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Abstract

This paper examines how monetary policy impacts household consumption across different income, wealth, and age groups in Malaysia. Using data from the 2022 Household Income and Expenditure Survey (HIES) by the Department of Statistics, Malaysia (DOSM), we quantify the effects of various transmission channels, including net interest rate exposure and indirect income channels, at the household level. We then compare the average impact across quintiles of income, wealth, and age groups. Our analysis reveals that while focusing on individual transmission channels may exaggerate disparities, given different effects for different households, an aggregate view across all channels shows a relatively uniform impact across households. Following a hypothetical contractionary monetary policy shock, low-income households face greater challenges from a tighter labour market but are less affected by higher debt repayments due to limited credit access. In contrast, high-income households experience the opposite effects.

Keywords: Monetary policy, Household income and wealth distributions, Household finance
JEL Codes: E52, D31, G51

†Any views expressed are solely the author's and should not be taken to represent those of the Central Bank of Malaysia. Any errors or omissions in this paper are the sole responsibility of the author.

1 Introduction

The aggregate transmission and macroeconomic effects of monetary policy on inflation and growth are well-documented in the literature. However, the micro-level impact across heterogeneous agents is less understood. Although research has expanded in recent years, it remains nascent, particularly in emerging market economies such as Malaysia. This issue has gained prominence in Malaysia post-COVID-19. Interest rate increases during monetary policy normalisation have raised public concerns. These concerns focus on higher debt repayment burdens and financial strain among lower-income households and small businesses. Inspired by McKay and Wolf (2023), this paper aims to estimate the distributional effects of contractionary monetary policy on households in Malaysia. We first analyse each transmission channel individually and then aggregate the results. We will then examine the average impact across income, net worth, and age groups to uncover distributional effects along these dimensions. In addition to highlighting household-level responses to monetary policy shocks, a more detailed micro-level analysis can reveal how the effectiveness of monetary policy at the aggregate level may depend on household-specific characteristics.

The transmission channels to households can broadly be categorised as direct or indirect. Direct channels stem from changes in households' net balance sheets. For example, an increase in the policy interest rate raises interest payments for households with net outstanding debt. At the same time, it may increase interest income for those holding net interest-bearing financial assets. Indirect effects, on the other hand, operate through general equilibrium responses in prices and wages, affecting labour earnings and employment. A rise in the policy rate reduces household consumption and business investment. This leads to a fall in output, which in turn puts downward pressure on employment and wages. The subsequent reduction in output due to lower employment and wages constitutes the indirect effect. The impact of these channels will intuitively vary across households, depending on their balance sheets and the exposure of their labour earnings and employment.

This paper aims to assess the relative importance of these channels in Malaysia using data from the 2022 Household Income and Expenditure Survey (HIES) conducted by the Department of Statistics, Malaysia (DOSM). By analysing the heterogeneous balance sheets and incomes of households across income, net worth, and age distributions, we seek to understand how these channels operate differently across these dimensions. Our findings suggest that focusing on any single channel in isolation may exacerbate the unequal impact of monetary policy, but when considered collectively, the impact appears more evenly distributed. For example, while low-income households may suffer more from a tighter labour market, they are less affected by higher debt repayments due to limited credit access. Conversely, high-income households, though more insulated from labour market pressures, are more exposed to higher debt repayments due to larger outstanding debts.

While this paper focuses on some key direct and indirect channels, several additional mechanisms that may shape household-level consumption responses to monetary policy are not covered. First, variation in the composition of consumption baskets, including differences in exposure to durable goods over time, may affect sensitivty to interest rates. Second, heterogenous inflation experiences across households (Cravino et al., 2020), may lead to varied real income effects and consumption responses. Third, changes on the supply side, such as firms' pricing behavior, may influence consumption patterns by altering relative prices. These mechanisms are highly relevant for a comprehensive assessment of monetary policy's heterogeneous effects, but they are not considered here due to data and methodological limitations.

Given that focusing on individual transmission channels may exaggerate disparities, an aggregate view across all channels shows a relatively uniform impact across households. This finding suggests that monetary policy should focus on its core mandate of maintaining macroeconomic stability, rather than pursuing explicit distributional objectives. A stable macroeconomic environment enables fiscal policy to more effectively address distributional concerns through targeted interventions. Nevertheless, central banks should continue to monitor heterogeneity across households, as it can shape transmission and effectiveness. Communication that is to some extent informed by knowledge of distributional effects in the pursuit of the macroeconomic stability mandate can strengthen understanding of policy decisions and support more effective expectations management.

The remainder of the paper proceeds as follows. In Section 2, the literature review is discussed. Section 3 presents the data used. Section 4 discusses the employed methodology. Section 5 presents the results. The final Section 6 concludes the paper.

2 Literature Review

The significant developments in the Heterogeneous Agent New Keynesian (HANK) literature over the past few years have opened new avenues for revisiting the transmission mechanism of monetary policy (Kaplan et al., 2018). In contrast to the traditional Representative Agent New Keynesian (RANK) framework, where monetary policy affects household consumption primarily through intertemporal substitution between consumption and saving due to unexpected changes in the interest rate, the HANK framework presents a more nuanced understanding of these effects. Luetticke (2021) found that heterogeneity in portfolio responses to monetary shocks also matters, in addition to the intertemporal substitution channel. In RANK, the intertemporal substitution channel plays a dominant role, but in HANK models, this channel is more muted and not the only pathway through which monetary policy operates.

The HANK framework captures additional channels of monetary policy transmission, both direct and indirect. As discussed in Slacalek et al. (2020), direct effects on household consumption from policy rate changes can generally be categorised into two broad mechanisms: the intertemporal substitution channel and the net interest rate exposure channel. The latter reflects how households' varying levels of exposure to interest rate changes (e.g., borrowers vs. savers) affect their consumption decisions. In addition to these direct effects, HANK models also take indirect channels into consideration. These include the indirect labor income effects, where changes in employment and wages due to a monetary policy shock affect consumption; Fisher effects, where nominal long-term assets are revalued due to inflation expectations; and capital gains effects, where changes in asset prices, such as housing and stocks, impact household wealth and thus consumption. These indirect channels typically operate through general equilibrium responses in the economy. For example, a monetary policy contraction reduces household consumption and firm investment. This lowers output, employment, and wages, which in turn further dampens aggregate demand. This feedback loop illustrates the essence of the indirect effects. The decomposition of monetary transmission channels into direct and indirect effects is crucial for offering a more nuanced perspective of the impact of monetary policy at the household level, as highlighted in recent theoretical developments (Auclert, 2019; Gornemann et al., 2016).

The magnitude of these indirect effects depends significantly on households' marginal propensities to consume (MPC) from these channels, but HANK models suggest that these indirect effects tend to be much larger than those captured by RANK models (Slacalek et al., 2020). As a result, RANK models may underestimate the overall impact of monetary policy on household consumption and may not capture the nuances of constrained households, who lack the liquidity to smooth consumption over time. For these households, the intertemporal substitution channel is ineffective. They are forced to consume based on their available income, highlighting the limitations of RANK models in addressing household heterogeneity. By incorporating household heterogeneity, HANK models are also better equipped to explain aggregate consumption responses that align more closely with empirical results from models like vector autoregressions (VARs). This decomposition of consumption channels enables HANK models to better account for country-specific differences in monetary transmission. Although in some cases the outcomes of models between HANK and RANK may not significantly differ, Broer et al. (2020) found that the HANK framework can help identify other transmission mechanisms that may not be captured by a representative agent framework.

To quantify the various transmission channels in HANK models, the literature typically employs two broad strategies. The first approach involves constructing rich Dynamic Stochastic General Equilibrium (DSGE) models that incorporate detailed household heterogeneity, allowing for a comprehensive analysis of business cycles and policy counterfactuals (Alves et al., 2020; Auclert and Rognlie, 2018). However, this approach often involves significant computational complexity. The second approach involves making simplifying assumptions to derive analytical solutions that provide clearer insights into the underlying mechanisms (Slacalek et al., 2020; McKay and Wolf, 2023). While this method may not fully capture the richness of household behaviour, it offers a transparent and tractable framework for understanding the relative magnitudes of the different monetary policy transmission channels. In this paper, we follow the second approach and aim to quantify the relative magnitude of the various monetary policy transmission channels. By focusing on these key channels, we hope to provide a clearer understanding of how monetary policy affects household consumption, especially in the context of heterogeneous households in Malaysia.

3 Data

The data used in this paper are divided into two main categories: macroeconomic variables and the Household Income and Expenditure Survey (HIES). The macroeconomic variables are employed in estimating VAR models. This approach helps assess real price changes across six different transmission channels in response to a contractionary monetary policy shock at the aggregate level. The HIES data is then used to map these aggregate estimates to household-level exposures. This mapping allows us to calculate subsequent changes in household consumption. A more detailed explanation of the empirical application of these data is provided in Section 4.

3.1 Macroeconomic Variables

This paper uses quarterly macroeconomic variables to estimate the VAR models. The acronyms, descriptions, and data sources for these variables are provided in Table 1 below.

Acronyms	Description	Source
rgdp	Real GDP	Department of Statistics, Malaysia (DOSM)
gdflt	GDP deflator	DOSM
inf	Inflation, annualised logarithmic change in GDP deflator	DOSM
pop	Population, constant quarterly population from annual data	DOSM
coe	Nominal compensation of employees	DOSM
housing	Total household housing wealth[1]	National Property Information Centre (NAPIC)
bursa	FTSE Bursa Malaysia index	Bursa Malaysia
tbill3	Quarterly average of 3-month Malaysia Treasury Bills	Bank Negara Malaysia (BNM)
alr_housing	Average lending rate on new mortgages	BNM
alr_other	Average lending rate on new other loans	BNM

Table 1: Macroeconomic variables used in VARs

The six different transmission channels that are evaluated are constructed based on the macroeconomic variables above as shown in Table 2 :

While the impact of a contractionary monetary policy shock on the six transmission channels is estimated at the aggregate level, the selected macroeconomic variables are chosen to align as closely as possible with household-level exposures as defined in Section 3.2, based on the HIES. These variables are then mapped to the corresponding household exposures to estimate the distributional effects across households. Nonetheless, some of the macroeconomic variables chosen may not perfectly reflect the detailed micro-level exposures captured in the HIES. Their selection is guided by data availability constraints, with the aim of approximating household exposure as accurately as possible.

[1]Housing wealth is calculated as total housing stock (for residential property) * average house price from NAPIC.

Transmission channels	**Construction**
#1 Real labour earnings	log real per capita of COE: $\ln(\text{coe}) - \ln(\text{pop}) - \ln(\text{gdflt})$
#2 Return on cash and cash equivalents	Annualised inflation measured by GDP deflator: inf
#3 Real return on housing	Log real per capita of housing wealth: $\ln(\text{housing}) - \ln(\text{pop}) - \ln(\text{gdflt})$
#4 Real return on stock	Real Bursa index return: $\ln(\text{bursa}) - \ln(\text{gdflt})$
#5 Real average lending rate on new mortgages	Real alr_housing: $\frac{\text{alr\_housing}}{100} - \frac{\text{gdflt}}{100}$
#6 Real average lending rate on new other loans	Real alr_other: $\frac{\text{alr\_other}}{100} - \frac{\text{gdflt}}{100}$

Table 2: Transmission channels

Firstly, inflation is used to proxy the return on cash and cash equivalents, due to its direct and erosive effect on the purchasing power of these assets. For deposits, we estimated the impact of monetary policy shocks on the real average fixed deposit (FD) rate. While FD rates do respond to policy shocks, the estimated transmission to real FD returns was relatively muted. This may reflect the averaging of rates across tenures with heterogeneous sensitivities, as well as deposit pricing influenced by banks' funding strategies and competitive pressures. When liquidity is ample or alternative funding sources are cheaper, banks may not fully adjust FD rates in line with policy changes. Additionally, strong competition for deposits may lead banks to smooth or delay rate changes to protect market share and margins, dampening the overall transmission to real FD returns. Given this relatively smaller variation in real FD returns than that of cash, for the purpose of approximating the household-level return on liquid assets, we adopt the return on cash as a conservative and simplifying proxy. While deposits nominally earn interest, the limited sensitivity of real deposit rates to monetary policy shocks may suggests that inflation dominates the real return dynamics for both components, justifying the use of inflation as a common return measure.

Secondly, for the mortgage channel, the real average lending rate on new mortgages is used. Ideally, we would prefer the rate on outstanding mortgages to match the HIES classification. However, such data are not available.

