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DISCUSSION PAPER SERIES

IZA DP No. 17299

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ABSTRACT

Navigating Unemployment without Unemployment Insurance: Evidence from Singapore*

This study investigates the short-term impacts of unemployment in Singapore, a setting without public unemployment insurance. Using monthly panel data from the Singapore Life Panel, we analyze dynamic effects on major life outcomes such as income, spending, health, and subjective well-being over two years post-unemployment. Our findings reveal substantial initial earnings losses with incomplete recovery, as income remains 50.6% below pre-unemployment levels after 24 months. Despite this persistent income gap, consumption responses are modest, with total household expenditure decreasing by 13–17% over two years. The two-year marginal propensity to consume is about 0.2 which is smaller than estimates in countries with more extensive social insurance, suggesting robust self-insurance mechanisms. We observe increased retirement and self-employment but no significant spousal earnings response. While health status remains largely unchanged, we find substantial declines in life satisfaction. Our study provides insights into unemployment dynamics in a UI-free environment, suggesting modest welfare gains from introducing unemployment benefits in Singapore.

JEL Classification: J14, J60, E24, D12

Keywords: unemployment shock, consumption spending, event study design, monthly panel

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1. Introduction

Job displacement can have significant and lasting welfare implications when household income is not fully insured, affecting not only economic outcomes but also health and well-being. Understanding the magnitude and persistence of these effects is crucial because these effects provide direct evidence of incomplete income insurance and inform policymakers about the optimal design of unemployment insurance (UI) programs and other social safety net measures.

Most existing studies investigate the impact of unemployment shocks in the context of public UI programs, as most developed countries offer temporary income assistance to displaced workers. This prevalent institutional feature poses a challenge in isolating the independent effect of unemployment from the moral hazard induced by UI benefits, which inherently mitigate the full impact of negative income shocks. Moreover, with some recent exceptions utilizing transaction data (Ganong and Noel, 2019; Gerard & Naritomi, 2021; Andersen et al., 2023) , the majority of studies have not employed high-frequency panel data, limiting the analysis of short-term dynamics which is crucial for understanding the immediate and evolving impacts of unemployment (Sullivan & Von Wachter, 2009; Green, 2011; Harmenberg & Öberg, 2021).

Our study addresses these challenges by examining the short-term dynamic response to unemployment using 53 monthly waves of individual-level panel data from the Singapore Life Panel (SLP). This unique dataset offers two distinct advantages. First, Singapore's institutional context provides a rare opportunity to observe the unmitigated impact of an unemployment shock. The country has traditionally emphasized individual responsibility and has not operated a public UI program except during the COVID-19 pandemic.[1] This absence of UI benefits allows us to capture the isolated effect of unemployment without the confounding influence of public income support. Second, the high-frequency nature of the survey data enables a more comprehensive examination of life outcomes compared to transaction data which typically capture only financial outcomes. We observe monthly changes not only in income and spending but also in other critical

[1] The Singapore government announced on August 27, 2024 that it will start implementing means-tested unemployment benefits from May 2025. New Zealand is another exception where they operate a means-tested cash transfer program for job seekers (Law, 2021).

dimensions such as health, subjective well-being, private transfers, and marital status, providing a holistic view of the multifaceted impacts of unemployment.

It is important to acknowledge a limitation of our study: the original cohort of the SLP data primarily comprises individuals aged 50–70, constraining our ability to analyze the behavior of younger workers. We address this limitation through two approaches. First, we restrict our baseline analysis to individuals below the official retirement age of 62 years. Second, we analyze how the short-term impact of unemployment varies by age within our sample, allowing us to assess the sensitivity of our results to age differences. We posit that our findings likely underestimate the average impact of unemployment across all age groups in magnitude (with the possible exception of retirement decisions) because younger workers are likely to be less insured against income losses due to lower accumulated savings (Ichino et al., 2017; Salvanes et al., 2024). As such, our estimates based on older workers can be interpreted as a lower bound of the overall impact of an unemployment shock.

Furthermore, understanding the behavioral and welfare responses of older workers to an unemployment shock is increasingly more important. Many developed countries are experiencing rapid population aging, with a growing portion of older individuals actively engaged in the workforce. While older workers may face a relatively lower risk of job loss (OECD, 2019), they nonetheless commonly experience job displacement. For instance, 13.8% of our Singapore-based sample experienced unemployment during the 5-year study period (2015–2019). In the United States, approximately half of full-time workers aged 51–54 experienced an involuntary job separation after turning 50 (Johnson & Gosselin, 2018). These statistics underscore the relevance of our research focus on older workers and suggest the external validity of our findings for older workers in other developed countries.

For the empirical analysis, we employ a matched event study difference-in-differences (DID) design. Our key findings are as follows. First, we find substantial initial earnings losses with steady but incomplete recovery over the next two years. Earnings remain 50.6% below pre-unemployment levels even after 24 months. Some of the persistent income gap is driven by an increase in retirement by 5-8%, but we do not find a change in the spouse's earnings. Second, despite this persistent income gap, consumption responses are modest. Total household expenditure decreases by 11–16% over two years post-unemployment suggesting robust self-insurance mechanisms. We find spending decreases in both necessities (foods and groceries) and discretionary items (visible spending). Third, while we observe no significant changes in self-reported health status and healthcare spending, we find a substantial decline in life satisfaction. Fourth, the cumulative propensity to consume (MPC) out of income losses reaches 0.182 over 24 months post-unemployment, notably smaller than estimates for older workers in countries with more extensive social insurance (e.g., Denmark), suggesting potentially modest welfare gains from introducing unemployment benefits in Singapore.

This study contributes to several strands of literature investigating the impact of job displacement. First, we provide evidence from a UI-free environment, allowing us to isolate the pure effects of unemployment without the confounding influence of public benefits. Existing research has primarily focused on prime-age workers in countries with established unemployment insurance (UI) systems. This study provides a benchmark for evaluating UI programs. The fact that consumption insurance of unemployed workers in Singapore is even stronger than that of a Nordic country known for a strong social safety net is consistent with the recent finding of Braxton et al. (2024) showing that many unemployed individuals have significant access to credit.

Second, we add to the literature that leverages high-frequency panel data (Ganong and Noel, 2019; Gerard & Naritomi, 2021; Andersen et al., 2023; Salvanes et al., 2024) and offer a more nuanced understanding of the immediate and evolving impacts of job loss across multiple dimensions, including income, consumption, private transfers, health, and subjective well-being and from a significantly different social policy environment.

Third, our focus on older workers addresses an important gap in the literature, providing insights into the labor market dynamics of an increasingly significant demographic group in many developed economies. To our best knowledge, Andersen et al., (2023) and Salvanes et al., (2024) only recently document heterogeneous responses to an unemployment shock by age in Denmark and Norway, respectively. Our findings on the persistent income decline among older workers in Singapore and their increased retirement following unemployment are consistent with the evidence from Nordic countries and suggest the difficulty of refinding a job for older workers and the importance of providing job search assistance.

The rest of this paper proceeds as follows. Section 2 describes the institutional background. Sections 3 and 4 present the empirical strategy and the data. The results are presented and discussed in Section 5. Section 6 concludes.

2. Institutional Background

Singapore's labor market is renowned for its flexibility and market-friendly approach. The World Economic Forum's 2019 Global Competitiveness Report ranked Singapore first in labor market flexibility among 141 evaluated countries (Schwab, 2019). Another distinctive feature of Singapore's labor market is its long-standing emphasis on individual responsibility and self-reliance (Ministry of Manpower [MOM], 2023). For instance, since its independence in 1965, Singapore has not implemented a public UI scheme, likely due to concerns about moral hazard and resulting efficiency losses. This approach is exemplified by Prime Minister Lee Hsien Loong's 2016 National Day speech, where he emphasized the government's preference for worker retraining programs over traditional UI:

"*...we have something even better than unemployment insurance because unemployment insurance, the worker has to pay out of his salary, maybe one percent of their salary for the insurance. And when he gets unemployed, you subsidise him, helping him to stay unemployed while he looks for a job. Ours is different. The scheme is not paid by the workers or the employers. It is paid by the government and the scheme is not to help you stay unemployed but to help you get employed. Get a job, upgrade yourself, and make yourself more valuable* (Ministry of Foreign Affairs [MFA], 2016)."

Singapore's historically low unemployment rates (averaging 2.2% between 2013 and 2023) have further justified the government's reluctance to introduce a publicly funded UI program despite several proposals and public debates (MOM, 2024). As a major shift in the social insurance policy, the Singapore government recently announced the launch of a means-tested retrenchment benefit program from April 2025.

The minimum notice period for contract termination is one day to four weeks depending on the length of service. Employers can choose to pay the employee a month's salary for the notice period instead of having the employee work through it (MOM). The severance pay is commonly practice but is not mandated by law (MOM).

While Singapore lacks a statutory minimum wage, it has implemented the Progressive Wage Model (PWM), a unique policy focused on upskilling and wage progression for low-wage workers. The PWM ensures incremental wage increases as workers acquire new skills and gain experience, effectively creating a sector-specific minimum wage that rises with worker productivity. Additionally, the Workfare Income Supplement (WIS) supports low-wage workers through salary augmentation by subsidizing employers' social security contributions for low-wage, older workers.

In Singapore, the minimum retirement age (hereafter, MRA) is 62 or 63, depending on the birth cohort. After reaching the MRA, employers must offer re-employment to eligible workers until they reach the age of 67 or 68 (depending on the birth cohort).[2] Our study sample includes individuals up to 62 years old, corresponding to the MRA during the study period.

Singapore's social security savings program, called the Central Provident Fund (CPF) is unique compared to typical pay-as-you-go style public pension programs in most developed countries. The CPF consists of government-run mandatory savings accounts designed to serve various spending needs such as retirement, medical care, education, and housing. Both employees and employers contribute to these accounts.[3] Upon turning 55, individuals can withdraw a portion of their CPF balances, with a predetermined minimum reserved for retirement spending needs. Upon reaching 65, individuals can enroll in CPF LIFE, a public annuity program offering monthly payouts using the above-stated minimum sum set aside for retirement.

Finally, Singapore's healthcare system, which is closely linked to the CPF system, emphasizes individual responsibility and cost-effectiveness. Medishield LIFE, a mandatory public health insurance plan, serves as a low-cost catastrophic healthcare plan. Individuals can pay for their out-of-pocket healthcare costs for inpatient care and some outpatient care using the balances of their medical savings account within the CPF system (Medisave) after sharing the total healthcare cost with Medishield Life. This structure provides an economic incentive to reduce overutilization of unnecessary healthcare.

This institutional context, characterized by the absence of UI, emphasis on individual responsibility, and unique social security system, provides a distinctive setting for examining the UI-free impacts of unemployment on older workers.

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[2] For those born between 1 July 1955 and 30 June 1960, the retirement age remains at 62, while the re-employment age for them has been raised from 67 to 68. For those born after July 1, 1960, the retirement age is 63, and re-employment is also set at 68. These changes aim to provide flexibility and encourage continued employment for older individuals. See https://www.mom.gov.sg/employment-practices/re-employment for the full detail.

[3] The CPF contribution rates vary based on age, ranging from 12.5% to 37% of monthly wages (as of July 2024). For individuals below 55, the contribution rate is 37% (17% by employer and 20% by employee). Then, it gradually decreases as individuals become older. See https://www.cpf.gov.sg/member/cpf-overview for the details.

3. Empirical Strategy

We employ a matched event study DID design to identify the effects of an unemployment shock on key life outcomes. Specifically, we estimate the following equation:

$$Y_{i,t} = \beta_0 + \sum_{t=-6}^{24} \beta_t S_{i,t} + \gamma X_{it} + \emptyset_t + \delta_i + \varepsilon_{i,t}, \qquad (1)$$

where $Y_{i,t}$ is the outcome of interest of individual i in standardized month t (e.g., income, retirement, spending, health, life satisfaction). t is the time from the incidence of an unemployment shock which ranges from -12 to 24. $S_{i,t}$ is an indicator of time relative to the month that the individual experienced an unemployment shock (t=0). For example, $S_{i,0}$ takes the value of 1 in the month (t_0) of the shock and 0 otherwise. $\emptyset_t$ are wave-fixed effects. δ_i are individual fixed-effects that capture time-invariant individual characteristics. X_{it} includes age and age square. For statistical inference, we cluster standard errors at the individual level. As unemployed individuals report zero labor income and sub-spending components or private transfers often include zeros, we do not consider log-like transformations for monetary variables following Chen and Roth (2024) to avoid the scaling problem, and estimate the level effects instead of percentage effects.

