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A pseudo-panel analysis of marginal propensity to consume from transfers along the income distribution in Malaysia

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A pseudo-panel analysis of marginal propensity to consume from transfers along the income distribution in Malaysia

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Abstract

Some government policies, particularly social assistance, tend to reflect the heterogeneity of households, e.g., tiering cash assistance based on income. In Malaysia, unconditional cash transfers with income-based eligibility conditions form the crux of social protection and assistance toolkit. Considering the relatively developed disbursement mechanisms and hence take-up rates, policymakers here are then interested in the effectiveness or welfare impact of cash transfers, particularly marginal propensity to consume (MPC) by income groups (sensitivity of spending to transfers). This paper provides a two-step analysis with the 2014, 2016, 2019 and 2022 Household Income and Expenditure Surveys (HIES) from the Department of Statistics, Malaysia. First, a descriptive analysis of household income, transfers and expenditure along the income distribution. Second, a pseudo-panel fixed effects analysis of the sensitivity of household spending to transfers. The paper finds that the MPC from transfers was highest for the bottom income quintile households at 0.61 (95%CI: 0.4 to 0.82) and lowest for the top income quintile households at 0.39 (95%CI: 0.21 to 0.56). The full-sample MPC was close to the MPC of the lower income households at 0.58 (95%CI: 0.33 to 0.84). These findings form the basis for policymakers to objectively evaluate and calibrate Malaysia's income-based cash transfers from an effectiveness perspective.

Keywords: Transfers, Household Spending, Pseudo-Panel, Marginal Propensity to Consume
JEL Codes: D1, D12, D31

† Views expressed are solely that of the author and should not be taken to represent those of the Advisory Committee to the Finance Minister, Bank Negara Malaysia or the Government of Malaysia.
‡ This research was conducted and provided as technical input for the Advisory Committee to the Finance Minister, Malaysia.

1 Introduction

Households often account for the largest expenditure share in gross domestic product (GDP) and have diverse spending behaviour. In Malaysia, private (household) consumption constituted 57.3% of real GDP in MYR (60.2% in 2022) and 57.2% of nominal GDP (57.6% in 2022) on average between 2015-2022. Moreover, Dhruva et al. (2013) documented heterogeneity in marginal propensities of consumption (MPCs), loan repayments, food expenditure and financial expenses along the income distribution in a cross-sectional analysis of Malaysia's 2009 Household Expenditure Survey (HES). DOSM (Accessed 2024) also provides the key aggregate statistics from the 2022 Household Income and Expenditure Survey (HIES), including from a distributional angle.

Eligibility for and quantum of cash transfers in social protection and assistance programmes are often tiered to reflect such heterogeneity. In Malaysia, unconditional cash transfers are primarily given to households at the bottom 40% of the income distribution via the Sumbangan Tunai Rahmah (STR), which is aimed at assisting needy households in meeting cost of living challenges. Historically, the STR's predecessors were also disbursed to households between the 40^{th} and 80^{th} of the income distribution, namely the Bantuan Keluarga Malaysia (BKM) in 2021-22, Bantuan Sara Hidup (BSH) in 2018-21 and the Bantuan Rakyat 1Malaysia (BR1M) in 2012-18. Pre-BR1M, cash transfers were primarily aimed at the extreme poor or specific vulnerable groups, such as the disabled and single mothers. Since BR1M, cash transfers complement a wider network of other cash transfers and social protection programmes, including mandatory retirement savings schemes[1], social insurance, employment insurance and a fully funded public healthcare system. The latest version of the STR, scheduled for implementation in 2024 as at the time of writing, disburses cash to households in the bottom 60% of the income distribution (MOF Accessed 2024).[2]

Given relatively developed disbursement mechanisms via both electronic (transfers to bank accounts associated with tax payments) and physical (collection at bank branches) and the broad coverage (60% of households), policymakers are less concerned with take-up and

[1]For instance, these are the defined contribution Employers Provident Fund for private sector and non-pensionable public sector workers, the defined benefit Retirement Fund for public sector pension and the defined benefit Armed Forces Fund Board for military pension.

[2]These measures are comparable to, but more expansive than, the Earned Income Tax Credits (EITC) and Temporary Assistance for Needy Families (TANF) in the US. The EITC is aimed at providing tax breaks to low- to moderate-income workers, while the TANF is aimed at meeting the basic needs of impoverished households via direct cash assistance. Chile, a comparable emerging economy, combines conditional and unconditional handouts aimed at impoverished households in the Chile Solidario, which complements child-oriented cash transfers for low income households, social security covering various pensions and benefits and a national health insurance system. The more expansive Chile Solidario aimed to reduce exclusion by linking impoverished households into the broader social protection system, as well as to improve the degree of coordination and welfare impact of constituent assistance programmes.

reach, compared to the effectiveness of cash transfers at translating into actual spending, hence empirical estimates of MPC from transfers are key. Moreover, given that the STR-type measures tend to be tiered along the income distribution, MPCs by income levels are key in assessing the relative degree in which transfers are translated into actual spending.

The literature has several estimates of MPC for Malaysia using both micro- and macroeconomic data sets and methodology. The first set of estimates correspond to MPC from income, rather than specifically cash transfers. Dhruva et al. (2013) estimated MPC from income based on the 2009 HES, which ranged from 0.25 for households earning above MYR10,000 to 0.81 for households earning below MYR1,000. Dhruva et al. (2015) also estimated the sensitivity of private consumption to income up with an error correction model (ECM) using 2002-2013 macroeconomic data. Zarinah & Pereira (2012) conducted a similar analysis using a vector ECM. The second set corresponds to MPC from cash transfers, which this paper is closely related to. Suah (2023) used the interrupted time series (ITS) methodology to estimate MPCs from cash transfers during the COVID-19 pandemic using daily aggregated transactions data, which ranged between 0.23 and 0.43.[3] These estimates serve as comparators for the MPC estimates to be discussed in this paper.

Evidence outside Malaysia is primarily US-oriented, reflecting data availability. Kaplan & Violante (2014) provided empirical estimates of the sensitivity of household spending to the size of 2001 tax rebates received in the US, which were between 0.22 to 0.38. This was followed by a theoretical discussion of the MPCs of households who are hand-to-mouth but differed in whether wealth held is liquid or illiquid. Crossley et al. (2021) used survey data fielded in July 2020 in the UK to evaluate hypothetical MPCs. Subjects were asked their hypothetical change in spending if given a GBP500 cash transfer. The average MPC was 0.11 but with notable bunching at < 0.1 and > 0.9.

This paper analyses the 2014, 2016, 2019 and 2022 vintages of the HIES in two ways. First, a descriptive analysis of household income, transfers[4], spending and select demographic characteristics, with special attention on stratification by income levels to contextualise the household sector. Second, a pseudo-panel fixed effects estimation of MPCs from transfers along the income distribution. As each HIES vintage comprises potentially different households, standard panel data estimates using within-household variation is not feasible. Verbeek (2008)'s pseudo-panel methodology offers a compromise. By building a panel data where

[3]The ITS methodology is described in Linden (2018), Bernal et al. (2017) and Lopez Bernal et al. (2019).

[4]The HIES handbook annex (DOSM Accessed 2024) defines income from current transfers received as "cash, goods or services and may be received from other households, the government or charities, both within or outside the country. Remittances, pensions, alimony and other assistance received periodically are among examples of income from current transfers received". We make a reasonable simplifying assumption that this component primarily comprises of government transfers. Further breakdown is unavailable in the vintages available for analysis.

the entities are cohorts defined by demographic observables, we can use the within-cohort variation of transfers and expenditure over time to estimate the MPCs. Seawright (2009) also discussed constructing individual-level pseudo-panel data using matching methods.

Empirical studies that implemented Verbeek (2008)'s cohort pseudo-panel methodology are abundant. Guillerm (2017) compared cross-section and pseudo-panel estimates of age effects on household wealth in France. Jæger (2013) used cohorts constructed from demographic groups in the European Social Survey to estimate the effect of economic conditions (e.g., economic growth and unemployment) on inclination to support or reject redistributive policies. Nyatanga & Matsuda (2010) used Japan's Family Income and Expenditure Survey to estimate the effect of taxation on cigarette consumption. Machado & Ribas (2010) applied survival models to a pseudo-panel of Brazil's Monthly Employment Survey to analyse the determinants of and effect of labour market movements on the probability of exiting poverty. Like these papers, the HIES is a set of repeated cross-section surveys with rich demographic variables, from which cohorts can be generated.

The remainder of this paper is structured as follows. Section 2 introduces the data set. Section 3 presents the descriptive findings. Section 4 discusses the MPC estimates and section 5 concludes.

2 Data

This paper uses the 2014, 2016, 2019 and 2022 vintages of the HIES, which is fielded by the Department of Statistics Malaysia (DOSM) twice every five years. The HIES estimates income, expenditure and documents various demographic characteristics of households in Malaysia, primarily to update consumer price index (CPI) weights. Table 1 describes all data fields and the corresponding transformation.

Table 1: Data fields

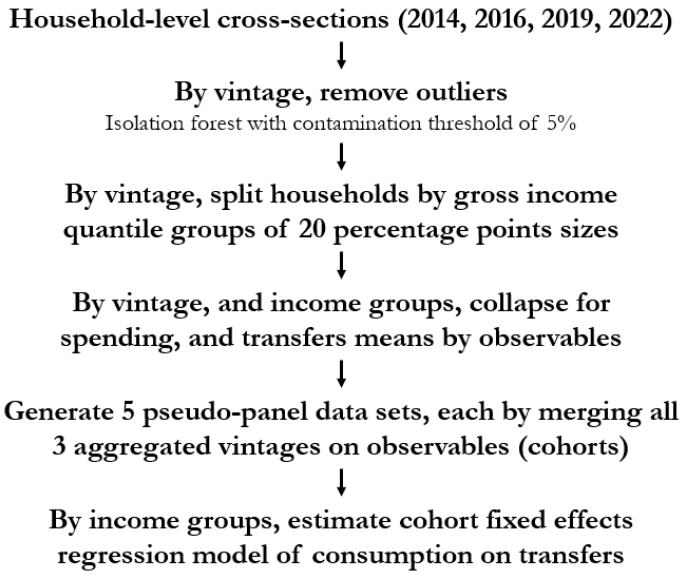
Variable	Description
ID	Anonymised household IDs, consistent within vintage
Gross income	Household income, summation of wages and salaries, asset returns, transfers and other income
Wage income	Wages and salaries
Asset returns	Returns from investment
Other income	Other income reported
Gross transfers	Current transfers, which includes transfers from governments to members of the household
Consumption	Expenditure on consumer goods and services
Financial expenses	Non-consumption expenditure, including loan repayments
Number of income-earners	Number of individuals who reported to have earned income in the household in the vintage year; expressed as categorical variable in adjusted analysis, with largest at '3+'
Birth year of head of household	Equivalent to the age of the head of the household head; expressed as 20-year categories in adjusted analysis
Number of children (age 0-11)	Expressed as categorical variable in adjusted analysis, with largest at '3+'
Number of adolescents (age 12-17)	Expressed as categorical variable in adjusted analysis, with largest at '3+'
Number of working age adults (age 18-59)	Expressed as categorical variable in adjusted analysis, with largest at '3+'
Number of elderly (age 60 and above)	expressed as categorical variable in adjusted analysis, with largest at '3+'
State of residence	Categories of 16 states, with the 3 federal territories expressed as individual states
Urban / rural	Indicates if residence is in a rural or urban locality
Ethnicity of the head of household	Dummy indicating if the head of household is a 'bumiputra' (native ethnicity), which includes Malays and Bornean natives or 'non-bumiputra', which includes primarily the Chinese and Indians; limited by binary classification in the 2014 vintage, whereas the 2016 and 2019 vintages have more detailed classifications
Employment status of the head of household	Categorical variable indicating if head of household is in the private sector, government sector, self-employed, a pensioner, housespouse, student, employer, unpaid family worker, unemployed or others
Occupation of the head of household	Categorical variable corresponding to the 10 occupations in the Malaysian Standard Classification of Occupations (MASCO) at the 1-digit level
Industry of the head of household	Categorical variable corresponding to the manufacturing, construction, mining, agriculture sectors and 18 services subsectors
Sex of the head of household	Male or female
Nationality of the head of household	Malaysian or non-Malaysian
Education level of the head of household	Middle school (SRP / PMR / PT3-equivalents), high school (SPM-equivalents), pre-university (STPM-equivalents), certificate, diploma and above and no formal qualifications
Marriage status of the head of household	Married, widowed, divorced, separated or never married; but collapsed to either married or single in subsequent analysis

