Three Essays on Applied Economics with High-Frequency Consumer Data

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Abstract

This thesis consists of three essays that study individual financial decisions and forecast the financial markets by exploiting rich high-frequency, transaction-level spending data from a United Kingdom (UK) online financial management provider.

The first essay documents UK individuals' irrational spending on payday at anticipated income arrivals (known as the payday effect). Consumers tend to spend more than their average daily amounts on even non-recurring consumption items at expected income arrivals, which is inconsistent with the standard consumption theory. This payday effect is pronounced regardless of i) income groups, ii) spending preferences (identified by marginal propensity to consume [MPC] on broad category items), iii) liquidity levels and iv) income uncertainty levels, while heterogeneous degrees of effects exist depending on the sample restrictions. I find that those in the lower income group, lower liquidity group, lower income uncertainty group and higher MPC group tend to show the most prominent payday effects.

The second essay studies the role of reference effects on consumers' choices. Guided by network interactions in a dynamic panel model, I compute the direct and global MPC elasticity with a network weighting matrix, taking 5,424 individuals into account to identify the indirect effect (interchangeably, the reference effect). The results show that the consumption items aggregated from the transaction-level data are clearly characterised as normal, luxury and inferior goods as suggested by microeconomic theory. I further investigate which consumption items generate the greatest reference effect and find that discretionary and visible items show the most pronounced indirect effect as expected. The income reference group is the main driver of the reference effect on most consumption items, followed by the age and region groups. The results are robust to a set of alternative weighting matrices, including sample restriction by gender. Consumption reference effects are evident; the sizes are dependent on the consumption item categories and sample restrictions.

The third essay addresses the stock profitability in the UK financial market according to the availability of consumer data. I evaluate the forecasting performances of candidate predictors constructed from transaction-level spending data by introducing an illustrative investment scenario. I assume that an investor who takes stochastic uncertainty and risk aversion into account would optimally allocate two stocks depending on the availability of consumer data-based predictors. I find that weekly investment decisions improved in the context of economic value when the suggested predictors were taken into account. Thus, it is advisable to set up a firm-level investment portfolio tracked by the ratio of two firm-level sales figures in order to secure information gain.

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Chapter 1

Introduction

1.1 Overview

The study of the determinants of individual financial decisions has always been at the centre of economics. Until recently, the majority of research papers on individual financial choice were mainly based on the use of aggregate data due to the lack of rich panel data. Even though some individual-level data compiled by government authorities exist, they are not accessible to the general public because of data protection policy in many cases. Usually, researchers bypass this data limitation by interviewing individuals with surveys, however, the survey method has its disadvantage in terms of accuracy, panel construction, coverage of the questionnaires and funding issues.

Fortunately, the use of big data has been on the rise over the past few years with the help of information technology (IT) advances, especially in the financial industry. As consumers are starting to rely more on electronic payments, debit cards and credit cards rather than using cash, individual spending and financial decisions are more likely to be recorded and tracked by real-time data processing systems. Financial big data provided by banking and credit card companies are more accurate and comprehensive than data obtained through traditional approaches such as consumer surveys. Therefore, it is expected that now we can revisit the existing theory on individual financial decisions and improve the forecasting performance in the financial market with this consumer big data. Since the past decade, we have been surrounded by a new generation of researchers who investigate financial markets with big datasets, but lots of questions remain unsolved.

In this thesis, I take advantage of UK consumer big data (from a UK online financial management provider called **Money Dashboard** [**MDB**]) to answer some questions regarding individual financial choices and forecasting financial markets.

The first essay uses transaction-level spending data from MDB to capture consumers' excessive co-movement of spending and income on payday (hereinafter, referred to as the *payday effect*). Although theoretical predictions of consumption decisions tell us that individuals will increase spending only to unanticipated income arrivals (known as *consumption smoothing*), I document similar empirical evidence as that in recent literature that counters the prediction of the standard consumption theory.

In the history of the household finance field, most studies on spending patterns used household consumption surveys (e.g. the US consumer expenditure survey) as the source of data (Attanasio and Browning, 1995) despite a few limitations in the survey data. Now, we are able to get into the details of how consumers actually spend and save as well as allocate their assets and debts through real-time, transaction-based data. In this essay, I use 14,881 individuals from the MDB data to find evidence of UK consumers' payday effect.

First, I show that UK consumers do not seem to smooth consumption perfectly within a monthly period. The consumers tend to spend more than their average daily amounts on non-recurring consumption items upon the arrivals of anticipated payments, regardless of their income level. Beyond the recent literature, I further narrow down the consumption items into non-recurring discretionary and non-recurring necessary items to capture the associated payday effects and find consistent results. Second, I study individual heterogeneity in terms of the marginal propensity to consume (MPC) on broad items in a monthly period to characterise consumer types beyond the income levels. To do this exercise, I estimate the individual MPC on discretionary and necessary items with time fixed effects to categorize individuals into high-MPC and low-MPC groups. Then, the payday effect estimation is performed with the restricted sample. The results indicate that those who are in the high-MPC group tend to show severe payday effects. Third, I identify the daily liquidity (stock) by calculating the daily debit and credit transactions (flow) in the individuals' debit accounts and find that the estimated payday effect is most pronounced in the lowest liquidity-level group as expected. Finally, considering income uncertainty as a proxy for precautionary motives of spending patterns, the standard deviation of the regular income arrivals during the whole period for each individual is introduced to split the sample into four groups. The estimation results show that the higher-income-uncertainty-group tends to show less pronounced payday effects than the lower-income-uncertainty-group.

Thus, I conclude that payday effects exist in UK consumers. I further explore robustness check exercises with modified specifications and relaxed definition of regular income, and these exercises all confirm that the payday effect estimations are robust.

The second essay studies the role of reference effects on consumers' choices. Following recent literature in which the dynamic network panel model is widely employed, I empirically show that individual's global MPC elasticity can be decomposed into the direct MPC and the indirect MPC (interchangeably, the reference effect). The associated long-run MPC elasticity can be further obtained by taking the lagged dependent variables (interpreted as habitual spending) into account. I apply this framework to a balanced panel of 5,424 individuals who have a regular income and spending history of 36 months in the MDB data.

I show that the global MPC elasticity framework clearly categorises consumption items into normal/luxury/inferior goods, as suggested by the microeconomic theory. The indirect effects computed from the difference of global and direct MPC elasticities show that discretionary, visible items generate bigger reference effects whereas necessary type items are less affected by references. I also find that the income reference group is shown to be the main driver for most spending items, whereas preference reference is the strongest factor in discretionary spending. Necessary type spending is driven more by habitual factors than the reference effect. I further explore robustness check exercises in which I restrict the samples by gender and construct corresponding weighting matrices for each gender group. These exercises confirm that the weighting matrices are suitably constructed. Last but not least, I compare the specification of all reference group variables to an alternative specification of a single weighting matrix to set up a more parsimonious model. Assuming that the estimation results of the indirect effect with five separate weighting matrices are true, I calculate the root mean square error (RMSE) of each single matrices' indirect effects across consumption items to measure the deviation from the true indirect effect. It is found that imposing a weighting matrices structure based only on the three important reference groups replicates the baseline indirect effects better than a simple structure of averaging five reference matrices.

The results imply that identified reference effects are crucial in revealing consumption item's characteristics as well as the affectability of individuals' spending to their reference groups. From a theoretical perspective, analyses on individual's consumption decisions should incorporate cross-section dependence and time non-separability if we want consumption theory to reflect realistic individual consumption choices. Otherwise, we will end up overestimating the direct MPC with toy models.

The third essay evaluates the forecast performances of candidate predictors constructed from transaction-level data in the context of UK stock market investment. The advent of high-frequency disaggregate data has diverted the existing attention to the way in which firms can directly use consumer data to maximise rents from stock markets. Although we have become able to approach granular consumer datasets, the understanding of how to exploit the data at the transaction-level in predicting stock markets is at an early stage. In this paper, I fill this gap by setting up an investment strategy in which portfolios are paired with a set of predictors extracted from the MDB data.

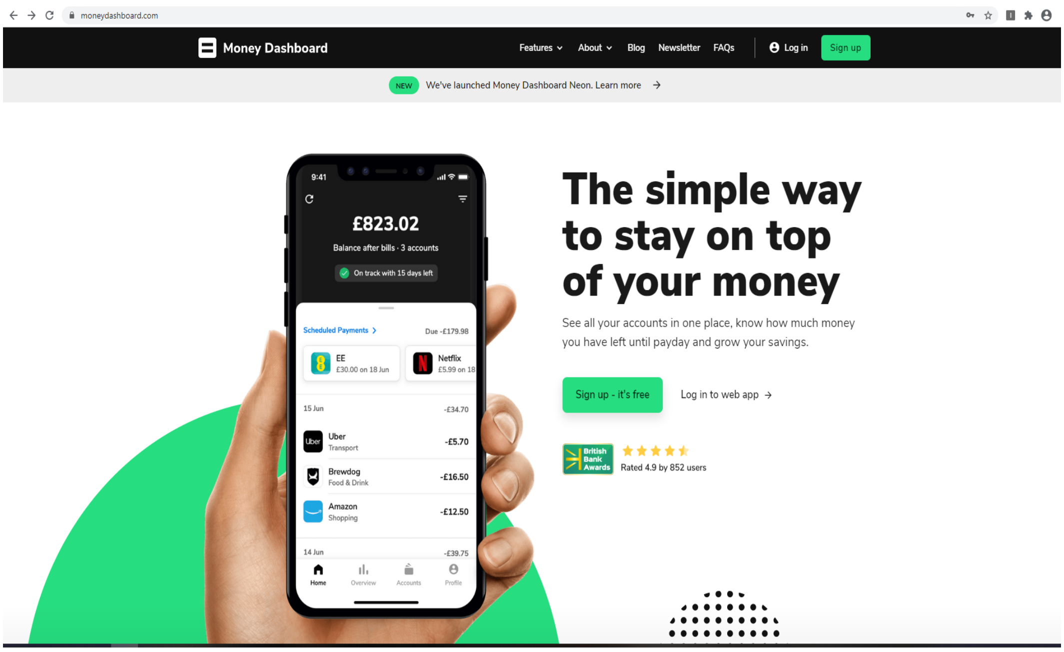
I evaluate the forecasting performances by introducing an illustrative investment scenario following that of Garratt and Lee (2010). I assume that an investor who takes stochastic uncertainty and risk aversion into account optimally allocates two stocks depending on the availability of consumer data based predictors. Weekly investment decisions improved in the context of economic value when suggested predictors are taken into consideration. Thus, it is advisable that we set up a firm-level investment portfolio (at the intra-aggregation level) tracked by the ratio of firm-level sales figures (intra-aggregation predictors) in order to secure information gain. In the case of inter-aggregation level portfolios, category-level predictors relatively perform better than firm-specific level predictors. However, when it comes to the portfolios between a highly disaggregate firm and a highly aggregate FTSE350 composite index, MDB predictors are found to be weak.

In sum, information gain from consumers' detailed spending data is pronounced when we can keep track of the sales of specific firms or, at least, the sales figures of all constituents in specific sectors. Intuitively, highly aggregated stock indices are more likely to have complicated factors other than just sales information whereas individual firm stocks from the intra-aggregation level will have shared factors. Thus, simple ratio predictors of sales within the intra-aggregation level can be effective in achieving profitability when our target forecasts in portfolios are in the intra-aggregation level.

1.2 Data source and structure

This thesis uses transaction-level spending data from the UK's financial management service provider **Money Dashboard** (Figure 1.1).

Figure 1.1: The Screenshot of Money Dashboard Website



Note: 1) Source: Money Dashboard

In the initial stage of this research project, what we can observe in the raw data are transaction amounts with some identifiable or unidentifiable tags.[1] As I clean and construct the data for the fit of the research questions, the time dimension is made daily for Chapter 2, monthly for Chapter 3 and weekly for Chapter 4. For each time dimension, there are various levels of aggregation for constructing spending variables, from the all-spending aggregate (highly aggregate variable) to the non-recurring sub-category item (highly disaggregate variable). From this aggregation dimension, I ask research questions related to information gain from different aggregation levels in the following chapters. Finally, it is possible to impose cross-section dependence on consumers' choices. In Chapter 3, I take this cross-section dimension into account to explain the role of social interactions in individual financial decisions in a more sophisticated way.

1.3 Thesis Outline

The thesis is organised as follows. Chapter 2 introduces data descriptions and documents the payday effects across consumption items with the suggested consumer heterogeneity. Chapter 3 studies the reference effect on consumer choices. Chapter 4 investigates whether real-time consumer data can be helpful in achieving stock profitability. Lastly, Chapter 5 concludes and suggests potential extensions in future research.

[1]For example, we can observe that a consumer shows a debit transaction of £30 from the Tesco supermarket on a specific date with a credit card.

Chapter 2

Are Some Types of Consumption Items Smoother than Others?

2.1 Introduction

Consumption expenditure matters in economics. Consumption is the most important determinant of economic agents' utility from the perspective of microeconomic theory, whereas consumption expenditure aggregate constitutes about two-thirds of the GDP in most countries. Furthermore, the variations in individual consumption compositions have distributional implications on top of income inequality (Attanasio and Pistaferri, 2016). We can get an idea of the dynamics of inequality from the composition changes in consumption aggregates if we know individuals' detailed financial choices. Until recently, hypothesis tests on consumption theory and the associated empirical evidence were based on consumption aggregates. This was especially due to the fact that most consumption disaggregate data were restricted to the national and regional aggregate levels. Even though some of the individual disaggregate data were captured for administrative purposes at the government level, such as tax agencies, it was not an easy task for general researchers to access those datasets. Naturally, the study of individual consumption choices employed the survey method to obtain detailed information on spending behaviour (e.g. the US Consumer Expenditure Survey) despite the disadvantages of survey data such as small sample and the potential unreliability of the interviewers (Attansio and Browning, 1995).

Recently, we have begun to see the availability of high-frequency data from online-based bank accounts for use. Thus, we can now get into the details of how people actually spend and save as well as allocate their assets and debts through real-time transaction-based data. However, the understanding of individual financial choices based on granular spending data is at an early stage. Motivated by this research gap in the literature, this chapter studies irrational individual spending patterns by exploiting UK individuals' detailed transactions from bank and credit card records.

Standard consumption theory explains that individuals will seek to keep the marginal utility of consumption smooth over time since individuals' utility function is assumed to be additively separable in consumption over time.[1] Under this rationality assumption, consumers will prefer a constant marginal utility generated by smoothed spending across time. Theoretical prediction tells us that individuals will increase spending only in response to unanticipated income changes. However, much empirical evidence has been provided to counter this theory. More recently, some papers have documented this evidence with disaggregate consumer data. Following the recent literature of the new generation (Gelman et al., 2014; Olafsson and Pagel, 2018), which uses high-frequency personal spending data to capture how individuals' spending amounts are shown to peak on payday, this chapter documents the stylised facts of payday effects with about 14,881 individual consumers across the UK over a period of five years.

The MDB dataset is the perfect disaggregate dataset to document stylised facts about consumer choices. The raw data have very extensive coverage of variables: recorded amounts in terms of debit and credit transactions, dates of transactions, names of merchants, gender and age, four-digit postcodes, account identification numbers and so on. With this information, I construct numerous variables such as daily credit amounts identified as the income category and daily debit amounts identified as several consumption item categories. With some further identification strategies explained in Section 2.3.3, I reasonably construct the derived regular income, irregular income, recurring spending and non-recurring spending amounts in a monthly period to restrict the sample only to economically active consumers. I rule out consumers who had abnormal transactions (e.g. too large amounts of monthly income arrivals or close-to-zero amounts of monthly spending). As a result, I finalise a well-cleaned sample in which the data shows descriptive statistics consistent with the UK's official data (Office of National Statistics [ONS]).

First, I show that the individuals do not seem to smooth consumption perfectly in a monthly period. The consumers tend to spend more than their average daily amounts on non-recurring consumption items upon the arrival of anticipated payments regardless of their income level. Beyond the recent literature, I further narrow down consumption items into non-recurring discretionary and necessary items to capture the payday effects and find consistent results. Second, I study the individual heterogeneity in terms of the MPC on a broad category within a monthly period to characterise consumer types beyond the income levels. To do this exercise, I estimate the individual MPC on discretionary and necessary items with time fixed effects to categorise individuals into the high-MPC or low-MPC groups. Then, payday effect estimation is performed

[1] Additionally, standard consumption theory assumes the utility function is separable from other's consumption. This motivation will be dealt with in Chapter 3 regarding consumption choice within cross-section dependence.

with the sample split. The results indicate that those in the high-MPC group tend to show severe payday effects. Third, I identify the daily liquidity by calculating the daily debit and credit transactions in the individual's debit accounts. I focus on only debit accounts in which frequent transactions were executed. This is because some debit accounts can be regarded as savings accounts for some consumers if abundant money is stored without transactions. I find that the estimated payday effect is most pronounced for the lowest liquidity level group, as expected. Finally, considering income uncertainty as a proxy for the precautionary motives of spending patterns, the standard deviation of the regular income arrivals during the whole period for each individual is introduced to split the sample into four groups. The estimation results show that the higher-income-uncertainty-group tends to show less pronounced payday effects than the lower-income-uncertainty-group. Thus, I conclude that payday effects exist in the UK consumers and that different degrees of payday effects exist across heterogeneous individuals. I further explore robustness check exercises with modified specifications and relaxed definitions of regular income, and these results all confirm that my payday effect estimations are robust.