Lastly, for other loans, we use a weighted average lending rate on new personal, securities, and other-purpose loans, with weights based on historical loan volumes. Optimally, we would use a rate reflecting all outstanding loan repayments, consistent with the HIES definition, but this is constrained by data limitations. For new lending rates across mortgages, and other loans, changes may reflect bank competition and other factors, alongside policy rate changes.

3.2 Household Income and Expenditure Survey (HIES)

This paper utilises the 2022 vintage of the Household Income and Expenditure Survey (HIES), conducted by the Department of Statistics, Malaysia (DOSM) twice within any five-year period. The HIES collects detailed data on household income, expenditure, and various demographic characteristics across Malaysia. The data from the HIES[2] can be broadly classified into three categories: (1) gross income, which includes salaried wages, other forms of wages, asset income, and gross transfers; (2) consumption expenditure, referring to household spending on goods and services; and (3) non-consumption expenditure, which encompasses transfer payments, loan repayments, fixed capital formation expenses, and acquisition of financial assets. To assess households' exposure to the six monetary transmission channels analysed in this paper, the following monthly flow variables were extracted from the 2022 HIES:

1. Labour earnings: Monthly salaried wages + Monthly other wages.
2. Cash and cash equivalents: Monthly (Cash + Deposits + Residual income[3] + Retained profits from business).
3. Housing value: Proxied using monthly imputed rentals of owner-occupiers for the main residence.
4. Stocks: Monthly purchase of household shareholdings.
5. Mortgage: Monthly total mortgage payments.[4]
6. Other loan repayments: Monthly total repayment of loans for furniture/fittings (home), business, personal, education, investment, and household expenses.

[2]It is important to note that there may be discrepancies with the HIES 2022 official summary statistics due to our limited access to a subsample of the full HIES dataset and variations in data processing methods. Given our lack of full visibility of the entire sample, our quintile calculations are based solely on the subsample available to us, rather than the weighted estimations that require complete access to the entire dataset.

[3]Residual income = Gross income - Consumption and non-consumption expenditure.

Net worth is calculated from the monthly flow of total assets and liabilities extracted from the HIES 2022 data. For a detailed breakdown of the components of total assets and liabilities, please refer to Figure 1. The assets and liabilities shown in bold in Figure 1 are considered sensitive to monetary policy and are included in one of the six transmission channels outlined above. Unbolded assets (5, 6, 7, and 9) typically constitute a small proportion of total household assets, and their detailed composition is unclear. Therefore, monetary policy shocks to these assets should have negligible effects on consumption. Similarly, since most car loans and credit card lending rates are fixed in Malaysia,[5] unbolded liabilities are assumed to be unaffected by monetary policy shocks.

For further details on the HIES data application, refer to Appendix A, which outlines data processing steps and provides a descriptive analysis of exposure to the six transmission channels across income, wealth, and age quintiles.

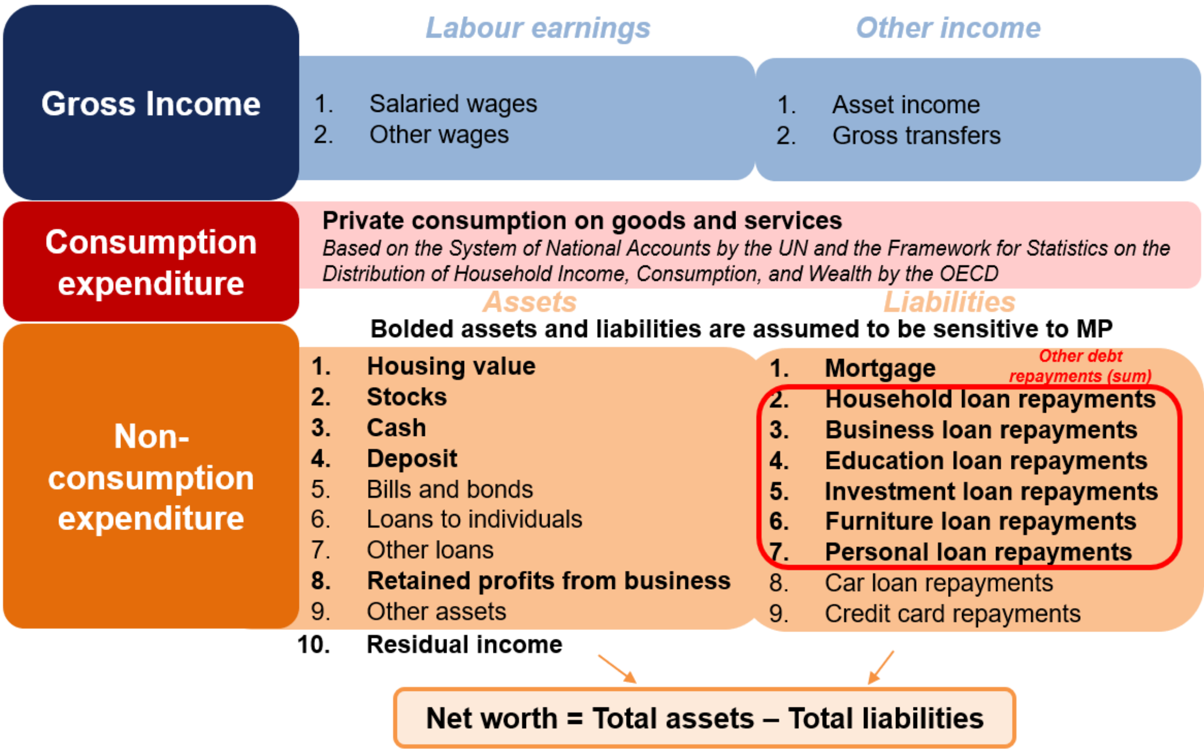

Figure 1: HIES data usage

[4]Include all mortgage loan repayments, regardless of the number of properties owned by the household.
[5]As of the end of 2022, 85.5% of car loans and 99.5% of credit card loans in Malaysia are fixed-rate, according to data from the Central Credit Reference Information System (CCRIS).

4 Methodology

This paper follows a similar approach to the indirect calculation of household consumption responses to monetary policy, as seen in McKay and Wolf (2023), applying this framework to the Malaysian context using data from the HIES. The theoretical foundation of this indirect calculation stems from the analytical decomposition introduced in Slacalek et al. (2020), which builds on the work of Auclert (2019), Kaplan and Violante (2018), and Patterson (2023). Rather than solving a complex household model that accounts for all transmission channels simultaneously, this paper examines the channels in isolation. This provides clearer insights and decomposition, guiding the empirical implementation. The individual channels capturing the effects of an exogenous monetary policy shock on household consumption can then be aggregated at the household level to assess how they vary across income, net worth, and age quintiles. Ultimately, the calculation of the consumption response to a monetary policy shock can be expressed as follows:

$$dc_i = \sum_j dp_j x_{ij} m_{ij}, \tag{1}$$

where:

- dc_i = Percentage change in consumption of household i after a contractionary monetary policy shock;
- dp_j = Percentage change in the 'price' of category $j \in \{\#1, \#2, \#3, \#4, \#5, \#6\}$ of the transmission channel;
- x_{ij} = Exposure of household i to price j; and
- m_{ij} = Marginal propensity to consume of household i out of cash-flows of type j.

There are three main components required to calculate the change in household consumption, dc_i. To determine dp_j, we will estimate the 'price' changes for each transmission channel following a contractionary monetary policy shock at the aggregate level using a simple recursive VAR model= (see Appendix B). The resulting shocks to these channels are then mapped to household heterogeneity based on their varying exposures x_{ij} to these channels, expressed as a share of total consumption using HIES data (see Appendix C). Additionally, the MPC, m_{ij} is allowed to vary across households along three dimensions: financial constraints, income quintiles, and transmission channels (See Appendix D). To assess the distributional impact of monetary policy, households are grouped into quintiles by income, net worth, and age, and the average change in consumption, dc_i, is calculated within each quintile.

4.1 Intuition Underlying the Empirical Results

Before delving into the results in Section 5, Table 3 and Figures 2, 3, 4 provide a comprehensive overview of the key drivers influencing the empirical results. The primary factor behind the distributional impact is the heterogeneity of household exposure across the various dimensions, as shown in Figures 2, 3, 4. It is important to note that the exposure is expressed in flow terms, prior to any transformation to stock,[6] and that labour earnings exposure has not yet been adjusted for the elasticity variations across income quintiles. Figures 2, 3, 4 also suggest that one of the primary contributors to consumption changes, resulting from an exogenous contractionary monetary policy, is the labour earnings channel due to its significant exposure levels. While asset exposure is also relatively large, its impact on consumption is more muted due to the assumption of lower MPCs for assets, as they tend to be illiquid or volatile. Although liabilities exposure appears minimal, it remains significant due to the more sensitive response to monetary policy, as reflected by their larger dp_j and higher MPCs. Table 3 highlights that the differences in magnitude across transmission channels, as seen in the main results, are influenced not only by household exposure but also by the aggregate price changes in each channel and their respective MPCs. This section serves as a useful reference point for interpreting the findings presented in the next section.

Transmission Channel	dp_j	x_{ij}	$m_{unconst}$	m_{const}
#1 Labour Earnings	-0.054%	`x_labour_earnings`	0.1 * m_{ijy}	m_{ijy}
#2 Cash	0.030%	`x_cash`	0.1 * m_{ijy}	m_{ijy}
#3 Housing Value	-0.051%	`x_housing`	0.03	0.03
#4 Stocks	-0.039%	`x_stock`	0.054	0.054
#5 Mortgage	0.30%	`x_mortgage`	0.8	1
#6 Other Loans	0.24%	`x_oth_loan`	0.8	1

Table 3: An overview of the key drivers of consumption inequality across transmission channels

[6] As further elaborated in Appendix C, the conversion of household-level exposure from flow to stock is done by assuming that household stocks are equivalent to annualised monthly flows across all transmission channels. The conversion is done to get a more accurate estimate of the magnitude of consumption response in the absence of detailed balance sheet data.

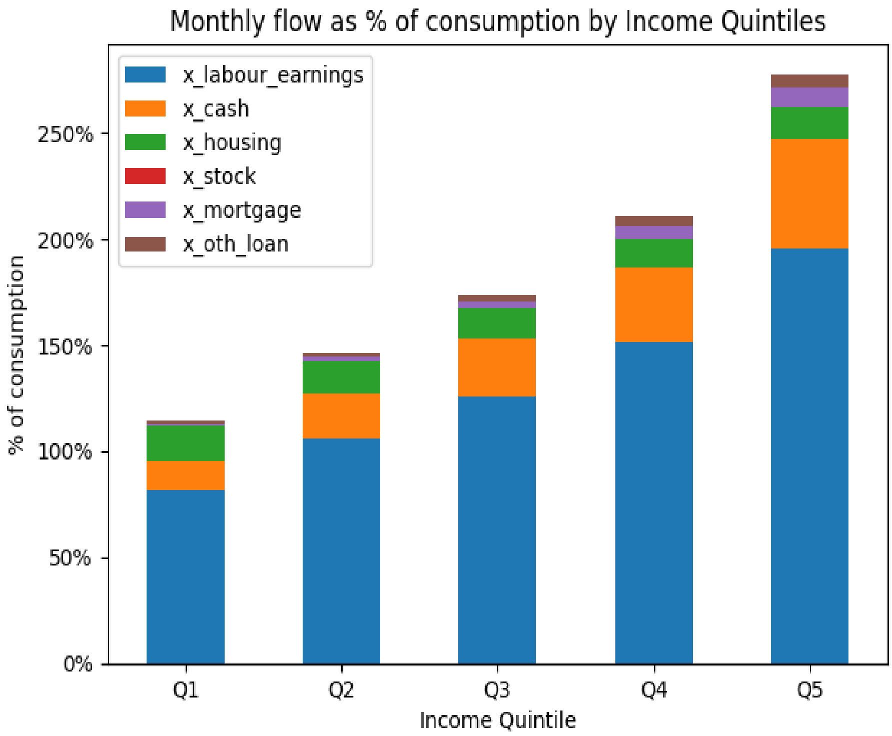

Figure 2: Household monthly flow exposure by transmission channel across income quintiles