Figure 1 describes the data processing steps for the pseudo-panel analysis.[5] Ideally, household-level panel data should be used to exploit the within-household variation over time when estimating the MPCs. However, the HIES is designed to represent the aggregate economy rather than to track specific households, hence is different from other well-known panel data sets, such as the Household, Income and Labour Dynamics in Australia (HILDA) survey. The HIES is also anonymised at source, making tracking as if a household-level panel data set

[5]Citizenship is adjusted for directly when constructing cohorts while the descriptive analysis excludes non-Malaysian households.

difficult. Tracking households is particularly useful if household income is generally volatile in terms of their position along the vintage-specific income distribution (e.g., a the 10^{th} percentile household in one vintage could be the 60^{th} in the next and then 20^{th} in the subsequent vintage). However, Khalid (2018) used a 4999-household survey data set to document intergenerational income mobility in Malaysia. In Vietnam, Nguyen & Nguyen (2020) documented that the incidence of intragenerational income mobility, (that is the change in the position of a household along the income distribution over time) fell over time.[6] Nonetheless, recent estimates of intragenerational income mobility in Malaysia are scarce, adding to another angle of uncertainty.[7] Importantly, even if tracking is possible in the HIES, doing so could erode representativeness of any resultant analysis. Hence, a pseudo-panel aggregation is chosen as a methodological compromise to retain the ability to exploit within-entity variation over time.

Figure 1: Data flow for the pseudo-panel analysis



Outliers of each vintage are first removed using Liu et al. (2008)'s isolation forest with a 5% contamination threshold.[8] Households of each vintage are stratified by income quintiles — B20- (0^{th} to 20^{th} percentiles), B20+ (20^{th} to 40^{th}), M20- (40^{th} to 60^{th}), M20+ (60^{th} to

[6]Nguyen & Nguyen (2020) also found heterogeneity in the degree of income mobility when stratified by some background observables, such as occupational skills.

[7]Given the relative positions of Malaysia and Vietnam in terms of economic development (e.g., measured by GDP per capita), intragenerational mobility may have been lower in Malaysia, especially over the short period of time covered by the HIES (2014 to 2022). The influence of potential volatility arising from intragenerational income mobility over the short-term (under a decade) could reasonably be minimal.

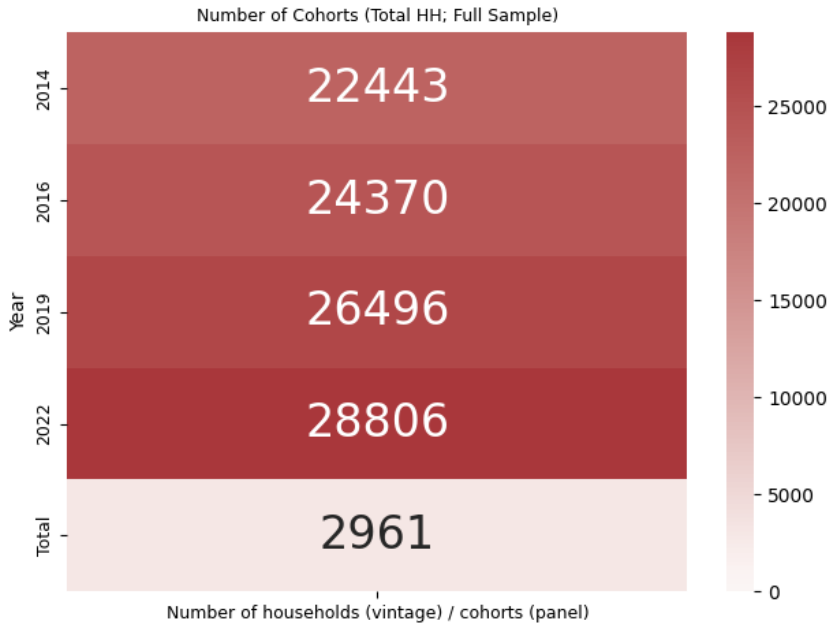
[8]A 5% contamination threshold is conceptually similar to removing 5% of observations at the both ends of the distribution as outliers.

80^{th}) and T20 (80^{th} to 100^{th}). These correspond to commonly used terminology in the Malaysian public policy sphere. Household transfers and expenditure of each vintage are then aggregated for their means by combinations of the background variables, i.e., cohorts, in table 2. This yields 5 data sets per HIES vintage, each corresponding to the cohort-means of respective income groups. The aggregated vintages are then merged for five pseudo-panel data sets, each corresponding to one income group. The pseudo-panel data sets each consist of 2,960 balanced cohorts constructed from 22,443 to 28,805 households over 4 time periods (2014, 2016, 2019 and 2022), as summarised in figure 2. The MPCs from transfers are then estimated with fixed effects regression.

Table 2: List of observables used in building cohorts

No.	**Observables**
1	State of residence
2	Urban / rural
3	Education level of head of household
4	Ethnicity of head of household
5	Nationality of head of household
6	Number of income-generating members
7	Sex of head of household
8	Birth year of head of household
9	Marriage status of head of household
10	Employment status of head of household
11	Industry of head of household
12	Occupation of head of household

Figure 2: Number of households by vintage and number of balanced cohorts



3 Descriptive analysis

For context-setting, we first curate the distribution of household incomes. Income groups are defined by total household income. For completeness, per capita and square root equivalised income[9] are also tabulated against the total household income distribution.

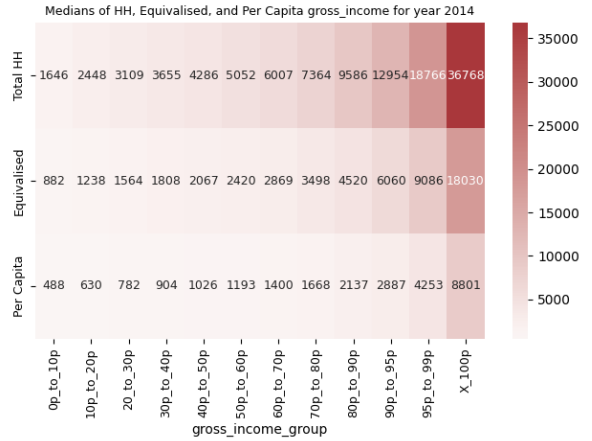
Tables 3a to 3d shows the median total household, per capita and equivalised incomes along total household income distribution for all four vintages of the HIES, while tables 4a to 4d show that of transfers received.[10] The median income of the top centile is about 3 times that of the 90th to 95th percentile groups and holds across years and definition of household income. The median of the ninth decile is also about 3 times that of the fourth decile. This upper tail skewness is not unique to Malaysia and is reflected in countries with comparable income gini coefficients. That transfers received diminishes along the income distribution could primarily reflect the general progressivism of government assistance programmes.

[9] $Y_i^{equiv} = \frac{Y_i}{\sqrt{N_i}}$. Square root equivalisation entails dividing total household income for household i by the square root of its size, as described in OECD (2021).

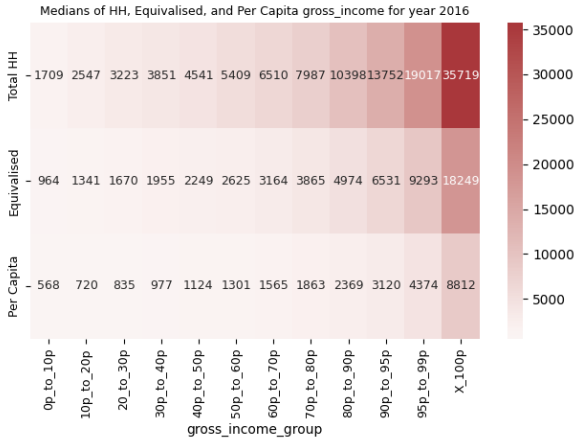
[10] Medians of the deciles of the total household income distribution are shown, except at the top decile, where the 90th to 95th, 95th to 99th and 100th percentiles are shown separately.