This paper is related to the literature on the classic consumption smoothing problem and co-movement of spending and income arrivals. Early discussions on this theory tell us that rational agents will smooth their consumption if the income arrivals are anticipated. Modigliani and Brumberg (1954) focus on the role of expected life-time wealth in determining current consumption expenditure; Friedman (1957) argues that permanent consumption is dependent only on permanent income, not transitory income change. The random walk hypothesis of Hall (1978) was modified as the stochastic version of the lifecycle-permanent income theory in which rational agents' information is all incorporated in the lagged consumption variables; thus, lagged income variables will not deliver extra information. Against these theories under strict assumptions, numerous papers have documented excessive co-movement of consumption-income. Flavin (1981) argues that current income changes affect expectations of future permanent income; Campbell and Mankiw (1989) use aggregate time-series data and show the strong relation between current income and consumption. Deaton (1991) and Shea (1995) use the concept of borrowing constraints to explain the excessive sensitivity of consumption. My work is based on these countless theoretical and empirical discussions but more focused on capturing the stylised facts of spending-anticipated income co-movement with the UK spending disaggregates.

My attempt at documenting the payday effects with transaction-level data is part of a recent study using big data from financial aggregation application. Gelman et al. (2014) show that consumers' spending spikes when income is received, even if it is regularly anticipated salary income, with a US financial management app (CHECK) for the first time. Olafsson and Pagel (2018) use well represented Icelandic data and document that spending tends to peak when a salary is received, regardless of income category and sample splits. Basically, I follow these two papers as the closest reference papers, however, my paper is different in these below points due to the data characteristics.[2] To be specific, I exploit the granularity of this data to set up spending and income categories and corresponding sub-categories. I also further characterise non-recurring spending into necessary spending and discretionary spending in detail to study payday effects compared to these two previous papers, which only deal with non-recurring spending.

More recently, we have seen household finance papers regarding consumers' patterns that are heavily driven by big data. Zhou et al. (2016) use prepaid card transaction data, which represent low-income consumers to capture payday effects. Keung (2018) and Ganon and Noel (2019) show that consumers even react to predictable changes in income payments based on the Alaska Permanent Fund and unemployment insurance data, respectively. Aydin (2019) exploits 45,307 credit lines data to examine the effect of exogenous shock to credit availability on consumption. However, my paper is different in line with the information available from the original dataset. Compared to these researchers' contributions, I identify the liquidity level, income uncertainty level and MPC on different consumption items to document heterogeneous payday effects.

This paper is partly related to the literature on consumption items' characteristics. When it comes to the classification of necessary and discretionary items, I mainly follow Kuchler and Pagel (2020) in classifying spending categories into 'regular', 'non-regular', 'non-regular discretionary' and 'non-regular non-discretionary' spending items. However, I define the items of 'pet expenditure', 'automotive expenditure' and 'healthcare/medical products' of Kuchler and Pagel (2020) as necessary items in this chapter.[3] Additionally, I introduce the concept of visible (conspicuous) items. Heffetz (2011, 2018) characterises consumption item's income elasticity according to their visibility. I refer to this paper in order to construct the visible item category which is used in Chapter 3.

The rest of this paper proceeds as follows. Section 2.2 describes theoretical backgrounds. Section 2.3 presents data and summary statistics. Section 2.4 illustrates the econometric methodology. Section 2.5 lays out the main results of payday effects. Section 2.6 provides heterogeneous payday effects depending on consumer characteristics. Section 2.7 tests the robustness of this paper's estimation strategy with the alternative specifications. Section 2.8 concludes.

[2] Granularity is the merit of this data. However, other important information such as balance, overdraft are only available at the end of data extraction which restricts some interesting policy analysis.

[3] The reason for this is that I believe those items have low price elasticities of demand since we are not able to reduce spending on them once we need them.

2.2 Theoretical Background

I describe the classical consumption theory, in which optimal consumption is derived from the permanent income hypothesis. Then, I introduce some theoretical rationales for the spending anomalies: excess sensitivity and smoothness of consumption to income innovations. The notations and derivations in this section are mainly based on the textbook of Bagliano and Bertola (2004).

2.2.1 Permanent Income and Optimal Consumption Dynamics

The theoretical background of the consumption smoothing problem can be summarised as the well-known Euler equation, which describes the optimal consumption and saving choice problem. Consider an optimisation problem in which infinitely-lived rational agents solve and maximise an intertemporal utility function in an uncertain environment.[4] Under further assumptions of intertemporal separability (or additivity over time) and intertemporal consistency (such as exponential discounting), we can set the consumer's problem as follows:

$$\max_{c_{t+i}, i=0,1,\ldots\infty} U_t = E_t\left[\sum_{i=0}^{\infty}(\frac{1}{1+\rho})^i u(c_{t+i})\right] \tag{2.1}$$

$$A_{t+i+1} = (1+r)A_{t+i} + Y_{t+i} - C_{t+i}, \quad A_t \;\; given \tag{2.2}$$

where U_t is the utility object of maximization at time t, Y_t is the income at time t, C_t is the consumption expenditure at time t, A_t is the asset at time t, ρ is the subjective discount rate and r is the market interest rate. Then, the first order condition generates the Euler equation which explains the dynamics of marginal utility between two periods.

$$u'(c_t) = \frac{1+r}{1+\rho}E_t u'(c_{t+1}) \tag{2.3}$$

Here, if we impose further restrictive assumptions in which ρ and r are the same for simplicity, we can derive the main implication of the intertemporal choice model with rational expectations.

$$c_{t+1} = c_t + u_{t+1} \tag{2.4}$$

$$E_t c_{t+1} = c_t \tag{2.5}$$

We can interpret equation (2.5) in that the best forecast of consumption in the next period is the current consumption. However, this solution of the consumer's intertemporal choice problem is not a consumption function because it only explains the consumption dynamics from one period to the next period. Thus, if we connect the intertemporal bud-

[4] If we use this assumption, we can impose income uncertainty heterogeneity across individuals.

get constraint to the optimal consumption dynamics, we finally have the consumption function below.

$$c_t = r(A_t + H_t) \equiv y_t^P \tag{2.6}$$

$$H_t = \frac{1}{1+r} \sum_{i=0}^{\infty} \left(\frac{1}{1+r}\right)^i E_t y_{t+i} \tag{2.7}$$

Human wealth H_t in equation (2.7) is the present value of the expected future labour incomes at time t. Now, the consumption in each period t can be derived as the permanent income y_t^P which is the return on the sum of financial and human wealth in a consumer's lifetime.

To incorporate saving in this framework, we introduce disposable income y_t^D and current income y_t

$$y_t^D = rA_t + y_t \tag{2.8}$$

Then, saving s_t can be derived as follows

$$s_t \equiv y_t^D - c_t = y_t^D - y_t^P = -\sum_{i=0}^{\infty} \left(\frac{1}{1+r}\right)^i E_t \Delta y_{t+i} \tag{2.9}$$

As we can see in equation (2.9), consumers save and accumulate financial assets to deal with expected future declines of labour income.

Finally and most importantly, in order to highlight the main purpose of this paper, the relation between current and permanent income is explored. If we introduce λ as a degree of persistency and $\overline{y}$ as the unconditional mean of income, we get a simple first-order autoregressive process generating income y:

$$y_{t+1} = \lambda y_t + (1-\lambda)\overline{y} + \epsilon_{t+1}, \quad E_t \epsilon_{t+1} = 0 \tag{2.10}$$

Equation (2.10) tells us that future income is composed of partly of past income and partly of permanent income. After some derivations, we get the direct linkage between current consumption and current income innovation ϵ_{t+1}

$$c_{t+1} = c_t + \left(\frac{r}{1+r-\lambda}\right)\epsilon_{t+1} \tag{2.11}$$

Intuitively, this derivation in equation (2.11) means that if persistency $\lambda = 0$, y_{t+1} in equation (2.10) depends mainly on permanent income and the effect of innovation in current income ϵ_{t+1} on consumption tomorrow is small, as a result, consumption change will be limited in the future. If $\lambda = 1$, the effect of innovation in current income ϵ_{t+1} is huge such that today's income shock (which is not permanent) matters in tomorrow's consumption. If we assume that consumers behave in a rational manner as classical consumption theory tells us (i.e. $\lambda = 0$), we should not see the spending anomalies in which anticipated changes in income affect spending. This paper aims to empirically explain this gap arising from potential *unknown* factors. Spending anomalies can happen provided any *unknown* factor that makes λ nonzero.

2.2.2 Excess Sensitivity and Smoothness of Consumption to Income

The applied consumption literature has documented empirical evidence of spending anomalies: excess sensitivity and smoothness of consumption to income innovations. The main explanations of these phenomena are based on imposing restrictions on theoretical consumption behaviours.

Numerous papers (Deaton, 1991; Shea, 1995) have focused on the role of **liquidity constraints** in consumption choices. Since we are often subject to intertemporal budget constraints, we might be able to encounter a lack of liquidity and be sensitive to money arrivals in the short-term. This means the λ in equation (2.11) can be perceived as higher when liquidity constraints are taken into account. To this end, we can see the **excess sensitivity** of consumption to the anticipated income increase due to the liquidity problem, even in the context of rational consumer assumptions.

Another example of a spending anomaly is the **excess smoothness** of consumption to income which is typically explained by the **precautionary saving** motive (Carroll and Samwick, 1998). In reality, we perceive uncertainty and this is incorporated in the context of the convex marginal utility function. If individuals are concerned about uncertainties in the future, even positive innovations in unanticipated income changes will just lead to consumption smoothing. An illustrative example of this precautionary saving motive is an old retired man who does not want to decumulate wealth with concerns on the rest of his life and spend only a small part of income arrivals.

In light of these theoretical explanations for spending anomalies, I examine whether my data provide empirical evidence consistent with liquidity constraints and precautionary saving motive. It is predicted that the high-liquidity-level (related to excess sensitivity) group and high-income-uncertainty (related to excessive smoothness) group would show the least pronounced payday effects. Details will be delivered in Section 2.6.

2.3 Data

2.3.1 Data Source: Financial Management Application

The raw data cover the period from January 2012 to February 2018 and are obtained from UK online financial aggregator **MDB**, which provides users with online financial management. As we can see in Table 2.1, MDB automatically captures and stores banking data and downloads at the transaction level and this allows users to keep track of transactions in their debit, credit and savings accounts and the associated balances and overdrafts. It also shows the dates of transactions, amounts of spending and bank account reference numbers. The individual information includes user reference numbers, postcodes, salary ranges, gender and age. There are also variables such as ‘transaction description’, ‘user precedence tagname’ and ‘manual tag name’ that contain descriptive information such as ’unemployment benefits’ or ‘presents for parents’ from which we can guess individuals’ current status or purpose of transaction. With all this information, I recategorise all transactions into 26 categories of debit transactions and 26 categories of credit transactions.[5]

Table 2.1: Preliminary Variables Extracted from MDB

Initial Info Variable	**Description**
Transaction Reference	A unique identifier for the transaction
User Reference	A unique identifier for the customer
User Registration Date	The date the user registered with the MDB website
Year of Birth	The year in which the customer was born
Salary Range	A field indicated the salary of the customer who made the transaction
Postcode	The outward code and postal sector for the customer’s postal address
Derived Gender	The gender of the user
Transaction Date	The date on which the transaction was posted to the banking system
Account Reference	A unique identifier for the account held by the user
Provider Group Name	The financial institution who provide the account
Account Type	The type of account to which the transaction relates
Transaction Description	The description relating to the transaction, provided by the merchant
Credit Debit	A flag of whether the transaction was a credit or debit transaction
Amount	The amount in GBP for the transaction
User Tag Name	A tag allocated to the transaction to indicate the type of transaction
Manual Tag Name	A tag to indicate the type of transaction entered by the user
Auto Tag Name	A tag assigned by the system through automatic algorithms
Merchant Name	The transaction related to a key UK merchant (list of top 1000)
Account Creation Date	The date when the relevant account was first added to MDB
Transaction Updated Flag	Whether the transaction has been updated since it was created

Note: 1) Source from MDB

[5]However, the majority of credit transactions are identified as income arrivals or refunded purchases. Thus, not all ’credit’ categories are meaningful by themselves.

2.3.2 Data Cleaning

Since this new form of high-frequency transaction data might also capture systematic errors, it is important to clean noises and construct variables in an appropriate way. First, I deal with individual-level data cleaning: identifying refunded purchases, associated initial purchases and various types of transactions such as spending, saving and transfers between/within individuals. Second, there are potential noises due to systematic problems including duplicate transactions and imperfect electronical information updates in the application. This subsection explains how I dealt with these potential noises and corrected errors in the raw dataset.

Panel Construction

Among the 100% sample of more than 80,000 users in the MDB data since 2012, I focus on individuals who i) receive regular income arrivals, ii) observed for longer than 3 years after sign-up, iii) appear to have spent money. This allows me to use about 14,881 active and sensible users (unbalanced panel) for the main analysis in this chapter.[6] The restricted sample mainly represents male, young and urban residents. The average transaction duration is about three years.

Duplicate and Dual Transactions

The majority of variables in the raw dataset are regularly updated with unique reference numbers. However, I suspect some variables contain duplicate transactions systematically.[7] This might have been the case where the system updates transactions without replacing the associated old records. In this case, I delete the old record with the old account reference number. Then, I rule out outliers: I trim individuals at the top and the bottom 1% at the distributions of monthly spending and income amounts to control for measurement error and the impact of extreme values. Additionally, there are dual transactions in which opposite transactions appear across different accounts of debit, credit and savings. For example, transactions of withdrawal and deposit might have happened at the same time. These transactions are not errors in terms of intra-individual accounts, but these transactions had to be flagged and put aside properly in order to identify the 'pure' spending amount. Thus, I identify pair transactions of the same amounts of money within the same or a few days' duration. To explain the cases in detail, consumers might have: i) saving transactions wherein money flows from their current account to their savings account; ii) withdrawal transactions where money

[6] In Chapter 3 and 4, I further cut out individuals to make a balanced panel of 5,424 individuals and 13,193 individuals, respectively, from 2015 to 2018.

[7] There were some cases wherein two transactions with the same amounts are always shown with different account numbers in the raw data.

flows from their savings account to their current account; iii) transferring loan fund arrivals or loan repayments across their savings and debit accounts. iv) transfers of money across the same debit accounts or same savings accounts that are not perceived as having an intention to spend. In sum, the final goal of this cleaning is to have 'non-dual spending' i.e. individuals' genuine spending after cleaning away all errors.

Categorisation of Consumption and Income Arrivals

I sort out 290 detailed tagnames designated by the MDB users in the first stage and then classify them further with automatically tagged information. Based on these detailed tagnames, I broadly construct 26 categories. Details are provided in Tables 2.5-2.6. In each category, there are debit and credit transactions. In the case of debit transactions, I identify discretionary and necessary spending only for the non-dual transactions. When it comes to the income arrivals category, I sub-categorise these further in detail: regular income, paycheck, irregular income, asset income, loan arrival and refunded purchases. Details will be provided in Subsection 2.3.3.

Recurring Transactions

I use the identification strategy to differentiate recurring transactions from non-recurring ones. Specifically, I identify and match transactions of similar amounts of money (20% higher or lower than previous transactions within designated durations: 25-120 days[8]) that appeared at a regular basis from the same merchants or tagnames. To explain in detail, one could purchase £100 from a merchant this month and repeat a purchase of £110 from the same provider in the following months. In this case, I identify these consecutive transactions as recurring spending cases.

Cash and Transfer Data

Dealing with unidentified uses of cash and cash transfers is a difficult task. Only well-identified cash uses with detailed tags or records can be classified into sub-categories. I look into the 'user-tagname', 'merchant-tagname' and 'auto-tagname' in depth to prevent cash transactions from remaining unidentified. Then, if any of transactions with cash could be identified, these are classified into categories as debit/-credit account transactions. After this cleaning, there remain many cases of unidentified cash transactions. Thus, I assume that spending with cash below £100 can be classified as discretionary spending whereas cash amounts higher than £100 can be considered as necessary spending.[9] Again, I apply the criteria of recurring spending on cash-transfers

[8] This is for capturing not only monthly routines but also bi-monthly payments

[9] This cleaning procedure is open to criticism in that the classification is arbitrary. I assume that individuals use both debit cards and cash at the same time so that small amounts of cash use can represent

or transactions with cash so that cash-based transactions are also classified into the necessary, discretionary, recurring or non-recurring spending, which is consistent with debit/credit account based transactions.