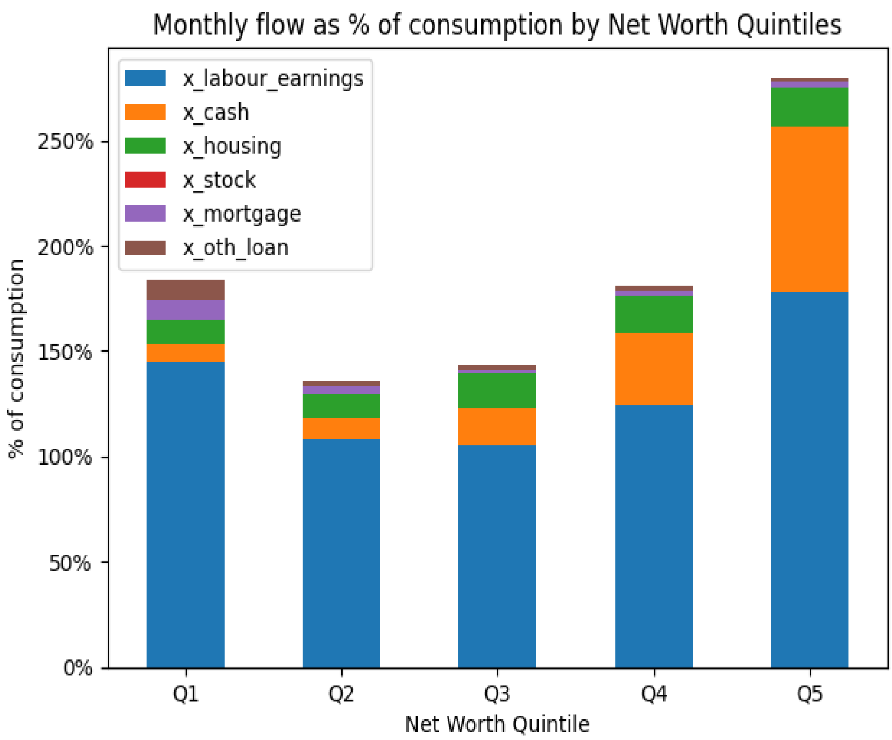

Figure 3: Household monthly flow exposure by transmission channel across net worth quintiles

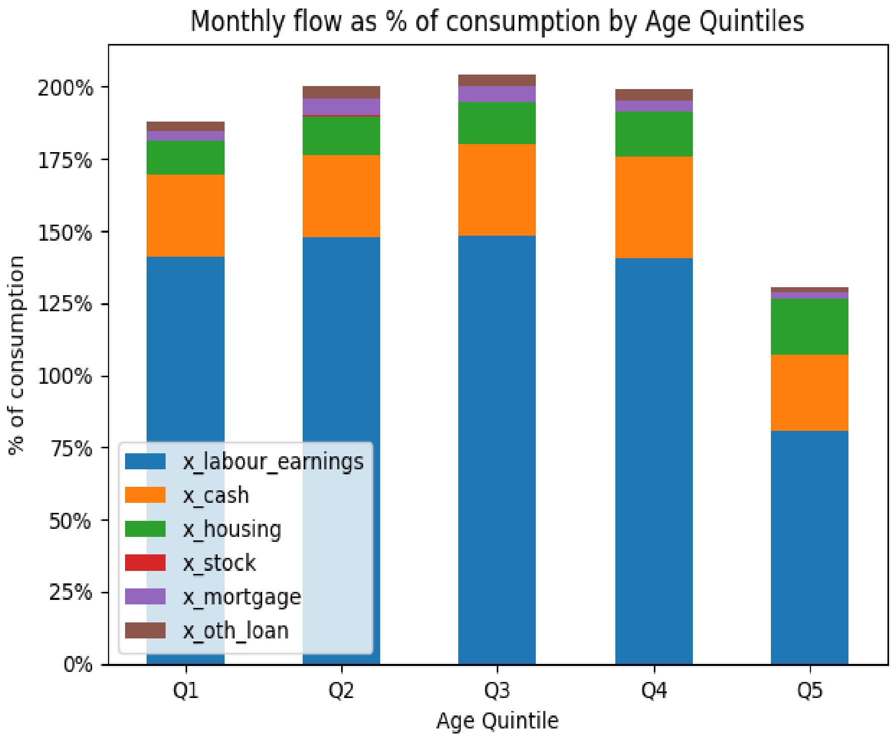

Figure 4: Household monthly flow exposure by transmission channel across age quintiles

5 Results

This section presents the distributional impact of contractionary monetary policy (MP) on households, segmented by income, net worth, and age quintiles. Given that most Malaysian mortgages are variable-rate contracts,[7] the asymmetry between expansionary and contractionary shocks is unlikely to be significant. The results follow the methodology discussed in Section 4, calculating the average change in consumption, dc_i, for each group. The findings provide insight into how different transmission channels influence household consumption across these dimensions.

Across income, net worth, and age quintiles, the cash, housing, and stock channels appear to be muted. As illustrated in Table 3, the cash channel is weak across all dimensions, characterised by relatively smaller values of dp_j. Similarly, the housing and stock channels exhibit limited effects, primarily due to their reliance on more illiquid or long-term assets that have lower MPCs.

[7]Variable-rate contracts adjust automatically with interest rate changes, reducing the asymmetry that arises under fixed-rate contracts where refinancing is possible when rates fall but not when they rise.

5.1 Income Distribution

As shown in Figure 5, contractionary MP tends to have a more pronounced impact on higher-income households. This is mainly due to their larger debt obligations, despite their relatively resilient labour earnings. The labour earnings channel plays a central role in the consumption response, particularly for lower-income households. These households are more vulnerable to job insecurity and lower bargaining power. They face a more immediate decline in consumption, even though their absolute exposure to labour earnings may be smaller compared to higher-income households. The mortgage channel disproportionately affects higher-income households, as they typically hold larger mortgages, and in some cases, multiple mortgages. Additionally, other loan repayments follow a similar pattern, with higher-income households bearing the brunt of these obligations due to their greater borrowing capacity. Despite these significant channels, lower-income households are not entirely insulated from MP effects; they face greater exposure to economic volatility but generally have smaller debt burdens. Overall, higher-income households experience larger consumption declines through the debt channels, despite stronger labour earnings protection. McKay and Wolf (2023) also found that the average consumption response following a monetary policy shock increases in income.

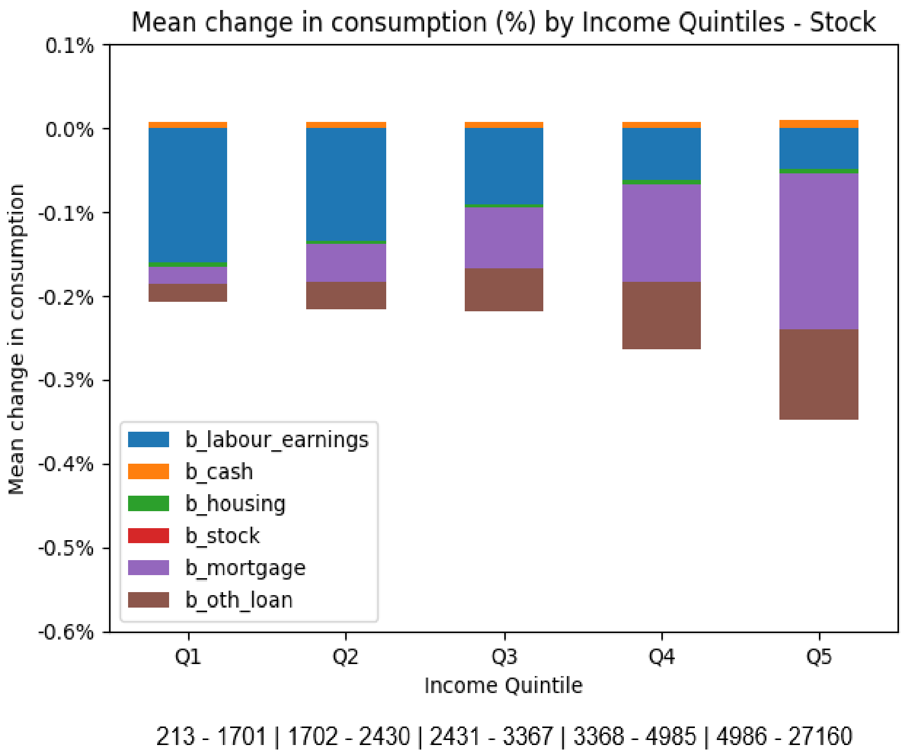

Figure 5: Mean change in consumption by income quintiles

5.2 Net Worth Distribution

Figure 6 highlights the differential impact of contractionary MP across net worth quintiles. Interestingly, the analysis reveals that lower-net-worth households are more affected by MP than higher-net-worth households. Lower-net-worth households are more exposed to economic shocks due to lower bargaining power and job security, as reflected in the labour earnings channel. They are also more affected due to larger debt obligations stemming from large liabilities. Moreover, this result arises partly due to the construction of net worth using monthly flow data, which tends to underestimate the value of assets relative to liabilities. In particular, assets are often irregular and difficult to capture accurately in the HIES, while liabilities such as debt repayments are more consistent and fully reflected in household balance sheets. As a result, many lower-net-worth households may, in fact, possess additional wealth that is not sufficiently captured in the HIES. Although asset income includes receipts from asset ownership, interest, dividends, and rent, which are captured under residual income and included in total assets, the issue of under-reporting of assets may still persist. This is because not all property owners can consistently rent out their properties. Additionally, the actual stock of assets may also include other assets that do not generate income during the survey period or at all. This data limitation underestimates the net worth of households that may own additional assets not captured in the HIES. Higher-net-worth households appear less affected by MP due to their greater financial flexibility. However, the impact may be more evenly distributed than it seems, as some low-net-worth households could, in fact, be high-net-worth if their asset stock were more accurately recorded.

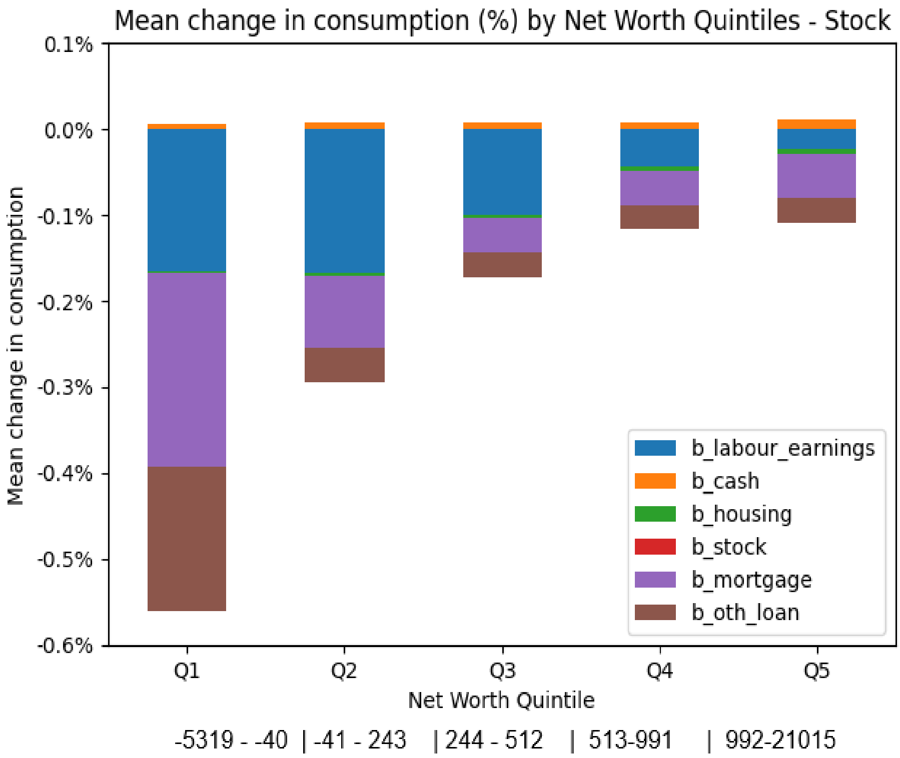

Figure 6: Mean change in consumption by net worth quintiles

5.3 Age Distribution

Figure 7 presents the distributional impact of MP across age quintiles, revealing that younger households, particularly homeowners, are more adversely affected. The mortgage channel is the most significant contributor to this result, as younger households typically hold larger outstanding mortgage balances and have only recently begun the repayment process. Other loan repayments also affect younger households disproportionately, as they are more likely to hold additional debt obligations which are more sensitive to interest rate changes. In contrast, older households, particularly those in retirement, are largely insulated from debt-related impacts, given their reduced reliance on credit. The labour earnings channel shows a relatively even distribution of effects among younger households, while the impact on older households is more muted due to their lower participation in the labour market. Overall, younger households experience the most pronounced consumption declines, driven by their higher debt exposure, while older households are better insulated from the effects of MP. This is consistent with McKay and Wolf (2023), who also found that younger homeowners tend to exhibit stronger consumption response following a monetary policy shock.