Figure 3: Median total household, equivalised and per capita gross income along the total household income distribution

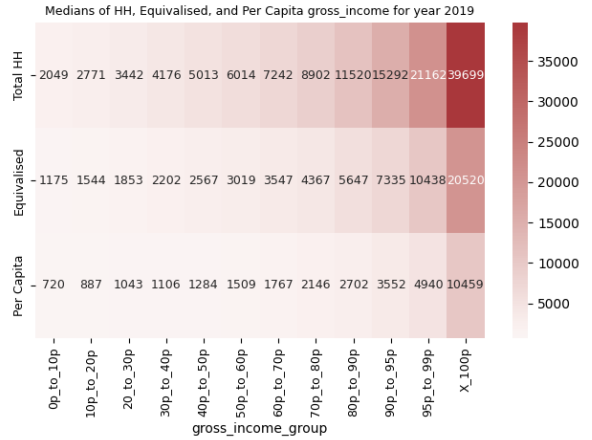
(a) 2014



(b) 2016



(c) 2019



(d) 2022

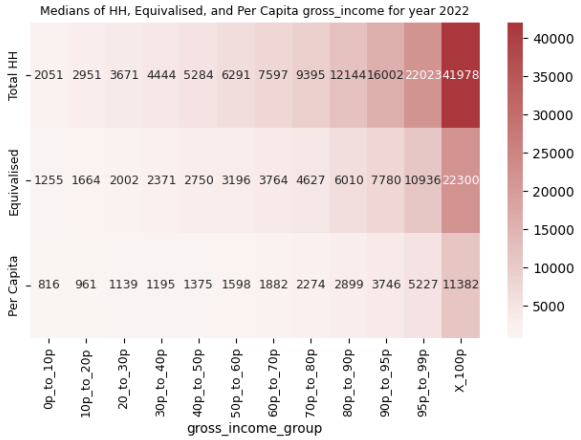
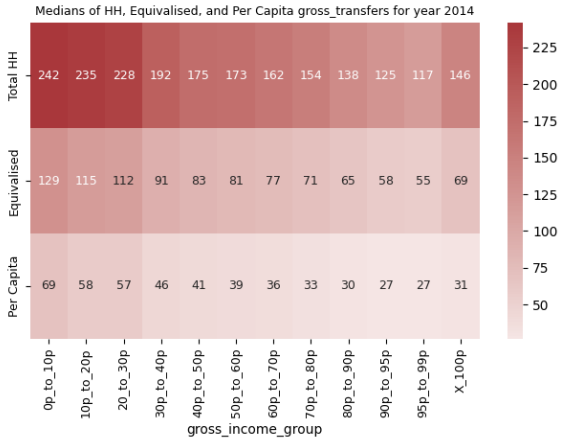
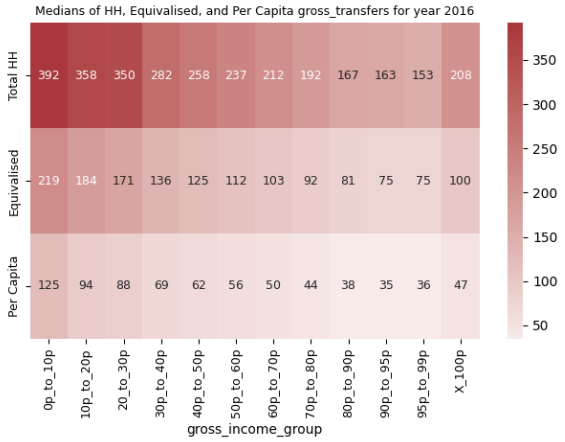


Figure 4: Median total household, equivalised and per capita gross transfers along the total household income distribution

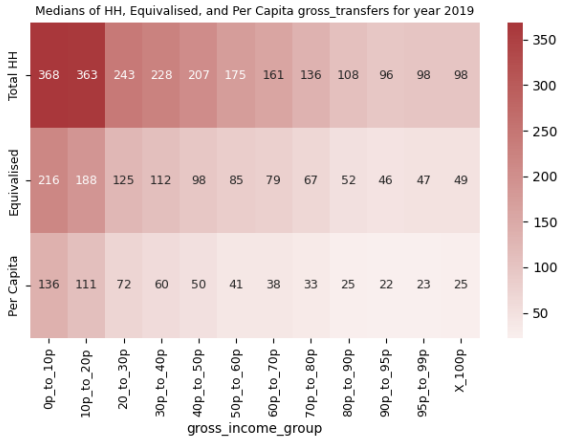
(a) 2014



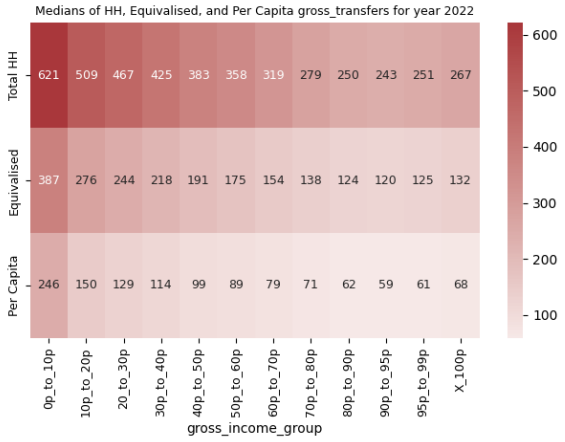
(b) 2016



(c) 2019



(d) 2022



With income out of the way, we then curate household spending along the income distribution. Figures 5 to 12 show boxplots of household consumption and various expenditure categories by income quintiles, such as fuel[11], as a percentage of household income. The top centile (100^{th}) is singled out.[12]

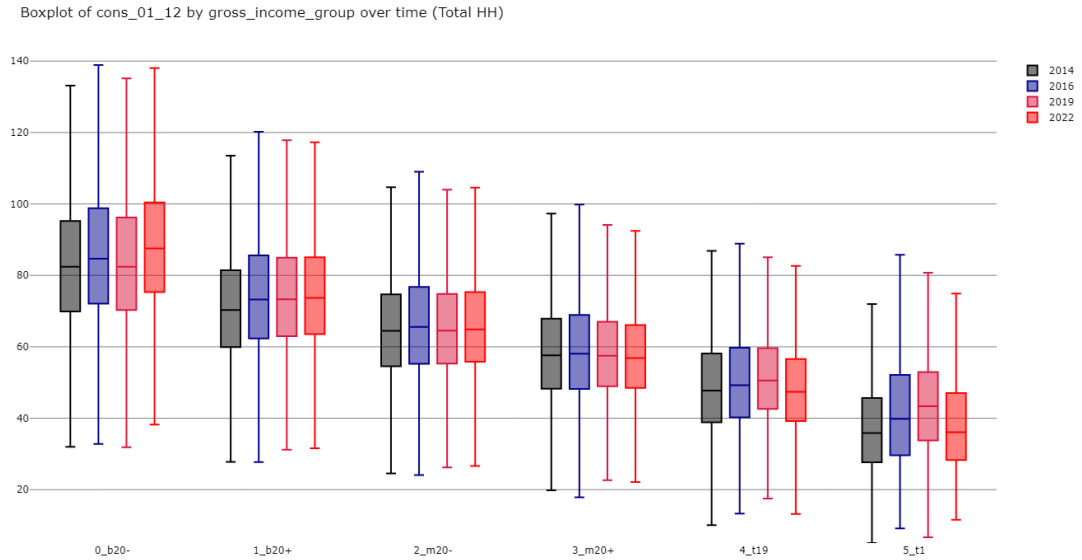
We begin with consumption expenditure in figure 5. Consistent with textbook theory, higher income households in Malaysia generally consumed less than lower income households as a percentage of income. Median consumption falls from about 80% of income for the bottom

[11]Fuel includes gasoline and diesel.

[12]Requests for additional cross-tabulation of welfare-relevant observables and income groups should be directed to the Department of Statistics Malaysia as accessing the underlying granular household-level data beyond the scope of this research used for the analysis requires separate and official permission.

quintile households (B20-) to about 40% for the top centile households (T1). The rate of decline is stable at about 10 percentage points of income per quintile. However, to single out the link between consumption and transfers, which is a subset of income, model adjustment is needed.

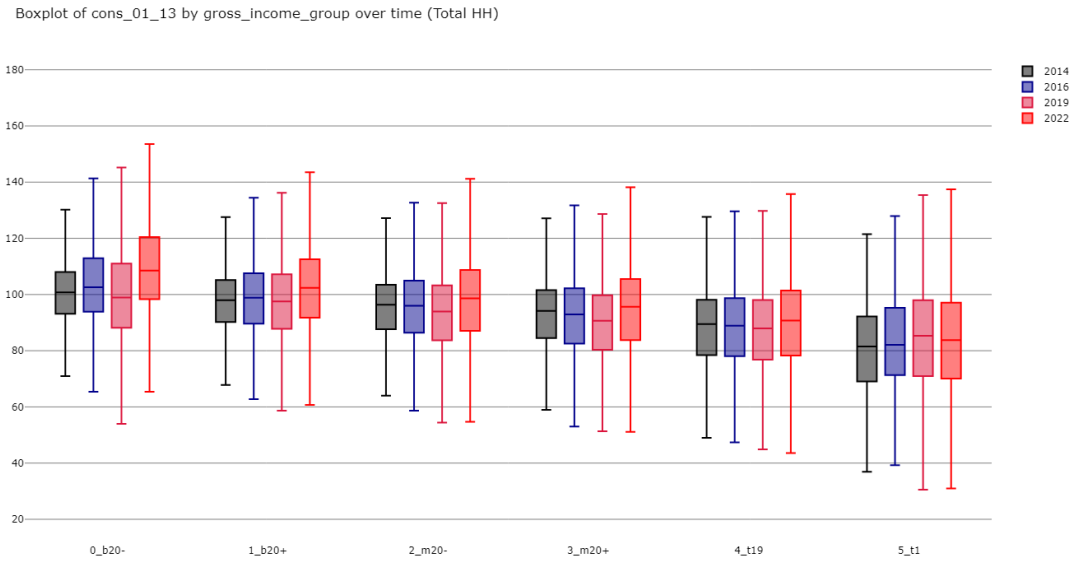
Figure 5: Boxplot of consumption (% of income) by income groups



When non-consumption expenditure, such as loan repayments are included in figure 6, there is less heterogeneity across the income distribution. The median households of each income group spent close to 100% of income. As the HIES is a snapshot of households' expenditure and income, a substantial share of households spent more than their income, which is not unique to Malaysia.[13] This could reflect utilisation of credit facilities by households, credit-rationing by lower income households who find accessing credit to be more difficult that higher income households, and the perceived security of future income streams by households by spending part of future income via credit.

[13]For example, Board of Governors of the Federal Reserve System (2022) reported that 19% of adults surveyed in the 2022 Survey of Household Economics and Decisionmaking (SHED) spent more than their income. Bui et al. (2024) also reported dissavers (defined as households with expenditure exceeding income) amounting to about one-third to half of households in small-scale surveys conducted in Thailand and Vietnam during the COVID-19 pandemic.

Figure 6: Boxplot of consumption and financial expenses (% of income) by income groups



Several descriptive statistics affirm the orthodoxy of consumption behaviour amongst Malaysian households along the income distribution. First, the disparity in non-alcoholic food and beverages spending (a necessity) between income groups is relatively clear. Figure 7 shows that the lowest quintile spent about 20-25% of income, while the highest quintile excluding the top centile spent about 8% of income. At the top centile, spending on this category is negligible, with most reporting less than 5% of income spent. Second, the bottom income quintile households spent more than other quintiles on on housing and utilities, which includes imputed rent, actual rent, fixtures and utilities (figure 8). However, spending amongst the subsequent quintiles are close to each other at about 10-15% of income.