2.3.3 Variable Construction

Income Arrivals

I set up the following **regular income** categories (credit transactions): benefits, bursaries, family benefits, other benefits and **paychecks** (which is categorised as main and secondary salary). I also have the following **irregular income** categories (credit transactions): expenses, tax rebates, business expenses, winnings, rewards and cashbacks. I also set **asset income**: financial asset income, housing rental, mortgage release. Even though **loan arrival** is not an income, I categorise this as one category since this is also money arrival: payday loan, personal loan, secured and unsecured loan and student loan. There are also **withdrawal** and **transfer income**. The details are summarised in Table 2.2. Figures 2.1-2.3 capture the basic characteristics of each income payment, where regular income payments tend to arrive on Friday and the third week of a month while irregular income payments show less typical patterns.

Table 2.2: Income Categories Description

Category	Components
Regular income	Benefits, Bursaries, Job seekers benefits, Work pension
Paycheck income	Salary, Overtime works
Irregular income	Bonus expenses, Tax rebates, Winnings
Asset income	Housing rental, Interest rate income
Loan arrival	Payday loan, Secured loan funds, Cash advance
Withdrawal	Withdrawal from banking account
Transfer income	Refund and transfer from unidentified accounts

Note: Data from MDB

Spending Categories

I construct broad spending categories as discretionary, necessary, durables, finance and others. **Discretionary spending** has alcohol and tobacco, clothing and appearance, charity, eating-out, family fun and hobby, gambling, social-outing, traveling, semi-durables and household management. In the case of **necessary spending**, transportation, private car use, eating-at-home, education and childcare, medical costs, pets,

discretionary spending.

housing costs, taxes and bills are included. There is **visible item** category in which, again, I reclassify private car use, education and childcare, pets, alcohol and tobacco, clothing and appearance, eating-out, family fun and hobby, gambling, social-outing, semi-durables and household management spending, except for bills. Semi-durables and household managements are further classified as **durable goods** (also as discretionary). There is also a **transfer type category**. Bank charges, credit card payments, savings, investments and pensions, insurance and loan arrivals are defined as **finance**. For **others**, I classify cash, current accounts and other transfers into this category. Table 2.3 summarises each category of the spending type transactions.

Balances and Overdrafts

Even though MDB provides balances and overdrafts for each account, these variables are unfortunately available only at the end of this dataset (Feb. 2018). Therefore, I am not in a position to directly observe the daily or monthly variations of this information. Instead, I define the daily balance of each account by keeping track of the net inflow and outflow after cleaning the data sensibly. Since I restrict individuals who appear to exist at the terminal period, this approach allows me to indirectly observe the daily and monthly balances of each account. Table 2.4 gives an example: given a balance of £100 at the end of the data, we can keep track of the daily net flows of individual balances to figure out the initial balance at the t-5 period as well as the daily balance. However, in the case of overdraft, there is no way of doing a similar calculation without specific detailed data from bank and credit card firms.

Monthly Variables

Although I focus on the daily transactions of specific categories of income and consumption expenditure, I define monthly variables for further analysis. For each variable defined on the daily transaction basis, income categories, spending categories, savings amounts, withdrawal amounts, loan fund arrivals and debt repayments can be also constructed as monthly variables. Furthermore, I define the monthly net inflow of money as a candidate for the concept of the liquidity level. In the end, I am able to identify the individual heterogeneity based on monthly transactions on spending, saving and income. These variables are used in the sample split analysis.

Table 2.3: Spending Categories Description

Broad	Category	Visibility	No	Sub-category	Components
Non-durable	Necessary		1	Transportation cost	Public transport, Taxi, Vehicle hire
		v	2	Private car use	Fuel, Parking, Vehicle running cost
			3	Eating-at-home	Food, Groceries, Supermarket
		v	4	Education & Childcare	Book, Nursery fee, School fee
			5	Medical cost	Dental, Eye care, Medication
		v	6	Pets	Pet food, Pet care
			7	Housing cost	Mortgage payment, Rent
			8	Tax and bills	Bills, Broadband, Gas, TV, Water
	Discretionary	v	9	Alcohol and Tobacco	Alcohol and Tobacco
		v	10	Clothing & Appearance	Accessories, Clothes, Hairdressing
			11	Charity	Charity, Donation, Sponsorship
		v	12	Eating-out	Dining, Restaurant, Snacks
		v	13	Family Fun and Hobby	Gym, Spa, Toys, Hobby
		v	14	Gambling	Gambling account
		v	15	Social-outing	Cinema, Flower, Gift
			16	Travel	Hotel, Flights, Camping
Durable	Disc.	v	17	Semi-durables	Electronics, Kitchen appliances
		v	18	Household MGT (No bills)	DIY, Furniture, Garden
Transfer type	Finance		19	Bank Charge	Bank charge, Interest rate charge
			20	Credit Card	Credit card payment/repayment
			21	Saving	Car fund, Wedding fund
			22	Investment and pension	Bond, Pension, Sharedealing account
			23	Insurance	Health/Income/Life insurance
			24	Loan arrival	Personal, Secured, Student loan
	Others		25	Cash & Transfer	Cash, Current account Transfer, One-off payment
			26	Income type	Benefits, Salary, Rental income

Note: 1) Data from the MDB. 2) This classification is applied to both debit and credit transactions. 3) External validation of the definitions of necessary and discretionary item is limited in the literature. I mainly follow Kuchler and Pagel (2020) in classifying spending categories into 'regular', 'non-regular', 'non-regular discretionary' and 'non-regular non-discretionary' spending items. However, I differently define items of 'pet expenditure', 'automotive expenditure', 'healthcare/medical products' in Kuchler and Pagel (2020) as necessary item in this current chapter. 4) Visible items are defined with apparel, car accessories, electronics, home furnishings and decorations (Agarwal et al., 2020) whereas visibility of items is introduced as ranks: cigarettes, cars, clothing, furniture, jewellery, recreation, food out, alcohol home, barbers, education (Heffetz, 2011)

Table 2.4: Tracking Past Balances

	t-5(initial)	t-4	t-3	t-2	t-1	t(terminal)
Debit	-	-100	-80	0	-100	0
Credit	-	100	0	100	0	180
Balance	**0**	0	-80	20	-80	**100**

2.3.4 Summary Statistics

Basic Statistics

Table 2.7 shows the summary statistics of the MDB users. After cleaning the raw data set, we can see that 14,881 MDB users' average age is 32 years and that their median salary range falls into the Group 3 (£25,000 to £35,000). The individuals tend to have two different account types and 916 days of transaction out of the 1,360 days of duration in the data. For the purpose of checking whether the data cleaning process is proper or not, I summarise the monthly aggregated data from the restricted sample (Table 2.8) and compare with the official statistics.[10] These summary statistics from the sample data are consistent with the survey data from the UK ONS (median disposable income: £2,192 [11] [£1,931 in the MDB data], monthly spending in the UK: £2,208 [£2,243 in the MDB data], and monthly spending in London: £2,633[12]). My final sample is slightly over represented by young people but this does make sense since financial aggregation application is easier for the young to approach and use.

Geographic Distribution of the Sample

Table 2.9 displays the geographic distribution of the 14,881 individuals in the sample. I report 60 counties out of the 125 counties in the UK. These 60 counties represent 78.0% of the population in the data; the actual population of ONS shows 75.6%, so it looks like a decent representative sample. When I look into the specific regions, London is overpopulated in the MDB data compared to the actual population shown by ONS. However, other counties show a similar or slightly lower population than the actual population (2011 census, UK ONS). As these MDB data have more samples from young people and those who are interested in financial management with high-end technology, it is reasonable that MDB has a geographical distribution like this.

[10] The UK ONS conducts a representative survey of household income and spending statistics every month.

[11] '*Household disposable income and inequality in the UK: financial year ending 2016*', UK ONS.

[12] '*Family spending in the UK: April 2017-March 2018*', UK ONS.

2.4 Econometric Methodology

In this chapter, I estimate the payday effect by running the below regression specification following Gelman et al. (2014) and Olafsson and Pagel (2018).

$$\left(\frac{Spending}{Average\ Daily\ Spending}\right)_{it} = \sum_{k=-6}^{7} \beta_k I_i(Paid_{t+k}) + \delta_{dow} + \phi_{wom} + \varphi_{moy} + user_i + \epsilon_{it}$$
$$where \quad i = 1, \dots, N \quad t = 1, \dots, T \tag{2.12}$$

where we have the dependent variable as a ratio of spending on date t by individual i to the average daily spending around date t, as well as, control variables: days of week δ_{dow}, weeks of month ϕ_{wom} and months of year φ_{moy}. The indicator variable $I_i(Paid_{t+k})$ is equal to one if individual i receives a payment at time $t + k$; otherwise, the variable is equal to zero. The coefficient of β_k at the lag of k measures the fraction by which today's individual spending deviates from the average daily spending in the days around the income payment arrival. The individual fixed effect variable $user_i$ controls for the unobserved individual heterogeneity. The standard errors are clustered at the unique individual level. When it comes to the different groups of income and salary, I categorise individuals with each quartile group.

Another similar specification is the MPC out of liquidity (MPCL) version for robustness check purposes in Section 2.7.

$$LogC_{it} = \alpha LogL_{it} + \sum_{k=-6}^{7} \beta_k I_i(Paid_{t+k}) + \delta_{dow} + \phi_{wom} + \varphi_{moy} + user_i + \epsilon_{it}$$
$$where \quad i = 1, \dots, N \quad t = 1, \dots, T \tag{2.13}$$

where $LogC_{it}$ is the log transformation of daily spending on each consumption item, $LogL_{it}$ is the daily liquidity in users' debit accounts and α is the associated coefficient, as it measures a daily MPC out of daily liquidity. Still, my interest lie in $\beta_k s$, with leads and lags terms, which represent payday effects.

2.5 Main Results of Payday Effects

2.5.1 Payday Effects of Regular Income Payments

In each month, I choose regular income arrivals until the fifth largest amount of income in order to estimate the payday effects. As we can see from Figure 2.4, all of the payday effects are pronounced across all types of spending, it is found that UK consumers do not smooth consumption in a monthly period despite the anticipated income arrivals which is inconsistent with the standard consumption theory.

All-Spending

Figure 2.6(A)[Table 2.10] shows that the all-spending item responses to the regular income payments. The coefficient of interest is $Payday(0)$, which displays that the consumers spend 49% more than they do on an average day. In addition, individuals spend less than their average daily spending right before the regular income payments. Figure 2.6(B)-(E) shows the spending responses to the regular income payments depending on income quartile. Both poor (Group1) and rich (Group 4) individuals show clear responses to their income arrivals; meanwhile, the low income group individuals spend 53% more than their average daily amounts, and the richest group individuals only spend 34% more.

Non-Recurring All-Spending

The focus of this chapter is non-recurring spending. Since it is considered that the majority of payday effects appeared due to regular payments on a monthly basis, the payday effects are expected to be less pronounced if monthly recurring spending such as rent or bill type transfer was excluded. Figure 2.8(A)[Table 2.11] shows that our coefficient of interest $Payday(0)$ that displays 37% more than the average daily spending without recurring spending and that these coefficients of the days surrounding payday are statistically significant. When we look into the control variables, the days of the week effects indicate that the users tend to spend on Monday (coefficient of 0.51).[13] Furthermore, we can see the third week has the highest effect on spending and the fourth week has the lowest.[14] These effects capture the phenomenon in which people are likely to spend more when they have income arrival even though this type of spending is non-recurring spending. When it comes to the different income

[13]However, there are some pending settlement transactions from the banking system so we can understand that this Monday effect has some of the weekend effect.

[14]I changed the entire duration to two weeks earlier to have lots of income arrival to be in the middle of a month (i.e. end of second week). Thus, the third week in this specification means the first week in the actual calendar.

groups, Figures 2.8(B)-(E) show that the payday effects on non-recurring spending exist regardless of income level.

Non-Recurring Discretionary/Necessary Spending

In the case of non-recurring discretionary spending, there was still a significant payday effect despite the effect level being quite low. In Figure 2.10(A)[Table 2.12], our coefficient of interest displays only 14% more than the average daily spending without recurring spending, but it is highly significant. In Figure 2.12(A)[Table 2.13], the non-recurring necessary spending coefficients explain that a 20% higher amount than average is spent on the payday and lasts until the second and fourth days after payday. Monday and the third-week effect also has the highest effect on spending, but the fourth-week effect is negative in the case of this discretionary spending compared to the non-recurring all-spending case.

2.5.2 Payday Effects of Irregular Income Payments

For each month, I choose irregular income arrivals until the fifth largest irregular income arrival in order to estimate the payday effects, in the same manner as the regular income arrival cases. Basically, all of the payday effects of irregular income arrivals are pronounced across all types of spending (Figure 2.7), so the payday effects of irregular income arrivals could be confirmed to exist in a month.

All-Spending

Figure 2.7(A)[Table 2.14] shows the all-spending responses to irregular income payments. Our coefficient of interest is $Payday(0)$, which displays 37% more than the average daily spending. In addition, individuals do not spend less than their average daily amounts right before the irregular payments. Thus, compared to the cases of regular income payments, irregular income payments tend to affect only the payday rather than the days around the payday. In terms of the different income groups, Figures 2.7(B)-(E) show the all-spending item responses to irregular income payments depending on income quartile.

Non-Recurring All-Spending

After excluding monthly recurring spending, the payday effects of irregular income are somewhat less pronounced; however, the estimate is still significant (Figure 2.9(A)[Table 2.15]). Our coefficient of interest here is $Payday(0)$, which displays 26% more than the average daily spending without recurring spending. In the case of the control variables, the majority of variables act in a similar manner as in the all-spending case. In terms of the different income groups, Figures 2.9(B)-(E) show that the poor consumers are likely to show severe payday effects once they have irregular payments compared to the rich consumers.

Non-Recurring Discretionary/Necessary Spending

When it comes to non-recurring discretionary spending only, there is a less significant payday effect (Figure 2.11(A)[Table 2.16]). Our coefficient of interest here displays only 12.5% more than the average daily spending, without recurring spending and it is less significant. Considering that many irregular income payments are small amounts of income, it is sensible that discretionary spending around irregular payments can be trivial. The remaining part is the non-recurring necessary spending category. After excluding recurring necessary spending items, the consumers still spend by responding to irregular income arrivals. The coefficient explains that 18.9% higher amount than average is spent on the payday and that coefficients around 14 days are positive (Figure 2.13(A)[Table 2.17]).

2.6 Heterogeneity

2.6.1 MPC Heterogeneity

This section employs a simple individual MPC estimation to characterise spending patterns on broad-category items. The estimated MPC distributions are exploited to construct consumer groups, and the payday effects are estimated with the identified sample restrictions. The below specification for each individual will be used to identify the MPC groups.

$$\begin{aligned} C_t =& \alpha + \beta Y_t + \sum_{m=2}^{12} \mu_m MD_{m,t} + \sum_{yr=2016}^{2017} \phi_{yr} YD_{yr,t} + \epsilon_t \\ & where \quad t = 1, ..., T \end{aligned} \tag{2.14}$$

Here, C_t is either monthly discretionary spending or necessary spending. Y_t is monthly income. β displays the parameter of interest (MPC), μ_m represents the coefficients of month dummies and ϕ_{yr} represents the coefficients of year dummies. I estimate two simple MPC estimations of discretionary and necessary items for every individual's monthly data and categorise consumer types with equation (2.14). I categorise consumers as those who have a higher-MPC (than average) and those who have a lower-MPC (than average) for both necessary and discretionary spending. In the end, there are four groups according to the combinations of the two groups for each of the two items. Figure 2.14 displays the distributions of MPC on necessary and discretionary items. The consumers have larger variance in the case of the MPC on discretionary item than on necessary item which is expected.[15]

Figure 2.15 captures the payday effects of the heterogeneous MPC consumers. They all show clear payday effects of regular income arrivals to consumption. Furthermore, those who are in the high-MPC group tend to show more pronounced payday effects (especially in the non-recurring discretionary item) while those in the low-MPC group display less pronounced effects. However, the payday effects of irregular income arrivals (Figure 2.16) between the two MPC groups do not show a statistical difference.

2.6.2 Liquidity Level Heterogeneity

I identify the individual liquidity level in each debit account with the end-of-transaction date balances (stock) and debit/credit transactions (flow) as mentioned in Table 2.4. Even though the individuals have debit accounts and savings accounts, I assume that savings accounts and debit accounts without frequent transactions are for other purposes such as long-term goals or durable goods purchases.[16] Therefore, the summation of all the debit accounts with frequent use could be understood as one individual's available liquidity level. After identifying the daily liquidity level, I categorise the consumers into four groups of liquidity level and then restrict the sample in the payday effect estimation. The results are consistent with the existing rationale for spending anomalies in which those who have less liquidity show a higher degree of payday effects. In Figure 2.17, we can confirm that payday effects exist at any liquidity level, though the least liquidity group shows a more severe payday effect than that of the abundant liquidity group. As we can see in Figure 2.18, it is clearly noted that the least liquidity group displays the highest spending anomaly in each income group. However, as we can easily guess, the richest group (income level 4) shows the least payday effects and does not reveal much difference across the liquidity groups.

