(1+Housing expenditure)	-0.279**	-0.175	-0.346***	-0.072***	-0.047	-0.080***
	(0.069)	(0.136)	(0.079)	(0.021)	(0.041)	(0.026)
Male	0.390			0.131		
	(0.326)			(0.110)		

3.3 Pre-retirement occupational characteristics and effects of RRA on retirement

To explore if pre-retirement occupational characteristics modulate the impact of the RRA on retirement, we classified the occupational characteristics of each unit group occupation listed in the Singapore Standard Occupational Classification (SSOC) using the methodology in Mihaylov and Tjidens (2019). The tasks in each unit group occupation are classified according to the routine/ non-routine / manual / analytical task contents. (See Annex A for details.) Routine/ non-routine task intensity scores (as first conceptualized by Autor, Levy and Murnane (2003)) are then computed. Given that the RHS only provides SSOC classifications at 2-digit sub-major group level, we computed the average for each sub-major group weighed by the number of individuals working in each occupation given in the administrative records. Each sub-major group is then classified into 4 categories, based on how the task intensity scores compared to the median routine and manual task intensities (as observed in the whole RHS sample). Subsequently, respondents of the RHS were assigned into these categories, based on their employment status as of 2012. Table 5 illustrates an example of 2-digit sub-major groups and occupations in each category.

Table 5. An illustration of occupational classification by task intensities

	Routine (High Routine)	Non-Routine (Low Routine)
Manual (High Manual)	• **Sales Workers** o Stall Holders • **Food Processing, Woodworking, Garment, Leather and Other Craft and Related Trades Workers** o Butchers, Fishmongers and Related Food Preparers	• **Personal Care Workers** o Teacher Aides • **Protective Service Workers** o Police Officers
Analytic/Interactive (Low Manual)	• **Hospitality, Retail and Related Services Managers** o Hotel Operations and Lodging Services Managers • **General And Keyboard Clerks** o General Office Clerks	• **Legislators, Senior Officials and Chief Executives** o Legislators • **Administrative And Commercial Managers** o Finance and Administration Managers

Using occupational classifications, we observed that the RRA has a differential impact on reemployment among each category. The regression results reported in **Table 6** shows that the RRA has a greater impact on occupations with lower manual task intensities than the median. This is evidenced in a significantly larger effect size in both low-manual quadrants compared to their high-manual counterparts.