Figure 7: Boxplot of non-alcoholic food & beverages spending (% of income) by income groups

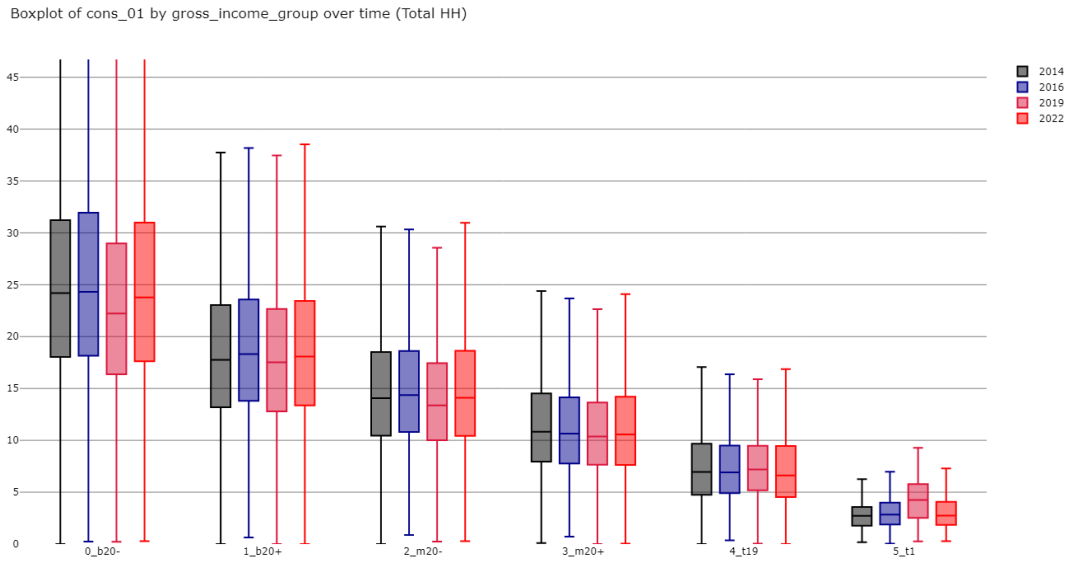
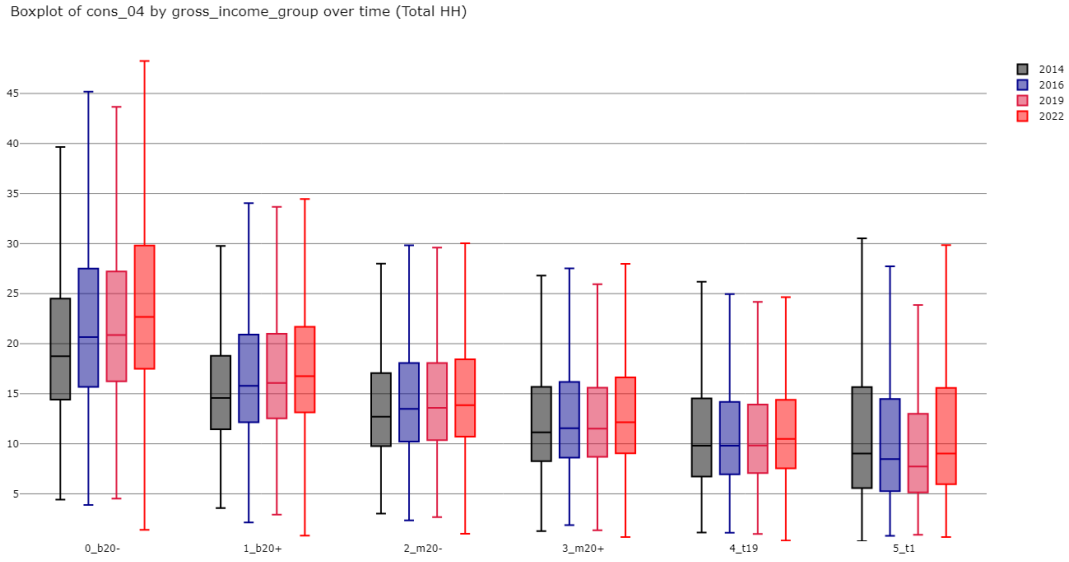


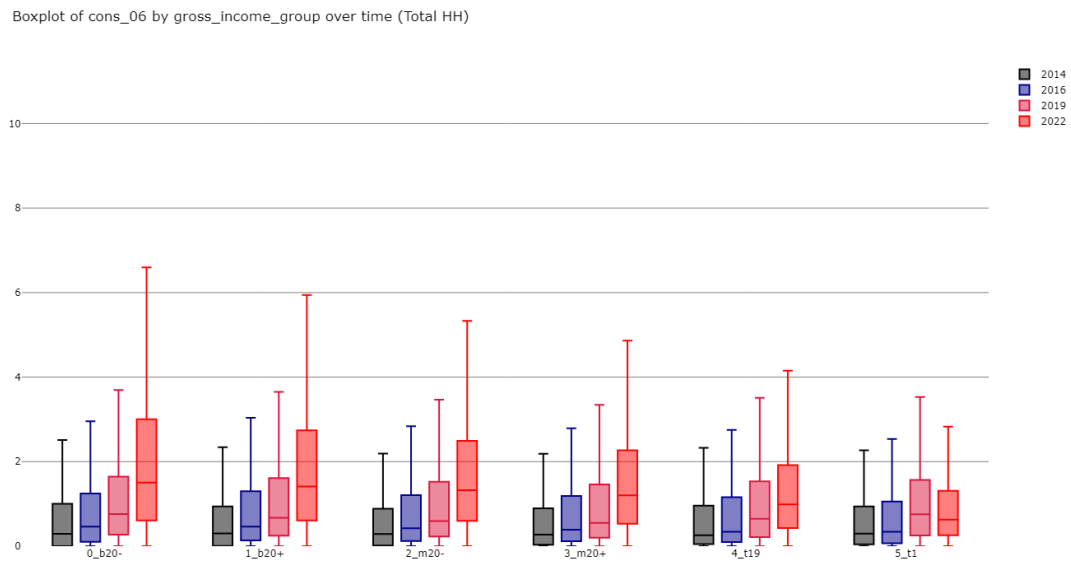
Figure 8: Boxplot of housing & utilities spending (% of income) by income groups



Healthcare spending (figure 9) is relatively homogeneous, which rarely exceeded 4% of income. Despite an apparent upward trend, median healthcare spending amounted to less

than 1% of income.[14] These observations may stem from three factors. First, Malaysia has a fully funded public healthcare with negligible price tags for citizens, which exists alongside a sizeable private healthcare sector. Second, healthcare product prices in the private sector likely increased, hence the uptrend over 2014-22. Third, healthcare access is rationed due to capacity limits despite being de jure universal. The low expenditure observed could be suboptimally low. Further research on this specific area is required before drawing healthcare-specific policy conclusions.

Figure 9: Boxplot of healthcare spending (% of income) by income groups



When expressed in % of income, the distribution of fuel and transportation expenditure across income groups is diametric to that of in levels. Conventionally, we expect richer households to spend more on fuel and transportation, reflecting higher ownership of personal transport vehicles and hence fuel consumption amongst richer households. When scaled against income, the opposite is true. Median spending on transport and fuel is mostly even across all income groups at about 5-10% of income, except for the top centile at about 3-5% (figure 10). This holds even if big ticket items (vehicles and maintenance) are excluded in

[14]Publications of directly comparable statistics from household surveys scaled to household income are scarce. However, out-of-pocket (OOP) healthcare expenditure as a percentage of GDP is well-documented and can serve as a cross-country comparator. OECD-surveyed advanced and emerging economies (Organisation for Economic Co-operation and Development (OECD) 2022) reported OOP healthcare expenditure amounting to between 0.5% (Luxembourg and South Africa) to 3.3% (Malta) of GDP in 2022. Amongst emerging economies, Turkey reported OOP healthcare expenditure of 0.7% of GDP, Argentina at 2.4% and India at 1.5%. Amongst advanced economies, the US reported 1.9% of GDP, UK at 1.6% of GDP and Germany at 1.4%. In comparison, Malaysia (Malaysian Ministry of Health 2019) reported OOP expenditure of 1.5% of GDP in 2019.

figure 11 and for only fuel expenditure in figure 12. This empirical fact underscores the importance of considering the welfare impact of reshaping transportation policies and fuel subsidies on poorer households.

Figure 10: Boxplot of transport & fuel spending (% of income) by income groups

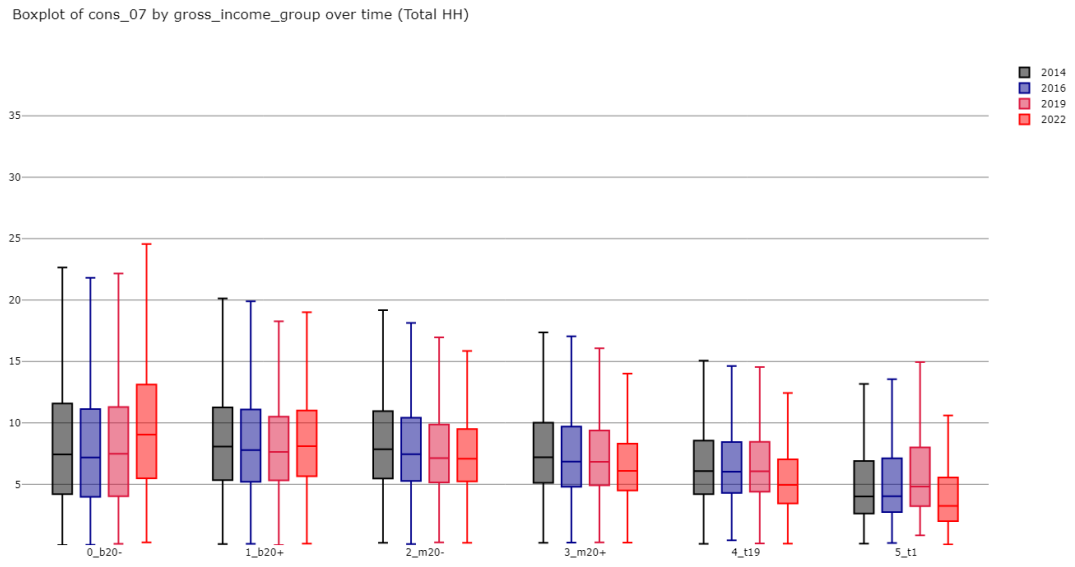


Figure 11: Boxplot of transport & fuel, excluding vehicles and maintenance, spending (% of income) by income groups