2.6.3 Income Uncertainty Heterogeneity

Another possible dimension of heterogeneity is income uncertainty, which people encounter in their daily lives. The motivation for this exercise is to examine precautionary saving motives to explain the excessive smoothness of consumption to income arrivals. Two types of income uncertainty measurements are introduced in this paper. The first hypothesis is that consumers' behaviours might be influenced by regional heterogeneity such as unemployment rates in their neighbourhoods. Considering that

[15] Although I did not classify consumer types with all the specific MPCs of the 26 consumption items, technically I could calculate distributions for each of the 26 items to characterise individual spending patterns.

[16] Kaplan et al. (2014) pointed out that wealthy consumers can have liquid hand-to-mouth spending behaviour due to illiquid savings. My assumption was motivated by their paper.

individuals' economic activity is closely linked to local economic conditions, this hypothesis is worthwhile to study. The second hypothesis is that individual's income uncertainty can be directly computed from the standard deviation of income arrivals in the sample period.

Regional Differences in Unemployment in the UK

I use the ONS regional unemployment data over the period from 2015 to 2018. There are 12 broad regions in the UK.[17] The average unemployment rate during the 2015-2018 period was the highest in the Northeast area, whereas the lowest in the Southwest area. Regions with higher unemployment rates show a higher variance of the figure during the period. After ranking the regions according to the level of variance of unemployment, I choose the high income uncertainty areas: the Northeast, Northern Ireland, Scotland, Wales, Northwest and London. The low income uncertainty areas include the Southwest, East Midlands, Southeast, West Midlands and East of England. Then, I run the payday effect regression with this binary categorisation, which stands for regional income uncertainty heterogeneity. The results in Figure 2.19 show that there is not much strong evidence regarding the effect of regional income uncertainty on payday effects because the confidence intervals from the payday effect estimation overlap between the high and low regional income uncertainty.

Individual Income Uncertainty

However, the individual income uncertainty provides a clearer explanation consistent with the precautionary saving motive. I calculate the individual-level standard deviation of regular income arrivals in the consumers and then split the samples into quartiles. As we can see in Figure 2.21, as the level of income uncertainty becomes higher (Group 1 to Group 4), consumers spend less and save more for dealing with future uncertainty. As a result, they show less pronounced payday effects. However, interestingly, the lowest income uncertainty group (Group 1) shows less payday effects than Group 2. I believe that the income uncertainty Group 1 jointly encompasses the high income group so that those consumers are less likely to have severe payday effects. The majority of the high-income-uncertainty group shows the least payday effects. This is especially convincing in Figure 2.22(B). In the lowest income group, the payday effects of Group 1 (lowest income uncertainty) and Group 4 (highest income uncertainty group) are significantly different since their confidence intervals do not overlap.

[17] 12 areas: Scotland, Nothern Ireland, Wales, North East, North West, Yorkshire and the Humber, West Midlands, East Midlands, South West, South East, East of England, Greater London

2.7 Robustness Check

2.7.1 Alternative Payday Effect Specification: MPC out of Daily Liquidity (MPCL)

I measure the daily liquidity in both main current accounts and savings accounts for each user and investigate the effect of daily liquidity on consumption expenditure. My strategy for identifying liquidity is to use main transaction debit accounts as the liquidity measure.[18] This is due to the fact that consumers tend to use their main debit account while they transfer money for either savings or liquidity purposes; thus, it is worthwhile to differentiate all of the debit account liquidity from the liquidity in the debit account for the purpose of main transactions. The regression specification for this MPC out of daily liquidity (MPCL) is as follows.

$$\begin{aligned} LogC_{it} =& \alpha LogL_{it} + \sum_{k=-6}^{7} \beta_k I_i(Paid_{t+k}) + \delta_{dow} + \phi_{wom} + \varphi_{moy} + user_i + \epsilon_{it} \\ & where \quad i = 1, ..., N \quad t = 1, ..., T \end{aligned} \tag{2.15}$$

where $LogC_{it}$ is the log transformation of daily spending on each consumption item, $LogL_{it}$ is the log transformation of daily liquidity in users' main accounts. α is the coefficient of a daily MPC out of daily liquidity measure. Still we are interested in β_ks to identify payday effects. As we can see in the results from Figures 2.23-2.24, the basic implication from this specification tells us that pronounced payday effects are still found when I investigate from the MPCL. In the case of non-recurring all-spending (Figure 2.25), I find that income level 2 has higher payday effects than income level 1 on the payday and the day after payday as well. A possible rationale for this is that we might think of the lowest income group's income uncertainty: even though the consumers have higher MPCL due to their liquidity constraint, they might show less payday effects than the Income Group 2 because they might pursue saving for precautionary motives.

2.7.2 Alternative Income Payment Arrivals: 1st-50th Biggest Income Amounts in a Year

The specification in the main analysis (Equation 2.12 in Section 2.5) in which I identify the first-to-fifth biggest income arrivals in a monthly period allows me to investigate more precise income arrivals close to payday (Figure 2.4). Generally, consumers who have monthly payments usually encounter the biggest regular money arrivals around the monthly payday. However, if we identify income arrivals differently

[18]The remaining parts are the non-main transaction debit accounts + savings accounts.

with the biggest amounts in a year rather than on a monthly basis, these money arrivals are not the ones identified as payday effects in a month. So, we could expect that the newly identified payday effects would be less pronounced and that consumers would not spend much on the alternatively defined payday. Figures 2.27-2.28 are the results of these modified income arrivals with the first-fiftieth biggest income payments on a yearly basis. Consistent with the initial prediction, the payday effects based on the new income arrivals selection are smaller than the baseline identification. Thus, we can say that the results in this subsection confirm the robustness of the baseline payday effect specification (Equation 2.12) with the first-to-fifth biggest income arrivals.

2.8 Conclusion

In this chapter, first, I document that payday effects are pronounced across broad consumption categories and income types by exploiting high-frequency, transaction-level UK consumer data. Furthermore, I explore potential individual heterogeneity to support evidence for theoretical rationales for the existence of spending-income co-movement. I find that UK individuals do not seem to smooth consumption with anticipated income arrivals within a monthly period. This finding is consistent with the existing literature on high-frequency spending data. Consumers tend to spend more than their average daily amounts on even non-recurring consumption items upon the arrival of anticipated payment, regardless of their income level. Beyond the recent literature, I further narrow down consumption items into non-recurring discretionary and necessary items to capture the payday effects and find consistent results. Second, I study individual heterogeneity in terms of the MPC in a monthly period to characterise consumer types. The results indicate that those who fall into the high-MPC group on discretionary spending tend to show severe payday effects. Third, I identify the daily liquidity by calculating the daily debit and credit transactions in the individual's accounts. The estimated payday effect is most pronounced for the lowest liquidity level group as expected. Finally, the sample restriction by income uncertainty as a proxy for the precautionary motives of the payday effect is introduced. The estimation results show that the high-income-uncertainty group tends to show less pronounced payday effects than the lower-income-uncertainty group, especially in the lowest income group. Thus, I conclude that the payday effects exist in UK consumers despite the different degrees of such effects across heterogeneous individuals. I further explore the robustness check exercises with the modified specifications and relaxed definitions of regular income, and these results all confirm that my payday effect estimations are robust.

Further research ideas related to this paper are the following: first, the classification of discretionary and necessary items is not based on rigorous theoretical backgrounds.

Instead, this paper refers to the recent literature works in the classification of broad consumption items. It is further required to classify consumption items rigorously according to item characteristics in order to explain consumer's spending patterns on the broad items properly. Second, regarding the MPC heterogeneity of specific sub-category consumption items, I only characterise consumer types with only two broad consumption items. However, we can characterise consumer types with the information of consumption item choices in both broad and narrow classifications. We might be able to find a relationship between the MPC on specific items and the heterogenous payday effects. Third, the payday effect estimation is based on the assumption of cross-section independence, which means individual's consumption decision is determined without any considerations on neighbours' or friends' consumption decisions. One can take peer or reference effects into account in explaining individual spending behaviour. In the field of behavioural science, they introduce the reference-dependence utility framework. This motivation of cross-section dependence will be dealt with in Chapter 3. Finally, regarding unused daily indicators and time-invariant heterogeneity, there are some constructed but unused variables or indicators in this paper. With this type of data, we could use lots of potential daily control variables that have numerous variations that have an impact on individuals' spending behaviours across dates. Possible candidates are the daily weather, stock price index and the associated volatility index (VIX) for those control variables. In the case of time-invariant heterogeneities, we could use this information in a possible sample-split analysis. For example, in this data set, I generate numerous dummy variables by extracting transaction tags in order to identify individual heterogeneity[19] for further restriction of the sample in estimating the payday effects. However, the use of all these information variables is beyond this paper's research question, so I will leave these ideas to future research.

[19]For example, demographics such as gender, children, insurance holder, secured job, car owner, loan user, job seeker, saver, asset holder, student and heavy credit card users.

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2.9 Appendix: Tables and Figures

2.9.1 Summary of Descriptive Statistics

Table 2.5: Summary Table: Debit Transactions in Each Category

	(1) Mean	(2) SD	(3) min	(4) p25	(5) p50	(6) p75	(7) p95	(8) max	(9) count
Transportation cost	20.4	44.5	0	5	8	18	80	500	2,348,199
Private car use	31.0	47.3	0	8	20	39	83	500	2,547,888
Eating-at-home	19.9	28.6	0	5	10	22	72	288	10,418,922
Education and Childcare	95.4	202.0	0	10	23	73	480	1,721	73,410
Medical cost	38.3	60.6	0	12	20	38	139	580	169,039
Pets	28.3	44.4	0	10	16	30	84	500	228,969
Housing Cost	496.3	455.9	0	120	400	711	1,400	2,750	321,813
Tax and Bills	55.1	80.1	0	12	30	68	170	850	2,294,351
Alcohol and Tobacco	21.3	31.1	0	7	12	20	70	344	140,706
Clothing & Appearance	27.0	34.3	0	7	16	33	90	305	2,747,048
Charity	25.6	70.7	0	5	9	17	100	787	204,471
Eating-Out	15.8	28.7	0	4	8	16	50	360	5,614,783
Family Fun and Hobby	29.0	51.9	0	5	14	32	100	561	3,334,538
Gambling	23.1	41.3	0	7	10	20	90	475	907,490
Social-Outing	21.4	35.3	0	5	10	22	78	364	2,961,831
Travel	94.4	162.3	0	10	34	100	403	1,335	406,428
Semi-durables	50.2	107.6	0	7	13	39	250	907	227,165
Household Management	40.1	70.9	0	8	18	39	154	699	1,189,565
Banking Charge	19.7	54.7	0	1	5	15	83	635	1,914,315
Credit Card	169.2	319.2	0	22	53	150	776	2,760	889,085
Saving	246.6	489.3	0	11	51	213	1,228	3,862	707,187
Investment and Pension	142.5	419.8	0	12	15	100	621	5,000	194,866
Insurance	37.1	65.3	0	10	19	37	123	674	950,770
Loan arrivals	166.4	314.5	0	10	59	200	600	3,500	1,219,737
Cash and Transfer	91.2	206.2	0	10	28	70	420	2,000	9,023,585
Income type	154.1	265.2	0	11	65	160	680	2,440	4,941

Note: 1) Data from **MDB**. 2) All the transaction amounts in this table are reported by a unit of GBP(£) except for the columns of 'SD' and 'Count'. 3) *Income type*(*debit*) is the transactions from the business owner who spends money (labour income) to their employees.

Table 2.6: Summary Table: Credit Transactions in Each Category

	(1) Mean	(2) SD	(3) min	(4) p25	(5) p50	(6) p75	(7) p95	(8) max	(9) count
Income_(credit)	425.5	2,783.9	0	17	64	250	1,903	1,245,000	6,666,057
Banking Charge_(credit)	385.5	1,810.1	0	1	3	97	2,121	113,354	29,971
Credit Card_(credit)	511.5	1,239.1	0	40	129	500	2,225	151,754	269,582
Saving_(credit)	497.0	2,637.8	0	20	80	300	1,900	262,250	140,999
Unexpected earnings_(credit)	995.7	5,382.9	0	57	150	300	3,771	52,562	99
Insurance_(credit)	917.4	3,666.1	0	40	130	975	3,190	161,596	9,893
Loan_(credit)	402.0	2,645.2	0	20	70	200	1,300	595,000	575,184
Cash and Transfer_(credit)	642.0	3,690.6	0	37	138	500	2,386	2,119,046	1,869,647
Income type_(credit)	343.1	1,969.8	0	15	51	200	1,554	1,000,000	5,765,961

Note: 1) Data from **MDB**. 2) All the transaction amounts in this table are reported by a unit of GBP(£) except for the columns of 'SD' and 'Count'. 3) $Income(credit)$ sub-category is identifed by credit transaction from majority of spending categories. This encompasses income arrivals from the spending category associated merchants. $Income\ type(credit)$ is the opposite transactions from the business owner who spends money (labour income) to their employees. Both cases are identifed as income arrivals.

Table 2.7: Summary Table: Transactions of 14,881 MDB Individuals

	(1) Mean	(2) SD	(3) min	(4) p25	(5) p50	(6) p75	(7) p95	(8) max	(9) count
Age (years old)	32.4	7.8	19	26	31	37	48	55	14,881
Salary range (0 to 9)	2.8	1.6	0	2	3	4	6	9	14,881
Gender (Male=0, Female=1)	0.4	0.5	0	0	0	1	1	1	14,881
Number of account types (per individual)	2	0.8	1	2	2	3	3	4	14,881
Number of days of individual transactions	916	176	100	800	895	1,013	1,251	1,482	14,881
Duration of individual transactions (Day)	1,360	105	428	1,273	1,369	1,443	1,505	1,532	14,881
Duration of individual transactions (Year)	5.0	0.2	2	5	5	5	5	5	14,811

Note: 1) Data from **MDB**. 2) Salary range: Group 1= (£5,000 - £15,000), Group 2= (£15,000 - £25,000) and so on.

Table 2.8: Summary Table: Statistics of 14,881 MDB Individuals

	(1) Mean	(2) SD	(3) min	(4) p25	(5) p50	(6) p75	(7) p95	(8) max	(9) count
Income (monthly AVG)	3,574.7	3,224.2	502	1,782	2,670	4,209	9,048	87,153	14,881
Disposable income	2,734.8	2,844.5	-686	1,277	1,931	3,123	7,346	85,314	14,881
All-spending	2,243.5	1,287.1	502	1,380	1,906	2,734	4,694	20,333	14,881
Discretionary spending	631.2	435.4	3	363	519	765	1,407	12,317	14,881
Necessary spending	1,128.3	772.6	9	585	914	1,449	2,676	6,535	14,881
Credit card spending	241.9	545.0	0	0	0	205	1,380	8,537	14,881
Debit card spending	1,957.8	1,124.6	0	1,245	1,695	2,381	3,996	20,333	14,881
Non-recurring spending	1,403.7	817.7	229	888	1,200	1,679	2,870	15,938	14,881
Recurring spending	839.8	616.3	3	399	681	1,102	2,048	5,603	14,881
Saving	224.1	363.5	0	9	87	293	892	6,542	14,881
Withdrawal	245.4	785.8	0	0	26	228	1,039	36,980	14,881
Borrowing	269.1	777.4	0	21	90	261	1,068	51,875	14,881
Repayment	286.3	362.6	0	48	169	384	978	5,159	14,881

Note: 1) Data from **MDB**. 2) All the transaction amounts in this table are reported by a unit of GBP(£) except for the columns of 'SD' and 'Count'. 3) Figures are reported based on monthly average (£).