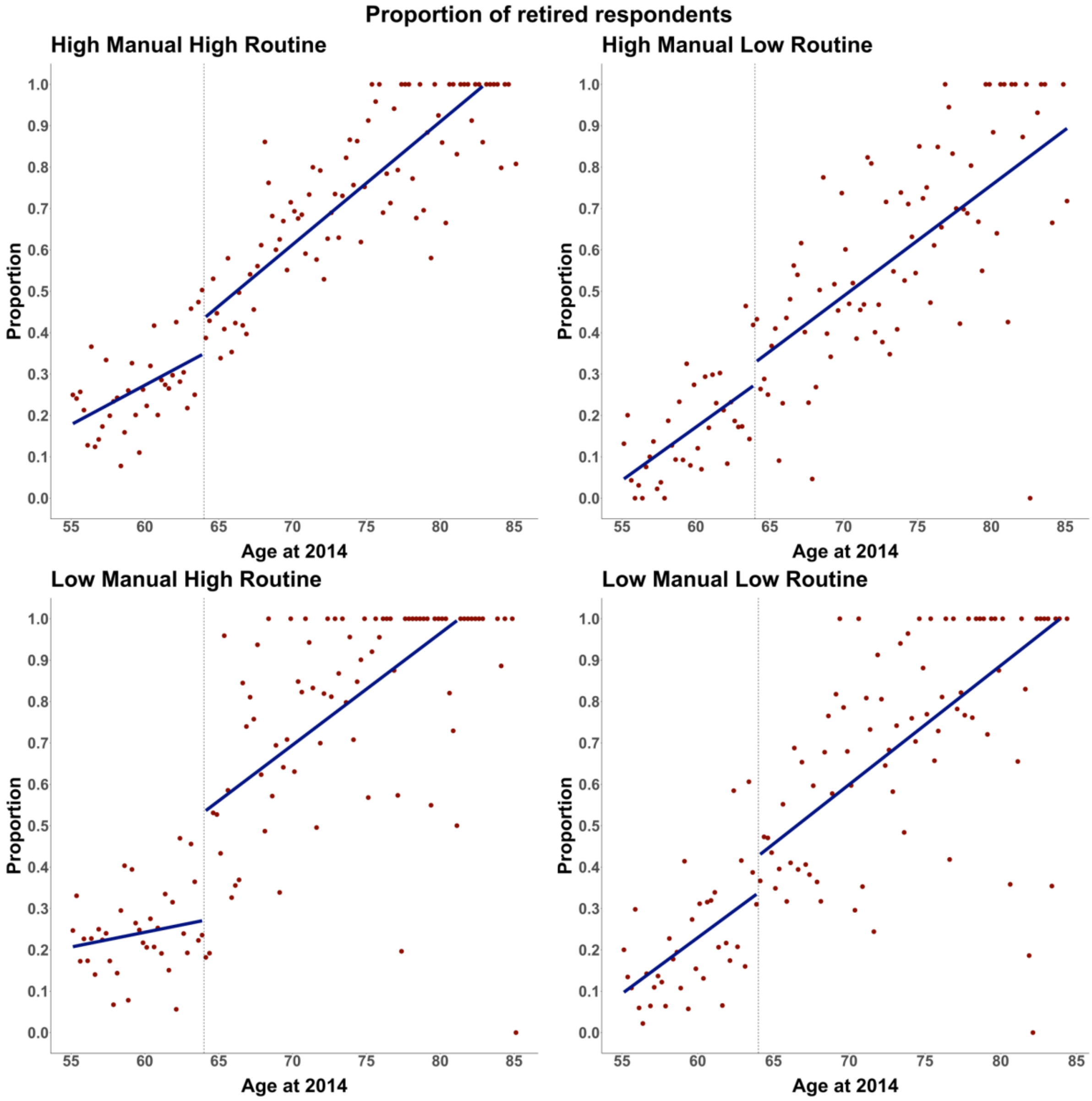
Increasing retirement age may impact workers of manual jobs in a different and possibly more intense way, as it may be harder for older workers in manual labour (Pensions Strategy Group (2005)). A possible reason for this large divergence in effect sizes is plausibly due to differences in the amount of physical exertion involved in these jobs. We observe that highly manual jobs tend to be more physically demanding, and thus current health status may play a greater role in determining whether workers choose to stay employed in these jobs. Empirically, studies have also found that health depreciates faster over the life cycle for individuals in manual occupations. Fletcher, *et al.* (2011) finds a detrimental impact of physically demanding job conditions on health, especially for older workers. In addition, older workers in Netherlands who retire from manual work in Wave 1 of the study experienced the highest decline in fatigue in Wave 2, compared to those who remained employed (Vanajan, *et al.* (2020)). Our finding is also consistent with other studies. For example, when Austria raised the retirement age, the employment response was largest among high-wage and healthy workers, whereas low-wage and less healthy workers continued to retire early (Staubli, *et al.* (2014)). In other words, mandatory reemployment offers may be less effective in inducing those in poor health to stay on in these jobs, reducing the effectiveness of the RRA for highly manual jobs.

As can be gleaned from **Table 6**, RRA has impacts on occupations with less manual tasks, with greatest impact on those with higher routine. . The occupation groups classified under this category includes mostly desk-bound managers, professionals and clerks that may not need to work in an environment as dynamic and physically demanding as other occupations. Our regression results suggest that the take up rate of reemployment offers may be higher for individuals who have jobs that require less physical labour and are more routine.

Table 6. RD estimates for the effect of the RRA on retirement based on occupational characteristics.

	High Routine	Low Routine
High Manual	**0.061*** **(0.033)**	**0.059** **(0.051)**
Low Manual	**0.269***** **(0.065)**	**0.071** **(0.055)**

Fig. 5: Average proportion of retired (partial and fully retired) individuals by occupational classification (as of 2012)



3.4 Job satisfaction/social connectedness and post-retirement outcomes

We hypothesized that job satisfaction and social connectedness could play an important role in post-retirement health outcomes, such as self-reported health state (e.g., ADLs and chronic conditions) as well as data from administrative health records (e.g., polyclinic and emergency department visits). The RHS allows us to examine this hypothesis, as it is a longitudinal panel survey which contains information about respondent attitudes towards their current job, as well as whether/how frequently do they communicate with their children/extended family/friends.

In order to measure the potential correlations between job satisfaction on post-retirement outcomes, we constructed an additive scale based on the responses for each job satisfaction question in Wave 1 of the RHS. For these questions, respondents were asked how strongly they agreed or disagreed with the given statement (e.g., they enjoyed their work). We summed up the number of positive responses to create the additive scale.

We then restricted the sample to respondents that appeared in both waves of the RHS. This allowed us to accurately identify respondents that are newly retired. Newly retired include respondents who worked in Wave 1 but became economically inactive in Wave 2. Among this subgroup, we excluded respondents who did not provide complete responses for all 5 job satisfaction questions in the first wave of the RHS. This is to avoid measurement error in the additive scale.