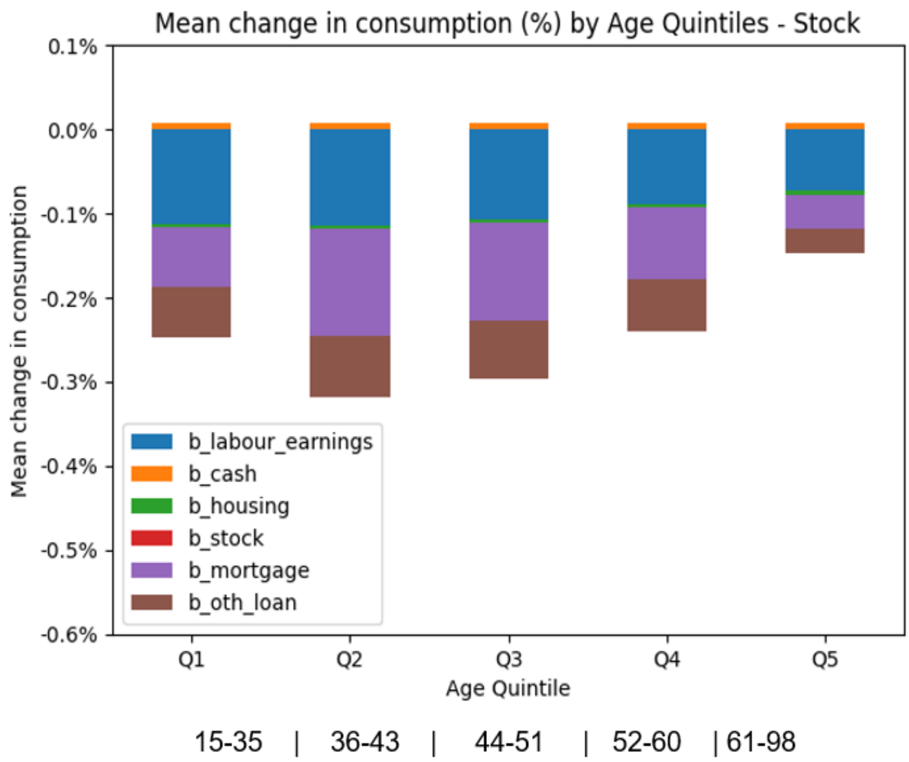

Figure 7: Mean change in consumption by age quintiles

5.4 Comparison of dc by Different Quintiles to the Average Household

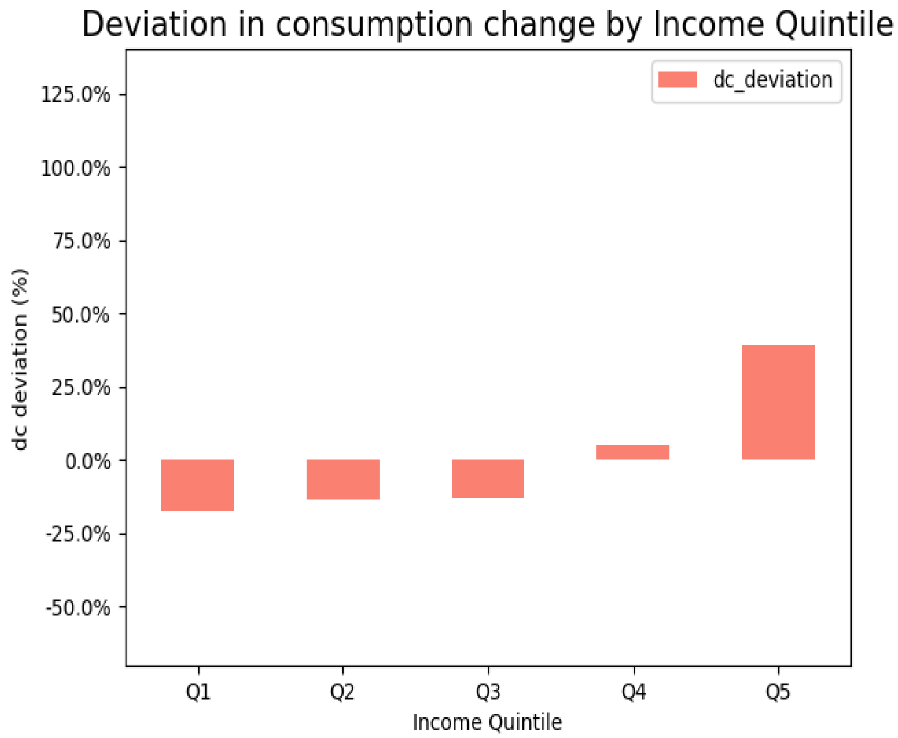

Figure 8: Deviation in consumption change by income quintiles

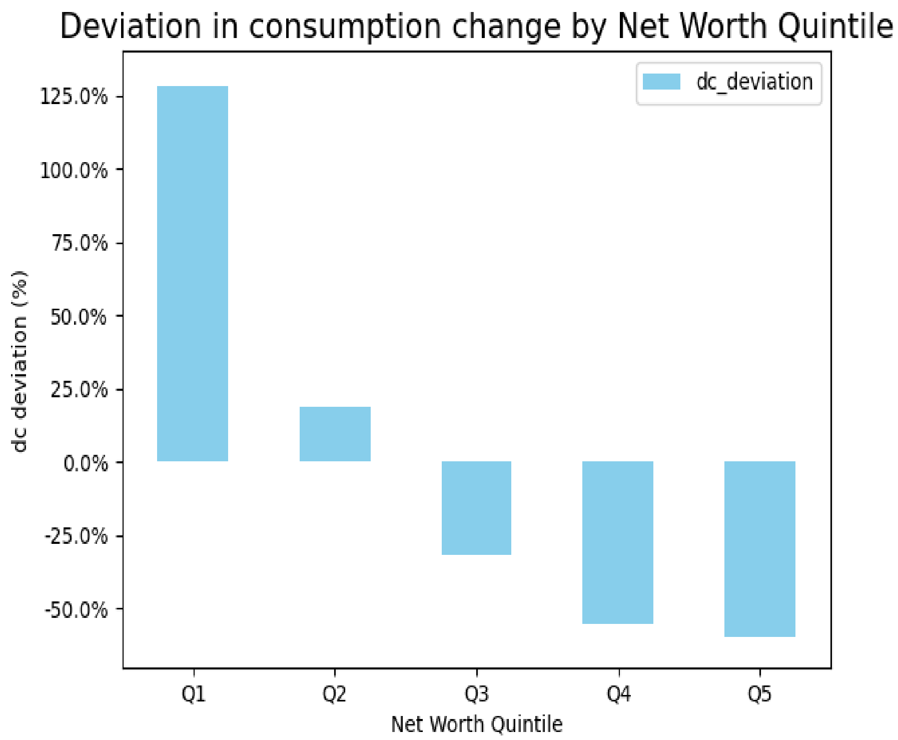

Figure 9: Deviation in consumption change by net worth quintiles

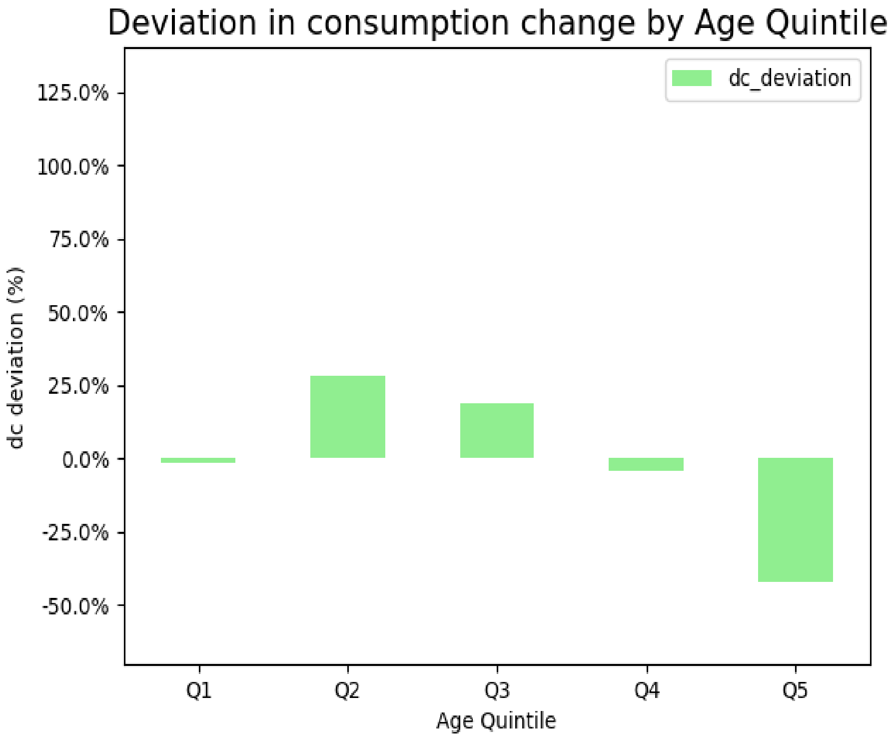

Figure 10: Deviation in consumption change by age quintiles

Comparison of dc by different quintiles to the average household affirms overall distributional results across heterogeneous households. Comparing dc to the average household would be agnostic to biases in dp_j since dp_j affects households proportionally. The distributional impact across net worth quintiles is uneven by construction. However, income and age quintiles show a more even and modest impact. Net worth distribution may also be more balanced in reality. This is because inferring balance sheet stock from monthly flow data underestimates assets more than liabilities. Asset contributions are irregular, while debt obligations are consistent.

5.5 Summary of Key Results

The analysis reveals that if the transmission channels of monetary policy were considered in isolation, their impact on households would be rather uneven. For instance, the effects of individual channels such as labour earnings, mortgages, and other loans vary significantly across different household groups. Notably, the labour earnings channel demonstrates a declining trend with increasing income, whereas the mortgage and other loan repayment channels show an increasing trend. In the context of net worth quintiles, the patterns are somewhat analogous; labour earnings, mortgages, and other loans tend to disproportionately affect lower-net-worth households, primarily due to the underestimation of their asset holdings. Among age quintiles, labour earnings effects are relatively uniform for younger households. Mortgage and other loan channels show a U-shaped pattern, hitting younger households harder due to higher debt obligations.

In interpreting the overall distributional results, the net worth distribution results should be approached with caution, as the actual distributional impact may be more evenly spread. This is because some seemingly low-net-worth households could, in fact, be of higher-net-worth if their asset stock were correctly accounted for. Despite these disparities in the impact of individual channels, it is important to highlight that overall consumption changes are much more evenly distributed across households by income and age quintiles. The fluctuations in consumption are relatively consistent, ranging from -0.15 to -0.34% across various household groups.

6 Conclusion

The key finding of this study suggests that all household groups experience varying degrees of reduction in consumption following a +25 bps increase in OPR. While variations exist among these groups, the impact differentials are relatively modest, ranging from approximately -0.15% to -0.34%. This finding underscores that the macroeconomic effects of monetary policy are broadly consistent with the aggregated micro-founded impacts on households, improving our understanding of the channels through which OPR influences consumption. Examining individual transmission channels in isolation can overstate disparities. When viewed across all channels, the overall impact appears relatively uniform. Consistent with the Tinbergen principle, monetary policy should remain focused on its primary mandate of macroeconomic stability, creating a stable, low-inflation environment that supports sustainable growth. Fiscal policy, in turn, is better positioned to address distributional concerns through targeted measures such as subsidies for essential goods or direct financial assistance to vulnerable households. While monetary policy can generate heterogeneous effects, it remains a blunt instrument unsuited for precise targeting, reinforcing the need for complementary, well-designed fiscal interventions.

In addition to the key finding, three additional insights can be drawn. Firstly, household sensitivity to MP can fluctuate depending on the prevailing economic environment. Specifically, under certain economic conditions that lead to an increase in financially constrained households, the sensitivity of household consumption to MP may be heightened. Exploring time-varying structural parameters may therefore offer valuable insights into the effectiveness of monetary policy over different economic cycles.

Secondly, recent literature has underscored the importance of indirect transmission channels in monetary policy. For instance, expansionary monetary policy can create tighter labour market conditions, which may lead to higher wages. Our analysis identifies and compares the relative significance of various monetary policy transmission channels, highlighting the substantial role that indirect channels, particularly labour earnings, play in this transmission process. Continuous surveillance and research into these channels will be vital for understanding their impact over time.

Thirdly, several additional mechanisms that could shape household-level consumption responses to monetary policy remain beyond the scope of this paper. Differences in consumption basket composition, including varying exposure to durable goods, represent an important dimension that may influence sensitivity to interest rates. Heterogeneous inflation experiences across households can lead to varied real income effects and, consequently, different consumption responses. In addition, supply-side factors, such as changes in firms' pricing behaviour, may also play a role. These mechanisms are highly relevant for a comprehensive assessment of monetary policy's heterogeneous effects and warrant future research as data and methodological advances permit.