To address the identification challenge posed by the non-random nature of unemployment shocks, we use the Coarsen Exact Matching (CEM) method (Iacus et al., 2012). The control group consists of matched respondents who never experienced an unemployment shock during our sample period. Subjects were matched according to age, highest education level (primary, secondary, post-secondary), gender, race (Chinese), and marital status. We randomly assigned fictitious unemployment shock timing to the control group respondents across the sample period.

For the empirical analysis, we define a 30-month observation window, which spans 6 months before and 24 months after the month of suffering the unemployment shock. The time periods of 12 to 7 months prior to the shock serve as a reference period. The terms β_t (t from -6 to 24) represent the change in Y a given month t relative to the average value Y over the reference period (t from -12 to -7).

To interpret the coefficients β_t as the causal effect of an unemployment shock, we assume that individuals who become unemployed are not systematically different from those who remain employed before the arrival of the unemployment shock. We indirectly test this identification assumption by estimating the lead effects for the outcome of interest up to 6 months prior to the onset of an unemployment shock. To address the individual-level variation in unemployment timing and resulting treatment effect heterogeneity, we also conduct a robustness check by using an alternative estimation method by Sun and Abraham (2021) in Section 5.

4. Data

Our study utilizes data from the Singapore Life Panel (SLP), a nationally representative longitudinal survey of Singaporean residents aged 50–70 at its inception in July 2015. We analyze 53 monthly waves from July 2015 to December 2019, excluding data from 2020 onwards to avoid the influence of the COVID-19 pandemic. About 7,000–8,000 individuals participate in the monthly surveys (Cheng et al., 2024).

The SLP data offers unique advantages for our study. First, the high frequency nature of the monthly survey allows researchers to assess short-term dynamics compared to other annual or biannual surveys. Second, unlike transaction-level data which contain a limited set of information other than card spending and card and bank account balances, our survey data contains a wide array of individual- and household-level information including household spending and income, health status, subjective well-being, spouse's labor supply, private transfers, etc. As such, our data allows us to have a comprehensive understanding of an unemployment spell. Third, as Singapore does not operate an UI program, we can isolate the unemployment impact without the influence of unemployment benefits.

We restrict our sample to individuals aged 50–62, the upper bound corresponding to Singapore's minimum retirement age during the study period. This focus on older workers, while limiting generalizability to the broader workforce, provides valuable insights into a demographic increasingly important in aging societies.

Leveraging the rich information available in the SLP, we use the following set of dependent variables to capture the comprehensive impacts of a job displacement experience. First, we measure a respondent's earnings and household income which is the sum of a respondent's and spouse's (if married) earnings, transfer income, and other household income (e.g., rents, annuities). Second, we construct total spending aggregated from data collected across over 36 spending subcategories to understand the degree of consumption insurance against an unemployment shock.[4] We also consider visible spending following the definition of Charles et al. (2009) which includes personal care products, clothing, jewelry, and footwear and spending on foods and groceries as measures of non-essential and essential consumption. Third, private transfers can provide informal insurance to an unemployment shock and thus we measure the net private transfer income which is the difference between the received amount of cash transfers from his/her family members, relatives, or friends and the amount s/he gave to them. Fourth, we also consider self-reported measures of health and well-being such as overall life satisfaction and happiness so that we can have a more comprehensive understanding of an unemployment shock beyond economic outcomes.

Although the monthly frequency of the survey significantly reduces recall bias, the self-reported nature of the data may still be subject to response error. First, the SLP data matches well with household spending and labor participation data from the Singapore Department of Statistics (Vaithianathan et al., 2021). We also find that the SLP's labor statistics are highly consistent with the government statistics produced by the National Survey on Employment. Second, to the extent that over-reporting or under-reporting behavior is time-invariant, individual fixed effects will absorb such patterns. Nonetheless, we acknowledge that the use of transaction data would complement and externally validate our analysis.

The key treatment variable is the timing from/to the incidence of an unemployment shock as follows. We first define the arrival of an unemployment shock if a respondent was working for pay over the last six months, but s/he becomes unemployed and looking for a job in the month of the survey. Then we measure the time distance from the unemployment incidence for the event study analysis. We identify the unemployment status based on self-reported responses to a monthly recurring labor status question. Compared to the existing literature that leveraged mass layoffs or establishment closures as a measure of an unemployment shock, our treatment variable cannot distinguish a voluntary quit (and subsequent job search) and an involuntary job displacement. We indirectly test the validity of this measurement by examining the pre-trends between those ever unemployed and those never unemployed in Section 5 below. All monetary values are adjusted to 2019 Singapore dollars to account for inflation over the study period.

Table 1 presents summary statistics for our sample, comparing pre-unemployment

[4] See Appendix B for the details of each spending category.

characteristics of individuals who experienced unemployment during the study period with those who did not.[5] While the groups are broadly similar in terms of socio-demographic characteristics, we observe some differences in economic outcomes, underscoring the importance of our matching approach in the empirical strategy.

5. Results

We begin the empirical analysis by estimating the dynamic impacts of an unemployment shock on individual-level labor income using equation (1).[6] Panel A of Figure 1 illustrates that respondent's own earnings were mostly unaffected up to one month prior to the unemployment shock supporting the validity of our identification strategy. The observed small drop in earnings one month before the unemployment incidence is likely driven by the standard one-month notice. Then, at the onset of unemployment, we see an abrupt and substantial drop in earnings. The impact peaks in the month following the incidence of unemployment, with an estimated earnings loss of S$2,681, representing a 76% reduction from the six-month average earnings prior to unemployment.

While we observe a slow but gradual recovery in earnings over time, income levels remain depressed even two years after the initial shock. Specifically, earnings are still 50.6% lower than pre-unemployment levels 24 months post-shock. The cumulative earnings losses over the first 12 and 24 months amount to S$25,201 and S$44,697, respectively. These substantial figures underscore the severity of unemployment experience for older workers in Singapore and justify the expected introduction of a public unemployment insurance benefits program in May 2025. This persistent income gap is also consistent with evidence from other developed economies (Davis and Watcher, 2011; Andersen et al., 2023; Salvanes et al., 2024), suggesting that older workers face challenges in fully recovering their earning potential following unemployment.

The protracted nature of these earnings losses is partially explained by transitions into retirement, as evidenced in Panel B. We find an increase in self-reported retirement status immediately following the unemployment shock. Compared to those who did not experience an unemployment spell, unemployed workers become 5–8 percentage points more likely to retire.

[5] For those never unemployed, we use randomly assigned fictitious unemployment timing to compute pre-unemployment statistics.

[6] The corresponding regression results are reported in Table A1.

This unemployment-induced increase in retirement among older workers is consistent with the findings from Norway (Salvanes et al., 2024). An implication of this finding is that adequate job finding support especially for older workers is critical in increasing old-age reemployment.

Self-employment can provide an effective alternative to reemployment (Boeri et al., 2020). This can be particularly true for older workers who may have difficulty in finding a new employer due to several factors such as ageism and skill mismatch (Chéron et al., 2013). In addition, they are also more likely to have better access to credit to start their own business than younger workers. In Panel C, we find that unemployed workers in our sample are increasingly more likely to become self-employed by 2–5 percentage points over the two years following unemployment.

Married respondents' response to an unemployment shock could be different because the loss of household income via an unemployment shock may be insured by intrahousehold labor supply adjustments (Lundberg, 1985). However, Panel D indicates that there is almost a one-to-one mapping between the loss of the respondent's earnings and his/her household income. This finding suggests a lack of the *added worker* effect, a conclusion further supported by Panel E, which shows no significant response in spousal earnings. One possible explanation is a limited scope to adjust labor supply upwards by the spouse. Our study population, aged over 50, may face significant barriers to rapidly adjusting labor supply in response to a household income shock (Blundell et al., 2016; Salvanes et al., 2024). In Figure A1, we also examine the spousal earning response by gender and find no gender difference.

Another potential self-insurance mechanism to respond to income loss induced by unemployment is private transfers from family, relatives, and friends. In Panel F, we find that the net private transfer amount, which is the difference between the received amount and the given amount, increases over the next two years post-unemployment, but the amounts are mostly small (less than 5% of the earning loss). This finding suggests that informal support from families and social contacts exists, but it is not strong enough to mitigate the income loss. However, a cautious interpretation is warranted as we observe a pre-trend, albeit statistically insignificant.

Turning to consumption responses, Figure 2 presents our findings on household expenditure dynamics following unemployment. Panel A reveals no significant changes in total household expenditure immediately before or during the month of unemployment, possibly due to severance pay or other forms of compensation. However, we observe a significant and persistent decrease of household spending post-unemployment by S$230–S$630, which corresponds to about 6–16 percent reductions. This result indicates that an older worker's unemployment has a modest but prolonged impact on household expenditure in Singapore.

To gain deeper insights into households' consumption adjustment strategies, we disaggregate the spending response by examining specific expenditure categories. Panel B focuses on visible spending, encompassing items such as clothing, jewelry, and personal care products. This category exhibits a sharp decline of S$32 (21.1%) in the month of unemployment, with effects persisting for over a year. Even in the seventeenth-month post-unemployment, visible spending remains depressed by S$50 (33.0%). The pronounced and persistent decline in visible spending may reflect the reduced need for professional attire and socially-visible spending during unemployment.

To assess differential spending impact on necessities, we examine the impact on food and groceries spending in Panel C. We find that expenditure on foods, drinks, and groceries also decreases by S$67 (10.2%) and S$94 (14.2%) of the six-month pre-unemployment average in the month of and the month following the unemployment shock, respectively. This decrease persists over the subsequent year. While the relative magnitude of this decline is smaller than that observed for visible goods, the absolute amount is still larger and economically significant. The reduction in food and groceries spending aligns with recent evidence from the United States and Denmark (Ganong and Noel, 2019; Andersen et al., 2023), suggesting that even essential consumption is not fully insured against unemployment shocks.

To contextualize the consumption response relative to the size of income change, we compute the cumulative marginal propensity to consume (MPC), presented in Figure 3. The MPC for post-unemployment month k is defined as the ratio of the estimated cumulative spending change from t=0 to t=k over the estimated income change during the same period. This measure can be interpreted as the degree of consumption insurance, à la Blundell et al. (2008).

We find that the cumulative MPC increases over time since unemployment. In the first month, the MPC is 0.033, indicating minimal initial adjustment in consumption spending. However, it gradually increases to 0.130 and 0.182 by the 12th and 24th month following unemployment, respectively. This temporal pattern in MPC is consistent with theoretical predictions and empirical evidence from existing studies (Sokolova, 2023), suggesting that households become more able to adjust their spending patterns over time as they adapt to their new economic circumstances.

Interestingly, the two-year MPC in our study (18.2%) is smaller than that observed for Denmark's older sample aged above 47 years (21.5%) (Andersen et al., 2023). This comparison is particularly striking given the common perception that Denmark has a stronger social insurance system than Singapore.[7] Our finding implies the presence of robust self-insurance mechanisms among older workers in Singapore, despite the absence of public UI. Stronger consumption insurance observed among older workers in Singapore can be partially explained by the early withdrawal of public pension wealth. Upon turning 55, Singaporeans can early-withdraw part of their pension wealth for any purpose after setting aside the minimum sum set by the government (Agarwal et al., 2020).[8] Although our data do not keep track of pension balance withdrawal behavior, we suspect that unemployed individuals may have tapped their pension wealth to mitigate part of their income shocks.[9]

Moreover, even within the same SLP sample, our MPC estimate is 64% smaller than the MPC estimate from lottery wins (Kim and Koh, 2024). This stark difference within the same population highlights the context-dependent nature of consumption responses. The lower MPC in response to an unemployment shock compared to lottery wins could reflect several factors: the difficulty of downward adjustments in spending, the absence of 'thrill-of-winning' effects associated with lottery gains, and the potentially different mental accounting applied to unexpected gains versus losses. This comparison underscores the importance of accounting for different contexts when estimating MPC and interpreting its implications for policy.