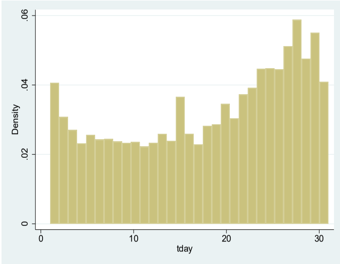
Table 2.9: Summary Table: Geographic Distribution of the Sample

County	% Individual Residing			County	% Individual Residing		
	Data	UK ONS	Data-ONS [%p]		Data	UK ONS	Data-ONS [%p]
London	13.0	7.7	5.3	Warrington	1.2	1.0	0.2
Birmingham	2.4	3.0	-0.6	Oxford	1.1	1.0	0.2
Northern Ireland	1.1	2.8	-1.8	Rochester	1.0	1.0	0.1
Sheffield	1.7	2.2	-0.4	Gloucester	1.3	1.0	0.3
Glasgow	2.4	1.9	0.6	Stockport	1.2	1.0	0.3
Manchester	2.5	1.8	0.7	Cleveland	0.7	1.0	-0.3
Nottingham	1.7	1.8	-0.2	Ipswich	0.8	0.9	-0.2
Newcastle upon Tyne	1.7	1.8	-0.2	Bradford	0.7	0.9	-0.2
Cardiff	1.7	1.6	0.1	York	0.8	0.9	-0.1
Leicester	1.1	1.6	-0.5	Bournemouth	1.0	0.9	0.1
Bristol	2.0	1.5	0.5	Exeter	0.7	0.9	-0.2
Peterborough	1.1	1.4	-0.3	Plymouth	0.8	0.9	0.0
Edinburgh	2.6	1.4	1.3	Llandudno	0.4	0.9	-0.4
Liverpool	1.0	1.4	-0.3	Redhill	1.1	0.8	0.2
Portsmouth	1.4	1.3	0.1	Kingston upon Thames	1.2	0.8	0.3
Coventry	1.2	1.3	-0.1	Preston	0.8	0.8	-0.1
Brighton	1.3	1.3	0.0	Southend-on-Sea	0.6	0.8	-0.3
Reading	1.8	1.2	0.6	Romford	0.7	0.8	-0.1
Leeds	1.5	1.2	0.3	Wakefield	0.6	0.8	-0.2
Doncaster	0.8	1.2	-0.4	Milton Keynes	1.0	0.8	0.2
Derby	1.0	1.2	-0.1	Aberdeen	1.1	0.8	0.3
Swansea	0.7	1.2	-0.5	Twickenham	0.8	0.8	0.0
Guildford	1.6	1.1	0.5	Hemel Hempstead	0.8	0.8	0.0
Norwich	0.9	1.1	-0.2	Newport	0.5	0.8	-0.3
Tonbridge	0.9	1.1	-0.2	Blackburn	0.6	0.8	-0.2
Southampton	1.1	1.1	0.0	Canterbury	0.8	0.8	0.0
Chester	0.8	1.0	-0.2	Harrow	0.6	0.8	-0.2
Chelmsford	0.9	1.0	-0.2	Oldham	0.5	0.7	-0.3
Northampton	1.0	1.0	-0.1	Swindon	0.7	0.7	0.0
Stoke-on-Trent	0.8	1.0	-0.3	Walsall	0.6	0.7	-0.1
				Total(60 counties)	78.0	75.6	2.4

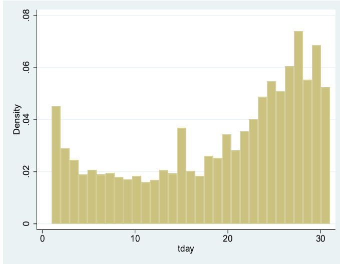
Note: 1) Comparison based on 14,881 MDB users in the cleaned data. 2) Only the biggest 60 counties are reported out of 125 counties in this table.

2.9.2 Distributions of Income Arrivals

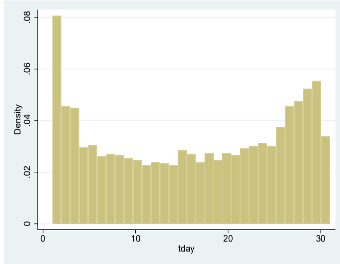
Figure 2.1: Distributions of Income Arrivals Frequency in a Month



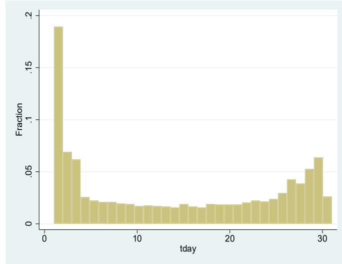
(A) Regular income



(B) Paycheck

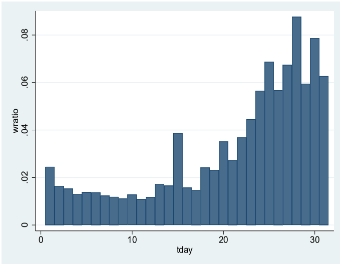


(C) Irregualr income

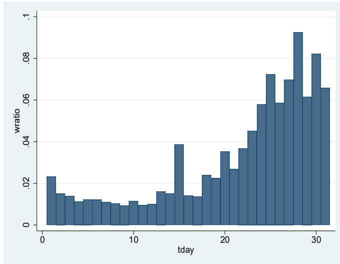


(D) Asset income

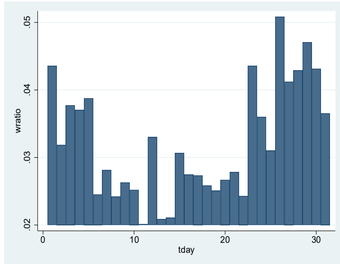
Figure 2.2: Distributions of Value Weighted Income Arrivals Frequency in a Month



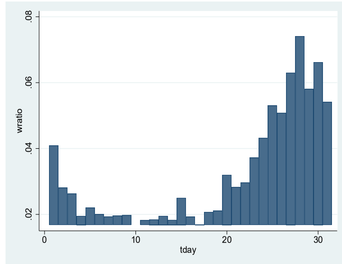
(A) Regular income



(B) Paycheck

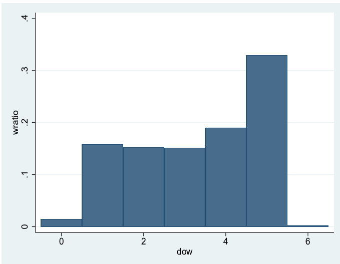


(C) Irregualr income

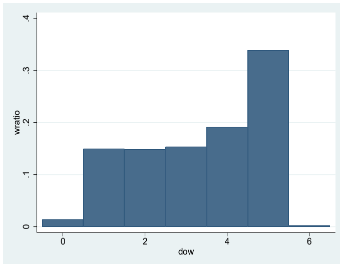


(D) Asset income

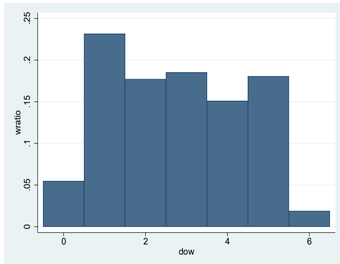
Figure 2.3: Distributions of Value Weighted Income Arrivals Frequency in a Week



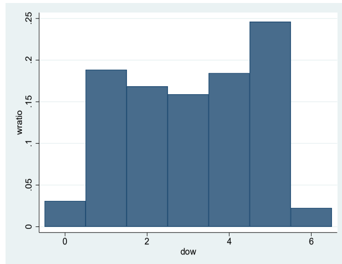
(A) Regular income



(B) Paycheck



(C) Irregualr income



(D) Asset income

Note: 1) **Regular income** = Benefits + Bursary + Family Benefits + Other Benefits+ Paycheck (Salary: Main, Secondary), **Paycheck** = Paycheck (Salary: Main, Secondary) nad overtime payment, **Irregular income** =Expenses + Tax Rebate + Business Expense + Winnings + (Refund Purchase + Rewards/Cashback), **Asset income** = Financial Asset Income + Housing Property Rental Income
2) **Days of Week** = 0: Sunday - 6: Saturday

2.9.3 Tables of Payday Effects: Main Estimation Results

Table 2.10: Payday Effect of Regular Income Payment on All-Spending

	Dependent Variable: Spending Ratio out of Avg Daily Spending				
	All Income Group	Income 1	Income 2	Income 3	Income 4
	(1) sratio_all b/se	(2) sratio_all b/se	(3) sratio_all b/se	(4) sratio_all b/se	(5) sratio_all b/se
Payday(-6)	-0.011***	-0.009	-0.015***	-0.007	-0.010**
	(0.003)	(0.006)	(0.005)	(0.005)	(0.005)
Payday(-5)	-0.012***	-0.019***	-0.014***	-0.005	-0.013***
	(0.003)	(0.007)	(0.005)	(0.005)	(0.005)
Payday(-4)	-0.029***	-0.045***	-0.046***	-0.020***	-0.016***
	(0.003)	(0.007)	(0.006)	(0.006)	(0.006)
Payday(-3)	-0.041***	-0.042***	-0.063***	-0.032***	-0.029***
	(0.003)	(0.006)	(0.005)	(0.006)	(0.005)
Payday(-2)	-0.048***	-0.061***	-0.063***	-0.041***	-0.034***
	(0.003)	(0.006)	(0.005)	(0.005)	(0.005)
Payday(-1)	-0.049***	-0.061***	-0.063***	-0.039***	-0.038***
	(0.003)	(0.006)	(0.005)	(0.005)	(0.005)
Payday(0)	0.487***	0.534***	0.608***	0.482***	0.336***
	(0.007)	(0.014)	(0.014)	(0.013)	(0.011)
Payday(+1)	0.276***	0.274***	0.359***	0.307***	0.179***
	(0.005)	(0.010)	(0.010)	(0.010)	(0.008)
Payday(+2)	0.136***	0.157***	0.173***	0.156***	0.081***
	(0.004)	(0.009)	(0.008)	(0.008)	(0.007)
Payday(+3)	0.240***	0.255***	0.315***	0.271***	0.146***
	(0.005)	(0.011)	(0.010)	(0.009)	(0.008)
Payday(+4)	0.162***	0.149***	0.199***	0.183***	0.119***
	(0.004)	(0.009)	(0.008)	(0.008)	(0.008)
Payday(+5)	0.120***	0.091***	0.144***	0.131***	0.102***
	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)
Payday(+6)	0.065***	0.048***	0.070***	0.072***	0.063***
	(0.004)	(0.007)	(0.006)	(0.007)	(0.008)
Payday(+7)	0.048***	0.035***	0.040***	0.055***	0.055***
	(0.003)	(0.006)	(0.006)	(0.006)	(0.007)
Daily Observations	3,432,117	555,262	883,876	964,303	1,028,676
Income Arrivals	69,124	14,501	17,354	18,005	19,264
Individuals	14,812	3,527	3,790	3,797	3,698
Day Control	Yes	Yes	Yes	Yes	Yes
Week Control	Yes	Yes	Yes	Yes	Yes
Month Control	Yes	Yes	Yes	Yes	Yes

Notes: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Standard errors in parentheses are clustered at the individual level. 3) **Daily Observations** indicates the number of observations. **Income Arrivals** indicates 'unique individuals (14,881) x number of income arrivals in a month (5)'. **Individuals** indicates the actual number of unique individuals.

Table 2.11: Payday Effect of Regular Income Payment on Non-Recurring All-Spending

	Dependent Variable: Spending Ratio out of Avg Daily Spending				
	All Income Group	Income 1	Income 2	Income 3	Income 4
	(1) sratio_anr b/se	(2) sratio_anr b/se	(3) sratio_anr b/se	(4) sratio_anr b/se	(5) sratio_anr b/se
Payday(-6)	-0.012***	-0.000	-0.017***	-0.011**	-0.016***
	(0.003)	(0.007)	(0.005)	(0.005)	(0.005)
Payday(-5)	-0.015***	-0.017**	-0.018***	-0.016***	-0.012**
	(0.003)	(0.007)	(0.006)	(0.006)	(0.005)
Payday(-4)	-0.021***	-0.031***	-0.039***	-0.021***	-0.007
	(0.003)	(0.008)	(0.006)	(0.006)	(0.006)
Payday(-3)	-0.044***	-0.044***	-0.068***	-0.045***	-0.025***
	(0.003)	(0.007)	(0.005)	(0.006)	(0.006)
Payday(-2)	-0.039***	-0.043***	-0.057***	-0.039***	-0.025***
	(0.003)	(0.007)	(0.006)	(0.006)	(0.006)
Payday(-1)	-0.047***	-0.064***	-0.070***	-0.037***	-0.023***
	(0.003)	(0.006)	(0.005)	(0.005)	(0.006)
Payday(0)	0.372***	0.445***	0.448***	0.354***	0.264***
	(0.006)	(0.013)	(0.012)	(0.011)	(0.010)
Payday(+1)	0.194***	0.242***	0.266***	0.194***	0.107***
	(0.004)	(0.009)	(0.009)	(0.008)	(0.007)
Payday(+2)	0.095***	0.127***	0.141***	0.100***	0.042***
	(0.004)	(0.008)	(0.007)	(0.007)	(0.006)
Payday(+3)	0.175***	0.226***	0.246***	0.181***	0.085***
	(0.004)	(0.010)	(0.009)	(0.008)	(0.007)
Payday(+4)	0.107***	0.116***	0.155***	0.115***	0.054***
	(0.004)	(0.008)	(0.008)	(0.007)	(0.007)
Payday(+5)	0.087***	0.099***	0.117***	0.086***	0.055***
	(0.004)	(0.008)	(0.007)	(0.007)	(0.007)
Payday(+6)	0.051***	0.060***	0.057***	0.051***	0.041***
	(0.003)	(0.007)	(0.006)	(0.006)	(0.006)
Payday(+7)	0.039***	0.035***	0.044***	0.037***	0.039***
	(0.003)	(0.007)	(0.005)	(0.006)	(0.006)
Observations	2,938,433	478,879	757,388	821,980	880,186
Income Arrivals	68,435	14,361	17,187	17,824	19,063
Individuals	14,813	3,528	3,790	3,797	3,698
Day FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Notes: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Standard errors in parentheses are clustered at the individual level. 3) **Daily Observations** indicates the number of observations. **Income Arrivals** indicates 'unique individuals (14,881) x number of income arrivals in a month (5)'. **Individuals** indicates the actual number of unique individuals.

Table 2.12: Payday Effect of Regular Income Payment on Non-Recurring Discretionary Spending

	Dependent Variable: Spending Ratio out of Avg Daily Spending				
	All Income Group	Income 1	Income 2	Income 3	Income 4
	(1) sratio_dnr b/se	(2) sratio_dnr b/se	(3) sratio_dnr b/se	(4) sratio_dnr b/se	(5) sratio_dnr b/se
Payday(-6)	-0.011**	-0.010	-0.004	-0.019**	-0.011
	(0.005)	(0.011)	(0.009)	(0.009)	(0.008)
Payday(-5)	-0.014***	0.007	-0.023**	-0.019**	-0.015*
	(0.005)	(0.012)	(0.009)	(0.009)	(0.009)
Payday(-4)	-0.026***	-0.026**	-0.044***	-0.031***	-0.012
	(0.005)	(0.011)	(0.009)	(0.009)	(0.009)
Payday(-3)	-0.042***	-0.029***	-0.053***	-0.061***	-0.025***
	(0.005)	(0.011)	(0.009)	(0.009)	(0.009)
Payday(-2)	-0.025***	-0.026**	-0.047***	-0.030***	-0.006
	(0.005)	(0.011)	(0.009)	(0.009)	(0.009)
Payday(-1)	-0.029***	-0.051***	-0.056***	-0.021***	-0.005
	(0.004)	(0.010)	(0.008)	(0.008)	(0.008)
Payday(0)	0.143***	0.182***	0.197***	0.121***	0.097***
	(0.006)	(0.014)	(0.012)	(0.011)	(0.011)
Payday(+1)	0.122***	0.183***	0.180***	0.117***	0.052***
	(0.005)	(0.012)	(0.011)	(0.010)	(0.009)
Payday(+2)	0.076***	0.134***	0.110***	0.075***	0.030***
	(0.005)	(0.013)	(0.011)	(0.010)	(0.009)
Payday(+3)	0.115***	0.167***	0.154***	0.129***	0.048***
	(0.006)	(0.013)	(0.011)	(0.011)	(0.010)
Payday(+4)	0.084***	0.110***	0.119***	0.077***	0.051***
	(0.005)	(0.012)	(0.010)	(0.010)	(0.010)
Payday(+5)	0.078***	0.087***	0.115***	0.073***	0.049***
	(0.005)	(0.012)	(0.011)	(0.010)	(0.010)
Payday(+6)	0.045***	0.047***	0.054***	0.042***	0.038***
	(0.005)	(0.011)	(0.009)	(0.009)	(0.009)
Payday(+7)	0.032***	0.029***	0.032***	0.039***	0.027***
	(0.004)	(0.010)	(0.008)	(0.008)	(0.009)
Observations	1,460,731	227,354	356,256	404,234	472,887
Income Arrivals	64,621	13,384	16,213	16,890	18,134
Individuals	14,839	3,552	3,791	3,798	3,698
Day FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Notes: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Standard errors in parentheses are clustered at the individual level. 3) **Daily Observations** indicates the number of observations. **Income Arrivals** indicates 'unique individuals (14,881) x number of income arrivals in a month (5)'. **Individuals** indicates the actual number of unique individuals.