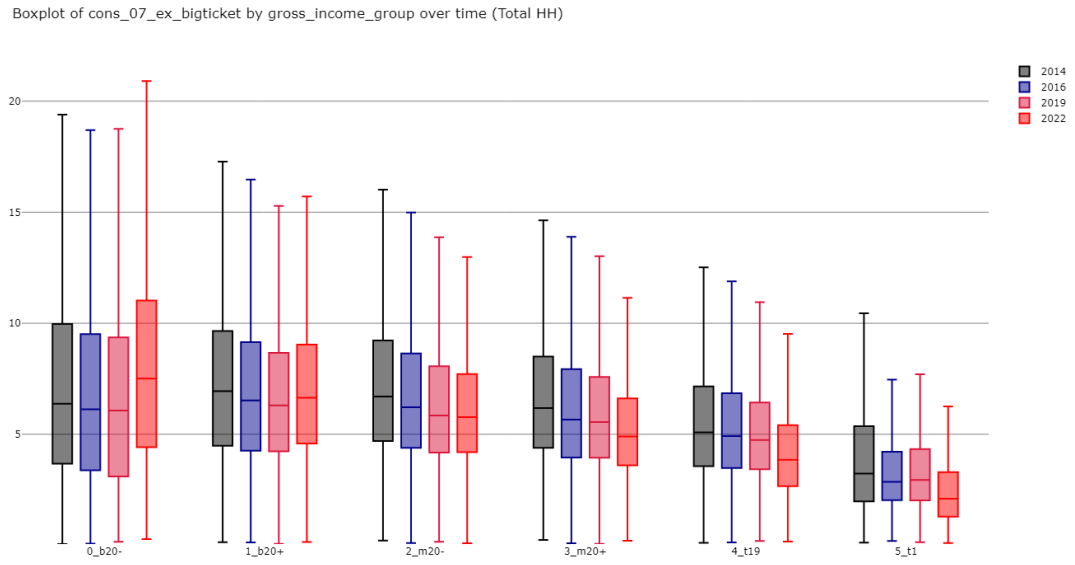
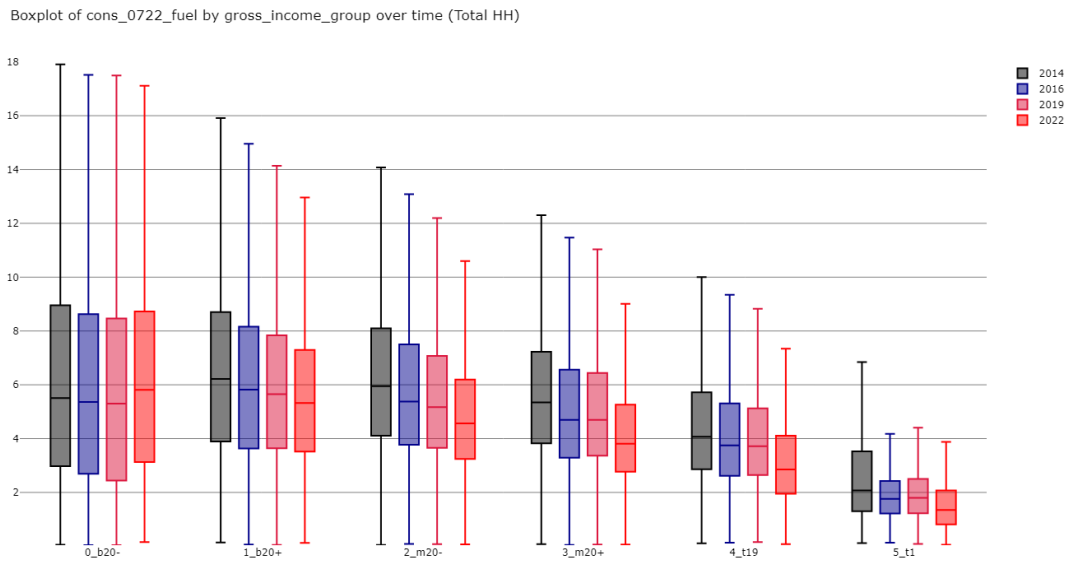


Figure 12: Boxplot of fuel spending (% of income) by income group

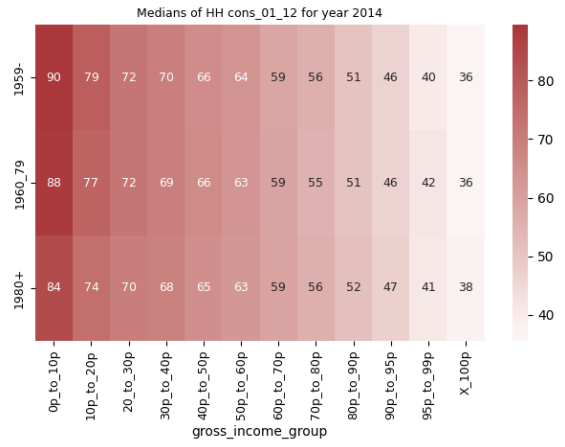


A plausible explanation for the variation in expenditure across income groups is that it reflects life-cycle allocation of income — as individuals age and retire, hence likely move from higher to lower income brackets, they begin to draw down on savings. To discern if the charts earlier reflect the changes in consumption behaviour affiliated with income growth or life-cycle behaviour, we further stratify consumption along the income distribution by birth years, shown in figures 13a to 13d. If the life-cycle explanation dominates, then conditional on being in the same income group, we can expect households whose head are older to spend a meaningfully larger share of income than younger ones. While this is observed for the bottom three to four income deciles (first 4 columns of each figure), the differences are small. Amongst the bottom decile in 2022 (first column in figure 13d), households whose head are born on or after 1980 spent about 90% of total income, while those born on or before 1959 spent 98% of income (a difference of 8% of income). The corresponding age-spending gap for the 2014, 2016 and 2019 vintages are 6%, 4% and 7%, respectively. In the top 6 income deciles, consumption also do not visibly differ between birth year groups, provided that the households are in the same decile. On balance, the life-cycle allocation of expenditure shows up in observed household consumption and income data at least for the lower income households but is unlikely to dominate the change in consumption-savings behaviour along the income distribution. Taken as is, policymakers may consider age as an additional delineating factor for cash transfers if they are interested in maximising the macroeconomic effects of transfers programmes. Granted, this could make the implementation of such social assistance policies excessively complex. Nonetheless, for the purpose of estimating MPCs from transfers, adjusting for birth year groups when estimating MPCs to account for any

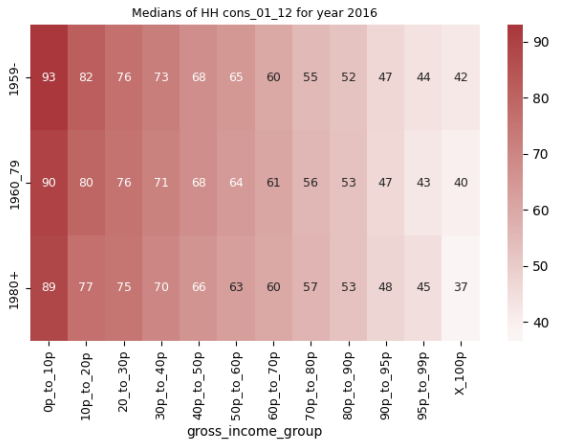
observable life-cycle behaviour is warranted.

Figure 13: Median consumption as a % of income along the total household income distribution

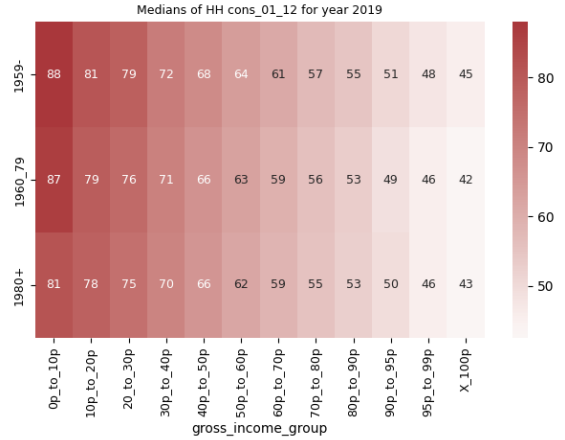
(a) 2014



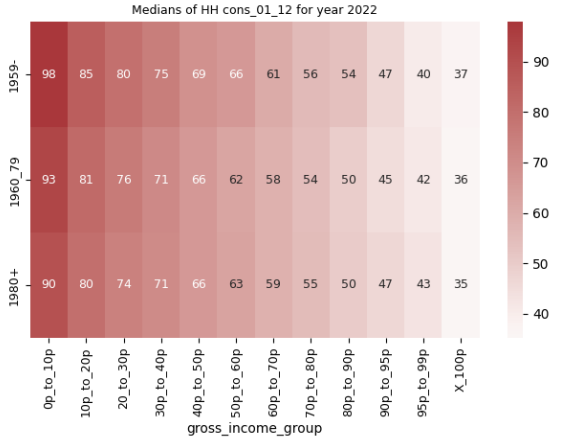
(b) 2016



(c) 2019



(d) 2022



4 Pseudo-panel fixed effects analysis

With the pseudo-panel data constructed using cohorts of observables described in table 2, we estimate a fixed effects regression model (equation 1). Verbeek (2008) described this approach of analysing cohort pseudo-panel data using fixed effects models. For cohort c, year t and income group y, $C_{ct}^{(y)}$ is the mean consumption, $T_{ct}^{(y)}$ the mean transfers, $\varepsilon_{ct}^{(y)}$ the error term and $\alpha_c^{(y)}$ the cohort fixed effects. The MPC for income group y is then $\beta^{(y)}$. We

estimate $\beta^{(y)}$ for each income quintile separately[15], as well as for the full sample.[16]

$$C_{ct}^{(y)} = \alpha_c^{(y)} + \beta^{(y)} T_{ct}^{(y)} + \varepsilon_{ct}^{(y)} \tag{1}$$

Before discussing the interpretation of $\beta^{(y)}$, there are two outstanding issues on estimation.

The first concerns the construction of cohorts. Verbeek (2008) argued that the choice of cohorts should be akin to instruments in instrumental variables approaches. Weis & Axhausen (2009) also noted that cohort variables should be time-invariant. In this paper, the cohort variables (table 2) are background characteristics of households, hence reasonable to assume that they are predetermined before consumption decisions. For instance, the ethnicity of the head of household cannot be determined after receiving income and making consumption decisions. The analysis should be reasonably acceptable as long as the cohort variables exclude time-variable factors that can be altered due to revealed consumption choices. Moreover, Dhruva et al. (2013) showed with the 2009 HES that these variables are related to components of income, hence consumption, supporting instrument relevance.

The second concerns constructing separate pseudo-panels for each income quintiles with the same cohort variables. As the income groups are defined based on the income distribution within each vintage, households can move across income quintiles. For example, a household that is surveyed for both years may show up in the bottom quintile in the first vintage and another in the subsequent vintage. However, as discussed in section 2, in the absence of true panel data, the use of cohort-averages is a methodological compromise. An implicit assumption when interpreting the MPCs estimated is that when households (or households with similar characteristics) move from one income group to another, conditional on background characteristics, change the parameters governing their income-spending relationship to match that of those in the new income group.[17]

The MPC $\beta^{(y)}$ then refers to the association between transfers and expenditure, conditional on cohort variables, hence how much expenditure is expected to change when income changes

[15]This corresponds to the B20- (0^{th} to 20^{th} percentiles), B20+ (20^{th} to 40^{th}), M20- (40^{th} to 60^{th}), M20+ (60^{th} to 80^{th}) and T20 (80^{th} to 100^{th}) income groups.