In summary, this study contributes to a nuanced understanding of how monetary policy affects household consumption across various demographic groups, including age, income, and net worth in Malaysia. While the distributional effects identified remain tentative, this is owing to the use of monthly flow data to approximate household asset and liability stocks, with assumptions on consumption–savings behaviour that may not fully reflect the Malaysian context. The results nonetheless suggest that a +25 bps increase in the OPR generates relatively modest differences in consumption responses across households. Ideally, access to a centralised, anonymised administrative panel dataset linking household income and balance sheets—similar to the high-quality Norwegian tax data used in Holm et al. (2021)—would provide policymakers with more accurate insights into household behaviour and improve policy decision-making. Beyond the key finding, the three additional insights—the role of time varying structural parameters, the significance of indirect transmission channels, and the need to account for additional consumption distribution mechanisms—highlight crucial avenues for future research. These investigations will be essential in refining our understanding of monetary policy's influence on households and enhancing its effectiveness in achieving desired economic outcomes.

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A Appendix: Household Income and Expenditure Survey (HIES)

A.1 Data Processing

All data in the HIES are presented as monthly flows, capturing household income, consumption, and non-consumption expenditure on a monthly basis. The gross income and non-consumption expenditure categories are particularly valuable, as they provide detailed information on household wages, housing expenditure, and the allocation of resources to assets such as stocks, cash, and deposits, as well as liabilities like mortgage repayments and other loans. This information allows us to infer households' exposure to the six different monetary transmission channels, as outlined in Section 3.

The granular data on monthly non-consumption expenditure enables us to classify these expenditures into assets and liabilities, allowing us to proxy household net worth using the formula: net worth = total assets − total liabilities. Although using monthly flows provides only an imperfect approximation of household balance sheets, we can anticipate the direction of the bias. Specifically, this approach tends to underestimate assets more than liabilities, as asset contributions tend to be relatively more irregular, while debt obligations are consistent. Thus, in subsequent analyses, we can intuitively account for the downward bias in net worth and better interpret the effects of monetary policy shock across net worth distribution.

To account for differences in household size and composition, income and expenditure figures are adjusted using the square root equivalisation method, as proposed by Chanfreau and Burchardt (2008). This adjustment is preferred over a simple per capita approach, as it reflects the economies of scale within households—acknowledging that larger households benefit from shared resources and costs, such as utilities. Unlike per capita measures, which assume equal financial needs for every household member, the square root method adjusts for the diminishing marginal cost of additional household members, offering a more accurate depiction of income sufficiency and living standards across different household sizes.

Outlier observations from the dataset were addressed using the isolation forest method developed by Liu et al. (2008), applying a 5% contamination threshold. This approach effectively removes extreme outliers, analogous to trimming 2.5% of the observations from both ends of the distribution, thereby ensuring the robustness of the dataset used in this analysis.

The HIES is a comprehensive and detailed cross-sectional dataset at the household level. However, it is anonymised at the source, making it difficult to track households over time as one would in a panel dataset. Therefore, this paper seeks to leverage the rich heterogeneity in household exposures found within the HIES and apply it to a simple, tractable framework, as described in Section 4.

It is important to note that the net worth estimates may be problematic, particularly for low-net-worth households with multiple mortgages, as the value of additional properties is not directly captured by the HIES. This may result in the underestimation of their net worth. Although asset income includes receipts from asset ownership, interest, dividends, and rent, which are captured under residual income and included in total assets, the issue of under-reporting of assets may still persist because not all property owners can rent out their properties consistently. Additionally, we only have data on asset income flow, not the stock, which may include other assets that do not generate income during the survey period or at all. Self-reported asset and inheritance data in household surveys also tend to be underestimated due to recall error, reluctance to disclose or difficulty in valuing certain assets (Piketty, 2014; Balestra and Tonkin, 2018). In contrast, liabilities are typically recorded more accurately as compulsory monthly obligations. Consequently, asset flows may be significantly underestimated, especially if households invested in previous years but reported no new investments during the survey year.

A.2 Descriptive Analysis

The following descriptive analysis based on the HIES data aims to present key stylised facts that will help readers intuitively understand how household exposure to the six different transmission channels varies across income, net worth, and age quintiles. Age quintiles are constructed based on the age of the head of household. These stylised findings provide valuable insights into the final results from the empirical analysis of the distributional impact on household consumption across these different dimensions.

Channel #1: Labour Earnings

It is unsurprising that labour earnings, which constitute a significant portion of total income, increase as total income rises. The U-shaped pattern observed in the distribution of labour earnings by net worth is due to the downward bias in net worth estimates. This bias occurs because flow data often understate the actual stock of assets relative to liabilities. If we can accurately capture the stock of assets, the positive correlation of labour earnings with net worth may be stronger. Households in the bottom net-worth quintile could shift to higher quintiles once additional assets, such as extra properties or non-income-generating holdings are considered. This adjustment would reduce the U-shape and reveal a more positive trend. However, some households may only achieve high indebtedness because they have greater access to credit, which typically requires higher labour earnings. This helps partially explain why households with negative net worth can still report high earnings. Further investigation is needed to clarify this income–net worth relationship. The inverted U-shaped distribution of labour earnings by age, skewed to the right, is also intuitive. Younger households generally have greater potential to earn higher wages as they advance in their careers, while older households typically have lower earnings, as many are in retirement.

Figure 11: Monthly labour earnings by income, net worth and age quintiles

Channel #2: Cash and cash equivalents

Higher-income households tend to hold more liquid assets, as do households with higher-net-worth. In contrast, older households typically have fewer liquid assets, as they often begin drawing down their savings for retirement. However, note that the actual proportion of cash relative to total assets may be lower for higher-net-worth households. This is partly due to the underestimation of asset stocks discussed earlier.

The definition of cash and cash equivalents in this paper includes not only cash holdings, but also deposits, residual income, and retained profits from business activity. This broader definition is adopted to ensure a more comprehensive capture of household liquid assets. Although these components are not strictly equivalent to cash in terms of immediacy of liquidity, they represent funds that are either already held in accessible accounts (e.g., deposits) or could potentially be drawn upon with minimal friction in response to shocks (e.g., residual income and retained business profits). Each of these components individually accounts for a relatively small proportion of total household consumption. Their inclusion as part of a broader measure of cash equivalents therefore improves the completeness of the estimation of liquid assets without materially biasing the estimated consumption responses. By capturing the totality of potentially accessible liquid assets, this measure ensures more consistent comparison of assets across households and transmission channels.

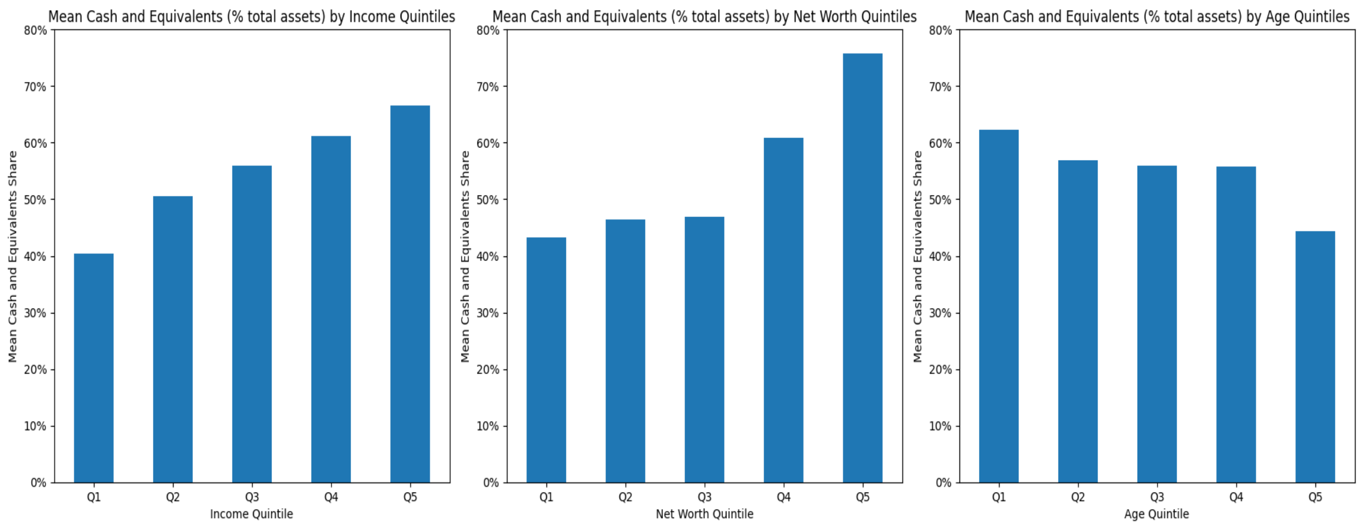

Figure 12: Mean flow of cash and equivalents as % of total flow of assets by income, net worth and age quintiles

Channel #3: Housing Value

Housing value is proxied using imputed rentals of owner-occupiers for the main residence. This introduces a downward bias for households that own multiple properties. While this bias affects the overall distribution, it is likely to impact high-income households more significantly, as they are more likely to afford multiple properties. However, for higher-income households, total assets may still be less reliant on housing value due to higher exposure to other assets shown in Figure 1. The net worth distribution presents a greater issue, particularly for low-net-worth households with multiple mortgages, where the values of additional properties are not captured in the HIES. This could lead to a significant underestimation of their net worth. If the values of additional properties were accurately included, the net worth distribution for housing would likely be more even. Some households currently classified as lower-net-worth would instead fall into higher-net-worth categories, with a larger share of wealth stemming from property holdings. Intuitively, older households' total assets are also more dependent on housing value because older households may have fewer liquid investments or income-generating assets, particularly after retirement, as they start drawing down on their savings. Thus, the distributional results for this channel should be treated with caution, as there are currently no datasets available to explore total housing value at the household level in Malaysia to the best of the author's knowledge. While NAPIC holds individual property ownership data, it is distinct from household-level ownership. Nevertheless, changes in housing value through the asset price channel are expected to have a minimal impact on consumption, as housing is an illiquid asset with a low marginal propensity to consume (MPC) out of this channel.

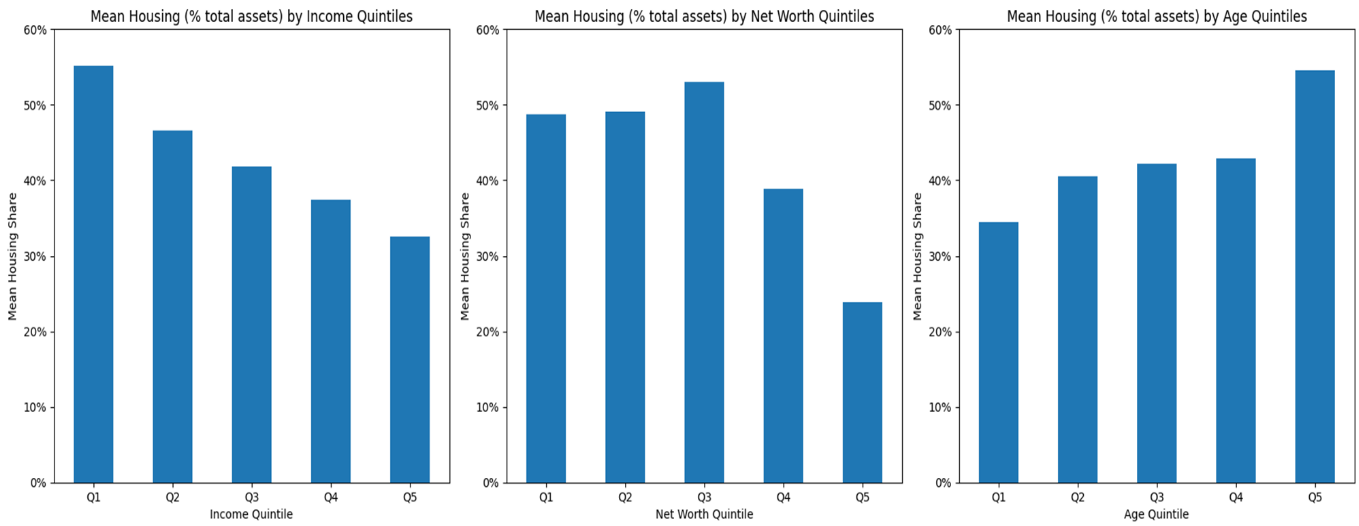

Figure 13: Mean flow of housing value as % of total flow of assets by income, net worth and age quintiles

Channel #4: Stocks

The distribution of stocks, as captured by flow-based HIES data, may not be fully representative of actual stock holdings. Generally, the percentage of households that own stocks across all quintiles is very small, less than 0.01%. If households did not invest in stocks during the survey year, their existing stock ownership would not be captured. Additionally, the classification used for stock ownership in the HIES may not accurately reflect ownership of public shares or equities. Nonetheless, changes in stocks are expected to have a minimal impact on consumption due to the volatile nature of equities. While stocks are relatively liquid, price volatility could discourage liquidation, resulting in a low MPC out of the equity price channel.