We found that higher job satisfaction in the first wave of the RHS (as measured in our scale) was associated with poorer self-reported health and higher incidence of depression amongst newly retired individuals in the second wave of the RHS (**Table 7**). A positive response on a job satisfaction question (i.e., an increase in the job satisfaction score by 1 unit) is associated with a decrease in a newly retired individual's self-reported health rating in Wave 2 by 0.074 points ($p<0.05$), as well as an 0.6 ($p<0.05$) percentage point increase in the incidence of depression in Wave 2. In other words, this finding suggests that retiring from jobs with low job satisfaction is subsequently associated with better physical/mental health during the retirement phase.

However, as much as there is a correlation between job satisfaction and physical/mental health, these findings may or may not suggest causal effects and thus should be interpreted with care. Nonetheless, this result allows us to have a more nuanced understanding of the relationship between job satisfaction and health amongst newly retired retirees and could potentially pave the way for future research in this direction.

Table 7. Selected Wave 2 regression estimates with Wave 1 job satisfaction

VARIABLES	Self-reported health rating	Depression incidence
Job satisfaction score	**-0.090****	**0.007****
	(0.035)	**(0.003)**
Age	0.004	-0.001
	(0.007)	(0.001)
Education (ref: Primary school)		
Secondary	-0.034	-0.005
	(0.128)	(0.007)
Post-secondary	-0.135	-0.040
	(0.170)	(0.029)
Diploma/University	0.143	0.027*
	(0.172)	(0.016)
Log(1+Housing asset)	-0.001	-0.001
	(0.010)	(0.001)
Log(1+Housing expenditure)	0.110	-0.001
	(0.078)	(0.007)
Male	-0.139	-0.001
	(0.095)	(0.007)

To measure the potential link between social connectedness and post-retirement outcomes, we similarly created an additive scale for social connectedness based on the Wave 1 RHS questions on frequency of social connections with their children/extended family/friends. We then restricted the sample to respondents that appeared in both waves of the RHS and removed respondents that did not provide complete responses for all 6 social connectedness questions in the first wave of the RHS.

Upon running regressions between our social connectedness measure, we did not find any statistically significant association between social connectedness and post-retirement outcomes. This may be because we were only able to measure the frequency of social connections among respondents, whereas other omitted factors (such as quality of social connections) may play a critical role in determining social connectedness as well as how social connectedness affects post-retirement outcomes.

3.5 Rejoining the workforce and health outcomes

Since RRA gives option for workers to remain or re-enter the workforce, we also explore the characteristics of those who rejoin the workforce. We examine whether rejoining the workforce in Wave 2 was associated with differences in other outcome variables. We explore changes in economic activity status between Wave 1 and Wave 2, for example, from economically inactive in Wave 1 to economically active in Wave 2. We then classified respondents into four major categories based on their economic activity status in both waves: individuals who remained economically active in both waves; individuals that remained economically inactive in both waves; newly inactive individuals and newly active individuals who are rejoined the workforce (re-employed). To do so, we restricted our sample to those that were interviewed in both Wave 1 and 2 (to ensure an accurate indicator of changes in employment status) and were 55 and above in Wave 2 (to exclude individuals who were still in their prime working years in Wave 2). After our sample selection criteria, 297 respondents were considered as newly active. We then compared the Wave 2 summary statistics for each category, as compiled in **Table 9**.

Compared to other categories, the "newly active" re-employed category is relatively younger, with a mean age of 63.54 years as of 2014. Only those who remained economically active has lower mean age. The "newly active" category is also relatively healthier with a mean of 1.44 chronic conditions compared to those who remained economically inactive (1.94) and the newly inactive (1.67). They have slightly worse health outcome compared to those who had remained economically active in both waves (1.3). 50.2% of the newly active reported having high blood pressure and 52.5% reported having high cholesterol. This reflects the prevalence of specific chronic conditions such as high blood pressure and high cholesterol in Singapore. The prevalence of these chronic condition among the "newly active" is higher than the prevalence among those who have remained economically active over the two waves (45.1% and 49.1% respectively), but lower than the prevalence among those who were economically inactive over the two waves (66.3% and 64.0% respectively).

In terms of healthcare visits, the newly active re-employed individuals reported an average of 3.69 healthcare visits in the past year, which is marginally similar to the visits made by the still economically active individuals (3.39). Indeed, on some metrics, the newly active re-employed individuals report having lower healthcare utilization than the other categories, such as mean hospital visits in the past year (0.45) and mean total healthcare cost ($1404).

People who rejoin the workforce are typically healthier and have similar health status as those who had remained in the workforce in both waves. Besides health condition which enables individuals to rejoin the workforce, we also posit that that re-entering the workforce force may be predicated on willingness to work. RHS questionnaire asked economically inactive respondents if they would consider rejoining the workforce under certain conditions. **Table 8** tabulates the proportion of respondents willing to consider rejoining the workforce for the newly active and those remained economically inactive by age range.