The health effects of job loss are well documented in the literature (Sullivan and von Wachter, 2009; Schaller and Stevens, 2015). Building on this research, we examine the short-term dynamic effects of an unemployment shock on health outcomes and life satisfaction among older adults in Singapore. Panels A and B of Figure 3 show no significant changes in self-reported health status or medical expenditures following an unemployment shock, indicating that the unemployment experience did not negatively affect health at least in the short run. In the US, many workers transition into the disability insurance program after a prolonged unemployment spell (Autor and Duggan, 2003), but we suspect that this is unlikely to be the case in Singapore

[7] The MPC response of the full sample in Denmark is 30.3%. The maximum UI benefit length is two years, which is considered longer than other developed countries (Andersen et al., 2023).

[8] Using the ad hoc survey module of the same SLP data, Kim and Koh (2020) documented that about 40% of respondents aged 56–65 ever withdrew their CPF balances and their average withdrawal amount was S$42,686.

[9] Braxton et al., (2024) also demonstrate that unemployed individuals in the US have significant access to credit suggesting room to reduce public transfers to the unemployed.

given the lack of self-reported health impact and due to the stringent screening criteria.[10]

However, our analysis reveals significant effects on subjective well-being (SWB). In Panel C, we find that the share of individuals who are either satisfied or very satisfied with overall life decreases by 8.1% during the month of the shock, and this decrease persists over the next two years, consistent with previous findings (e.g., Clark and Oswald, 1994). Although the effect sizes are smaller and often statistically insignificant, Panel D reveals that self-reported happiness among unemployed individuals decreases by 7.4%, with this reduction lasting for the subsequent six months, but the results seem somewhat noisy. If we consider SWB data as a proxy for an individual's (experienced) utility (Kahneman and Sugden, 2005), this result suggests that unemployment may have broader implications for social well-being, potentially driven by factors such as reduced social participation or the stigma associated with job loss (Brand, 2015). The regression results corresponding to Figure 3 are presented in Table A3.

Lastly, the unemployment experience could put a strain on a couple's relationship. Previous studies document evidence of an increase in divorce following unemployment (Eliason, 2012; Keldenich and Luecke, 2020). Thus, we examine the short-term dynamics on the respondent's marital status. However, the result reported in Figure A3 shows no meaningful patterns possibly due to the stable nature of the relationship at older age. This result is consistent with Salvanes et al. (2024) showing increased post-unemployment divorce only among younger couples below 50s.

Heterogeneity Analyses

As stated above, the Singapore government announced to launch a means-tested UI benefits program from May 2025.[11] Eligible workers may receive up to S$6,000 in tiered payouts over six months. One of key eligibility criteria is that workers earned an average monthly income of S$5,000 or less in the last 12 months. To inform policymakers about the optimal design of this program, we conduct a set of heterogeneity analyses using the pre-unemployment earning cutoff of S$5,000.

[10] Applicants should be able to prove that they cannot perform at least three out of the six activities of daily living: washing, dressing, feeding, toileting, walking or moving around, and transferring (Ministry of Health, 2023).

[11] See the eligibility and program details at https://www.wsg.gov.sg/home/individuals/jobseeker-support.

In Panel A of Figure A4, we first find that both high-income and low-income households experience a substantial decline in income in terms of the pre-unemployment earnings as they lose 77.9% and 74.6% of the pre-unemployment earnings, respectively. However, due to the large difference in the baseline earnings level, the absolute amount difference is much larger: S$7,482 versus S$1,555 in the first month following unemployment. In Panels B and C, we observe that higher-income workers are both more likely to retire and become self-employed than lower-income workers, reflecting large differences in economic resources to afford retirement and initial investment following unemployment, while low-income households face different economic pressures.

In Panel D, we document that higher-income workers reduce household spending significantly more than lower-income households, reflecting the large baseline differences in the spending level. However, we compute that those likely eligible for the future UI benefit program exhibit a higher 2-year MPC of 0.218 compared to higher-income households (0.143), suggesting that lower-income households are indeed more vulnerable to unexpected financial shocks. Restricting to the results using the sample whose pre-unemployment earning was below $5,000, our findings imply that the proposed UI benefit will replace 70.3% of their income loss over the first six months and the transfer amount to be disbursed will exceed the six-month sum of spending drop. As such, the new UI program will likely replace self-insurance and help not exhaust unemployed older workers' retirement savings.[12]

As stated in the introduction, a major limitation of this study is that our baseline sample consists of workers aged 50–62. To partially address this limitation, we divide the sample between those aged 50–54 and 55–62 because individuals turning 55 can withdraw from the social security savings account balance (CPF) once a year (Agarwal et al., 2020). Hence, treated individuals could access their retirement savings to smoothen consumption spending in the short run. In Figure A6, Panel A shows that in the first month following unemployment, unemployment workers' earnings decrease by S$ 3,134 for those aged 55–62 and by S$ 2,291 for those aged 50–54, but their percent changes compared to the pre-unemployment earnings were similar at 75.8% and 76.9%, respectively. In Panel B, we find that the older group is significantly more likely to retire than the younger group reflecting lower returns to job search, more accumulated wealth, and access to

[12] In Figure A5, we include the heterogeneity analysis results on other outcomes.

pension benefits. By contrast, in Panel C, the younger group exhibits a larger increase in self-employment reflecting longer career horizons to recoup investments. Panel D reveals little difference in post-unemployment spending between the two age groups. The two-year MPC for the older group is 0.193, while that for the younger group is 0.214 MPC. Although we cannot examine the effects of an unemployment shock for those below 50, this finding suggests the importance of accounting for a life-course perspective in designing a UI system as other countries differentiate duration or benefit amounts by age (e.g., South Korea).[13]

Robustness and Falsification Checks

To validate the robustness of our baseline findings and strengthen our causal interpretation, we conduct a series of additional analyses. First, to address potential bias arising from treatment effect heterogeneity, we implement the method proposed by Sun and Abraham (2021). This approach provides consistent estimates in the presence of heterogeneous treatment effects when treatment timing varies. Figure A8 presents the results using the Sun and Abraham method. The estimates remain qualitatively similar to our baseline findings, with only minor differences in magnitude.

Second, to mitigate potential measurement error in monthly self-reported data and improve statistical power, we re-estimate our main models using data aggregated to the quarterly level. The results, shown in Figure A9, are consistent with our baseline findings, with similar magnitudes and increased statistical significance, further confirming the robustness of our baseline findings.

Third, to rule out the possibility that our results are driven by chance rather than a true unemployment effect, we conduct a permutation test following the approach of Fisher's exact test. This falsification check involves the following steps: i) We randomly assign a fictitious unemployment month to our unemployed sample respondents, ii) We re-estimate our main specification (equation 1) using these randomly assigned unemployment dates. iii) We repeat this process 1,000 times to generate a distribution of placebo treatment effects. If our baseline findings genuinely capture the causal effect of unemployment, we would expect the true estimates to be outliers in the distribution of placebo effects. Table A4 presents the results of this analysis, showing the percentile rank of our true estimates within the distribution of placebo estimates for key outcome variables, supporting our causal interpretation of the baseline estimates.

[13] In Figure A7, we include the heterogeneity analysis results on other outcomes.

6. Concluding Remarks

This study provides a comprehensive analysis of the short-term dynamic effects of unemployment among older workers in Singapore, a unique setting characterized by the absence of public unemployment insurance. Our findings offer several insights into labor market dynamics and policy implications for aging societies.

First, we find that unemployment leads to substantial and persistent earnings losses, with income remaining 50.6% below pre-unemployment levels even after 24 months. This highlights the challenges older workers face in fully recovering their earning potential following unemployment. The persistence of these losses underscores the potentially long-lasting impacts of late-career job separations and suggests a need for targeted policies to support re-employment and skill development for older workers.

Second, despite the absence of public UI, we observe relatively modest consumption responses. Total household expenditure decreases by 13-17% over two years post-unemployment. The degree of consumption insurance measured by the two-year MPC was lower than that of older workers in Denmark. These results suggest robust self-insurance mechanisms among older Singaporean workers and challenge conventional wisdom about the necessity of a strong public UI system for consumption smoothing. Our findings also highlight the potential effectiveness of alternative forms of social security system, such as Singapore's mandatory savings schemes.

Third, while we find no significant changes in self-reported health status, the declines in subjective overall life satisfaction point to important psychosocial impacts of unemployment. These effects underscore the need for holistic support systems that address both financial and psychological well-being of displaced workers.

Fourth, the marginal propensity to consume out of income loss induced by unemployment (0.182 over 24 months) is relatively lower in our study compared to countries with more extensive social insurance. This suggests that the potential welfare gains from introducing public UI in Singapore, where the social norm of individual responsibility and resilience is well-entrenched, may be limited for older workers. Instead, leveraging the existing mandatory retirement savings scheme, allowing a temporary withdrawal from the social security savings account balance could be more effective in providing adequate income insurance without the cost of moral hazard.

While our study provides valuable insights into the dynamics of unemployment in a setting without public UI, it also points to several avenues for future research. First, extending this analysis to younger workers could help determine whether the patterns we observe are specific to older workers or generalizable across age groups. Second, longer-term follow-up studies could help elucidate the full economic, health, and social impacts of late-career unemployment. Third, after the launch of a public UI program in Singapore, it would be important to examine how individuals respond differently to an unemployment shock to understand the extent of moral hazard in a UI system.

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Tables and Figures

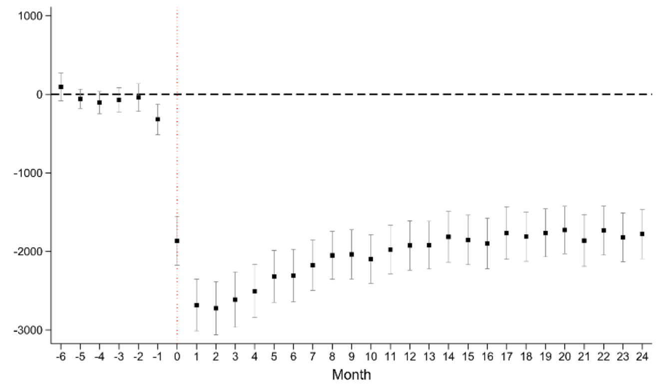
Table 1. Pre-unemployment Sample Statistics (July 2015 – December 2019)

	(1) Ever Unemployed ($t_{-6} - t_{-1}$) Mean (SD)	(2) Never Unemployed ($t_{-6} - t_{-1}$) Mean (SD)
Age	55.33 (3.38)	56.13 (3.43)
Primary Education	0.19 (0.40)	0.17 (0.38)
Secondary Education	0.41 (0.49)	0.43 (0.50)
Post-secondary Education	0.40 (0.49)	0.39 (0.49)
Male	0.52 (0.50)	0.46 (0.50)
Ethnic Chinese	0.86 (0.35)	0.88 (0.33)
Married	0.79 (0.41)	0.82 (0.38)
Own monthly earnings	3510.2 (3861.7)	2969.6 (4084.8)
Monthly household income	5370.9 (5381.5)	5708.3 (6149.6)
Monthly household spending	3801.9 (4407.9)	4108.8 (4881.8)
Self-reported health	0.13 (0.34)	0.17 (0.38)
# Respondents	762	6,575

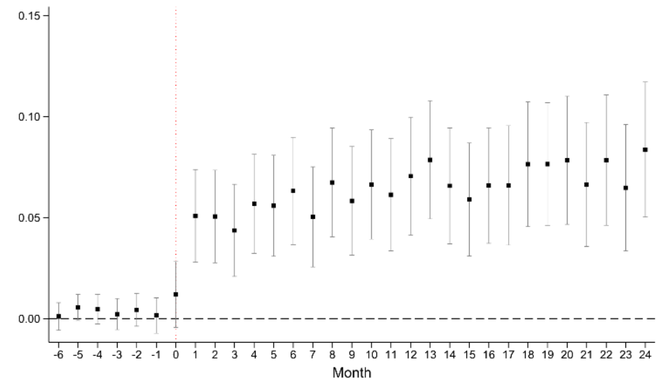
Notes. "Ever Unemployed" refers to respondents who have had an unemployment shock over the sample period. Monetary values are in 2019 Singapore dollars.