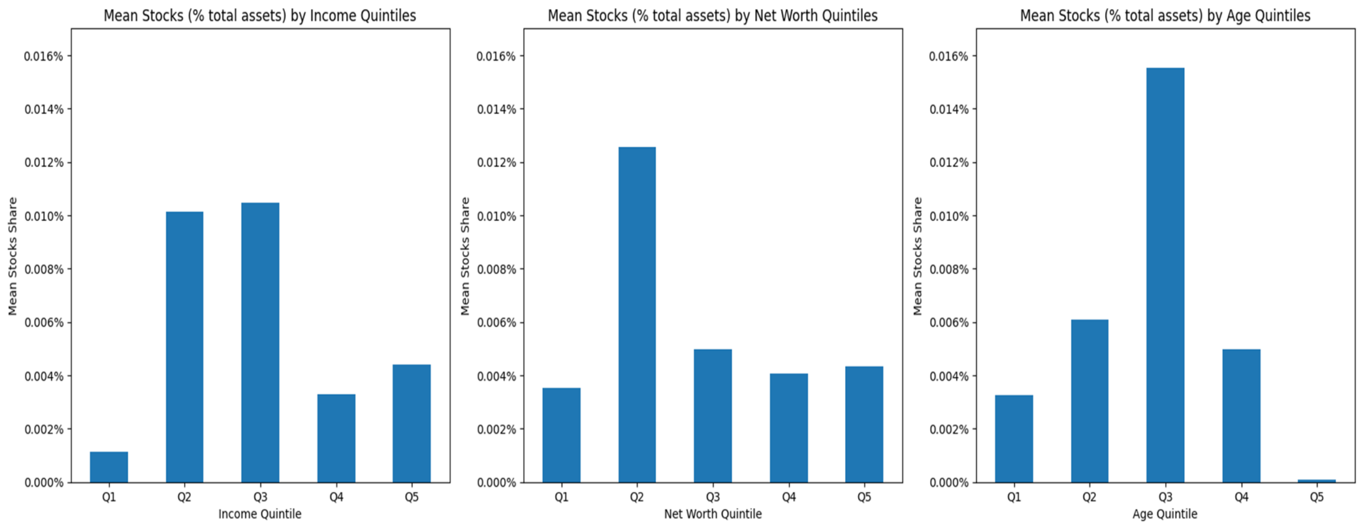

Figure 14: Mean flow of stocks as % of total flow of assets by income, net worth and age quintiles

Channel #5: Mortgage

Higher-income households are typically able to afford larger or more mortgages. However, wealthier households tend to have proportionally lower mortgages as a percentage of their total assets. It is important to note that there is a downward bias in net worth due to the underestimation of assets relative to liabilities, which arises from the use of monthly flow data. As a result, the actual distribution of mean mortgage values by net worth would likely be more evenly spread. Younger households generally have larger mortgages as a percentage of their total assets, while older households are more likely to have paid off their mortgages and accumulated more assets over time.

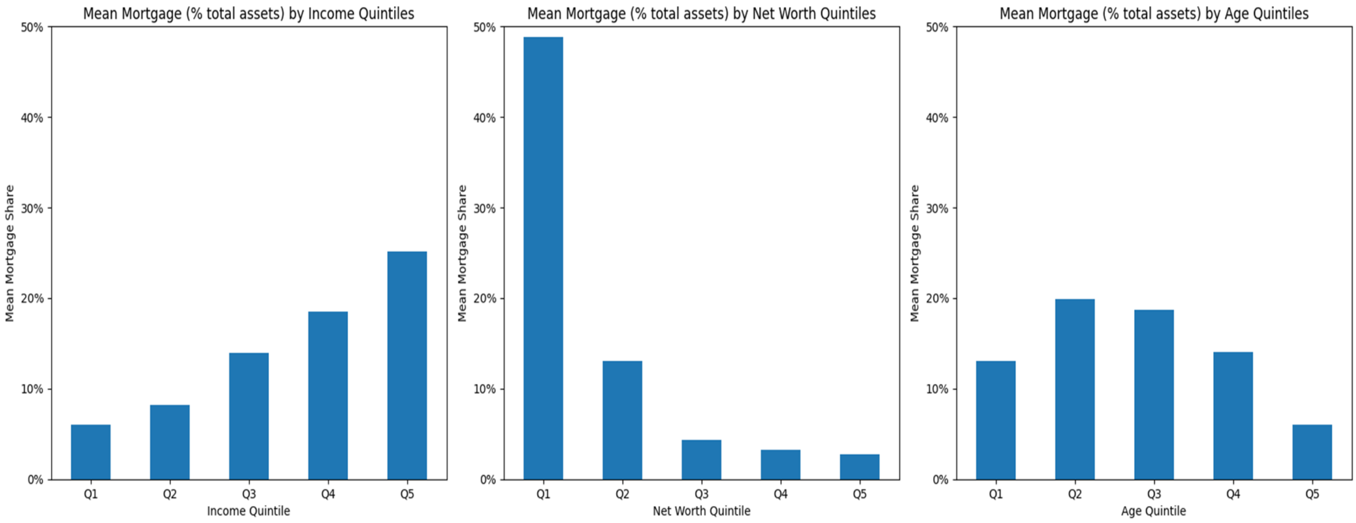

Figure 15: Mean monthly mortgage repayment as % of total flow of assets by income, net worth and age quintiles

Channel #6: Other Loan Repayments

Higher-income households tend to qualify for more credit and may borrow more to support their higher living standards. Lower-net-worth households by construction of the net worth measure are most likely to suffer from underestimation of total assets relative to debt repayments as discussed earlier. As such, the actual distribution of other loan repayments is likely to be more evenly spread if their assets are properly accounted for. These affected households will have a lower share of other loan repayments as a percentage of total assets and may also shift to higher-net-worth quintiles. Younger households typically have larger loan repayments as a percentage of total assets, gradually accumulating more assets as they age and progress in their careers.

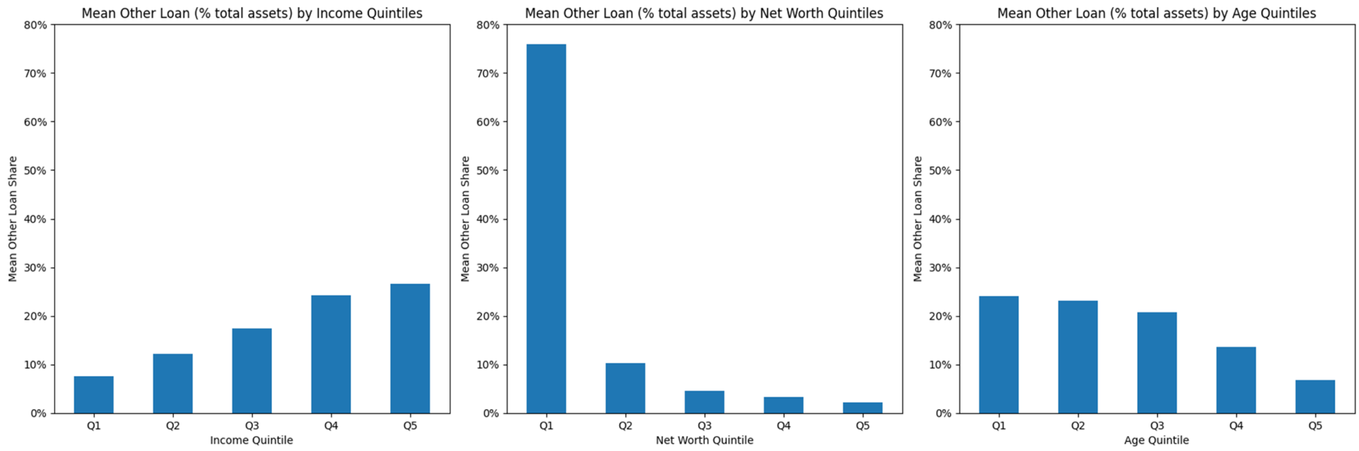

Figure 16: Mean monthly other loan repayments as % of total flow of assets by income, net worth and age quintiles

B Aggregate-level 'price' changes in transmission channels, dp_j

For each category j of transmission channels, the price change following an exogenous contractionary monetary policy shock is calculated by constructing an aggregate measure of how prices evolve. This is achieved by running a simple recursive VAR model, where the monetary policy shock is ordered first, followed by real GDP, inflation, the 3-month treasury bill rate, and the 'price' of category j variable, P_{jt}. This approach allows for structural estimation using an instrument (or proxy VAR) by placing the instrument first in the recursive VAR ordering, which is particularly beneficial even in the presence of noninvertibility (Plagborg-Møller and Wolf, 2021). The sample period for most VARs spans from the third quarter of 2006 to the fourth quarter of 2022.[8] While a higherfrequency VAR would be preferable, real GDP figures in Malaysia are only available at the quarterly level, which limits the sample size.

$$Y_t = \begin{pmatrix} \text{MP Shock}_t \\ \text{Real GDP}_t \\ \text{Inflation}_t \\ \text{Treasury Bills, 3M}_t \\ P_{jt} \end{pmatrix} = A_0 + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t, \qquad (2)$$

where:

- Y_t = Vector of endogenous variables;
- A_0 = Vector of intercepts;
- A_i = Coefficient matrices for lags $i = 1, 2, \ldots, p$; and
- ε_t = Vector of error terms, assumed to be normally distributed with a covariance matrix Σ.

The MP shock series used in this paper is estimated by Ong (2023) using high-frequency MP surprises from Ho and Karagedikli (2021), following the methodologies established in Kuttner (2001) and Gürkaynak et al. (2004) and controlling for the Bank's information set. High-frequency identification (HFI) of MP shocks is a leading approach to study the effects of monetary policy, leveraging revisions in financial market variables around the release of Monetary Policy Statement by the Monetary Policy Committee. To accurately identify the causal effects of MP shocks, it is essential to isolate shocks that are perceived as new information by agents and are orthogonal to the prevailing economic conditions Miranda-Agrippino and Ricco (2021). For agents with imperfect information, policy actions can convey insights about both monetary policy and the current state of the economy (Romer and Romer, 2000; Melosi, 2017), even if the central bank does not possess superior information. The information effects arising from policy announcements may complicate the analysis (Nakamura and Steinsson, 2018; Jarociński and Karadi,

[8] The sample period begins in the third quarter of 2006, coinciding with the earliest availability of the MP shock series, and extends to the fourth quarter of 2022, aligning with the static HIES data for 2022 to ensure consistency and prevent the introduction of any information that was not available to households at that time. All six VARs for each transmission channel category j are based on this sample period, except for the real average lending rate on new mortgages and real average lending rate on new other loans, which start from the fourth quarter of 2009 to the fourth quarter of 2022. This later start period is due to the availability of these two series only from the fourth quarter of 2009.

2020), particularly in the context of Malaysia, where Bank Negara plays a crucial role in assessing the state of the economy. Consequently, the MP shocks utilised in this study are considered as policy shocks that remain orthogonal to the Bank's projections.

$$
\begin{aligned}
MPS_d = \alpha_0 &+ \delta_1 F_d^{CB} \pi_{12m} + \delta_2 F_d^{CB} GDP_{12m} \\
&+ \delta_3 \left(F_d^{CB} \pi_{9m} - F_{d-1}^{CB} \pi_{9m} \right) \\
&+ \delta_4 \left(F_d^{CB} GDP_{9m} - F_{d-1}^{CB} GDP_{9m} \right) + MPS_d^{info},
\end{aligned} \tag{3}
$$

where:

- MPS_d = HFI MP surprise;
- $F_d^{CB} \pi_{12m} + F_d^{CB} GDP_{12m}$ = 12-month ahead internal forecasts at each Monetary Policy Committee meeting;
- $\left(F_d^{CB} \pi_{9m} - F_{d-1}^{CB} \pi_{9m} \right) + \left(F_d^{CB} GDP_{9m} - F_{d-1}^{CB} GDP_{9m} \right)$ = Revisions in the 9-month ahead internal forecasts at each Monetary Policy Committee meeting; and
- MPS_d^{info} = MP shock used in the VAR.