Table 2.13: Payday Effect of Regular Income Payment on Non-Recurring Necessary Spending

	Dependent Variable: Spending Ratio out of Avg Daily Spending				
	All Income Group	Income 1	Income 2	Income 3	Income 4
	(1) sratio_nnr b/se	(2) sratio_nnr b/se	(3) sratio_nnr b/se	(4) sratio_nnr b/se	(5) sratio_nnr b/se
Payday(-6)	-0.017***	-0.001	-0.019***	-0.017**	-0.023***
	(0.004)	(0.009)	(0.007)	(0.007)	(0.007)
Payday(-5)	-0.013***	-0.014	-0.011	-0.015**	-0.014*
	(0.004)	(0.010)	(0.008)	(0.007)	(0.007)
Payday(-4)	-0.016***	-0.020**	-0.043***	-0.004	-0.007
	(0.004)	(0.010)	(0.008)	(0.008)	(0.008)
Payday(-3)	-0.037***	-0.039***	-0.057***	-0.035***	-0.024***
	(0.004)	(0.009)	(0.007)	(0.008)	(0.007)
Payday(-2)	-0.043***	-0.053***	-0.058***	-0.053***	-0.022***
	(0.004)	(0.009)	(0.007)	(0.007)	(0.008)
Payday(-1)	-0.045***	-0.051***	-0.064***	-0.042***	-0.027***
	(0.004)	(0.008)	(0.007)	(0.007)	(0.007)
Payday(0)	0.197***	0.195***	0.249***	0.190***	0.160***
	(0.006)	(0.013)	(0.012)	(0.011)	(0.011)
Payday(+1)	0.184***	0.213***	0.267***	0.186***	0.097***
	(0.005)	(0.011)	(0.011)	(0.010)	(0.009)
Payday(+2)	0.097***	0.129***	0.153***	0.101***	0.038***
	(0.005)	(0.011)	(0.010)	(0.009)	(0.008)
Payday(+3)	0.150***	0.184***	0.240***	0.155***	0.055***
	(0.005)	(0.012)	(0.011)	(0.010)	(0.009)
Payday(+4)	0.108***	0.129***	0.159***	0.109***	0.052***
	(0.005)	(0.011)	(0.010)	(0.009)	(0.009)
Payday(+5)	0.081***	0.087***	0.109***	0.085***	0.050***
	(0.005)	(0.011)	(0.009)	(0.009)	(0.009)
Payday(+6)	0.046***	0.041***	0.056***	0.052***	0.034***
	(0.004)	(0.009)	(0.008)	(0.008)	(0.009)
Payday(+7)	0.028***	0.036***	0.040***	0.020***	0.023***
	(0.004)	(0.009)	(0.007)	(0.007)	(0.008)
Observation	1,797,612	278,545	461,563	509,098	548,406
Income Arrivals	65,693	13,515	16,570	17,216	18,392
Individuals	14,840	3,553	3,791	3,798	3,698
Day FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Notes: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Standard errors in parentheses are clustered at the individual level. 3) **Daily Observations** indicates the number of observations. **Income Arrivals** indicates 'unique individuals (14,881) x number of income arrivals in a month (5)'. **Individuals** indicates the actual number of unique individuals.

Table 2.14: Payday Effect of Irregular Income Payment on All-Spending

	Dependent Variable: Spending Ratio out of Avg Daily Spending				
	All Income Group	Income 1	Income 2	Income 3	Income 4
	(1) sratio_all b/se	(2) sratio_all b/se	(3) sratio_all b/se	(4) sratio_all b/se	(5) sratio_all b/se
Payday(-6)	-0.008	-0.039**	-0.012	-0.014	0.009
	(0.007)	(0.018)	(0.016)	(0.014)	(0.012)
Payday(-5)	-0.012	0.011	-0.002	-0.004	-0.028**
	(0.007)	(0.021)	(0.017)	(0.014)	(0.012)
Payday(-4)	0.017**	0.045*	0.022	0.003	0.014
	(0.008)	(0.024)	(0.019)	(0.016)	(0.013)
Payday(-3)	-0.020**	-0.057***	-0.020	-0.004	-0.022*
	(0.008)	(0.020)	(0.019)	(0.016)	(0.013)
Payday(-2)	0.030***	0.016	0.009	0.031*	0.039***
	(0.009)	(0.024)	(0.019)	(0.016)	(0.014)
Payday(-1)	0.014	-0.013	0.054***	-0.002	0.012
	(0.009)	(0.020)	(0.020)	(0.015)	(0.014)
Payday(0)	0.366***	0.334***	0.405***	0.412***	0.318***
	(0.015)	(0.035)	(0.034)	(0.029)	(0.026)
Payday(+1)	0.070***	0.084***	0.109***	0.069***	0.045***
	(0.008)	(0.018)	(0.019)	(0.015)	(0.013)
Payday(+2)	0.051***	0.051**	0.089***	0.068***	0.022*
	(0.008)	(0.022)	(0.019)	(0.016)	(0.013)
Payday(+3)	0.056***	0.118***	0.071***	0.058***	0.028**
	(0.009)	(0.026)	(0.020)	(0.016)	(0.014)
Payday(+4)	0.033***	0.048**	0.063***	0.057***	-0.001
	(0.009)	(0.023)	(0.020)	(0.017)	(0.014)
Payday(+5)	0.030***	-0.007	0.053**	0.024	0.035**
	(0.009)	(0.023)	(0.022)	(0.019)	(0.015)
Payday(+6)	0.002	0.036	0.036*	0.001	-0.023
	(0.009)	(0.024)	(0.019)	(0.017)	(0.014)
Payday(+7)	0.009	0.032	0.026	0.012	-0.011
	(0.008)	(0.021)	(0.017)	(0.015)	(0.014)
Observations	457,144	61,388	86,804	127,814	181,138
Income Arrivals	21,173	4,043	4,683	5,717	6,730
Individuals	13,059	2,907	3,218	3,432	3,502
Day FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Notes: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Standard errors in parentheses are clustered at the individual level. 3) **Daily Observations** indicates the number of observations. **Income Arrivals** indicates 'unique individuals (14,881) x number of income arrivals in a month (5)'. **Individuals** indicates the actual number of unique individuals.

Table 2.15: Payday Effect of Irregular Income Payment on Non-Recurring All-Spending

	Dependent Variable: Spending Ratio out of Avg Daily Spending				
	All Income Group	Income 1	Income 2	Income 3	Income 4
	(1) sratio_anr b/se	(2) sratio_anr b/se	(3) sratio_anr b/se	(4) sratio_anr b/se	(5) sratio_anr b/se
Payday(-6)	-0.001	-0.002	0.007	-0.016	0.008
	(0.008)	(0.019)	(0.017)	(0.016)	(0.014)
Payday(-5)	0.001	0.025	0.013	-0.022	0.004
	(0.008)	(0.022)	(0.018)	(0.015)	(0.013)
Payday(-4)	0.007	0.003	0.018	0.001	0.005
	(0.009)	(0.025)	(0.022)	(0.017)	(0.015)
Payday(-3)	-0.014	0.014	-0.010	-0.020	-0.020
	(0.009)	(0.024)	(0.020)	(0.017)	(0.014)
Payday(-2)	0.023^{**}	0.002	0.025	0.002	0.039^{***}
	(0.009)	(0.024)	(0.022)	(0.017)	(0.015)
Payday(-1)	-0.011	0.006	0.017	-0.036^{**}	-0.013
	(0.009)	(0.022)	(0.021)	(0.016)	(0.014)
Payday(0)	0.258^{***}	0.261^{***}	0.344^{***}	0.268^{***}	0.200^{***}
	(0.014)	(0.034)	(0.031)	(0.026)	(0.022)
Payday(+1)	0.053^{***}	0.106^{***}	0.068^{***}	0.066^{***}	0.018
	(0.008)	(0.022)	(0.018)	(0.016)	(0.013)
Payday(+2)	0.033^{***}	0.070^{***}	0.048^{**}	0.024	0.021
	(0.008)	(0.025)	(0.019)	(0.016)	(0.013)
Payday(+3)	0.038^{***}	0.110^{***}	0.044^{**}	0.032^{*}	0.014
	(0.009)	(0.027)	(0.020)	(0.017)	(0.014)
Payday(+4)	0.014	0.056^{**}	0.041^{**}	-0.023	0.015
	(0.009)	(0.024)	(0.021)	(0.016)	(0.015)
Payday(+5)	0.017^{*}	0.001	0.047^{**}	0.017	0.008
	(0.010)	(0.025)	(0.021)	(0.018)	(0.016)
Payday(+6)	0.025^{***}	0.029	0.041^{**}	0.020	0.017
	(0.009)	(0.025)	(0.019)	(0.018)	(0.015)
Payday(+7)	0.018^{**}	0.056^{***}	0.019	0.006	0.008
	(0.008)	(0.021)	(0.018)	(0.015)	(0.014)
Observations	391,920	52,946	74,429	109,152	155,393
Income Arrivals	20,954	4,007	4,654	5,640	6,653
Individuals	13,038	2,896	3,214	3,426	3,502
Day FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Notes: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Standard errors in parentheses are clustered at the individual level. 3) **Daily Observations** indicates the number of observations. **Income Arrivals** indicates 'unique individuals (14,881) x number of income arrivals in a month (5)'. **Individuals** indicates the actual number of unique individuals.

Table 2.16: Payday Effect of Irregular Income Payment on Non-Recurring Discretionary Spending

	Dependent Variable: Spending Ratio out of Avg Daily Spending				
	All Income Group	Income 1	Income 2	Income 3	Income 4
	(1) sratio_dnr b/se	(2) sratio_dnr b/se	(3) sratio_dnr b/se	(4) sratio_dnr b/se	(5) sratio_dnr b/se
Payday(-6)	0.010	0.026	-0.013	0.007	0.019
	(0.013)	(0.033)	(0.028)	(0.025)	(0.021)
Payday(-5)	-0.003	-0.000	-0.006	-0.034	0.018
	(0.014)	(0.038)	(0.031)	(0.024)	(0.022)
Payday(-4)	0.015	0.028	-0.006	0.033	0.006
	(0.014)	(0.036)	(0.031)	(0.027)	(0.022)
Payday(-3)	0.012	0.018	0.033	0.003	0.008
	(0.014)	(0.039)	(0.032)	(0.027)	(0.022)
Payday(-2)	0.020	-0.030	0.013	0.003	0.044**
	(0.014)	(0.038)	(0.030)	(0.028)	(0.022)
Payday(-1)	0.001	0.033	0.034	-0.031	-0.003
	(0.013)	(0.034)	(0.032)	(0.024)	(0.020)
Payday(0)	0.125***	0.083**	0.119***	0.126***	0.135***
	(0.017)	(0.041)	(0.036)	(0.032)	(0.028)
Payday(+1)	0.029**	0.042	0.058**	0.031	0.011
	(0.012)	(0.032)	(0.027)	(0.025)	(0.019)
Payday(+2)	0.069***	0.061*	0.084***	0.055**	0.073***
	(0.014)	(0.035)	(0.031)	(0.026)	(0.022)
Payday(+3)	0.038***	0.077**	0.061*	0.061**	0.004
	(0.014)	(0.039)	(0.034)	(0.029)	(0.021)
Payday(+4)	0.018	0.011	0.040	0.017	0.012
	(0.014)	(0.037)	(0.032)	(0.027)	(0.021)
Payday(+5)	0.029**	0.027	0.070**	0.034	0.010
	(0.015)	(0.045)	(0.032)	(0.030)	(0.022)
Payday(+6)	0.031**	-0.003	0.028	0.021	0.046**
	(0.014)	(0.034)	(0.031)	(0.027)	(0.023)
Payday(+7)	0.007	0.008	0.011	-0.029	0.027
	(0.013)	(0.036)	(0.028)	(0.022)	(0.022)
Observations	203,089	26,099	36,124	55,197	85,669
Income Arrivals	19,224	3,662	4,251	5,144	6,167
Individuals	12,681	2,775	3,110	3,330	3,466
Day FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Notes: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Standard errors in parentheses are clustered at the individual level. 3) **Daily Observations** indicates the number of observations. **Income Arrivals** indicates 'unique individuals (14,881) x number of income arrivals in a month (5)'. **Individuals** indicates the actual number of unique individuals.

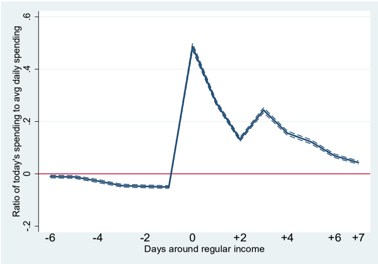
Table 2.17: Payday Effect of Irregular Income Payment on Non-Recurring Necessary Spending

	Dependent Variable: Spending Ratio out of Avg Daily Spending				
	All Income Group	Income 1	Income 2	Income 3	Income 4
	(1) sratio_nnr b/se	(2) sratio_nnr b/se	(3) sratio_nnr b/se	(4) sratio_nnr b/se	(5) sratio_nnr b/se
Payday(-6)	-0.003	0.013	0.014	-0.024	-0.000
	(0.011)	(0.028)	(0.023)	(0.018)	(0.018)
Payday(-5)	-0.005	0.038	0.021	-0.020	-0.018
	(0.011)	(0.031)	(0.025)	(0.019)	(0.017)
Payday(-4)	0.011	0.033	0.009	0.000	0.013
	(0.012)	(0.031)	(0.028)	(0.021)	(0.020)
Payday(-3)	0.008	-0.028	-0.004	0.001	0.027
	(0.012)	(0.031)	(0.025)	(0.023)	(0.019)
Payday(-2)	0.023*	0.006	0.013	0.031	0.024
	(0.013)	(0.038)	(0.029)	(0.025)	(0.020)
Payday(-1)	-0.005	-0.002	0.007	-0.007	-0.009
	(0.012)	(0.030)	(0.025)	(0.023)	(0.019)
Payday(0)	0.189***	0.176***	0.230***	0.224***	0.148***
	(0.016)	(0.041)	(0.039)	(0.033)	(0.025)
Payday(+1)	0.055***	0.089***	0.101***	0.059***	0.020
	(0.011)	(0.029)	(0.024)	(0.020)	(0.017)
Payday(+2)	0.030**	0.040	0.040	0.070***	-0.003
	(0.012)	(0.032)	(0.027)	(0.023)	(0.018)
Payday(+3)	0.034***	0.097***	0.080***	0.025	0.005
	(0.013)	(0.036)	(0.029)	(0.024)	(0.019)
Payday(+4)	0.018	0.016	0.054**	0.035	-0.007
	(0.012)	(0.033)	(0.027)	(0.024)	(0.019)
Payday(+5)	0.030**	0.033	0.048*	0.034	0.018
	(0.013)	(0.035)	(0.029)	(0.025)	(0.021)
Payday(+6)	0.023*	0.072*	0.007	0.052**	-0.004
	(0.012)	(0.038)	(0.025)	(0.022)	(0.019)
Payday(+7)	0.026**	0.079**	0.040*	0.019	0.006
	(0.011)	(0.031)	(0.024)	(0.021)	(0.018)
Observations	236,680	30,123	44,488	66,983	95,086
Income Arrivals	19,546	3,671	4,370	5,284	6,221
Individuals	12,784	2,792	3,152	3,373	3,467
Day FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

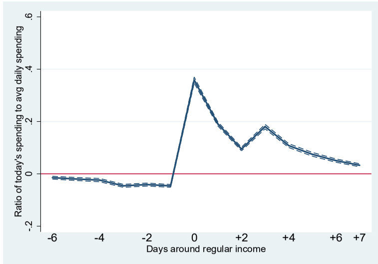
Notes: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Standard errors in parentheses are clustered at the individual level. 3) **Daily Observations** indicates the number of observations. **Income Arrivals** indicates 'unique individuals (14,881) x number of income arrivals in a month (5)'. **Individuals** indicates the actual number of unique individuals.