For the newly active, i.e. those who rejoined the workforce in Wave 2, 61.52% had indicated that they were willing to consider rejoining the workforce under at least one circumstance. The proportion compares better than the youngest age group among the still economically inactive category. This suggests that most newly active individuals observed in Wave 2 were already predisposed to consider reemployment in Wave 1.

The table also shows that the willingness of economically inactive individuals to consider rejoining the workforce declines with age. Amongst those aged 55-64, 46.65% of those who were economically inactive in Wave 2 indicated willingness to consider rejoining the workforce when surveyed in wave 1. The proportion of those willing to do so falls precipitously with age. A third of those in age range 65-69 of the still economically inactive were willing to consider rejoining the workforce, compared to only 12.42% for older respondents aged 75+.

Table 8. Willingness to consider rejoining the workforce among economically inactive individuals in Wave 1, stratified by their economic activity status in Wave 2

	Newly Active	**Still Economically Inactive**			
		55-64	**65-69**	**70-74**	**75+**
Willing to consider rejoining the workforce under at least 1 circumstance	**61.52%**	**46.65%**	**33.60%**	**23.70%**	**12.42%**
Not willing to consider rejoining the workforce at all	38.48%	53.35%	66.40%	76.30%	87.58%

Table 9. Selected Wave 2 summary statistics, by economic activity status

	W1-W2 work categories				
Variables	Still Economically Active	Still Economically Inactive	Newly Inactive	Newly Active	p-value
N	3396	3748	633	297	
Demographics					
Age in 2014, mean (SD)	60.71 (6.03)	68.97 (7.78)	64.69 (6.95)	63.54 (6.72)	<0.001
Gender					<0.001
Female	1335 (39.3%)	2519 (67.2%)	270 (42.7%)	160 (53.9%)	
Male	2061 (60.7%)	1229 (32.8%)	363 (57.3%)	137 (46.1%)	
Education levels					<0.001
PSLE	1378 (40.6%)	2385 (63.7%)	325 (51.3%)	156 (52.5%)	
Sec	1274 (37.5%)	930 (24.8%)	178 (28.1%)	94 (31.6%)	
Post-sec	319 (9.4%)	199 (5.3%)	52 (8.2%)	16 (5.4%)	
Diploma and University	424 (12.5%)	233 (6.2%)	78 (12.3%)	31 (10.4%)	
Marital status					<0.001
Single	301 (8.9%)	222 (5.9%)	37 (5.8%)	22 (7.4%)	
Married	2586 (76.1%)	2303 (61.4%)	446 (70.5%)	219 (73.7%)	
Cohabit	247 (7.3%)	168 (4.5%)	46 (7.3%)	15 (5.1%)	
Separate	262 (7.7%)	1055 (28.1%)	104 (16.4%)	41 (13.8%)	
Total housing asset (in thousands), mean (SD)	321 (706)	289 (705)	364 (708)	294 (577)	0.048
Non-healthcare expenditure ($), mean (SD)	3339 (2854)	2495 (2314)	2778 (2555)	2769 (2310)	<0.001
Monetised home property?					<0.001
DK/RF	40 (1.4%)	73 (2.9%)	4 (0.8%)	6 (2.7%)	
No	2300 (80.9%)	2056 (81.7%)	404 (82.3%)	193 (85.4%)	
Yes	502 (17.7%)	386 (15.3%)	83 (16.9%)	27 (11.9%)	
Healthcare utilisation and health outcomes					
Self-reported health					<0.001
Poor	80 (2.4%)	257 (7.1%)	52 (8.3%)	11 (3.7%)	
Fair	760 (22.4%)	1133 (31.2%)	170 (27.1%)	71 (23.9%)	
Good	1875 (55.2%)	1800 (49.5%)	315 (50.2%)	171 (57.6%)	
Very good	508 (15.0%)	370 (10.2%)	65 (10.4%)	35 (11.8%)	
Excellent	171 (5.0%)	77 (2.1%)	26 (4.1%)	9 (3.0%)	
Total number of chronic conditions, mean (SD)	1.30 (1.16)	1.94 (1.26)	1.67 (1.27)	1.44 (1.18)	<0.001
Total healthcare visits, mean (SD)	3.39 (5.08)	4.54 (5.15)	4.93 (5.41)	3.69 (4.19)	<0.001

Total hospital visits, mean (SD)	0.48 (1.12)	0.91 (1.99)	1.06 (2.00)	0.45 (1.07)	<0.001
Number of polyclinic visits, mean (SD)	2.91 (4.76)	3.63 (4.47)	3.87 (4.84)	3.24 (3.99)	<0.001
Total healthcare cost, mean (SD)	1763 (5773)	3310 (9529)	4153 (11058)	1404 (4320)	<0.001
Total hospital cost, mean (SD)	1499 (5743)	2917 (9501)	3774 (11066)	1107 (4285)	<0.001
Cost of polyclinic visits, mean (SD)	265 (399)	394 (508)	379 (518)	297 (418)	<0.001

4. Conclusion

This paper uses regression discontinuity design and data from the Singapore's Retirement and Health Study (RHS) data to explore the work, retirement, and health impacts of retirement policy, such as the Retirement and Re-employment Act (RRA). The findings provide important insight into the impacts of such policies on retirement and employment outcomes. Besides employment outcomes, we also consider the impacts of retirement on health and healthcare utilisation. If retirement affects health and increases healthcare utilisation, this will further add to the costs of retirement.