The impulse response function (IRF) of the category j variable to the MP shock is constructed using the estimated VAR and Cholesky decomposition. The average level of the impulse response over the first two years following the shock serves as a measure of the price effect of the MP shock. All price change estimates are expressed in real terms and are scaled by taking the average level of the impulse response over the first two years for the category j variable, divided by the average level of the impulse response for real GDP. This scaling corresponds to a monetary contraction that results in a 1% decrease in GDP on average over the first two years following the policy change, providing a basis for comparison with McKay and Wolf (2023). The resulting price change estimates are then rescaled to a +25 basis points hike equivalent,[9] which is the typical magnitude of such moves in Malaysia, for easier interpretation throughout the remainder of the paper.

The results of the price change estimates for each transmission channel are presented in Table 4. However, the VAR may underestimate the impact of a +25 basis points (bps) change on channels #2, #5, and #6 due to the chosen variables, which will be discussed in detail below. To address this, we have supplemented these estimates with alternative assessments of the impact of a +25 bps change on these channels, which are

[9] The rescaling is done by multiplying the IRF of the targeted variable, P_{jt} to one standard deviation of MP shock by 0.25, before calculating the average level of this impulse response as the rescaled price change. This is conceptually similar to a +25 basis points MP shock to the target variable. We then converted this to a +25 basis points OPR hike equivalent by dividing this rescaled impulse response by the simple correlation of the MP shock with changes in OPR, which is 1.1101.

Category j variable (Transmission channels)	Price change, %	Rescaled price change, +25bps OPR
#1 Real labour earnings	-1.85%	-0.054%
#2 Return on cash and cash equivalents	0.18%	0.03%
#3 Real return on housing	-1.77%	-0.051%
#4 Real return on stock	-1.35%	-0.039%
#5 Real average lending rate on new mortgages	0.30%	0.20%
#6 Real average lending rate on new other loans	0.24%	0.15%

Table 4: Aggregate-level 'price' changes in transmission channels, dp_j

highlighted in yellow in Table 4. While the literature consistently reports a muted impact on returns from cash—proxied by its effect on inflation—as shown in studies by McKay and Wolf (2023) and Slacalek et al. (2020), we take a different approach for this channel. Instead of relying on the VAR estimate, we opted to use an alternative derived from an internal Dynamic Stochastic General Equilibrium (DSGE) model.[10] The average impact of 25bps OPR hike over two years on inflation from the DSGE model is adopted. This estimate is slightly more than double our original VAR estimate but remains relatively small, reflecting the potentially higher sensitivity of other cash equivalent components as defined in Section 3, providing a more conservative adjustment. Regarding the muted VAR estimate for real mortgage rates, it is important to note that this series is based on the lending rates of new loans. Hence, this rate may also be driven by competition among banks, rather than solely by changes in the Overnight Policy Rate (OPR). To address this, we assume an OPR pass-through rate of 80%, particularly since the Standardised Base Rate[11] was only introduced in August 2022, resulting in changes in mortgage rates aligning one-to-one with the OPR. For the real average lending rate on new other loans,[12] we anticipate a muted direct impact from the OPR relative to mortgage rates as a sizeable portion of these other loans may be fixed-rate loans, unlike mortgages.[13] Since this is also the rate on new loans, it may also be influenced by bank competition among other factors, in addition to changes in the policy rate. Thus, we apply a pass-through rate of 60% to account for this. This adjustment illustrates the flexibility of our framework, allowing for

[10]This internal DSGE model is adopted from the Bank of England's COMPASS (Central Organising Model for Projection Analysis and Scenario Simulation), calibrated to Malaysia. The impact of a monetary policy shock on aggregate macroeconomic variables is assumed to be symmetric in this model. For more details, please refer to Burgess et al. (2013).

[11]For more information, please refer to the box article titled 'Standardised Base Rate' in the BNM Quarterly Bulletin 2Q 2022.

[12]Ideally, we would prefer to use a rate that accurately represents all household loans, excluding mortgage rates. However, this is not feasible due to data limitations.

the incorporation of alternative estimates for specific channels.

Overall, every transmission channel exhibits the expected sign following a contractionary monetary policy shock. Although the magnitudes of these effects are sensitive to factors such as sample selection, the choice of monetary policy shocks and variables—largely due to the relatively small sample size—the relative magnitudes across transmission channels align broadly with existing literature (e.g., McKay and Wolf (2023)). Consequently, the VAR estimates should be viewed as tentatively indicative of the potential dynamics of selected macroeconomic variables in response to monetary policy shocks. These estimates are likely to be revised and updated as longer time series data become available. This expectation is consistent with our reliance on a high-frequency identification scheme within a large VAR framework utilising quarterly data (Slacalek et al., 2020). It is worth noting that monetary policy shocks account for only a modest share of the volatility in the variables modeled within the VAR (Castelnuovo, 2016). Nonetheless, the inequality results by transmission channel remain robust, as any potential bias in magnitude affects all households equally.

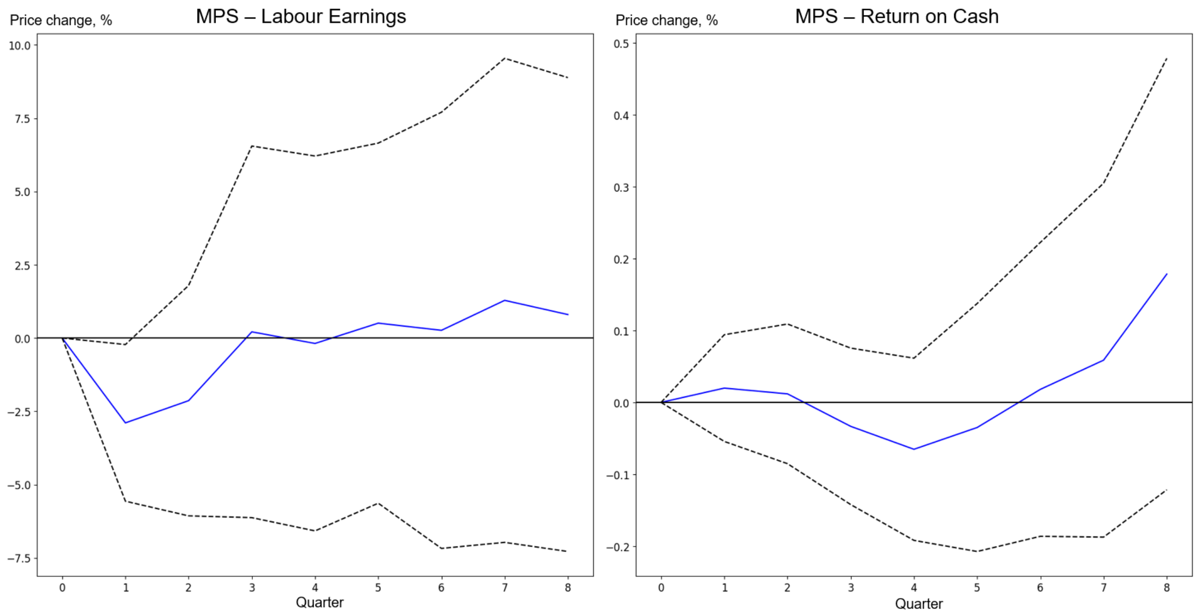

Figure 17: Individual IRFs for each category j of transmission channel (Real labour earnings, return on cash and cash equivalents)

[13] As of the end of 2022, 98.9% of mortgages in Malaysia are subject to floating interest rates. Additionally, the average proportion of floating rate loans across various categories, including the purchase of securities, personal use, and other purposes, stands at 85.9%. It is important to note that these ratios are derived from data provided based on the CCRIS. There may be minor discrepancies in the precise definitions of loan categories between CCRIS and the HIES.

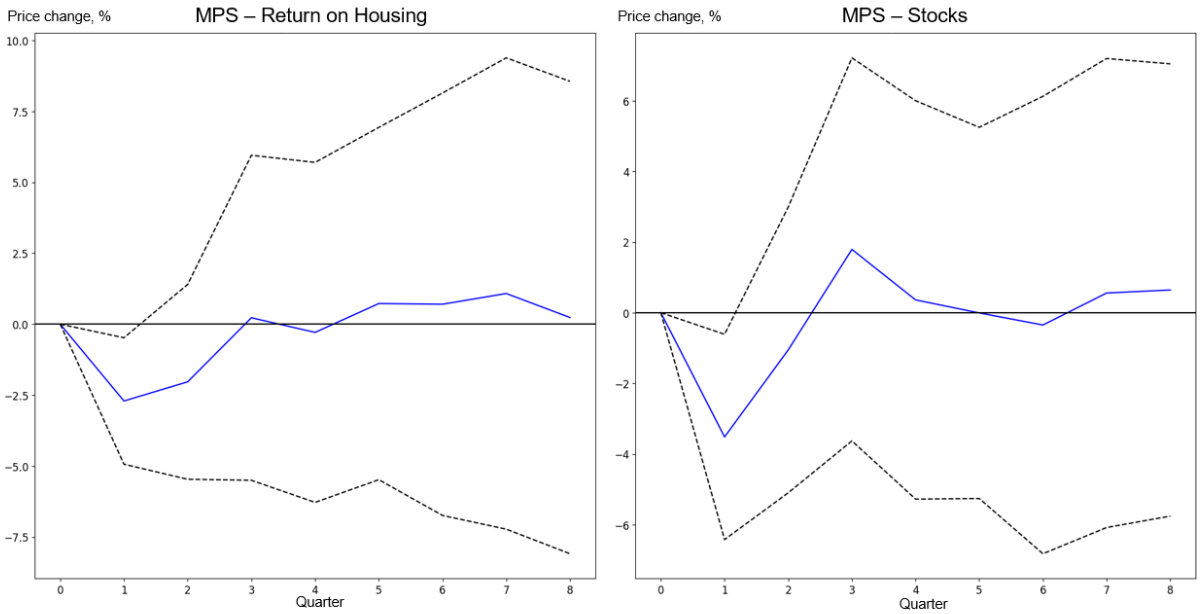

Figure 18: Individual IRFs for each category j of transmission channel (Real return on housing, real return on stock)

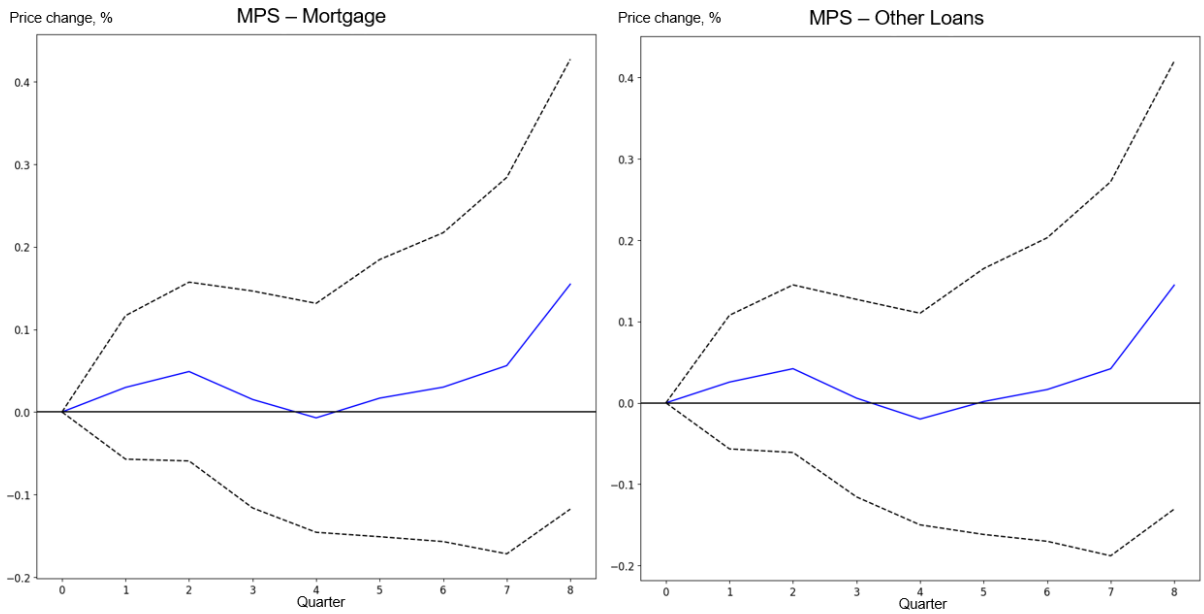

Figure 19: Individual IRFs for each category j of transmission channel (Real average lending rate on new mortgages, real average lending rate on new other loans)
The dotted lines represent the 5th and 95th percentiles of the impulse response functions, reflecting the uncertainty around the estimated responses. The highlighted VAR estimates have been replaced by alternative estimates as described above.