2.9.4 Payday Effects: Main Estimation Results

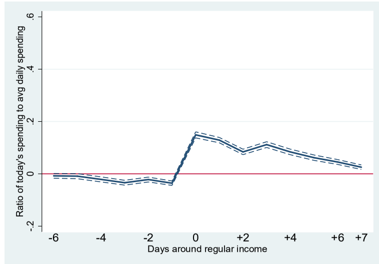
Figure 2.4: Payday Effects of Regular Income Payments on Consumption items



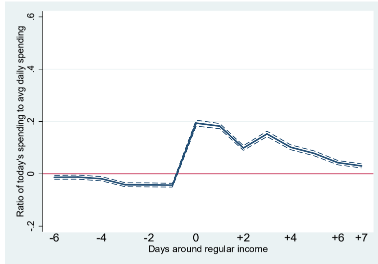
(A) All-Spending



(B) Non-Recurring All-Spending

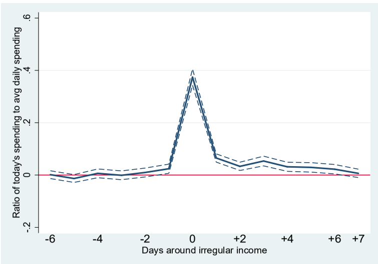


(C) Non-Recurring Discretionary

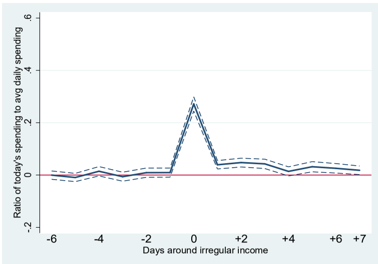


(D) Non-Recurring Necessary

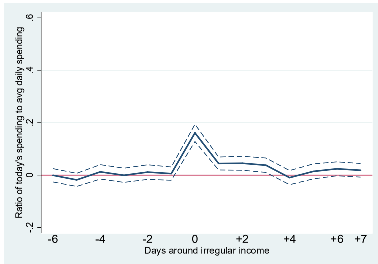
Figure 2.5: Payday Effects of Irregular Income Payments: Spending Categories



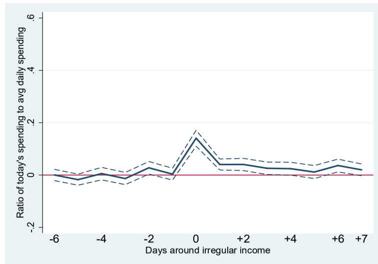
(A) All-Spending



(B) Non-Recurring All-Spending



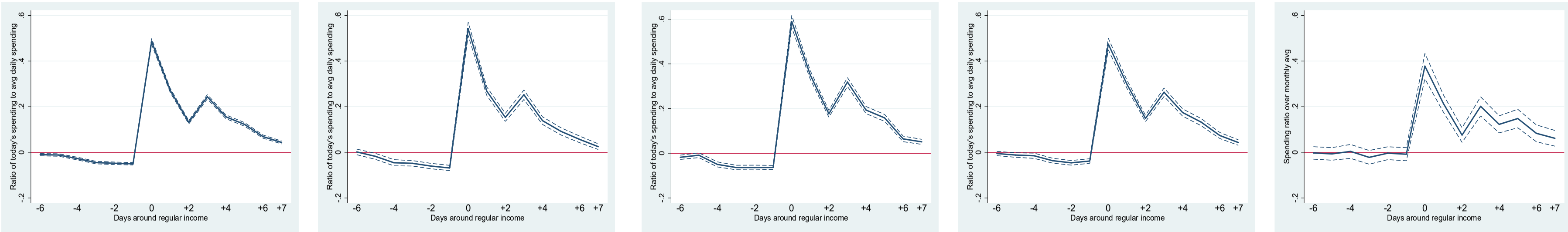
(C) Non-Recurring Discretionary



(D) Non-Recurring Necessary

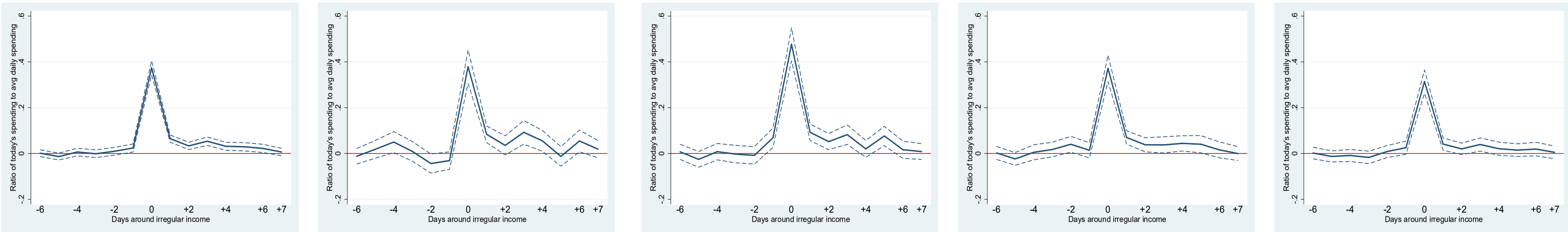
Note: 1) The horizontal axis displays two weeks around paydays. 2) The vertical axis shows the estimated coefficients of payday effects: the fraction by which individual spending deviates from average daily spending in the days around an income arrival. 3) The dashed line shows 95% confidence interval. 4) The estimation is based on the first-to-fifth biggest income payments in each month.

Figure 2.6: Payday Effects of Regular Income Payments by Income Levels: All-spending



(A) All income group (B) Income level 1 (C) Income level 2 (D) Income level 3 (E) Income level 4

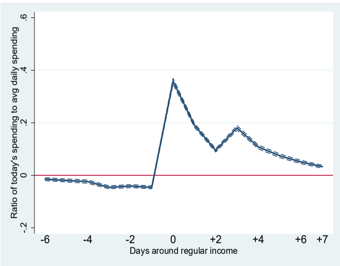
Figure 2.7: Payday Effects of Irregular Income Payments: All-spending



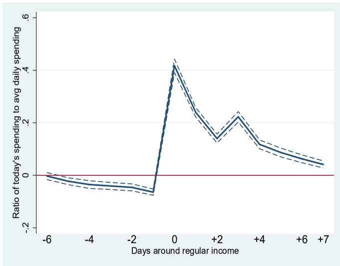
(A) All income group (B) Income level 1 (C) Income level 2 (D) Income level 3 (E) Income level 4

Note: 1) The horizontal axis displays two weeks around paydays. 2) The vertical axis shows the estimated coefficients of payday effects: the fraction by which individual spending deviates from average daily spending in the days around an income arrival. 3) The dashed line shows 95% confidence interval. 4) The estimation is based on the first-to-fifth biggest income payments in each month.

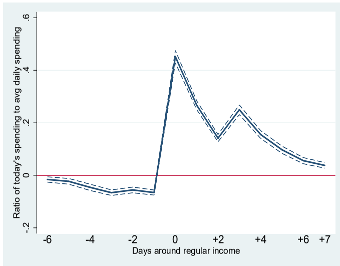
Figure 2.8: Payday Effects of Regular Income Payments by Income Levels: Non-recurring All-Spending



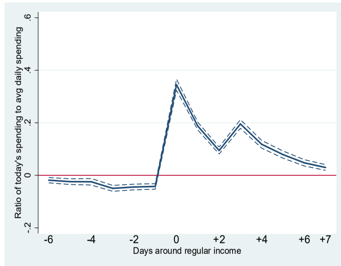
(A) All income group



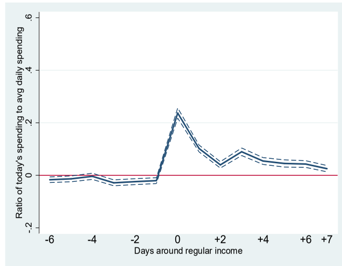
(B) Income level 1



(C) Income level 2

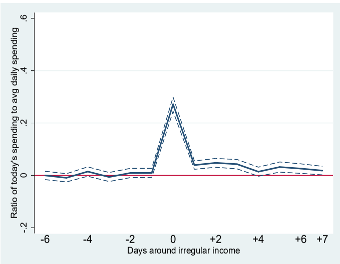


(D) Income level 3

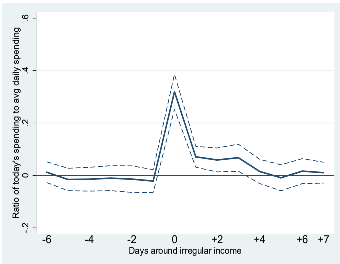


(E) Income level 4

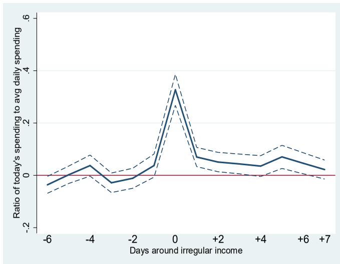
Figure 2.9: Payday Effects of Irregular Income Payments by Income Levels: Non-recurring All-Spending



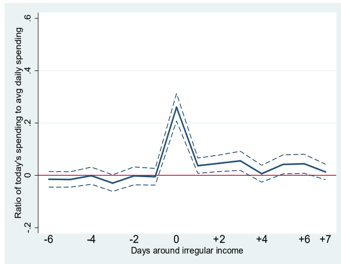
(A) All income group



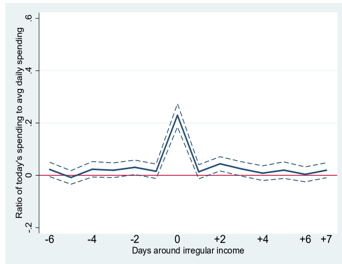
(B) Income level 1



(C) Income level 2



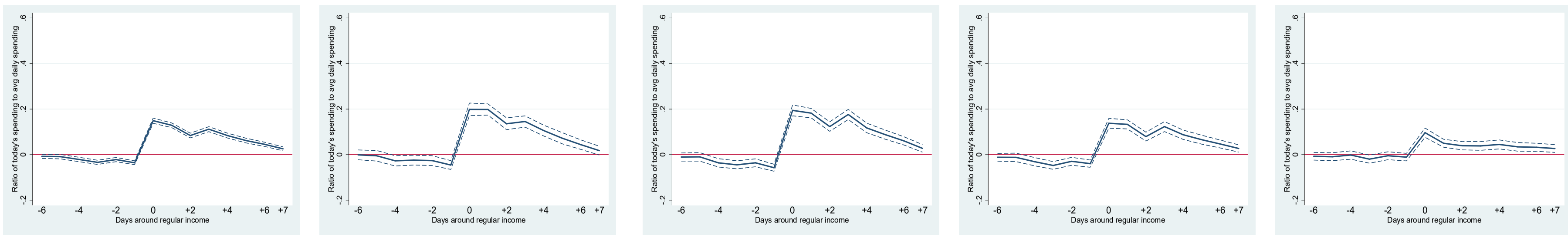
(D) Income level 3



(E) Income level 4

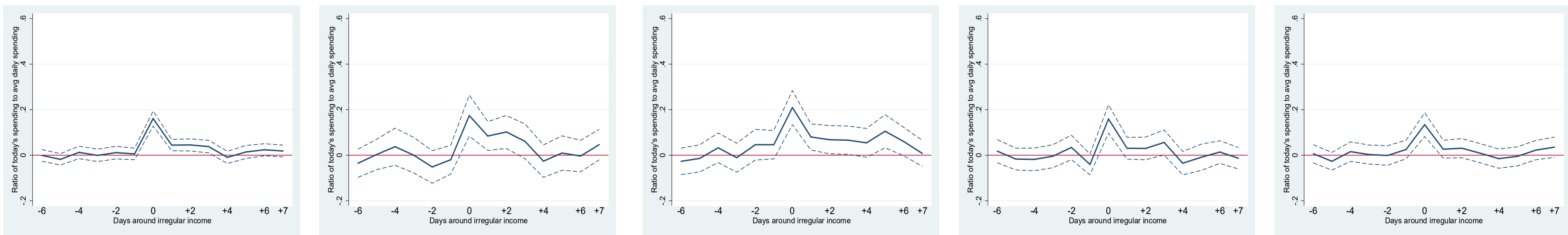
Note: 1) The horizontal axis displays two weeks around paydays. 2) The vertical axis shows the estimated coefficients of payday effects: the fraction by which individual spending deviates from average daily spending in the days around an income arrival. 3) The dashed line shows 95% confidence interval. 4) The estimation is based on the first-to-fifth biggest income payments in each month.

Figure 2.10: Payday Effects of Regular Income Payments by Income Levels: Non-recurring Discretionary Spending



(A) All income group (B) Income level 1 (C) Income level 2 (D) Income level 3 (E) Income level 4

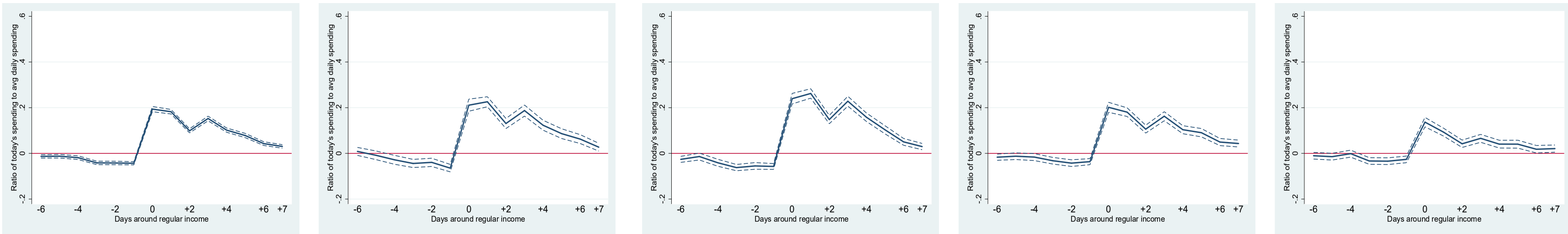
Figure 2.11: Payday Effects of Irregular Income Payments by Income Levels: Non-recurring Discretionary Spending



(A) All income group (B) Income level 1 (C) Income level 2 (D) Income level 3 (E) Income level 4

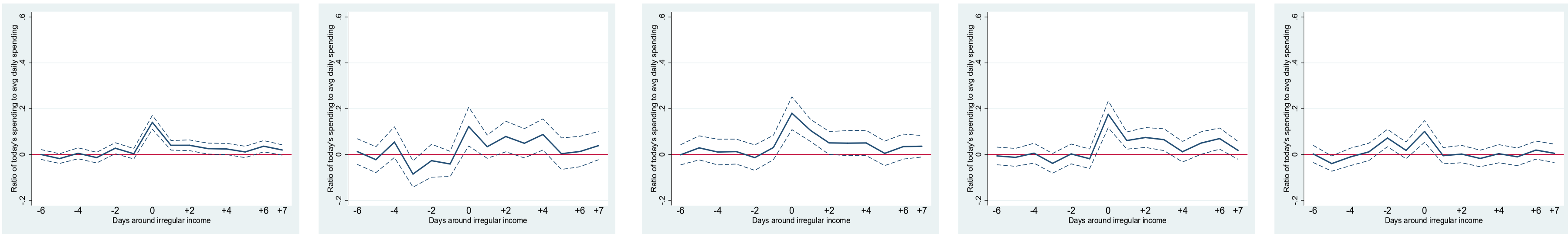
Note: 1) The horizontal axis displays two weeks around paydays. 2) The vertical axis shows the estimated coefficients of payday effects: the fraction by which individual spending deviates from average daily spending in the days around an income arrival. 3) The dashed line shows 95% confidence interval. 4) The estimation is based on the first-to-fifth biggest income payments in each month.

Figure 2.12: Payday Effects of Regular Income Payments by Income Levels: Non-recurring Necessary Spending



(A) All income group (B) Income level 1 (C) Income level 2 (D) Income level 3 (E) Income level 4

Figure 2.13: Payday Effects of Irregular Income Payments by Income Levels: Non-recurring Necessary Spending

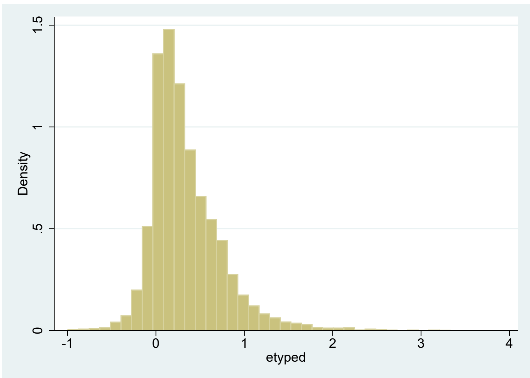


(A) All income group (B) Income level 1 (C) Income level 2 (D) Income level 3 (E) Income level 4

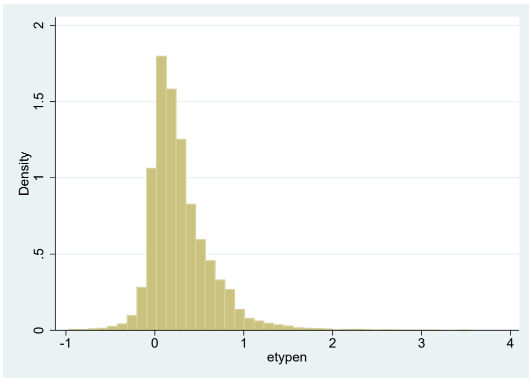
Note: 1) The horizontal axis displays two weeks around paydays. 2) The vertical axis shows the estimated coefficients of payday effects: the fraction by which individual spending deviates from average daily spending in the days around an income arrival. 3) The dashed line shows 95% confidence interval. 4) The estimation is based on the first-to-fifth biggest income payments in each month.