In this paper, we have explored the following: (1) the impact of mandatory re-employment offers on retirement; (2) the impact of retirement on cognition, health and healthcare utilization; (3) pre-retirement occupational characteristics and post-retirement outcomes; (4) pre-retirement job satisfaction/ social connectedness and post-retirement outcomes and (5) the characteristics of respondents who rejoin the workforce. The findings are summarized below.

After adjusting for education, marital status, housing asset and expenditure, RRA decreases retirement in the overall population (9.1%, $p<0.01$). The impact is greater for males (9.6%, $p<0.01$) compared to females (7.8%, $p<0.05$). While we found a positive impact of RRA on employment similar to the MOM study (Lee 2017), our estimate is larger. The MOM study suggests that RRA raises employment rates by 1.6 percentage points on average per annum. The difference in the size effect could be due to different study design and different data used. The MOM study used difference-in-differences analysis comparing individuals aged 60-61 as control group, and individuals aged 62-64 as treatment group. They used panel administrative data spanning 2011 to 2015 and included workers who worked with the same employer for the past three years. The DID analysis could be biased due to manpower policies implemented during the period of study; and the sample selection could influence the estimate. As part of the RD design, we used all individuals aged above 55 in order to estimate the impact of the RRA, whereas the MOM study focused on individuals aged between 60-64. Another possible reason for the higher causal impacts in our study could be the use of age in quarters in this study instead of age in years as the instrument in the RD design. Studies have shown that the use of more granulated data in RD design, for example using age in months, tends to provide better estimate (Dong, 2015).

We find that retirement increases polyclinic utilization, especially among males. One possible mechanism is deteriorating health after retirement. Males have a higher incidence of self-reported diseases such as diabetes, hypertension and high blood cholesterol compared to females (**Appendix Fig 1a-c**), which may also lead to the observed higher polyclinic expenditure ($p<0.01$) post-retirement. Another explanation could be due to the reduced opportunity cost of time to seek healthcare at the polyclinic after retirement. This may explain the increase in self-reported chronic diseases among males. This finding of retirement increasing health utilization is in line with findings elsewhere, for examples, Yi *et al*. (2018) for Chinese retirees, Blake and Garrouste (2012) for French retirees and Johnston and Lee (2009) for the UK. Our findings suggest that retirement may increase demand for primary healthcare. However, it is also important to note that we do not observe evidence that retirement has significant impacts on other healthcare utilization metrics, such as hospital utilization. Therefore, the implementation of the RRA and similar policies is unlikely to strain other aspects of the healthcare system beyond primary care.

We also explore if pre-retirement occupational characteristics influence the impacts of the RRA on reemployment. The regression results show that RRA has greater impact on occupations with lower manual task intensities than the median. Consistent with empirical studies in Austria, Netherlands and elsewhere, we also find mandatory reemployment offers to be less effective in inducing those in poor health to stay on in physically demanding jobs.

Next, we explore if there is any correlation between job satisfaction and health outcomes post-retirement. Higher job satisfaction in the first wave of the RHS was associated with poorer self-reported health and higher incidence of depression amongst newly retired individuals in the second wave. A positive response on a job satisfaction question (i.e., an increase in the job satisfaction score by 1 unit) is associated with a decrease in a newly retired individual's self-reported health rating in Wave 2 by 0.074 points ($p<0.05$), as well as an 0.6 ($p<0.05$) percentage point increase in the incidence of depression in Wave 2. In other words, this finding suggests that retiring from jobs with low job satisfaction is subsequently associated with better physical/mental health during the retirement phase. However, as much as there is a correlation between job satisfaction and physical/mental health, these findings may or may not suggest causal effects and thus should be interpreted with care. Nonetheless, this result allows us to have a more nuanced understanding of the relationship between job satisfaction and health amongst newly retired retirees and could potentially pave the way for future research in this direction.

We find no statistically significant association between social connectedness and post-retirement outcomes. This may be because due to data limitations, we were only able to measure the frequency of social connections among respondents, and not other factors (such as quality of social connections). Future research should include these omitted factors may play a critical role in determining social connectedness as well as how social connectedness affects post-retirement outcomes.