Figure 1. Income and labor supply response to an unemployment shock

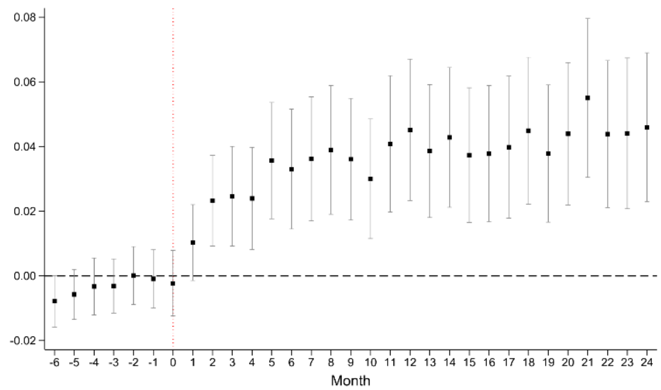
Panel A. Own earnings (in S$)



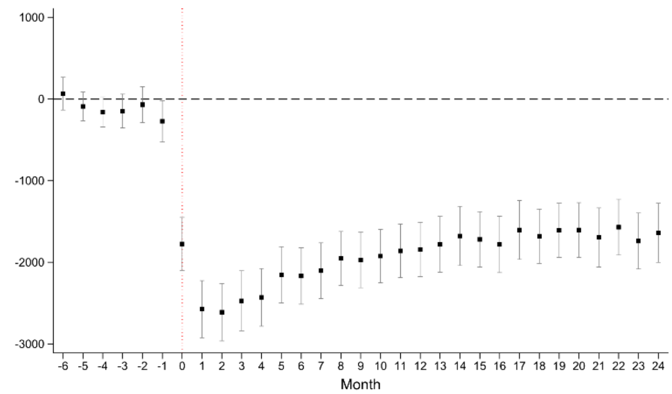
Panel B. Retirement status



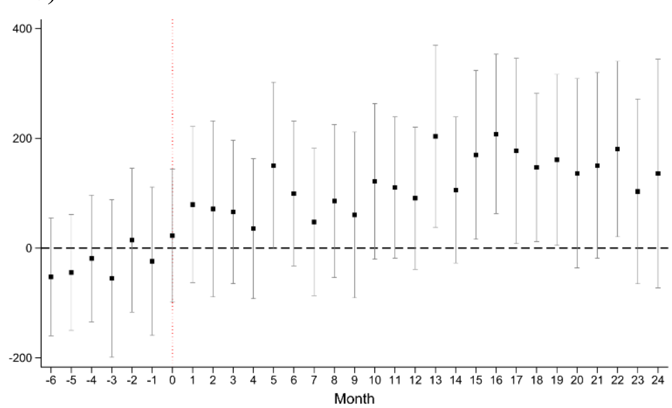
Panel C. Self-employment



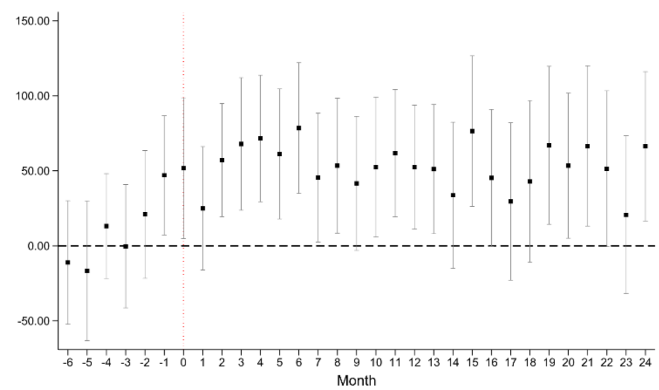
Panel D. Household income (in S$)



Panel E. Spouse's earnings (married respondents only; in S$)



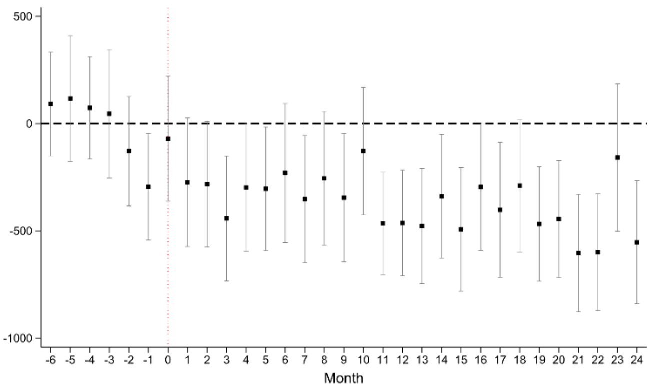
Panel F. Private transfer income (in S$)



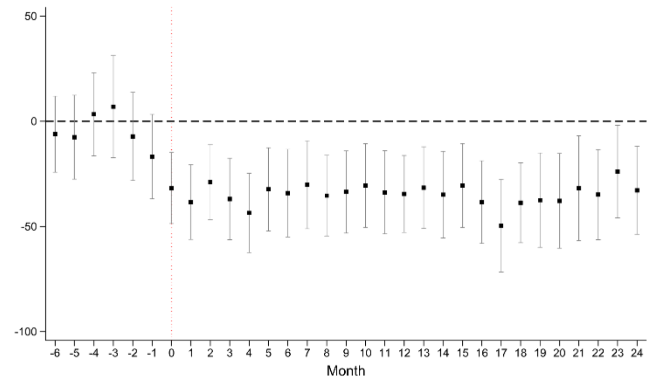
Notes. Square dots represent the coefficient estimates of the event study design specification using equation (1). Gray bars represent 95% confidence intervals.

Figure 2. Spending response to an unemployment shock

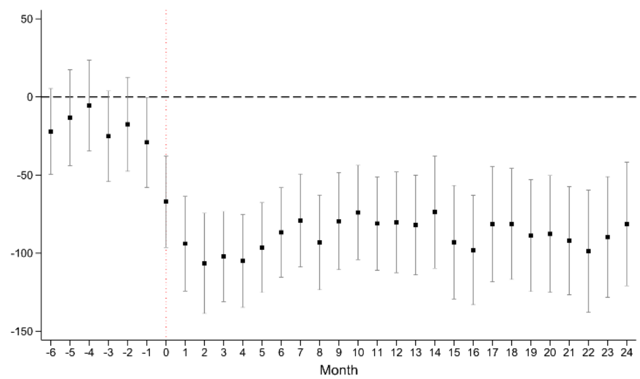
Panel A. Total consumption spending



Panel B. Visible goods



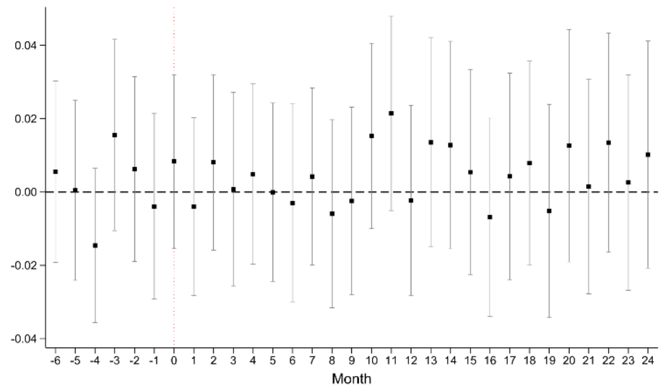
Panel C. Foods and groceries



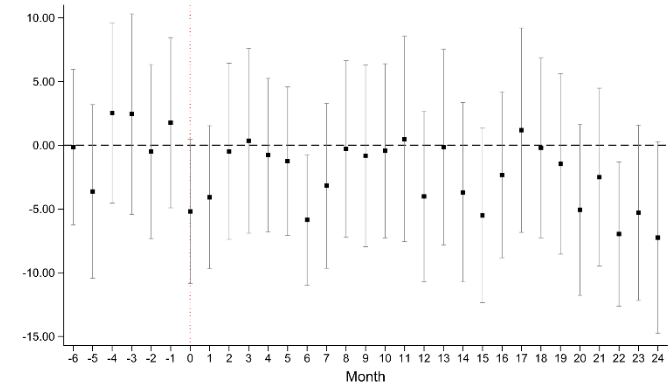
Notes. Square dots represent the coefficient estimates of the event study design specification using equation (1). Gray bars represent 95% confidence intervals.

Figure 3. Effect of an unemployment shock on health and subjective well-being

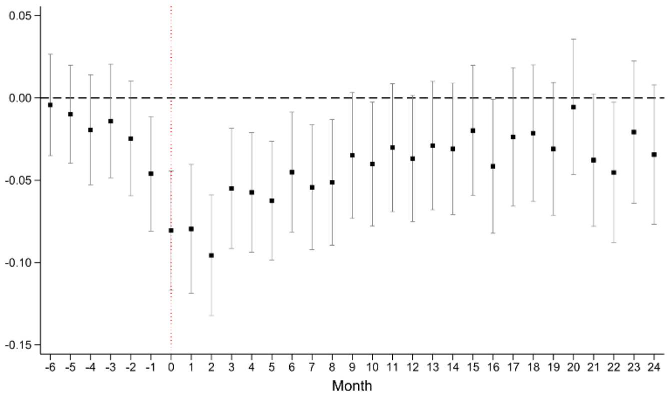
Panel A. Self-reported health status



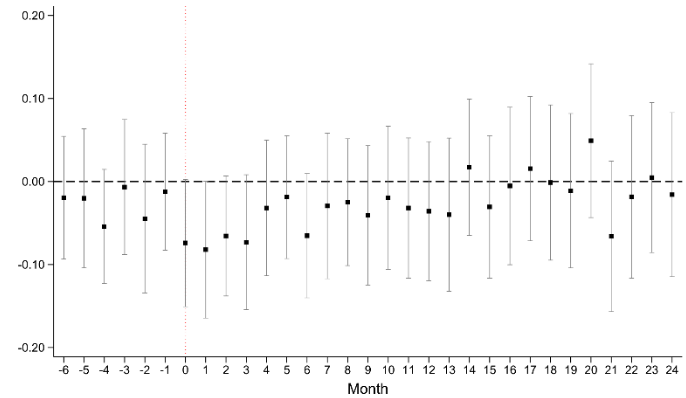
Panel B. Healthcare spending



Panel C. Overall life satisfaction



Panel D. Happiness



Notes. Self-reported health is defined as 1 if the response is “Excellent” or “Very good” and 0 for responses “Good,” “Fair,” or “Poor.” Healthcare refers to out-of-pocket expenses and any payments made from Medisave for traditional medicines, over-the-counter medications, other medical products, and therapeutic equipment. Overall life satisfaction is defined as 1 if the response is “Very satisfied” or “Satisfied.” and 0 for responses “neither satisfied nor dissatisfied,” “dissatisfied,” or “very dissatisfied.” The happiness variable is defined as 1 if the response is “All of the time,” “Most of the time,” or “A good bit of the time,” and as 0 for responses “Some of the time,” “A little of the time,” or “None of the time.” Square dots represent the coefficient estimates of the event study design specification using equation (1). Gray bars represent 95% confidence intervals.