[16]The appendix further reports MPC estimates by income quintiles and for the full sample for households stratified by ethnicity of the head of household (figure A.3), strata (figure A.2), birth years of the head of household (figure A.4) and gender of the head of household (figure A.5). In general, MPCs were lower for higher income groups than for lower income groups over the B20- to M20+ segments. Estimates for the T20 segment, when stratified, may reflect volatility arising from excessive slicing and splicing beyond that of the main analysis.

[17]Additionally, see discussion on income mobility in section 2.

by MYR1. This is similar to Dhruva et al. (2013) and Dhruva et al. (2015) who described their estimates as how much household spending responds to disposable income (regression analysis with the 2009 HES) and as the long-run relationship between aggregate private consumption and aggregate household disposable income (error correction model analysis with 2002-13 Malaysian macroeconomic data). Both papers framed MPC as simply a model-adjusted relationship between income and spending without asserting directional causality, which requires a experimental setup or at the very least a 'natural experiment'. Generally, ascribing causality is difficult in repeated cross-sectional surveys, single cross-sectional surveys and macroeconomic time series analysis. Nevertheless, empirical estimates of MPCs from real-world settings can be useful for policymakers where experimental conditions are difficult to replicate. Moreover, the time skip of two to three years between HIES vintages means that the MPCs reflect long-term relationships between transfers and spending.[18]

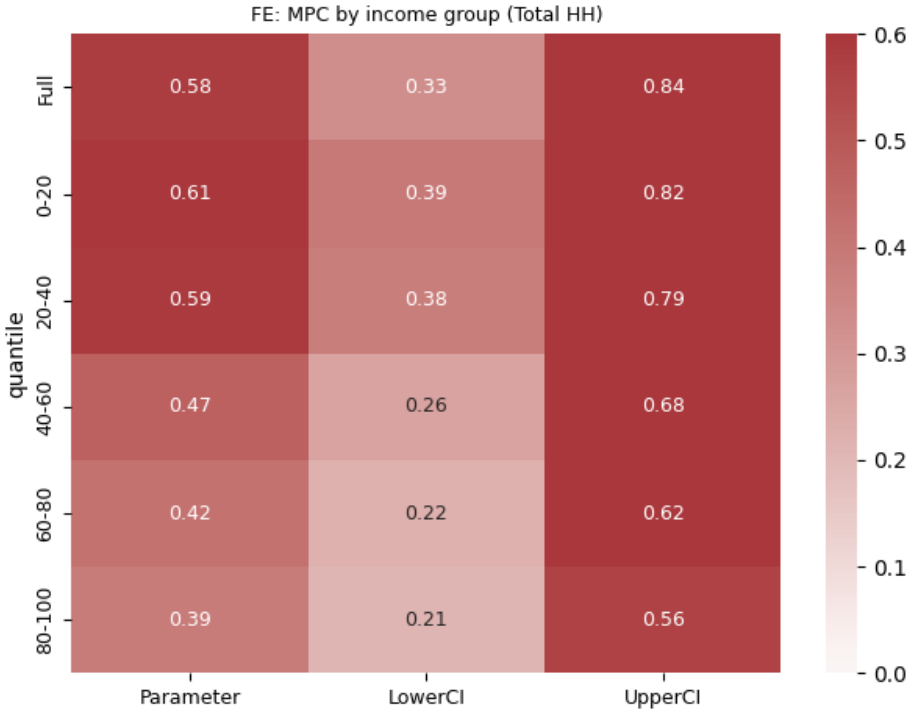
Figure 14a shows the MPCs for the full sample and by income quintiles, while figure 14b shows the corresponding regression statistics. Amongst the B20-, every MYR1 increase (decrease) in mean transfers is associated with a MYR0.61 (95%CI: 0.39 to 0.82) increase (decrease) in mean consumption. The corresponding MPCs are 0.59 (95%CI: 0.38 to 0.79) for the B20+, 0.47 (95%CI: 0.26 to 0.68) for the M20-, 0.42 (95%CI: 0.22 to 0.62) for the M20+ and 0.39 (95%CI: 0.21 to 0.56) for the T20. The MPC for the full sample is 0.58 (95%CI: 0.33 to 0.84), which is close to that of the B20+.[19] These estimates, like estimates in Dhruva et al. (2013) with the 2009 HES, show that MPCs declined along the income distribution. Quantitative differences are expected for three reasons. First, Dhruva et al. (2013) was a cross-section analysis of household-level data rather than a panel analysis of cohort-level data. Second, Dhruva et al. (2013) estimated the MPC from income, whereas this paper estimates the MPC from transfers. Third, Dhruva et al. (2013) segmented households by MYR1,000 buckets rather than income quintiles. Nonetheless, the MPCs in this paper are comparable to those from Suah (2023)'s analysis of aggregate transactions data in 2020-22, which were between 0.231 to 0.431.

[18]Ideally, surveys fielded with at least an annual frequency should be used. Nonetheless, the literature has precedence in using repeated cross-sections with long time skips, such as in Bobonis et al. (2015), Sabelhaus & Feiveson (2018) and Boachie et al. (2022).

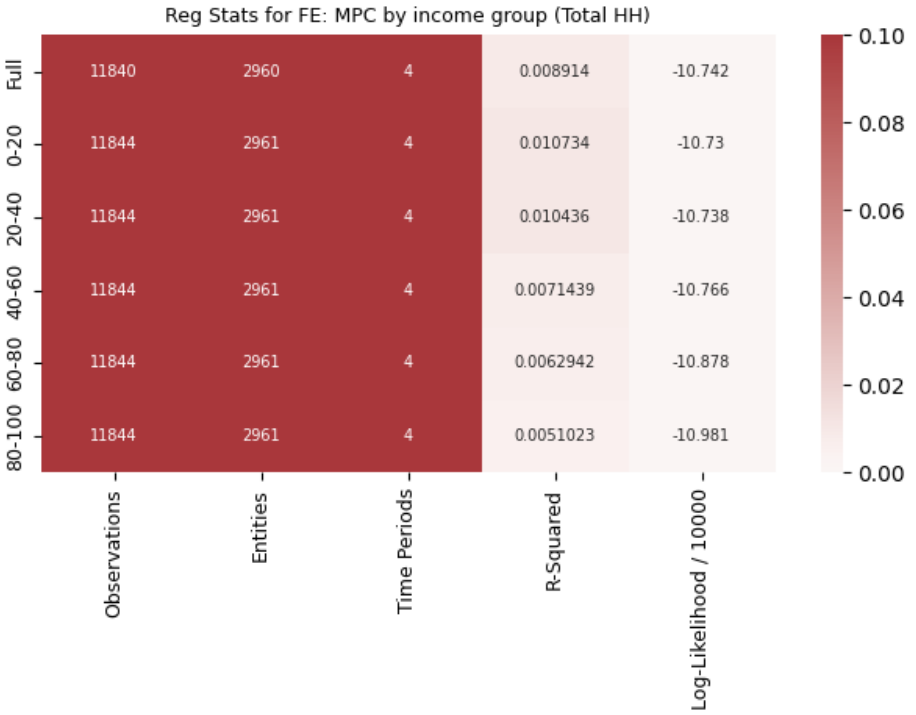
[19]The 95% confidence intervals are computed with heteroscedastic-robust standard errors. Confidence bands that exclude 0 indicate statistical significance at a 5% level.

Figure 14

(a) Pseudo-panel fixed effects estimates of marginal propensities to consume from transfers by income groups



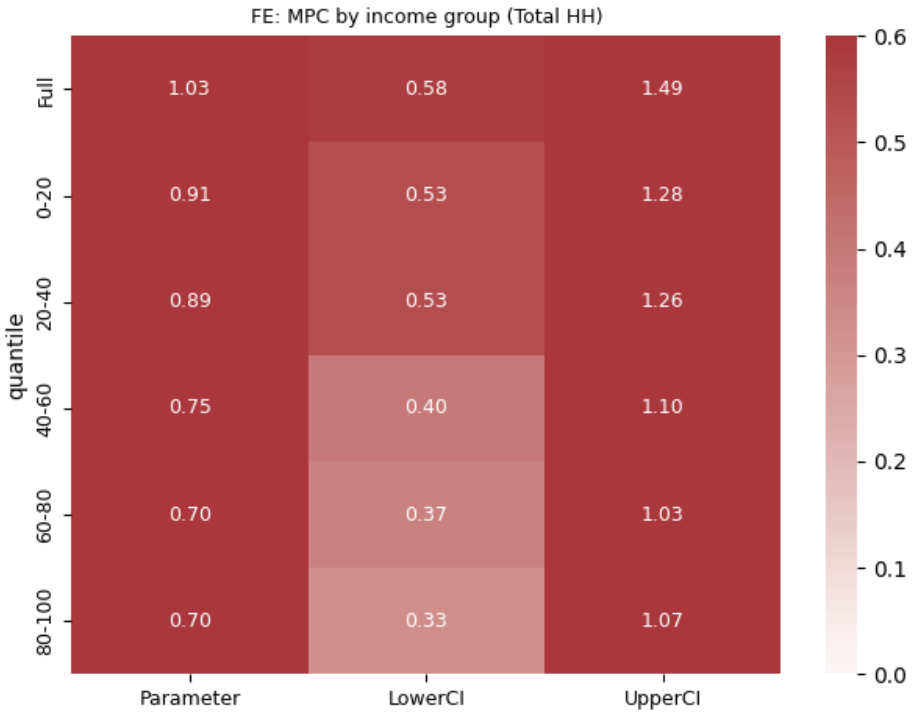
(b) Pseudo-panel fixed effects regression statistics: MPC for consumption