Since RRA gives option for workers to remain or re-enter the workforce, we also explore the characteristics of those who rejoin the workforce. Using the RHS data for wave 1 and 2, we identify the "newly active" who rejoin the workforce in wave 2 when they were identified as economically inactive in wave 1. The newly active are typically healthier as they have similar health status as those who had remained in the workforce in both waves. We posit that to re-entering the workforce may be predicated on ability and willingness to rejoin the workforce. It is interesting that among the newly active (rejoined in Wave 2), 61.52% had indicated that they were willing to consider rejoining the workforce under at least one circumstance in Wave 1. The proportion compares better than the youngest age group among those under the "still economically inactive" category. This suggests that most newly active individuals observed in Wave 2 were already predisposed to consider reemployment in Wave 1. The willingness to rejoin falls with the age of respondents.

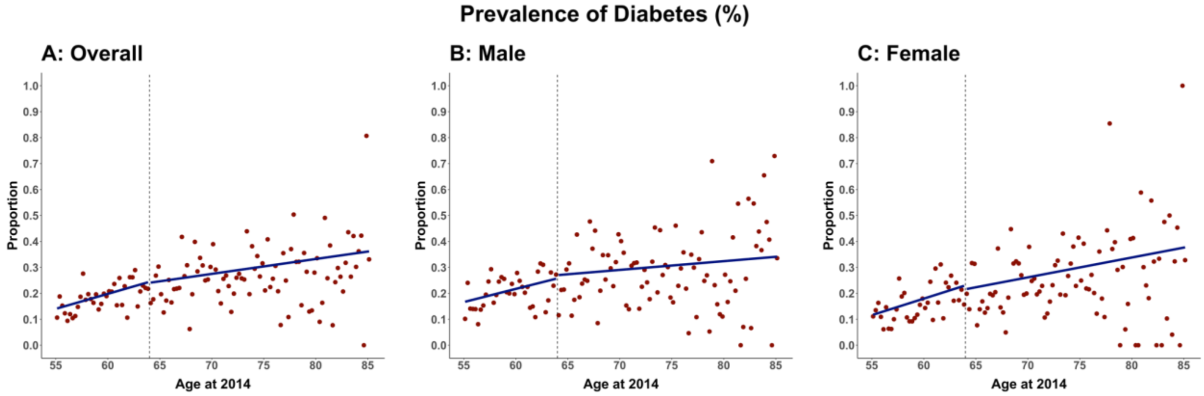
While some of these findings are novel and yield interesting policy implications, we recognize that this study has its limitations. For example, the bandwidth choice is crucial in non-parametric RDD with the trade-off between bias and variance. In this study, the age variable (in quarters) was used, resulting in insufficient local variation in the age variable to estimate a local polynomial around the discontinuity. This was especially true for the MMSE, which was assessed among those aged 60 and above. The limited data points before the cut-off causes the robust estimation of the regression discontinuity to be unstable, preventing non-parametric RDD from being used.. Rounding in the age variable also introduces rounding error in the estimates. The direction of this error varies and is dependent on how the outcome variable changes around the discontinuity. Studies have shown that using age in months tends to lead to better estimates (Dong, 2015).

The study on the effects of retirement on cognitive health may be marred by missing data. The MMSE test is administered to RHS respondents aged 60 and above. Besides the different sample size for the control and treatment group, the quality of the data received from the treated group is affected by missing data. About 27.5% (n=1,676) of respondents who took the MMSE administered have missing data, as they did not respond to one or more questions in the questionnaire. Additionally, about 10% of these respondents had not responded to at least three questions in the MMSE. For these respondents, the MMSE may potentially be underestimated due to the missing responses. Furthermore, the MMSE was not administered to those below age 60 (n=2,276), making it difficult to identify the effect of age on the MMSE prior to age 60. These missing data which might not be missing at random requires imputation techniques on observables which can be explored. In addition, other constructs on mental health, such as depression and anxiety has been found in other studies to be associated with retirement. However, as individuals tend to under-report depressive symptoms, objective assessment using the Center for Epidemiologic Studies Depression Scale (CES-D) will be more accurate.