Appendix A. Tables and Figures

Table A1. Coefficient estimates of the effects of unemployment shocks on income

	Own earnings	Retirement status	Self-employment	Household income	Spouse income	Private transfer income
Period t_{-6}	94.548	0.001	-0.008*	65.257	-52.491	-11.037
	(89.826)	(0.003)	(0.004)	(102.237)	(54.829)	(20.997)
Period t_{-5}	-56.326	0.006*	-0.006	-91.449	-44.536	-16.554
	(62.565)	(0.003)	(0.004)	(89.653)	(53.744)	(23.788)
Period t_{-4}	-104.304	0.005	-0.003	-158.282*	-18.934	13.265
	(71.397)	(0.004)	(0.004)	(94.693)	(58.928)	(17.795)
Period t_{-3}	-71.743	0.002	-0.003	-146.793	-55.459	-0.226
	(80.278)	(0.004)	(0.004)	(105.739)	(73.200)	(20.963)
Period t_{-2}	-40.950	0.004	0.000	-68.944	14.371	21.029
	(89.793)	(0.004)	(0.005)	(112.190)	(66.882)	(21.719)
Period t_{-1}	-318.680***	0.002	-0.001	-273.068**	-24.069	47.049**
	(99.503)	(0.004)	(0.005)	(129.468)	(68.929)	(20.249)
Period t_{0}	-1,866.708***	0.012	-0.002	-1,775.554***	22.483	51.799**
	(157.314)	(0.008)	(0.005)	(165.352)	(61.812)	(23.925)
Period t_{1}	-2,680.683***	0.051***	0.010*	-2,574.701***	79.287	25.030
	(168.673)	(0.012)	(0.006)	(178.379)	(72.511)	(21.009)
Period t_{2}	-2,722.662***	0.051***	0.023***	-2,611.928***	71.382	57.175***
	(173.065)	(0.012)	(0.007)	(179.573)	(81.846)	(19.249)
Period t_{3}	-2,612.704***	0.044***	0.025***	-2,471.985***	65.956	67.975***
	(180.014)	(0.012)	(0.008)	(187.494)	(66.659)	(22.528)
Period t_{4}	-2,504.169***	0.057***	0.024***	-2,429.766***	35.438	71.625***
	(172.349)	(0.012)	(0.008)	(179.879)	(65.064)	(21.517)
Period t_{5}	-2,316.372***	0.056***	0.036***	-2,152.837***	150.456*	61.291***
	(168.900)	(0.013)	(0.009)	(175.374)	(77.357)	(22.114)
Period t_{6}	-2,304.616***	0.063***	0.033***	-2,167.528***	99.321	78.522***
	(169.811)	(0.014)	(0.009)	(176.280)	(67.241)	(22.239)
Period t_{7}	-2,175.833***	0.050***	0.036***	-2,102.351***	47.545	45.467**
	(163.085)	(0.013)	(0.010)	(173.565)	(68.384)	(21.912)
Period t_{8}	-2,048.551***	0.067***	0.039***	-1,953.628***	85.656	53.475**
	(155.568)	(0.014)	(0.010)	(168.534)	(71.082)	(22.908)
Period t_{9}	-2,036.587***	0.058***	0.036***	-1,972.090***	60.398	41.720*
	(159.356)	(0.014)	(0.010)	(173.074)	(77.134)	(22.788)
Period t_{10}	-2,095.074***	0.066***	0.030***	-1,923.851***	121.376*	52.564**
	(158.088)	(0.014)	(0.009)	(166.040)	(72.307)	(23.797)
Period t_{11}	-1,977.880***	0.061***	0.041***	-1,860.552***	110.245*	61.854***
	(158.624)	(0.014)	(0.011)	(167.033)	(65.705)	(21.638)
Period t_{12}	-1,924.118***	0.071***	0.045***	-1,842.413***	90.821	52.544**
	(159.687)	(0.015)	(0.011)	(169.767)	(66.113)	(21.106)
Period t_{13}	-1,918.706***	0.079***	0.039***	-1,780.576***	203.568**	51.211**
	(154.987)	(0.015)	(0.010)	(174.853)	(84.575)	(21.970)
Period t_{14}	-1,813.826***	0.066***	0.043***	-1,678.223***	105.747	33.727
	(164.804)	(0.015)	(0.011)	(184.970)	(67.883)	(24.847)
Period t_{15}	-1,852.415***	0.059***	0.037***	-1,719.945***	169.993**	76.577***
	(160.914)	(0.014)	(0.011)	(173.388)	(78.544)	(25.586)
Period t_{16}	-1,898.055***	0.066***	0.038***	-1,780.763***	207.961***	45.343*
	(164.195)	(0.015)	(0.011)	(176.400)	(74.127)	(23.322)

Period t_{17}	-1,764.785***	0.066***	0.040***	-1,604.409***	176.792**	29.635
	(170.812)	(0.015)	(0.011)	(184.372)	(86.107)	(26.769)
Period t_{18}	-1,811.499***	0.077***	0.045***	-1,680.843***	146.713**	42.971
	(160.191)	(0.016)	(0.012)	(169.688)	(68.881)	(27.507)
Period t_{19}	-1,762.857***	0.077***	0.038***	-1,608.046***	160.710**	67.080**
	(155.717)	(0.015)	(0.011)	(169.029)	(79.526)	(26.860)
Period t_{20}	-1,725.997***	0.078***	0.044***	-1,605.008***	136.404	53.482**
	(153.781)	(0.016)	(0.011)	(170.729)	(87.888)	(24.665)
Period t_{21}	-1,860.322***	0.066***	0.055***	-1,695.630***	150.608*	66.638**
	(168.388)	(0.016)	(0.013)	(184.314)	(86.315)	(27.245)
Period t_{22}	-1,734.580***	0.079***	0.044***	-1,569.720***	180.509**	51.479*
	(158.469)	(0.016)	(0.012)	(174.471)	(81.568)	(26.509)
Period t_{23}	-1,820.120***	0.065***	0.044***	-1,739.276***	103.159	20.794
	(158.534)	(0.016)	(0.012)	(174.684)	(85.895)	(26.851)
Period t_{24}	-1,777.713***	0.084***	0.046***	-1,639.552***	135.836	66.439***
	(160.510)	(0.017)	(0.012)	(184.827)	(106.327)	(25.375)
# Respondents	7,337	7,337	7,337	7,337	6,092	7,291
R-squared	0.055	0.022	0.004	0.038	0.011	0.008
# Observations	144,123	144,123	144,123	144,123	117,380	143,252

Notes. Standard error in parenthesis, with standard errors clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A2. Coefficient estimates of the effects of unemployment shocks on consumption

	Total spending	Visible goods	Foods and groceries	Non-durable goods
Period t_{-6}	91.354	-6.129	-22.050	87.621
	(123.424)	(9.230)	(14.020)	(103.613)
Period t_{-5}	117.183	-7.557	-13.313	138.828
	(149.407)	(10.180)	(15.693)	(133.054)
Period t_{-4}	73.406	3.300	-5.578	100.052
	(121.797)	(10.076)	(14.834)	(96.629)
Period t_{-3}	45.219	6.963	-25.172*	62.216
	(152.938)	(12.372)	(14.796)	(144.012)
Period t_{-2}	-128.614	-7.210	-17.492	-141.306
	(130.035)	(10.702)	(15.336)	(103.750)
Period t_{-1}	-294.492**	-16.796	-29.098**	-260.085***
	(126.680)	(10.236)	(14.706)	(95.275)
Period t_{0}	-70.406	-31.744***	-67.033***	-73.403
	(148.417)	(8.605)	(14.929)	(132.530)
Period t_{1}	-273.546*	-38.420***	-93.938***	-313.245**
	(152.723)	(9.053)	(15.450)	(129.268)
Period t_{2}	-282.629*	-28.934***	-106.487***	-272.747**
	(149.445)	(9.058)	(16.376)	(129.534)
Period t_{3}	-442.119***	-36.964***	-102.132***	-448.523***
	(148.501)	(9.902)	(14.727)	(131.189)
Period t_{4}	-297.257**	-43.591***	-105.005***	-337.112***
	(151.638)	(9.607)	(15.155)	(128.284)
Period t_{5}	-304.088**	-32.349***	-96.434***	-417.896***
	(146.923)	(10.083)	(14.673)	(112.527)
Period t_{6}	-230.253	-34.141***	-86.667***	-301.465**
	(165.279)	(10.616)	(14.611)	(135.640)
Period t_{7}	-352.456**	-30.164***	-79.096***	-412.355***
	(151.333)	(10.676)	(15.179)	(116.433)
Period t_{8}	-255.512	-35.347***	-93.144***	-312.397**
	(159.309)	(9.777)	(15.471)	(127.614)
Period t_{9}	-345.433**	-33.601***	-79.519***	-403.086***
	(152.790)	(9.965)	(15.867)	(122.917)
Period t_{10}	-128.800	-30.573***	-73.899***	-265.697**
	(151.614)	(10.168)	(15.416)	(113.670)
Period t_{11}	-465.398***	-33.777***	-81.041***	-461.629***
	(121.545)	(10.068)	(15.269)	(98.311)
Period t_{12}	-463.150***	-34.549***	-80.244***	-342.940***
	(125.087)	(9.326)	(16.439)	(111.192)
Period t_{13}	-477.510***	-31.575***	-82.001***	-479.069***
	(137.027)	(9.926)	(16.267)	(111.421)
Period t_{14}	-338.393**	-34.902***	-73.706***	-447.224***
	(146.969)	(10.516)	(18.327)	(121.023)
Period t_{15}	-492.596***	-30.574***	-92.948***	-521.023***

	(146.813)	(10.195)	(18.535)	(112.777)
Period t_{16}	-295.587*	-38.415***	-98.038***	-395.538***
	(150.949)	(10.032)	(17.841)	(113.882)
Period t_{17}	-402.036**	-49.615***	-81.466***	-410.347***
	(160.219)	(11.244)	(18.820)	(134.775)
Period t_{18}	-288.914*	-38.734***	-81.259***	-248.786*
	(157.653)	(9.698)	(18.132)	(144.031)
Period t_{19}	-467.537***	-37.475***	-88.812***	-437.850***
	(136.382)	(11.448)	(18.275)	(114.222)
Period t_{20}	-444.879***	-37.840***	-87.710***	-395.873***
	(139.378)	(11.478)	(19.082)	(115.951)
Period t_{21}	-603.447***	-31.790**	-91.967***	-604.130***
	(139.489)	(12.694)	(17.634)	(117.401)
Period t_{22}	-599.202***	-34.849***	-98.758***	-540.497***
	(138.393)	(10.920)	(19.968)	(114.603)
Period t_{23}	-158.232	-23.919**	-89.610***	-141.190
	(174.976)	(11.221)	(19.690)	(161.125)
Period t_{24}	-553.199***	-32.831***	-81.320***	-503.497***
	(146.246)	(10.654)	(20.161)	(123.657)
# Respondents	7,337	7,337	7,337	7,337
R-squared	0.011	0.015	0.013	0.010
# Observations	144,123	144,123	144,123	144,123

Notes. Standard error in parenthesis, with standard errors clustered at the individual level. Models are estimated using linear fixed effects estimation on the outcomes for each time t_{-6} to t_{24} prior to or after the shock. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A3. Coefficient estimates of the effects of unemployment shocks on health and life satisfaction

	Self-reported health status	Medical spending	Overall life satisfaction	Happiness
Period t_{-6}	0.006	-0.144	-0.004	-0.020
	(0.013)	(3.118)	(0.016)	(0.038)
Period t_{-5}	0.000	-3.624	-0.010	-0.020
	(0.013)	(3.476)	(0.015)	(0.043)
Period t_{-4}	-0.015	2.547	-0.019	-0.054
	(0.011)	(3.605)	(0.017)	(0.035)
Period t_{-3}	0.016	2.453	-0.014	-0.007
	(0.013)	(4.010)	(0.018)	(0.042)
Period t_{-2}	0.006	-0.494	-0.025	-0.045
	(0.013)	(3.484)	(0.018)	(0.046)
Period t_{-1}	-0.004	1.768	-0.046***	-0.012
	(0.013)	(3.409)	(0.018)	(0.036)
Period t_{0}	0.008	-5.185*	-0.081***	-0.074*
	(0.012)	(2.893)	(0.018)	(0.039)
Period t_{1}	-0.004	-4.080	-0.080***	-0.082*
	(0.012)	(2.866)	(0.020)	(0.042)
Period t_{2}	0.008	-0.472	-0.096***	-0.066*
	(0.012)	(3.524)	(0.019)	(0.037)
Period t_{3}	0.001	0.359	-0.055***	-0.073*
	(0.013)	(3.703)	(0.019)	(0.041)
Period t_{4}	0.005	-0.770	-0.057***	-0.032
	(0.013)	(3.069)	(0.019)	(0.042)
Period t_{5}	-0.000	-1.250	-0.062***	-0.019
	(0.012)	(2.975)	(0.018)	(0.038)
Period t_{6}	-0.003	-5.852**	-0.045**	-0.065*
	(0.014)	(2.608)	(0.019)	(0.038)
Period t_{7}	0.004	-3.178	-0.054***	-0.029
	(0.012)	(3.304)	(0.019)	(0.045)
Period t_{8}	-0.006	-0.294	-0.051***	-0.025
	(0.013)	(3.535)	(0.019)	(0.039)
Period t_{9}	-0.002	-0.813	-0.035*	-0.041
	(0.013)	(3.640)	(0.020)	(0.043)
Period t_{10}	0.015	-0.432	-0.040**	-0.020
	(0.013)	(3.485)	(0.019)	(0.044)
Period t_{11}	0.021	0.490	-0.030	-0.032
	(0.014)	(4.110)	(0.020)	(0.043)
Period t_{12}	-0.002	-4.014	-0.037*	-0.036
	(0.013)	(3.421)	(0.020)	(0.043)
Period t_{13}	0.014	-0.142	-0.029	-0.040
	(0.015)	(3.925)	(0.020)	(0.047)
Period t_{14}	0.013	-3.694	-0.031	0.017
	(0.014)	(3.590)	(0.020)	(0.042)