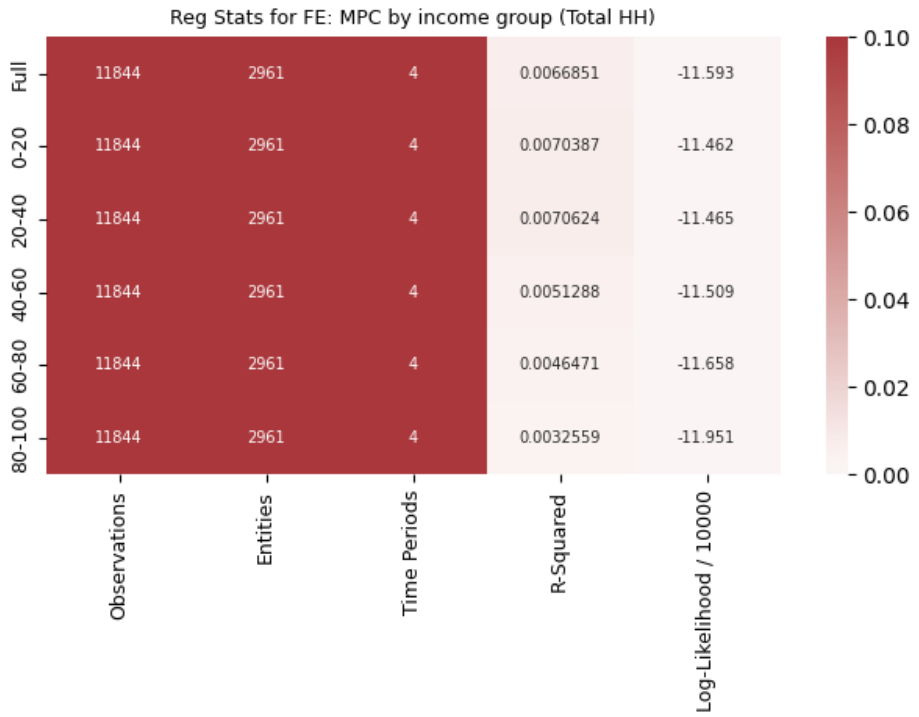
A natural follow-up question is how much of these transfers are saved after accounting for all expenditure, essentially the marginal propensity to save (MPS), $1 - \beta^{(y)}$. Figure 15a shows the MPCs for total consumption and financial expenses for the full sample and by income quintiles, while figure 15b shows the corresponding regression statistics. These MPCs range from 0.7 (95% CI: 0.33 to 1.07) amongst the T20 to 0.91 (95% CI: 0.53 to 1.28) amongst the B20-, essentially a downtrend along the income distribution. A major limitation is that financial expenses (also shown in figure 6) here include both loan repayments and payments related to acquisition of financial assets, e.g., equity. Hence, the MPCs for consumption (14a), and consumption including financial expenses (figure 15a) serve as the upper and lower bounds for inferring the MPS from transfers, which ranges from 0.3-0.61 amongst the T20 to 0.09-0.39 amongst the B20-. Not unlike conventional wisdom, the share of transfers saved tend to be larger amongst the richer households. The relatively substantive gap between both sets of MPS suggest that a sizeable portion of transfers received are redirected to paring down debt repayments and possibly saved as financial instruments.

Figure 15

(a) Pseudo-panel fixed effects estimates of MPC for consumption and financial expenses from transfers by income groups



(b) Pseudo-panel fixed effects regression statistics: MPC for consumption and financial expenses



While cash transfers are unconditional in that they are not tied to specific expenditures, unlike food stamps and redeemable vouchers, policymakers may still be interested in how different types of spending co-move with transfers. For instance, the effect of unconditional transfers on food spending may be of interest if the policy is a result of a consolidation of a variety of conditional assistance aimed at addressing food affordability. To investigate this, we estimate equation 2, which essentially replaces the dependent variable in equation 1 with category h-specific mean spending $C_{ct}^{(y,h)}$.

$$C_{ct}^{(y,h)} = \alpha_c^{(y,h)} + \beta^{(y,h)} T_{ct}^{(y)} + \varepsilon_{ct}^{(y,h)} \tag{2}$$

The MPCs for all 15 spending sub-categories by income quintiles $\beta^{(y,h)}$ are shown in figure 16.[20] The same MPCs are also grouped by spending categories in figures A.1a to A.1q in the appendix.

The estimated MPCs show that specific categories may be driving the downtrend in headline

[20]The distributions of spending on select categories by income groups are also displayed in figures 7 to 12 earlier.

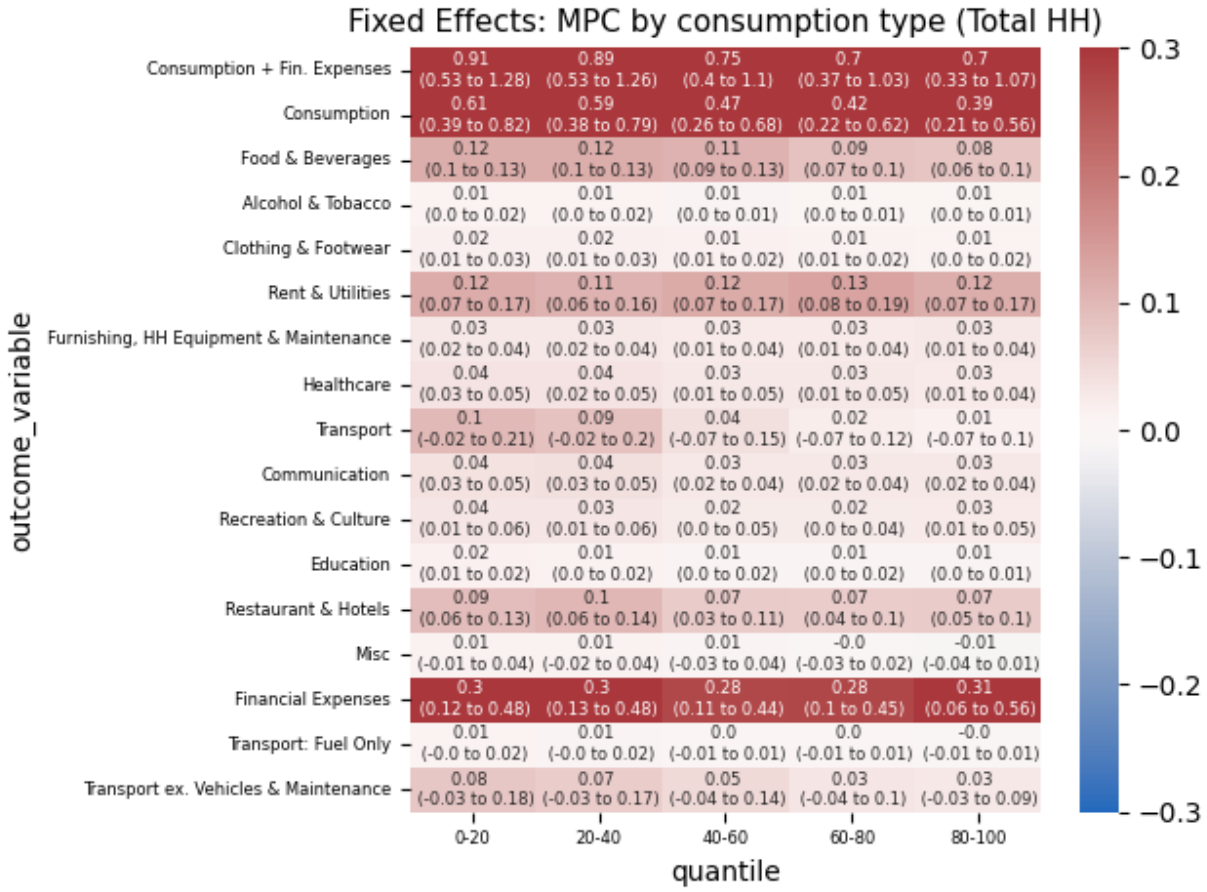
MPC along the income distribution. The MPCs for transport and its subcategories, fuel and transport excluding vehicles and maintenance exhibited the most drastic downtrend. The MPCs for expenditure on non-alcoholic food and beverages, transport, and restaurant and hotels also displayed a visible downtrend. For instance, the estimated MPCs for non-alcoholic food and beverages fell from 0.12 (95%CI: 0.1 to 0.13) for the B20- to 0.08 (95%CI: 0.06 to 0.1) for the T20. As most MPCs of the remaining categories, a mixture of discretionary and non-discretionary spending, are relatively small and stable along the income distribution, the downtrend in headline MPC may be primarily attributable to these select categories (non-alcoholic food and beverages, transport, and restaurant and hotels).

Moreover, the MPCs estimated for discretionary consumption categories tend to be larger than that of non-discretionary consumption categories, except for spending on restaurant & hotels.[21] Additionally, these categories, except for rent & utilities, also tended to trend downwards along the income distribution. These estimated MPCs suggest that for every 1MYR of transfers received, households spent a majority on these non-discretionary items, as well as restaurants & hotels, which categorically includes basic restaurant establishments. For instance, the MPCs ranged from 0.08 to 0.12 for food & beverages, 0.11 to 0.13 for rent & utilities, and 0.01 to 0.1 for transport. By comparison, the MPCs out of transfers for other discretionary categories ranged from 0.01 (alchohol & tobacco) to 0.04 (recreation & culture). In sum, the findings here suggest that households primarily spend transfers on necessities and restaurants rather than disproportionately discretionary items, hence aligned with cash transfers programmes aimed at alleviating cost of living concerns.

The income contours in the estimated MPCs are useful for calibrating cash transfers programmes with specific welfare goals, e.g., improving food affordability, replacement for fuel subsidies and countercyclical economic support for restaurants. For instance, a subsidy replacement cash transfers programme may seek to overweight the lower income households in its disbursement for maximal coverage of higher fuel and transportation cost post-removal of subsidies. In contrast, if the primary aim of a cash transfers programme is to increase healthcare utilisation, then differentiation by income groups yield little efficiency gains as the estimated MPC is similar across all income groups.

[21] For the purpose of this discussion, **non-discretionary consumption** refer to food & beverages, rent & utilities, healthcare, transport, communication, and education; **discretionary consumption** refers to alcohol & tobacco, clothing & footwear, furnishing, household equipment & maintenance, recreation & culture, restaurant & hotels and miscellaneous spending.

Figure 16: Pseudo-panel fixed effects estimates of marginal propensities to consume from transfers by spending category and income group



Note: Figure shows the estimated MPCs for total consumption and financial expenses, consumption and 15 spending sub-categories stratified by income quintiles. In each cell, the point estimates of the MPCs are shown on the top and the 95% confidence interval in parentheses at the bottom. "Transport: Fuel Only" and "Transport ex. Vehicles & Maintenance" are subsets of "Transport". All other sub-categories are mutually exclusive and collectively exhaustive.

5 Conclusion

This paper presents a two-part analysis on household income and spending with the 2014, 2016, 2019 and 2022 HIES.

First, a descriptor of household income and expenditure categories along the income distribution over the years in Malaysia using the four most recent HIES vintages. The gaps in income within the top decile were similar to that of between the top and bottom deciles, whether income is expressed in equivalised, per capita or total household terms. Transfers diminished

in income, which partly reflects progressivism in government assistance over the past decade. Total household consumption and most subcategories as a share of income declined along the income distribution but not in select subcategories, e.g., healthcare, transport and fuel.

Second, estimation of MPCs from transfers, rather than total income, along the income distribution that incorporates HIES vintages spanning nearly a decade (2014-22). To balance between the incorporation of variation over time and that the HIES is a cross-section survey not designed to tracked a panel of households, a cohort pseudo-panel analysis was implemented as a methodological compromise. This provides policymakers a focused interpretation of how spending co-moves with transfers disbursed via cash assistance programmes. The estimated MPCs ranged from 0.61 (95%CI: 0.4 to 0.82) amongst households in the bottom income quintile to 0.39 (95%CI: 0.21 to 0.56) amongst those in the top income quintile. A stratified analysis of MPCs by expenditure type then shed light on the specific spending subcategories drove the downward slope in MPCs along the income distribution. The MPCs of necessities, such as non-alcoholic food and beverages, fuel and transport, as well as restaurant and hotel expenditures diminished MPCs along the income distribution. These subcategorical MPCs may be useful for calibrating cash transfers programmes with specific welfare goals (e.g., replacements for fuel and transportation subsidies).