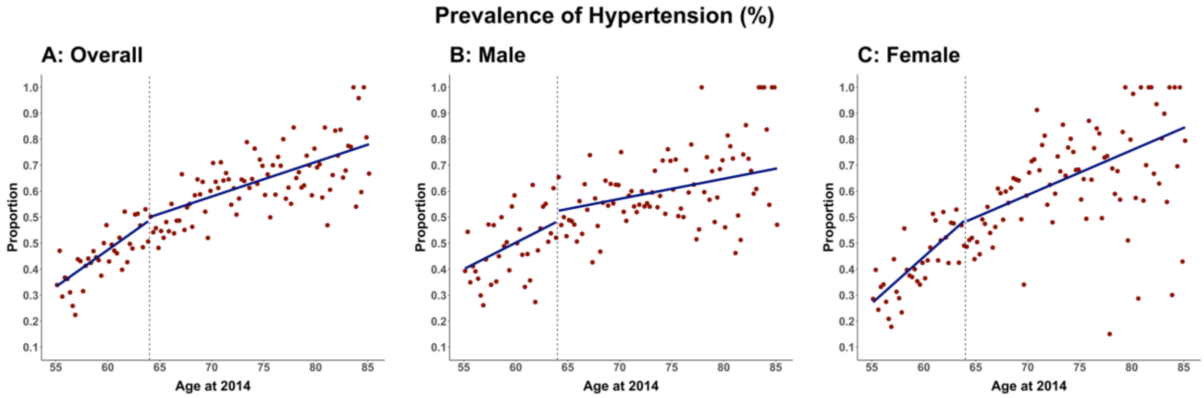
For future research, we plan to study the long-run impact of retirement on health and healthcare utilisation using longitudinal data from subsequent waves of RHS. This will help to capture effects of retirement on cognition and other health outcomes which are time varying and will occur over a period of time. Pending on availability of administrative health data, we could also perform a difference-in-differences (DID) analysis using subsequent waves of the RHS. Like the regression discontinuity framework, the RRA also generates a treatment and control group that can be used for the DID analysis as it stratifies individuals into those below 62 on 1st January 2012 and thus received mandatory re-employment offers, and those above 62 on 1st January 2012 and thus did not receive such offers. By observing the health outcomes for these two groups and comparing how they change over time in subsequent waves of the RHS, we can estimate the impact of retirement on health trends over the long term. Another direction of future research could be to investigate how the effect of retirement on healthcare utilisation changes as the working population becomes more educated and better paid in the future.

In conclusion, aging society faces multi-faceted issues and requires multi-faceted research approach. This paper has used to the RHS data to examine work, retirement and health. To better understand the societal and economic impact of aging, future research can make use of the RHS data linked to administrative records from the Ministries' and Statutory Boards' database to study impacts of national-level policy changes on individuals and society. For example, how CPF and housing policies affect monetization behavior and its impact on retirement outcomes.

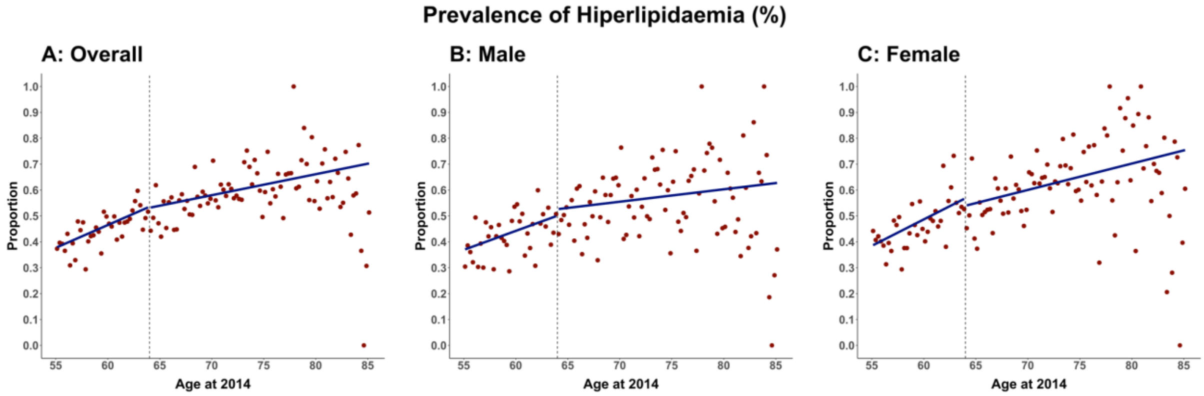
Appendix Figures



Appendix Fig. 1a: Diabetes (%), with the age-eligibility cut-off.



Appendix Fig. 1b: Hypertension (%), with the age-eligibility cut-off.



Appendix Fig. 1c: Hyperlipidaemia (%), with the age-eligibility cut-off.

Annex A

This Annex provides details on the methodology used to estimate the routine and manual task intensities of the respective 2-digit SSOC sub major group.

Methodology:
To adequately classify each 2-digit SSOC sub major group into above median-routine or above median-manual categories, we used the SSOC detailed definition released by the Ministry of Trade and Industry to distinguish each task per occupation into five main categories: routine cognitive, routine manual, non-routine manual, non-routine analytic and non-routine interactive.