Period t_{15}	0.005	-5.511	-0.020	-0.031
	(0.014)	(3.496)	(0.020)	(0.044)
Period t_{16}	-0.007	-2.314	-0.042**	-0.005
	(0.014)	(3.323)	(0.021)	(0.048)
Period t_{17}	0.004	1.189	-0.024	0.016
	(0.014)	(4.093)	(0.021)	(0.044)
Period t_{18}	0.008	-0.192	-0.021	-0.001
	(0.014)	(3.605)	(0.021)	(0.048)
Period t_{19}	-0.005	-1.457	-0.031	-0.011
	(0.015)	(3.614)	(0.021)	(0.047)
Period t_{20}	0.013	-5.059	-0.005	0.049
	(0.016)	(3.426)	(0.021)	(0.047)
Period t_{21}	0.001	-2.501	-0.038*	-0.066
	(0.015)	(3.561)	(0.021)	(0.046)
Period t_{22}	0.013	-6.963**	-0.045**	-0.018
	(0.015)	(2.887)	(0.022)	(0.050)
Period t_{23}	0.003	-5.296	-0.021	0.005
	(0.015)	(3.510)	(0.022)	(0.046)
Period t_{24}	0.010	-7.242*	-0.035	-0.016
	(0.016)	(3.840)	(0.022)	(0.050)
# Respondents	7,337	7,320	7,337	6,728
R-squared	0.002	0.002	0.009	0.003
# Observations	144,090	143,246	144,071	48,066

Notes. Standard error in parenthesis, with standard errors clustered at the individual level. Models are estimated using linear fixed effects estimation on the outcomes for each time t_{-6} to t_{24} prior to or after the shock. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

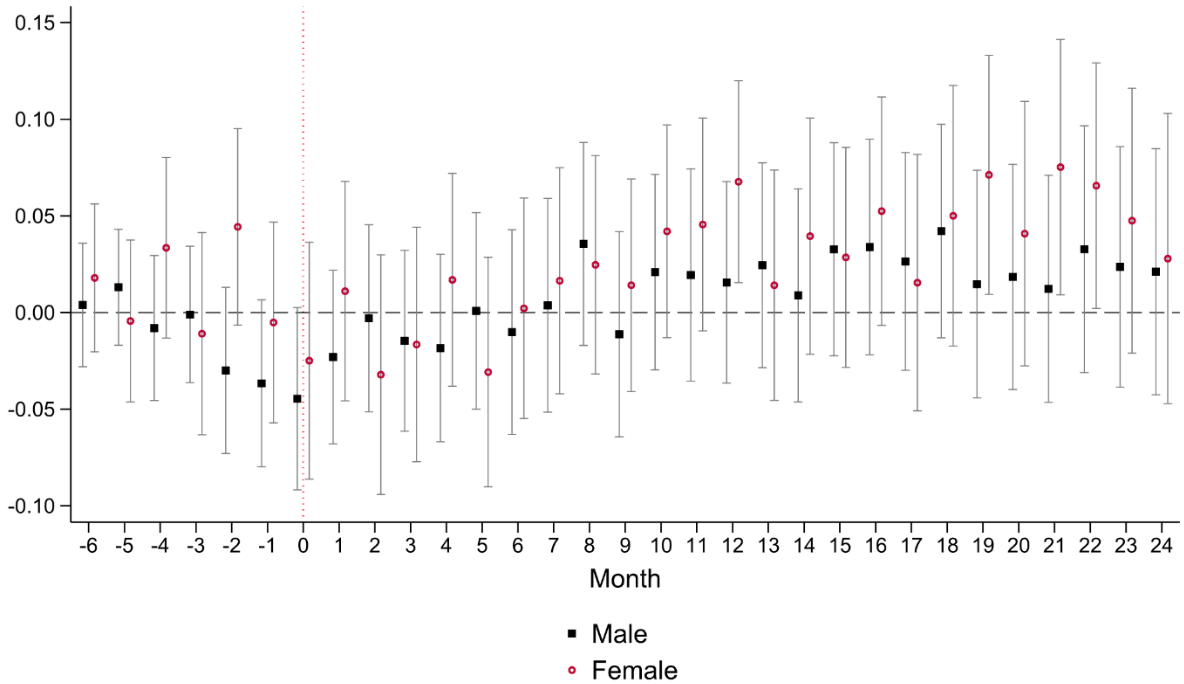
Table A4. Permutation test

	Own earnings	Total consumption	Self-reported health status
Period t_{-6}	-31.36	-19.68	-0.00179
	(150.2)	(165.8)	(0.0146)
Period t_{-5}	-49.96	-20.86	-0.00311
	(149.0)	(173.1)	(0.0150)
Period t_{-4}	-58.89	-33.15	-0.00173
	(152.4)	(167.3)	(0.0153)
Period t_{-3}	-48.01	-46.89	-0.00153
	(155.0)	(168.9)	(0.0152)
Period t_{-2}	-44.16	-50.75	-0.00299
	(165.6)	(173.9)	(0.0150)
Period t_{-1}	-44.38	-41.78	-0.00180
	(162.0)	(170.7)	(0.0156)
Period t_{0}	-60.36	-69.63	0.00103
	(166.2)	(157.7)	(0.0153)
Period t_{1}	-50.76	-65.34	0.00126
	(170.5)	(165.3)	(0.0155)
Period t_{2}	-55.92	-59.30	0.00441
	(174.3)	(169.7)	(0.0157)
Period t_{3}	-59.94	-62.31	0.00331
	(177.5)	(171.2)	(0.0159)
Period t_{4}	-52.99	-42.58	0.00305
	(183.0)	(181.1)	(0.0158)
Period t_{5}	-46.57	-55.36	0.00300
	(180.4)	(173.0)	(0.0160)
Period t_{6}	-43.06	-53.03	0.00420
	(185.0)	(184.2)	(0.0165)
Period t_{7}	-51.93	-51.09	0.00312
	(186.9)	(183.2)	(0.0169)
Period t_{8}	-52.60	-42.85	0.00406
	(194.7)	(192.7)	(0.0173)
Period t_{9}	-45.48	-34.96	0.00393
	(193.6)	(196.0)	(0.0166)
Period t_{10}	-49.10	-44.93	0.00426
	(195.5)	(197.0)	(0.0173)
Period t_{11}	-46.95	-49.81	0.00409
	(198.1)	(200.5)	(0.0180)
Period t_{12}	-38.03	-45.36	0.00401
	(203.8)	(201.2)	(0.0173)
Period t_{13}	-31.11	-36.80	0.00447
	(203.4)	(203.2)	(0.0182)
Period t_{14}	-21.03	-40.50	0.00462
	(210.7)	(201.3)	(0.0174)
Period t_{15}	-23.79	-23.59	0.00607

	(209.6)	(204.0)	(0.0177)
Period t_{16}	-6.425	-33.69	0.00454
	(211.9)	(214.0)	(0.0182)
Period t_{17}	-1.552	-44.83	0.00288
	(207.1)	(210.7)	(0.0190)
Period t_{18}	-1.331	-38.25	0.00353
	(208.9)	(219.3)	(0.0185)
Period t_{19}	-8.085	-14.35	0.00434
	(210.1)	(227.3)	(0.0189)
Period t_{20}	0.779	-9.071	0.00311
	(210.5)	(226.3)	(0.0191)
Period t_{21}	-8.221	-16.66	0.00379
	(211.9)	(228.2)	(0.0196)
Period t_{22}	-6.997	-11.42	0.00529
	(213.8)	(242.0)	(0.0191)
Period t_{23}	-2.976	-10.76	0.00446
	(212.3)	(242.7)	(0.0202)
Period t_{24}	-4.081	-29.04	0.00318
	(203.3)	(230.6)	(0.0205)

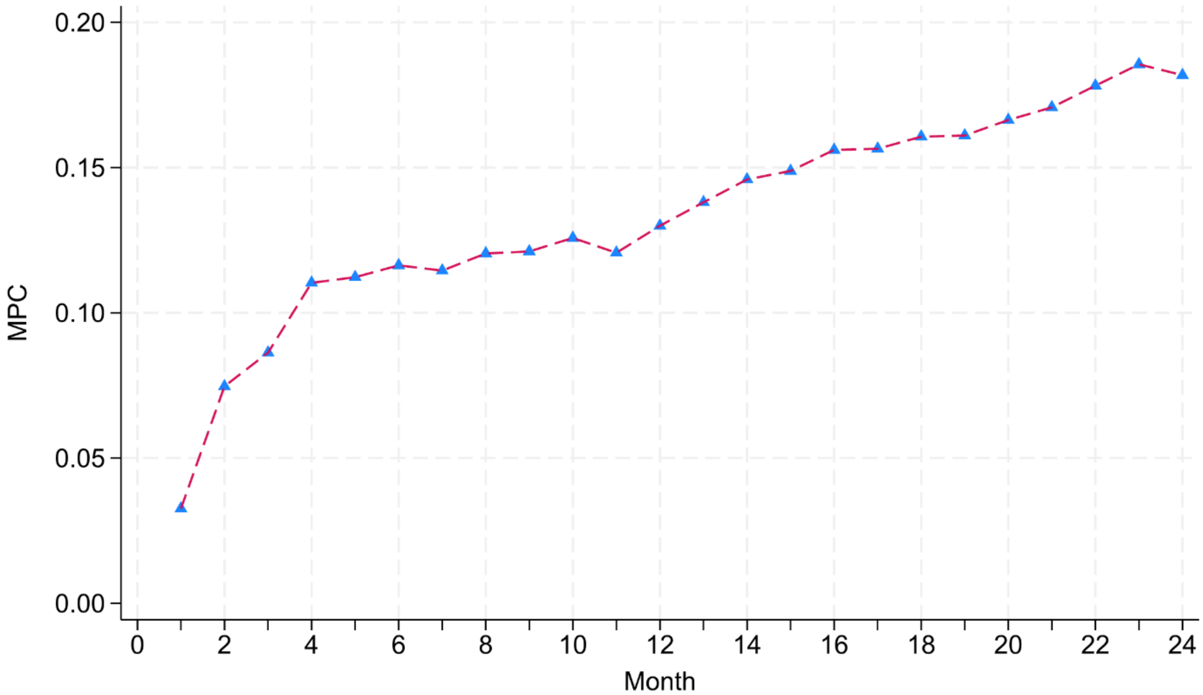
Notes. Standard errors are reported in parenthesis. We perform Fisher's permutation test with 1,000 iterations, randomly assigning unemployment months to test if baseline findings indicate a true unemployment shock impact for each time t_{-6} to t_{24} prior to or after the shock. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Figure A1. Dynamic effects of an unemployment shock on spousal income by gender



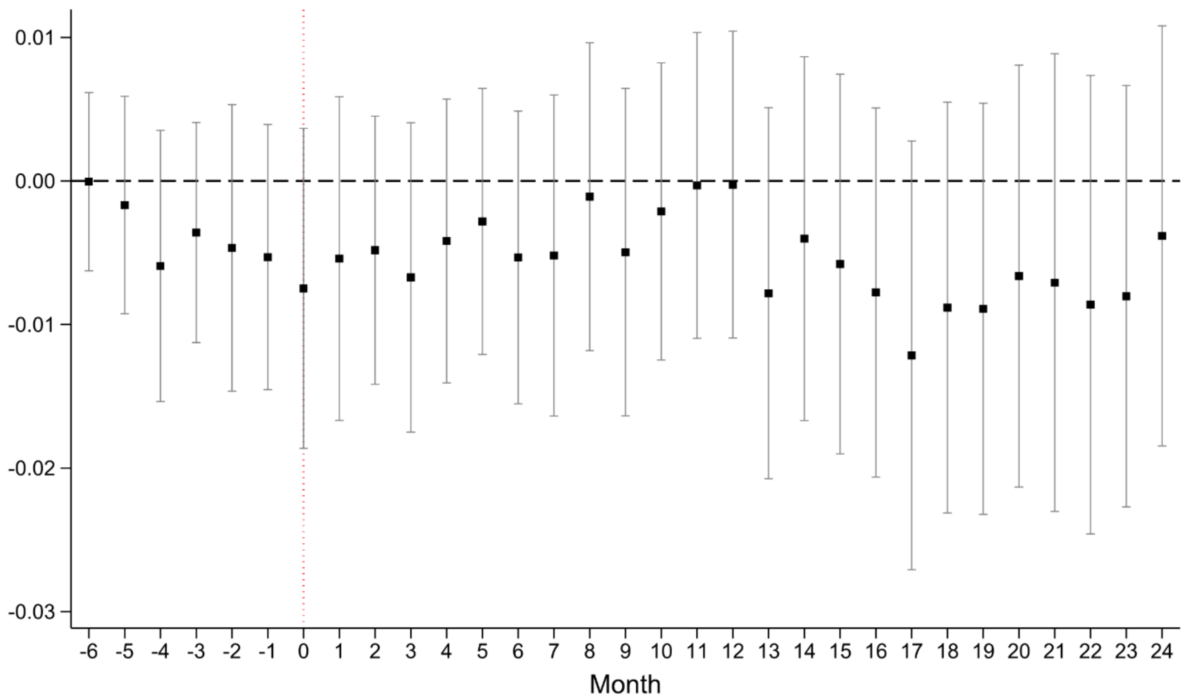
Notes. Square dots represent the coefficient estimates of the event study design specification using equation (1). Gray bars represent 95% confidence intervals.