Nonetheless, there are limitations. Without granular panel data and given that cross-sectional analysis may result in estimation bias due to the lack of time dynamics, this paper opted for a cohort pseudo-panel analysis as a methodological compromise. The benchmark for estimating MPCs empirically is with household- or individual-level panel data or with 'natural experiments'. However, the pseudo-panel data set here is constructed with 12 cohort variables, substantially richer in granularity than most pseudo-panel studies that typically face a shortage of observables to construct cohorts on. The time skip between vintages is also relatively large at about 2 to 3 years, hence the MPCs reflect long-term dynamics.

Overall, this paper yields three policy implications. One, cash transfers ought to be wide encompassing as implemented in Malaysia, given that the income distribution is largely flat, except at the top end. Two, cash assistance should be tiered in favour of lower income households as a larger share tend to translate into actual expenditure, hence larger welfare effects per ringgit transferred. Three, government data infrastructure ought to be improved to maximise observation of income, given that administrative data sources are likely to only cover the formal sector and higher-income earners. While surveys such as the HIES can estimate income and spending in a representative manner, the implementation of policies require nationally comprehensive administrative data.

Data and replication statement

Codes are made available at github.com/suahjl/impact-household. Access to the original data requires separate and official permission from the Department of Statistics Malaysia.

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- Mohamad Hasni Sha'ari, Bank Negara Malaysia

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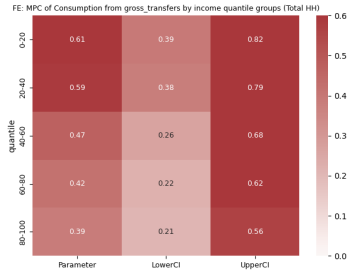
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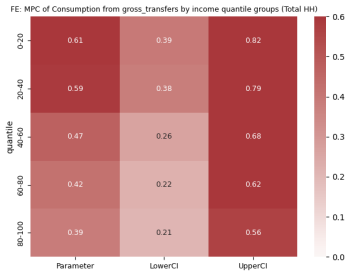
A Additional findings from the pseudo-panel fixed effects analysis

Figure A.1: Estimated marginal propensities to consume from transfers by spending category and income group

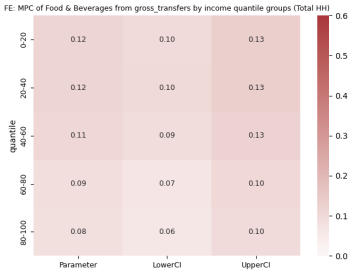
(a) Consumption



(b) Consumption and Financial Expenses



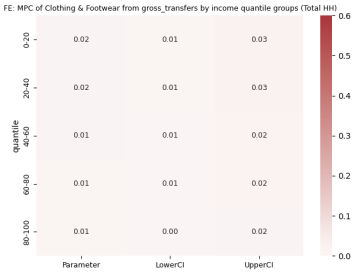
(c) Food & Beverages



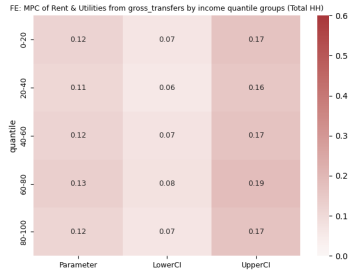
(d) Alcohol & Tobacco



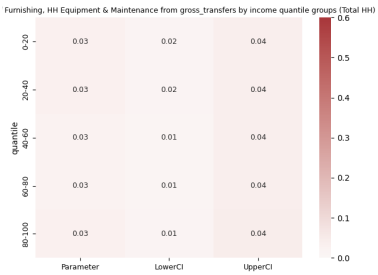
(e) Clothing & Footwear



(f) Rent & Utilities



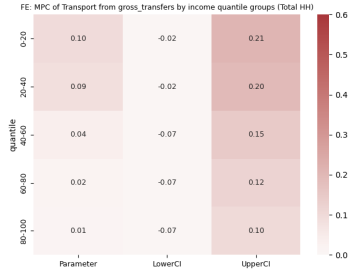
(g) Furnishing, HH Equipment & Maintenance



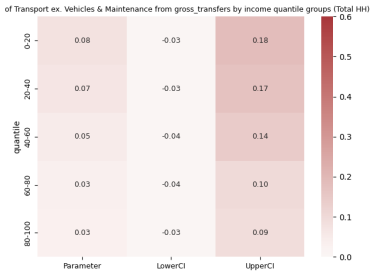
(h) Healthcare



(i) Transport



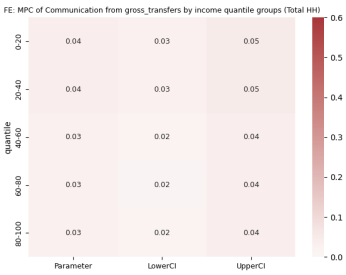
(j) Transport ex. Vehicles & Maintenance



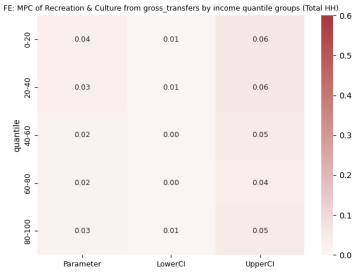
(k) Fuel



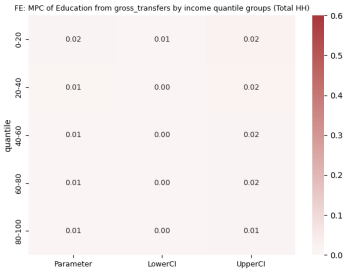
(l) Communication



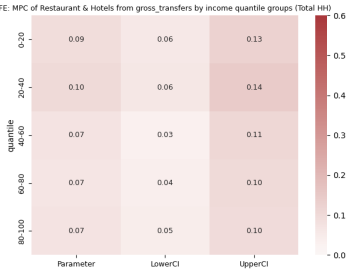
(m) Recreation & Culture



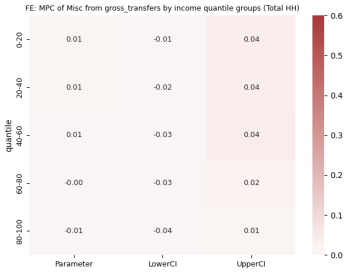
(n) Education



(o) Restaurants & Hotels



(p) Miscellaneous



(q) Financial Expenses

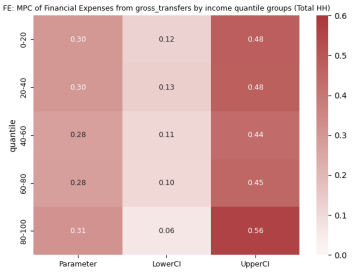


Figure A.2: Stratified by strata (urban = 1; rural = 0): Pseudo-panel fixed effects estimates of marginal propensities to consume from transfers by income groups

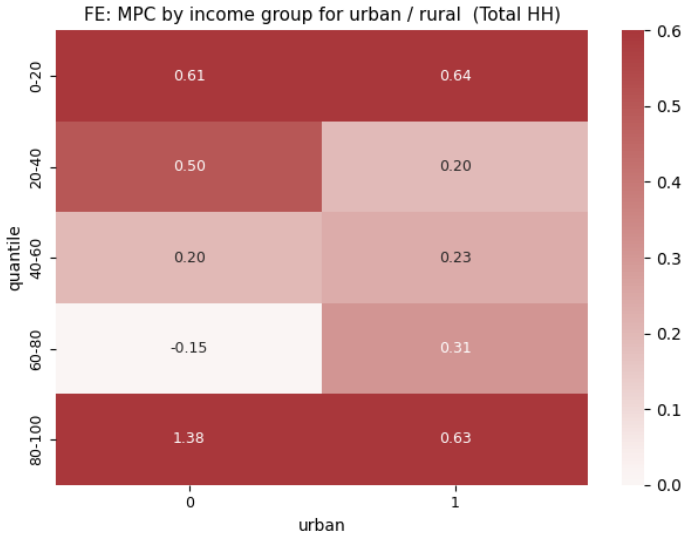


Figure A.3: Stratified by ethnicity: Pseudo-panel fixed effects estimates of marginal propensities to consume from transfers by income groups

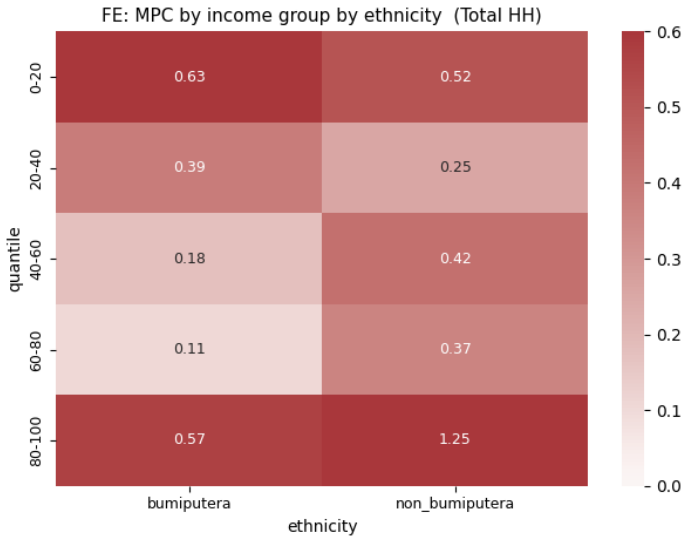


Figure A.4: Stratified by birth years: Pseudo-panel fixed effects estimates of marginal propensities to consume from transfers by income groups

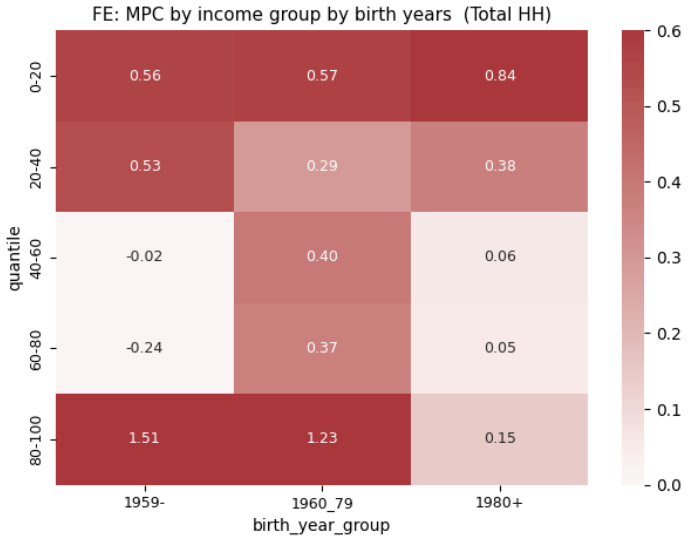


Figure A.5: Stratified by gender: Pseudo-panel fixed effects estimates of marginal propensities to consume from transfers by income groups