Step 1: Task classification
To ensure consistency in the categorisation process, we employed a three-stage procedure to discern between the five task types. Firstly, we distinguish if a specific task can be automated and replaced by our present state of computer technology. If the task is replaceable by automation, we classify the activity as routine and vice versa. For example, driving is considered non-routine as we still do not have self-driving cars in Singapore. However, food packaging and record keeping are considered as routine. Secondly, we examine if the task requires cognitive or manual skills. Based on this, we classify the tasks into four main categories, non-routine manual, non-routine cognitive, routine manual and routine cognitive. Thirdly, we subdivided tasks which are non-routine cognitive into non-routine analytic and non-routine interactive, subject to the amount of analysis or interaction that is required for proficient completion of the task. In accordance with the classification procedure, we manually classified the 2,816 tasks into one or more of the five domains.

The task classification is specific to the Singapore context and is occupation specific. By employing the SSOC definitions instead of the general International Standard Classification Occupations (ISCO) definitions, we ensure that the tasks are sorted in a way that adequately fits the frame of reference.

Step 2: Calibrating task intensities
Subsequently, we calculated the routine and manual task intensities by the following equations adapted from Antonczyk, Fitzenberger and Leuschner (2009) and refined by Mihaylov and Tijdens (2019).

First, we calculated the task content, T, of each of the five task type domains, j, for each of the 401 4-digit SSOC unit group, k.

$$T_{jk} = \frac{\text{number of tasks in task category } j \text{ in occupation } k}{\text{total number of task assignments in occupation } k}$$

Second, we combined the task content indexes into a sole measure of routine task intensity and manual task intensity.

$$\mathrm{RTI}_k = \mathrm{RC}_k + \mathrm{RM}_k - \mathrm{NRI}_k - \mathrm{NRA}_k - \mathrm{NRM}_k$$

$$\mathrm{MTI}_k = \mathrm{RM}_k + \mathrm{NRM}_k - \mathrm{NRI}_k - \mathrm{NRA}_k - \mathrm{RC}_k$$

where RTI_k indicates the routine task intensity of a specific occupation k and RC, RM, NRI, NRA and NRM refers to the five-task category Routine Cognitive, Routine Manual, Non-Routine Interactive, Non-Routine Analytic and Non-Routine Manual. Likewise, MTI_k stands for the manual task intensity of the respective occupations and it is derived from the subtracting the non-manual task indexes from the manual task indexes.

Step 3: Calibrating weighted task intensities for each of the 2-digit SSOC unit group

Using administrative data provided by the Ministry of Manpower, we computed the weighted routine and manual task intensities for each of the 2-digit SSOC unit group. Then, we derived the median routine task intensity and median manual task intensity for the exhaustive list of 2-digit SSOCs to be -0.54 and -0.59

respectively. Expectedly, we observe that the median routine task intensity and median manual task intensity are negative. We posit that this is because Singapore has relatively high human capital and thus most tasks can be automated. In a similar vein, the low median manual task intensity observed could be due to its workforce having higher schooling attainment thus enabling them to work in sectors that require less physical labour.

Table A1 classifies the 2-digit SSOCs into its respective quadrants based on their manual task intensity and routine task intensity in comparison to the Singapore median.

	Routine (High Routine)	**Non-Routine (Low Routine)**
Manual (High Manual)	• Customer services officers and clerks (42) • Personal service workers (51) • Sales workers (52) • Metal, machinery and related trades workers (72) • Precision, handcraft, printing and related workers (73) • Food processing, woodworking, garment, leather and other craft and related trades workers (75) • Stationary plant and machine operators (81) • Assemblers and quality checkers (82) • Drivers and mobile machinery operators (83) • Labourers and related workers (93) • Food preparation and kitchen assistants (94) • Waste collection, recycling and material recovery workers and other elementary workers (96)	• Health associate professionals (32) • Personal care workers (53) • Protective services workers (54) • Building and related trade workers, excluding electricians (71) • Electrical and electronic trades workers (74) • Cleaners and related workers (91) • Agricultural, fishery and related workers (94)
Analytic/Interactive (Low Manual)	• Hospitality retail and related service managers (14) • Physical and engineering science associate professionals (31) • Business and administration associate professionals (33) • Information and communications technicians (35) • General and keyboard clerks (41) • Numerical and material recording clerks (43) • Other clerical support workers (44)	• Legislators, senior officials and chief executives (11) • Administrative and commercial managers (12) • Production and specialised services managers (13) • Science and engineering professionals (21) • Health professionals (22) • Teaching and training professionals (23) • Business and administration professionals (24) • Information and communications technology (ICT) (25) • Legal, social, religious and cultural professionals (26) • Legal, social, cultural and related professionals (34) • Teaching associate professionals (36) • Other associate professionals not elsewhere classified (39) • Clerical supervisors (40)

Table A1. Classification table of full list of 2-digit SSOC sub major units.

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