Figure A2. MPC after the shock



Notes. To compute the Marginal Propensity to Consume (MPC), we conduct fixed effects regressions for income and spending using dummy variables that represent each month in a 24-month period following the event. We extract coefficients from these regressions for each month and aggregate them separately for income and spending over each month from 1 to 24. Next, we calculate the cumulative changes in income and spending for these periods. Finally, the MPC is determined by dividing the cumulative change in spending by the cumulative change in income across these months, illustrating how income fluctuations affect spending patterns over these specific time intervals.

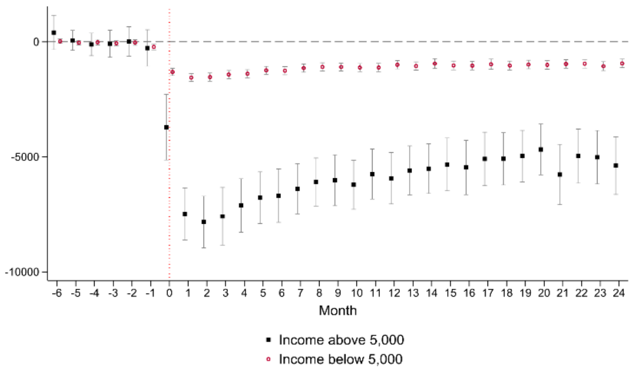
Figure A3. Dynamic effect of an unemployment shock on marital status



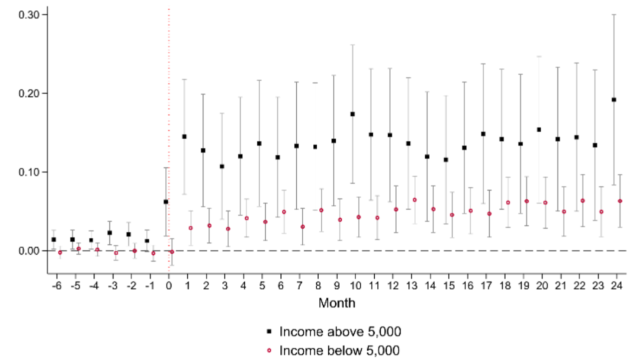
Notes. Square dots represent the coefficient estimates of the event study design specification using equation (1). Gray bars represent 95% confidence intervals.

Figure A4. Heterogeneity analysis by income

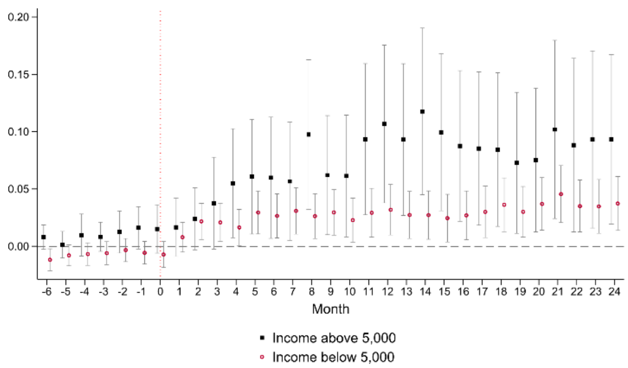
Panel A. Own earnings (in S$)



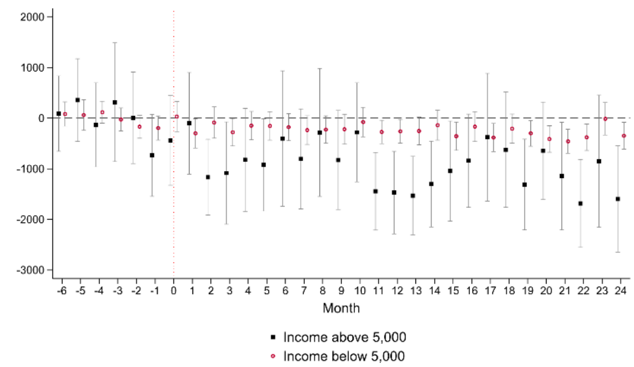
Panel B. Retirement status



Panel C. Self-employment



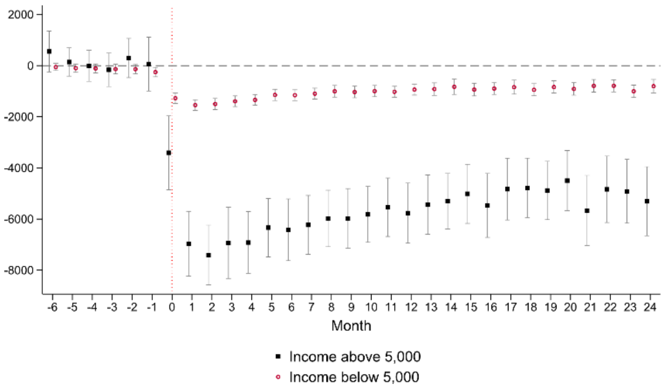
Panel D. Total consumption spending (in S$)



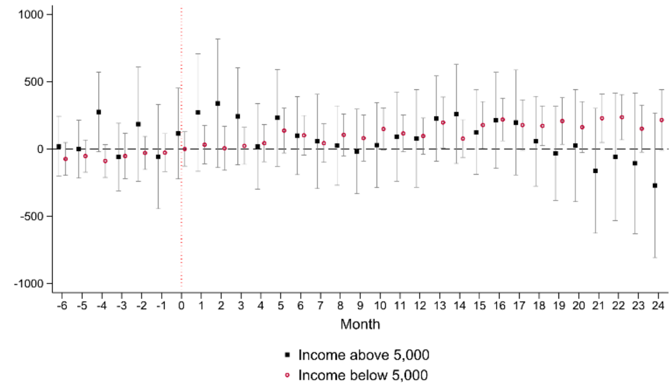
Notes. Square dots represent the coefficient estimates of the event study design specification using equation (1). Gray bars represent 95% confidence intervals.

Figure A5. Heterogeneity analysis by income

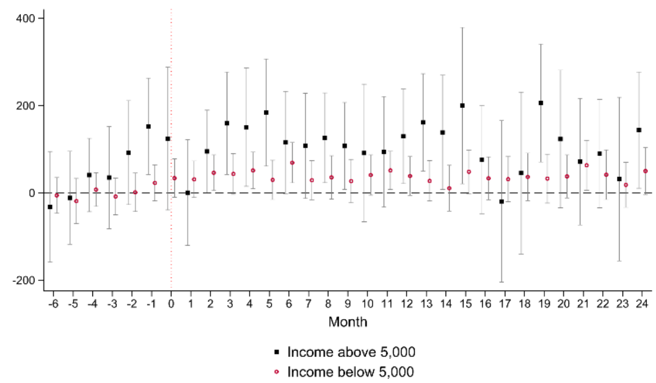
Panel A. Household income (in S$)



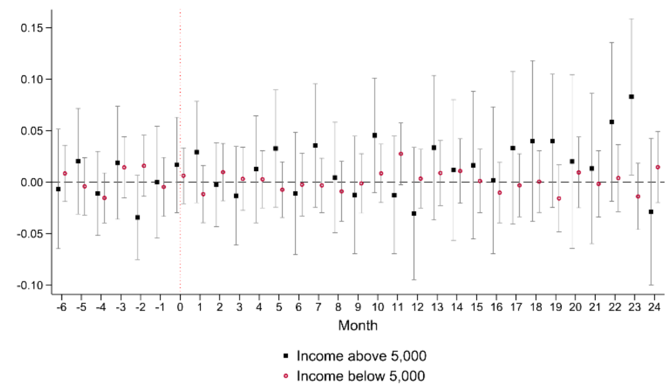
Panel B. Spouse's earnings (married respondents only; in S$)



Panel C. Private transfer income (in S$)



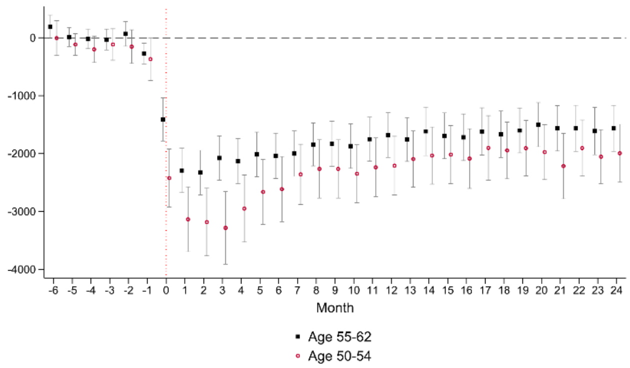
Panel D. Self-reported health status



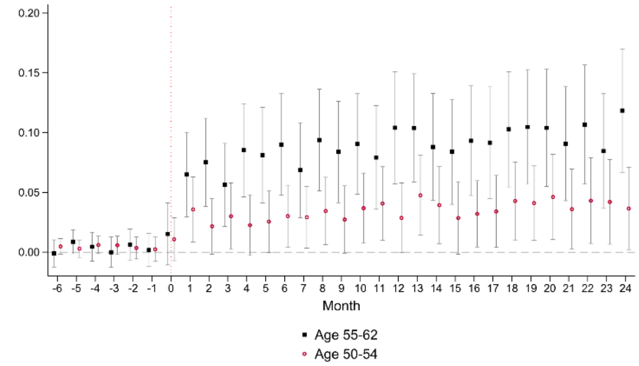
Notes. Square dots represent the coefficient estimates of the event study design specification using equation (1). Gray bars represent 95% confidence intervals.