C Household-Level Exposure, x_{ij}

The household-level exposure to specific categories of transmission channels is calculated as a proportion of baseline consumption:

$$x_{ij} = \frac{\varepsilon_{ij} y_{ij}}{c_i}, \tag{4}$$

where:

- x_{ij} is the exposure of household i to price change in category j;
- ε_{ij} is the elasticity of household i with respect to aggregate changes in category j channel;
- y_{ij} represents the implied stock of category j channel for household i; and
- c_i is the aggregated monthly consumption flow of household i.

The variable y_{ij} is estimated as stock from flow data. For simplicity and transparency, we assume that household stocks are equivalent to annualised monthly flows across all transmission channels. The conversion details are outlined in Table 5. Since monthly flow data likely results in a downward bias on the consumption response of households, as assets and liabilities flows tend to be smaller than their underlying stock, converting flows to stock provides a more accurate estimate of the actual consumption response. While more sophisticated conversion methods exist, such as those outlined by Saez and Zucman (2016), their application here is constrained by the structure of the HIES data. Saez and Zucman capitalise income from asset holdings—reported in tax records—into wealth stock estimates by assuming an asset-specific rate of return. However, this approach requires detailed information on the composition of asset income by asset class, which is not available in the HIES. Assuming a uniform rate of return across all households would result in significant estimation errors, given the wide variation in returns across asset types. For example, an income of RM100 could stem from RM500 in equity yielding 20%, or from RM10,000 in a low-yield deposit at 1%. Without information on asset composition, such back-calculations are not feasible. Moreover, the cross-sectional design of the HIES, which captures income and expenditure at a single point in time, precludes the use of dynamic techniques to infer asset accumulation paths from flow behaviour.

Despite these limitations, the inequality results across transmission channels remain robust. Any bias introduced by using annualised flows to approximate stocks is likely to be systematic and proportionate across households, thereby preserving relative comparisons. This approach ensures internal consistency and avoids the risk of introducing unobservable and uneven measurement errors into the stock estimates. While our estimates likely understate household assets relative to liabilities and may not reflect the true accumulated positions, this bias is directionally clear and allows for a cautious interpretation of the results, pending availability of richer balance sheet data.

Transmission Channels	**Conversion**	**Assumptions**
#1 Labour Earnings	Labour earnings * 12 months	Annualised labour earnings
#2 Cash and cash equivalents	Cash * 12 months	Assumes the average household holds 1 year of monthly cash savings in stock
#3 Housing Value	Implied rental * 12 months / Average gross rental yield[14]	Property value inferred from inverse of rental yield
#4 Stocks	Stocks * 12 months	Assumes the average household holds 1 year of monthly stock investments in stock
#5 Mortgage	Mortgage * 12 months	Assumes the impact of +25 bps lasts for 1 year
#6 Other Loans	Other loans * 12 months	Assumes the impact of +25 bps lasts for 1 year

Table 5: Conversion of monthly flow to stock, y_{ij}

For all transmission channels, the household exposure to aggregate price changes is assumed to be equal ($\varepsilon_{ij} = 1$), except for labour income, where the elasticity differs. Specifically, the elasticity of labour income, $\varepsilon_{i,\text{labour income}}$, is modelled as $\varepsilon_{i,\text{labour income}} = a - b \cdot \min(q_i, 0.8)$. This formulation is inspired by (Guvenen et al., 2014, 2017), where $q_i \in [0, 1]$ represents the household's rank in the wage income distribution. The parameter b is chosen such that labour income is three times more sensitive at the 10th percentile than at the 80th percentile, while a is normalised so that aggregate earnings have a unit elasticity with respect to aggregate earnings. This framework reflects the observation that low-income households are more exposed to business cycle fluctuations, with $\varepsilon_{i,\text{labour income}}$ decreasing as income increases. Above the 80th percentile, sensitivity is assumed to remain constant. Further refinements could be made by incorporating heterogeneous elasticities of household-level ε_{ij} to aggregate y_{ij}. However, doing so would

[14] Average gross rental yield = 4.83% (Source: Global Property Guides as at 2022)

require strong and potentially unverifiable assumptions in the absence of detailed balance sheet data. For example, it is difficult to credibly model variation in the elasticity of housing values, stock holdings, or other loans across households without granular information on property characteristics, the composition of financial assets, or the structure of other loans, such as the share of fixed versus variable interest loans. Without such detail, imposing heterogeneity risks introducing noise or bias, rather than improving the accuracy of household-specific exposures.

D Marginal Propensity to Consume (MPC), m_{ij}

The Marginal Propensity to Consume (MPC) varies across households depending on three key dimensions: financial constraints, income quintiles, and transmission channels, as outlined in Table 6.

Transmission Channels	MPC (Unconstrained)	MPC (Constrained)
#1 Labour Earnings	0.1 * m_{ijy}	m_{ijy}
#2 Cash	0.1 * m_{ijy}	m_{ijy}
#3 Housing Value	0.03	0.03
#4 Stocks	0.054	0.054
#5 Mortgage	0.8	1
#6 Other Loans	0.8	1

Table 6: MPC variation across financial constraints, income quintiles, and transmission channels

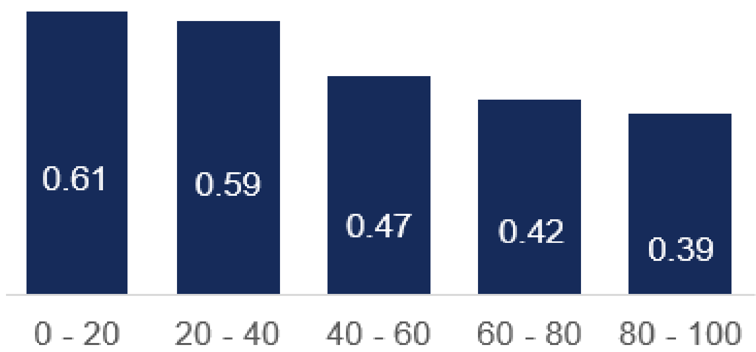

Figure 20: MPCs, m_{ijy}, by income quintiles from Suah (2024)

Identifying whether households are financially constrained is crucial, as such households are more likely to exhibit stronger consumption responses to income changes due to a lack of savings or access to credit. To classify financially constrained households, we follow an approach similar to Kaplan et al. (2014), where households are deemed constrained if their liquid assets (cash, deposits, and residual income) are below a certain threshold relative to gross income, defined by the formula: Liquid assets $< a *$ Gross Income. We calibrate $a = 0.1$, such that the percentage of financially constrained households by income quintiles in the HIES is consistent with the results from the monthly Consumer Sentiment Survey (CSS) conducted by BNM in 2022. In this survey, households reported how easily they could make ends meet, with those responding 'not very easy' or 'difficult' being classified as financially constrained. Unlike Kaplan et al. (2014), who use a threshold of $a = 0.5$ (liquid assets less than two weeks' income), our adjustment to $a = 0.1$ accounts for the fact that the HIES captures monthly flow data, which may underestimate the true stock of liquid assets, leading to an overestimate of constrained households under a higher threshold. Our approach, cross-validated with the CSS survey, aligns intuitively with the data.

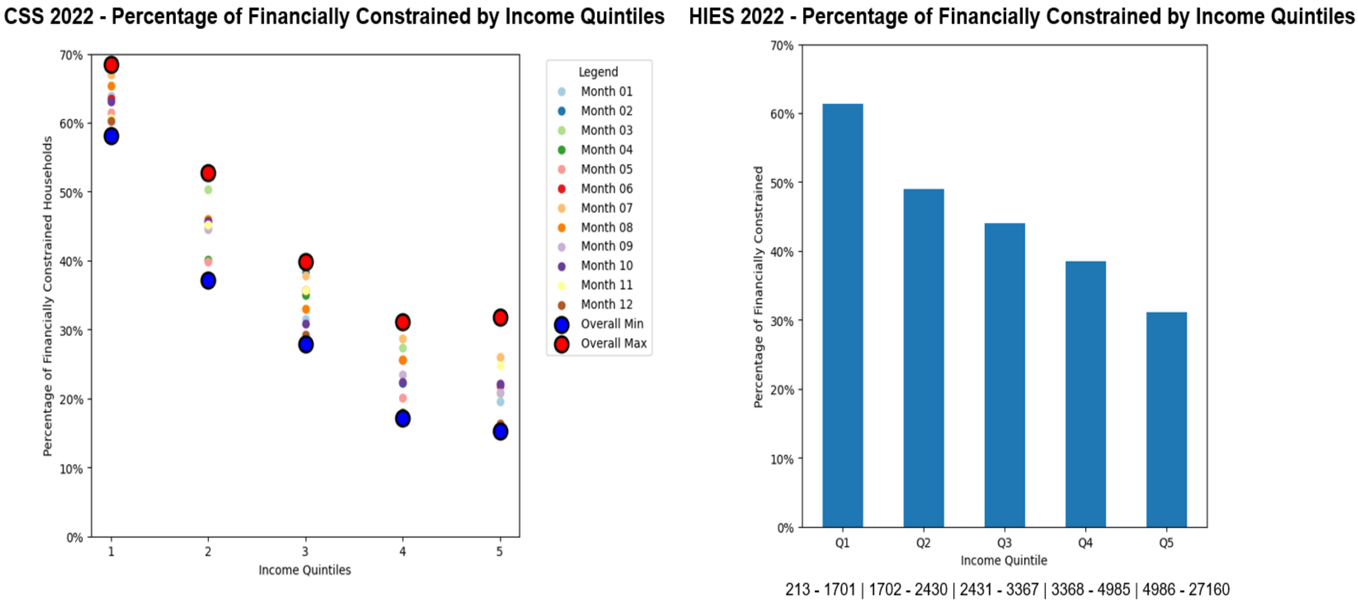

Figure 21: Identification of financially constrained households using BNM CSS 2022

In selecting MPCs across different transmission channels, we rely primarily on the Malaysian literature where available. Most empirical MPC estimates in Malaysia focus on transitory income changes, with limited work on asset channels and none, to our knowledge, on liability channels. These studies are based on different methodologies and datasets (Zarinah and Pereira, 2012; Murugasu et al., 2013, 2015; Suah, 2023, 2024). The most recent estimates by Suah (2024) find that the MPC out of gross transfers declines with income, consistent with earlier findings in Murugasu et al. (2013). Based on this, we adopt the MPCs from Suah (2024) and allow income-varying MPCs for labour earnings and cash transfers, shown in the green rows of Table 6, as these channels resemble transitory income changes. Following Slacalek et al. (2020), we assume that unconstrained households have MPCs ten times lower than constrained households for these channels, as transitory income shocks are less likely to affect the consumption of unconstrained households.

For the asset channels (housing and stocks), shown in the red rows of Table 6, we assign relatively low MPCs of 0.054 and 0.03 respectively, based on Murugasu et al. (2015)—the only Malaysian study estimating MPCs from housing and financial wealth to our knowledge. These values are consistent with international evidence from Guren et al. (2021) and Chodorow-Reich et al. (2021), which show that MPCs from housing and stocks wealth tend to be an order of magnitude lower than those from transitory income. This is largely because housing is relatively more illiquid compared to stocks, while the volatility and uncertainty of stock returns may discourage liquidation. If constrained households hold such assets, they are by definition illiquid. We therefore apply these low MPCs uniformly across households.

For the liability channels (mortgage and other loans), shown in the blue rows of Table 6, we assume higher MPCs, consistent with the persistent impact of debt repayments on disposable income. High-income households typically allocate a smaller share of their income to debt servicing and are thus more likely to be unconstrained (Di Maggio et al., 2017). Moreover, households are incentivised to meet repayment obligations fully to avoid penalties or interest surcharges. Although our assumptions for the debt channels draw from US-based literature, the underlying behavioural mechanisms should remain theoretically valid in the Malaysian context.

We acknowledge that this approach relies on pooled or averaged MPC estimates and does not fully capture state-dependent or household-level heterogeneity, which is a key feature in heterogeneous agent models. Ideally, conditioning MPCs on business cycle phases and household-specific states would provide a more accurate representation of consumption dynamics. However, this is constrained by data availability: the HIES is cross-sectional, and while conducted twice within a five-year period, the sampled households differ across different surveys. A panel dataset tracking the same households over time would be necessary to estimate truly state-dependent MPCs. Given these limitations, our strategy represents a pragmatic compromise, introducing heterogeneity along three dimensions (financial constraints, income quintiles, and transmission channels) based on the best available Malaysian evidence. We view this as an important area for future research, particularly in developing dynamic, state-contingent MPC estimates for Malaysia.

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