Figure A6. Heterogeneity analysis by age

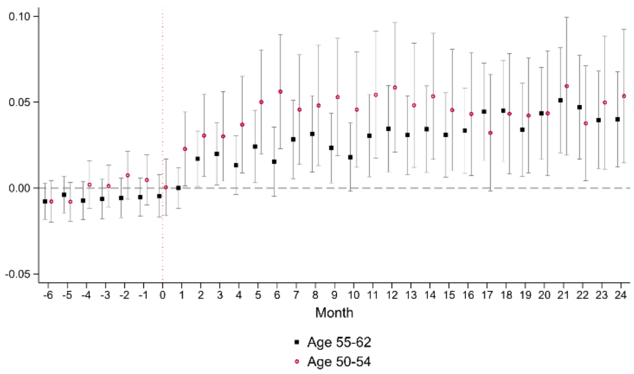
Panel A. Own earnings (in S$)



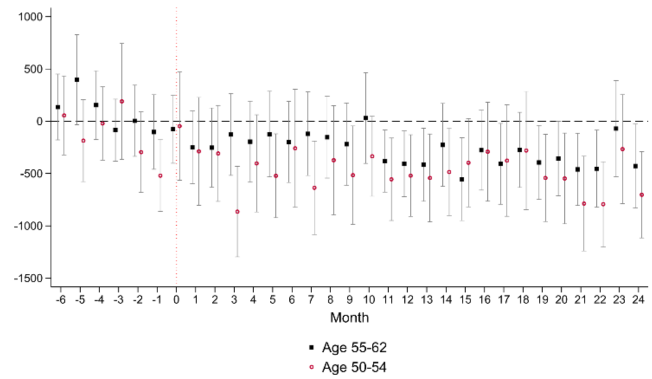
Panel B. Retirement status



Panel C. Self-employment



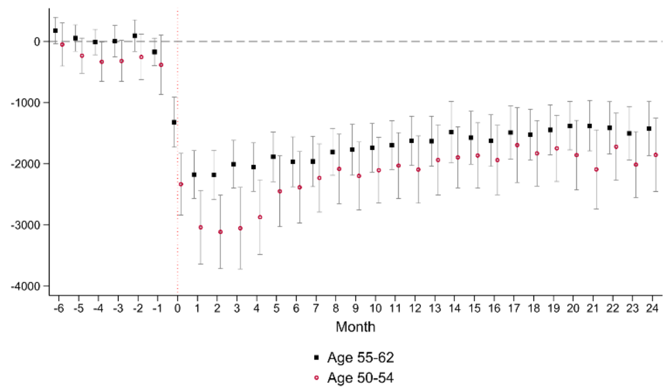
Panel D. Total consumption spending (in S$)



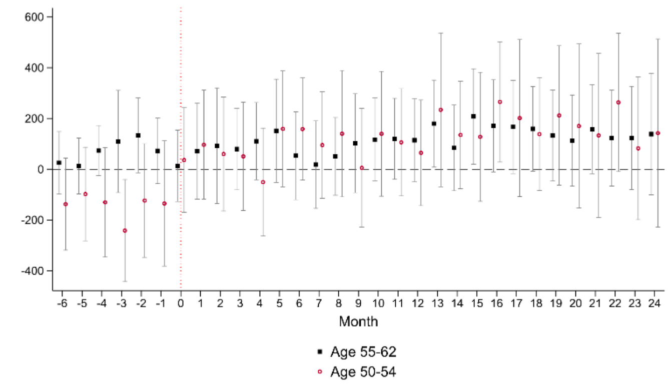
Notes. Square dots represent the coefficient estimates of the event study design specification using equation (1). Gray bars represent 95% confidence intervals.

Figure A7. Heterogeneity analysis by age

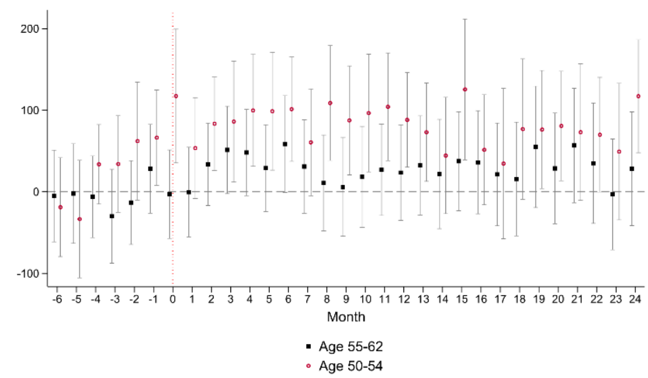
Panel A. Household income (in S$)



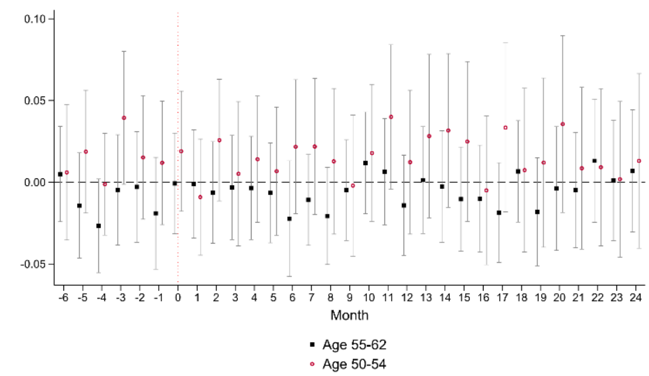
Panel B. Spouse's earnings (married respondents only; in S$)



Panel C. Private transfer income (in S$)



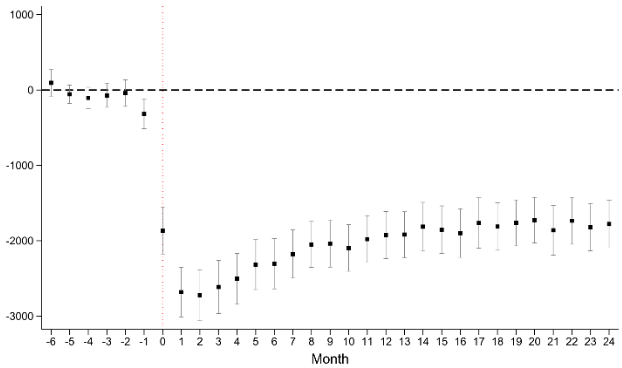
Panel D. Self-reported health status



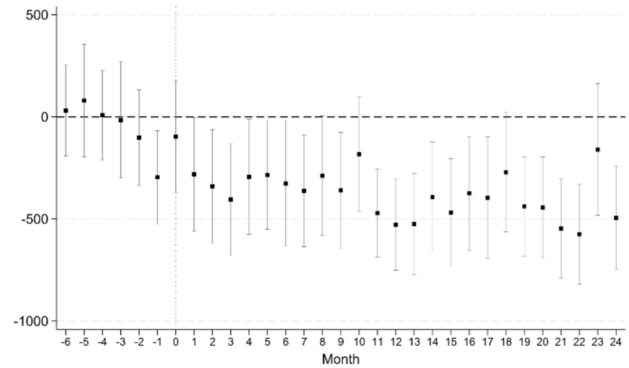
Notes. Square dots represent the coefficient estimates of the event study design specification using equation (1). Gray bars represent 95% confidence intervals.

Figure A8. Robustness check using Sun and Abraham (2021)'s alternative method

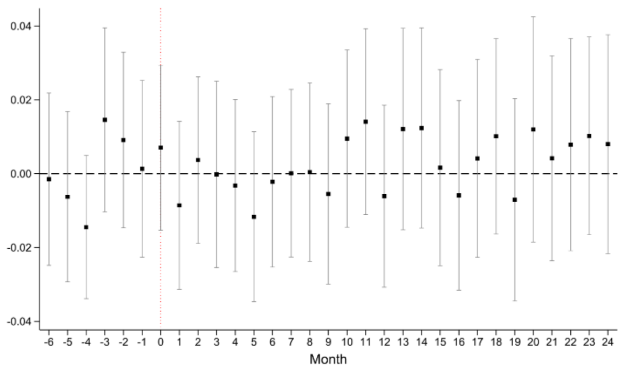
Panel A. Own earnings (in S$)



Panel B. Consumption Spending (in S$)



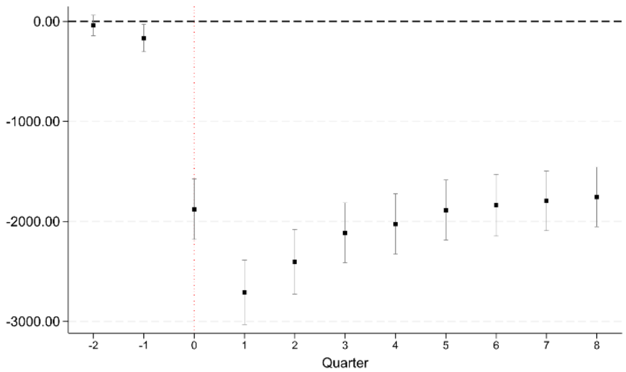
Panel C. Self-reported health status



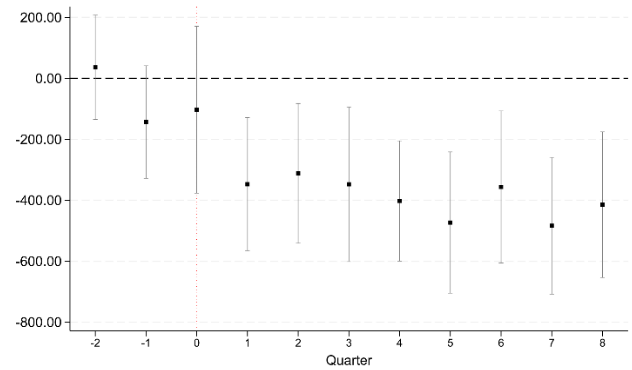
Notes. Square dots represent the coefficient estimates of the event study design specification using equation (1). Gray bars represent 95% confidence intervals.

Figure A9. Robustness check using the aggregated data at the quarterly frequency

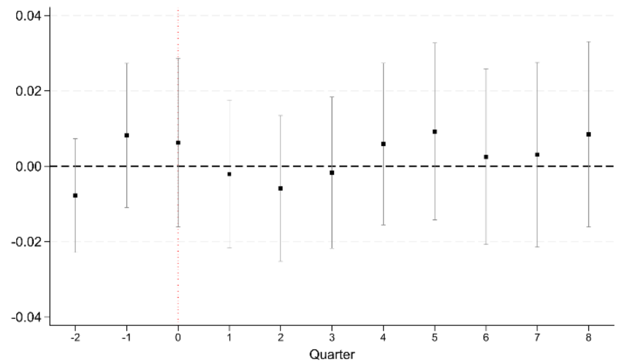
Panel A. Own earnings (in S$)



Panel B. Consumption Spending (in S$)



Panel C. Self-reported health status



Notes. The quarter values are aggregated over three months rather than monthly observations. Square dots represent the coefficient estimates of the event study design specification using equation (1). Gray bars represent 95% confidence intervals.

Appendix B. Spending Variable Definition

Number	Name	Detail or definition
1	Mortgage	interest and principal
2	Property tax	
3	Home and content insurance	
4	Rent	
5	Utilities and other fuels	Water supply, electricity, gas, other fuels, refuse disposal
6	Communication	Internet, telephone, handphone, cable TV subscription
7	Furniture and furnishings	Furniture, carpets, household textiles, glassware, tableware, household utensils
8	Home repair and maintenance	Materials, tools, and services for maintenance and repair of home
9	Housekeeping supplies	Cleaning and laundry products
10	Domestic and housekeeping services	Cost of hiring maids, baby sitters, dry cleaning and laundry services
11	Food and beverages (including alcohol)	Purchased in grocery shops, provision shops, supermarkets, wet markets, or other stores
12	Dining and/or drinking out	In restaurants, cafes, pubs, hawker centers, food courts, coffee shops, canteens, street vendors, including take-away and home delivery food
13	Tobacco	Cigarettes and other tobacco products
14	Cloth	Clothing, footwear, jewelry, watches, accessories
15	Personal care products and services	Hair care, beauty, grooming, and skin products; spending on haircut, beauty treatment, manicure/pedicure, etc.
16	Health insurance premium	
17	Prescription medications	Out-of-pocket cost and anything paid from Medisave for prescription
18	Other medications	Out-of-pocket cost and anything paid from Medisave for traditional medicines (e.g. Chinese and Ayurvedic medicine), over-the-counter medications, other medical products (e.g. wheelchair, crutches) and therapeutic equipment
19	Outpatient services	Out-of-pocket cost and costs paid from Medisave for visits to doctors, traditional physicians (e.g. traditional Chinese physicians), physiotherapists, and psychologists; eye care and dental service fees; lab tests.
20	Hospital services	Out-of-pocket cost and costs paid from Medisave for hospital and nursing home care
21	Home nursing	Hiring costs of a helper due to health problems (do not include domestic help services)

22	Entertainment	Tickets to movies, sporting events, concerts, and museums.
23	Sports	Gym, exercise equipment such as bicycles, and boats, etc.
24	Hobbies and leisure equipment	Photography, stamps, reading materials (newspapers, magazines, books), camping, gardening, pets, electronic entertainment (e magazines, e-books, iTunes, Netflix).
25	Package tours and vacations	Transportation, accommodation, and recreational expenses on tours and trips
26	Vehicle payments	Interest and principal
27	Road use fees	Road taxes, road use charges (e.g. ERP), parking including traffic / parking fines
28	Vehicle insurance	
29	Petrol	
30	Vehicle repair and maintenance	VICOM inspection and other vehicle related services
31	Spending on public transportation	Mass rapid transit (MRT; subway name in Singapore), taxi, bus
32	Home appliances	Television, DVD/BLU-RAY player and recorder, refrigerator, Microwave, vacuum cleaner, washing machine, clothes dryer, air conditioner
33	Education	School fees, private tuition fees, books and supplies, assessment papers, study guides
34	Life insurance	Term policies only, excluding premiums for plans with a saving component
35	Other insurance	Travel insurance or maid insurance
36	Contributions to religious or charitable organizations	