2.9.5 Payday Effects: MPC Heterogeneity

Figure 2.14: Distributions of Individual MPC of Discretionary and Necessary Items

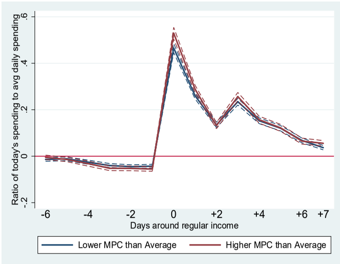


(A) MPC of discretionary items

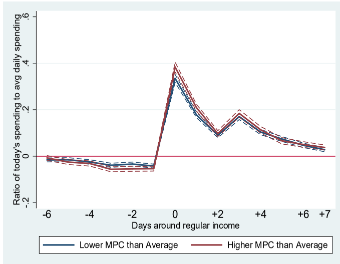


(B) MPC of necessary items

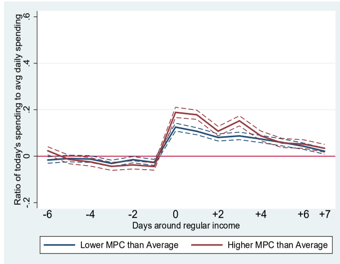
Figure 2.15: Payday Effects of Regular Income Payments on Consumption Items: MPC Heterogeneity



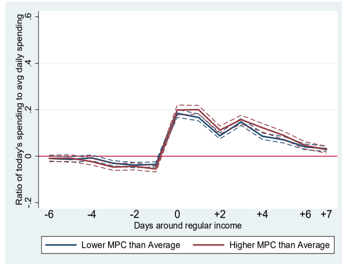
(A) All-Spending



(B) Non-Recurring All-Spending

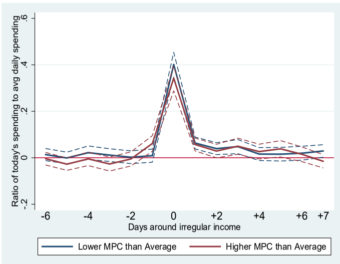


(C) Non-Recurring Discretionary

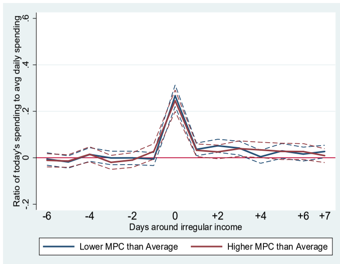


(D) Non-Recurring Necessary

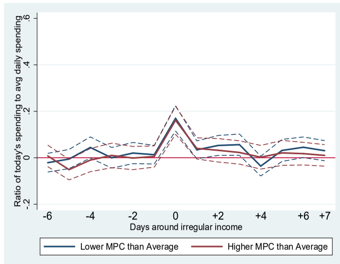
Figure 2.16: Payday Effects of Irregular Income Payments on Consumption Items: MPC Heterogeneity



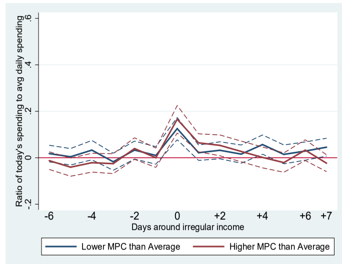
(A) All-Spending



(B) Non-Recurring All-spending



(C) Non-Recurring Discretionary

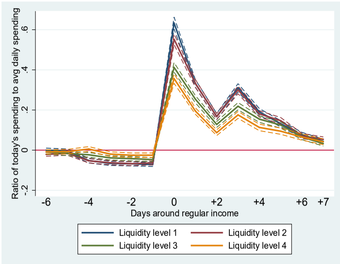


(D) Non-Recurring Necessary

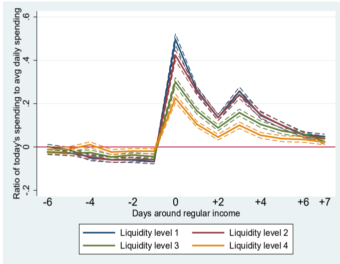
Note: 1) The horizontal axis displays two weeks around paydays. 2) The vertical axis shows the estimated coefficients of payday effects: the fraction by which individual spending deviates from average daily spending in the days around an income arrival. 3) The dashed line shows 95% confidence interval. 4) The estimation is based on the first-to-fifth biggest income payments in each month.

2.9.6 Payday Effects: Liquidity Level

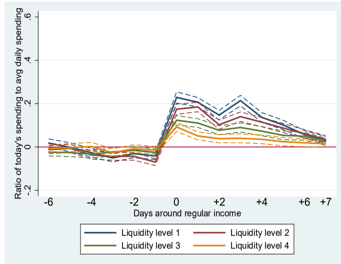
Figure 2.17: Payday Effects of Regular Income Payments on Consumption Items: Liquidity Level Comparison



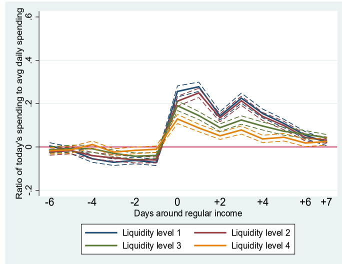
(A) All-Spending



(B) Non-Recurring All-Spending

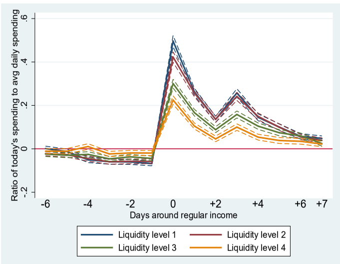


(C) Non-Recurring Discretionary

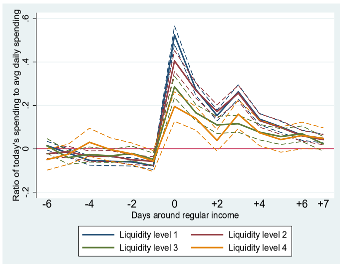


(D) Non-Recurring Necessary

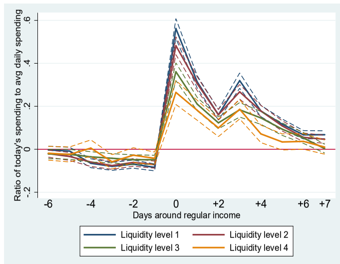
Figure 2.18: Payday Effects of Regular Income Payments on Non-recurring All-spending by Income Levels: Liquidity Level Comparison



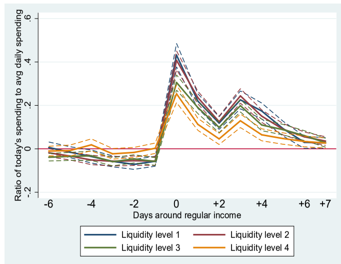
(A) All income group



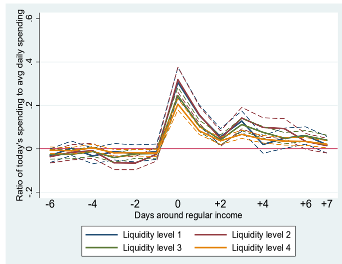
(B) Income level 1



(C) Income level 2



(D) Income level 3

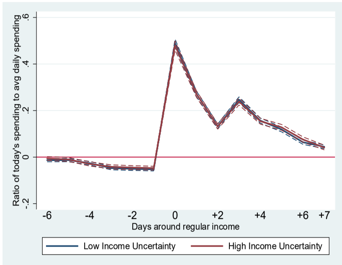


(E) Income level 4

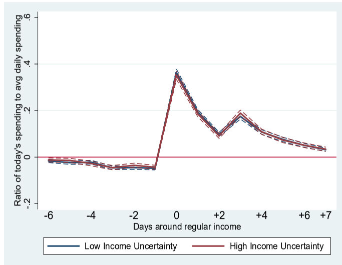
Note: 1) The horizontal axis displays two weeks around paydays. 2) The vertical axis shows the estimated coefficients of payday effects: the fraction by which individual spending deviates from average daily spending in the days around an income arrival. 3) The dashed line shows 95% confidence interval. 4) The estimation is based on the first-to-fifth biggest income payments in each month.

2.9.7 Payday Effects: Regional Income Uncertainty

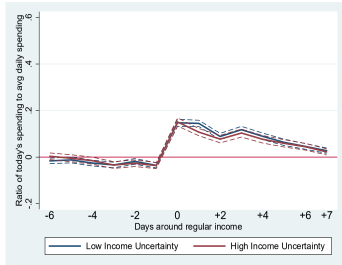
Figure 2.19: Payday Effects of Regular Income Payments on Various Consumption Items: Regional Income Uncertainty Comparison



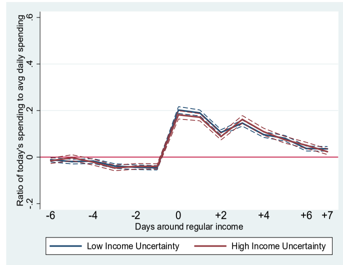
(A) All-Spending



(B) Non-Recurring All-Spending

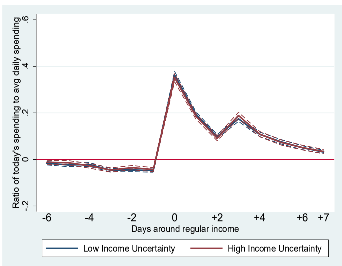


(C) Non-Recurring Discretionary

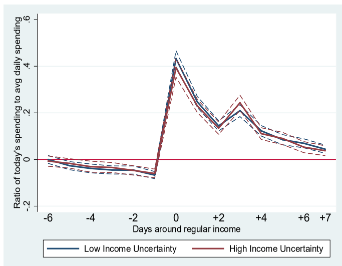


(D) Non-Recurring Necessary

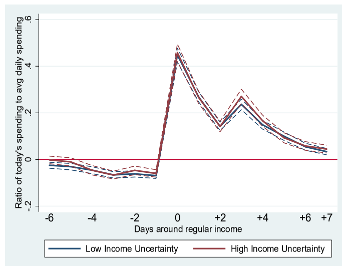
Figure 2.20: Payday Effects on Non-recurring All-spending by Income Levels: Regional Income Uncertainty Comparison



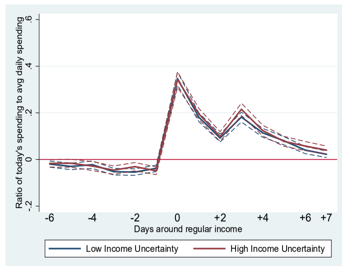
(A) All income group



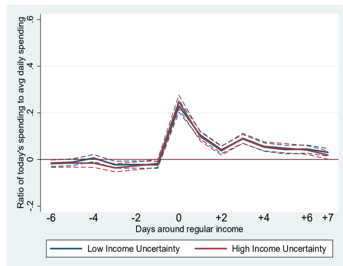
(B) Income level 1



(C) Income level 2



(D) Income level 3

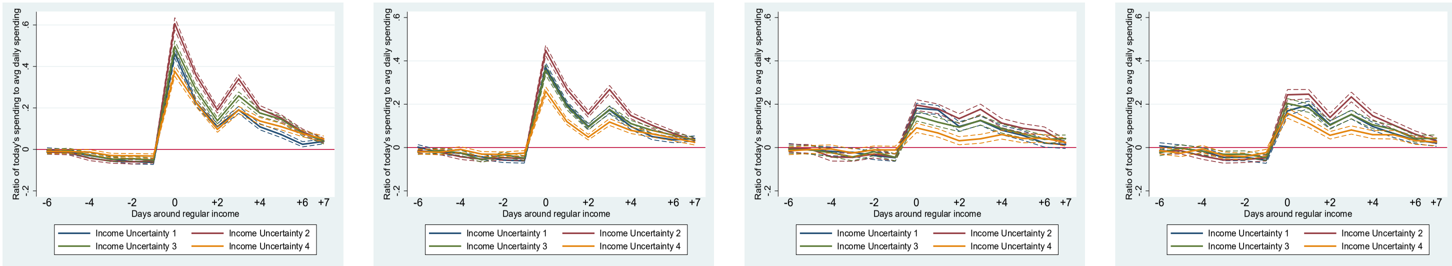


(E) Income level 4

Note: 1) The horizontal axis displays two weeks around paydays. 2) The vertical axis shows the estimated coefficients of payday effects: the fraction by which individual spending deviates from average daily spending in the days around an income arrival. 3) The dashed line shows 95% confidence interval. 4) The estimation is based on the first-to-fifth biggest income payments in each month.

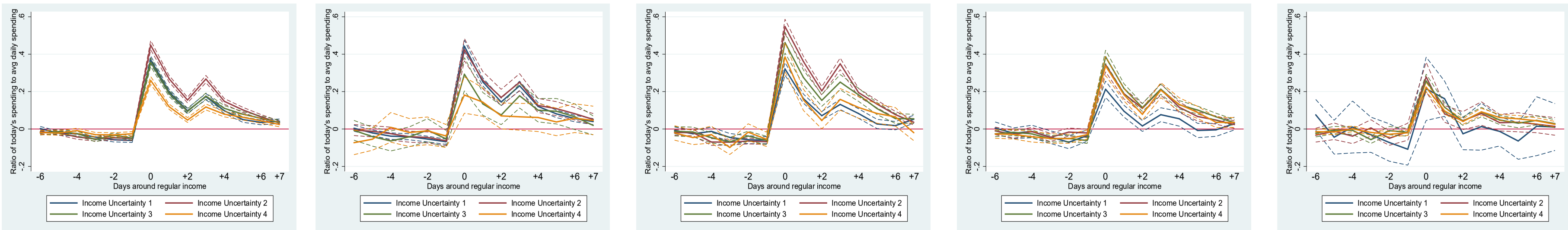
2.9.8 Payday Effects: Individual Income Uncertainty

Figure 2.21: Payday Effects of Regular Income Payments on Consumption Items: Individual Income Uncertainty Comparison



(A) All-spending (B) Non-recurring All-spending (C) Non-recurring Discretionary (D) Non-recurring Necessary

Figure 2.22: Payday Effects on Non-recurring All-spending by Income Levels : Individual Income Uncertainty Comparison

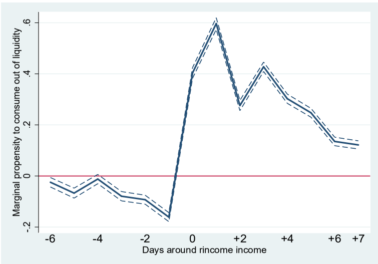


(A) All income group (B) Income level 1 (C) Income level 2 (D) Income level 3 (E) Income level 4

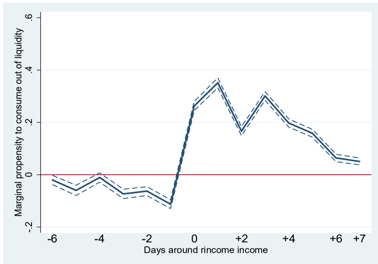
Note: 1) The horizontal axis displays two weeks around paydays. 2) The vertical axis shows the estimated coefficients of payday effects: the fraction by which individual spending deviates from average daily spending in the days around an income arrival. 3) The dashed line shows 95% confidence interval. 4) The estimation is based on the first-to-fifth biggest income payments in each month.

2.9.9 Payday Effects: MPCL Specification

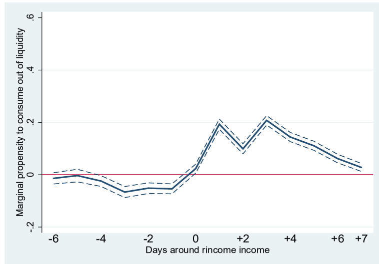
Figure 2.23: Payday Effects of MPCL around Regular Income Payments



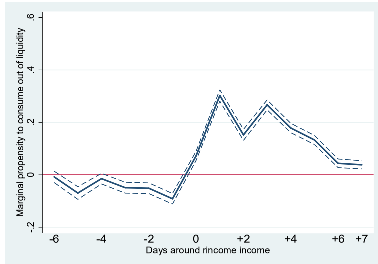
(A) All-Spending



(B) Non-Recurring All-Spending

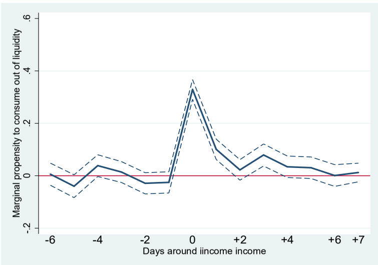


(C) Non-Recurring Discretionary

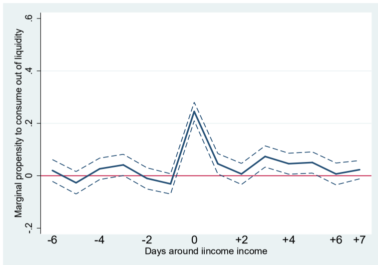


(D) Non-Recurring Necessary

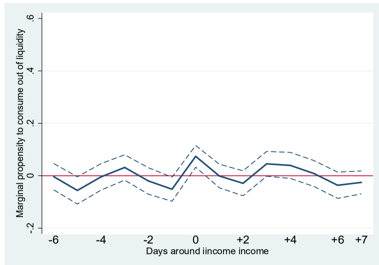
Figure 2.24: Payday Effects of MPCL around Irregular Income Payments



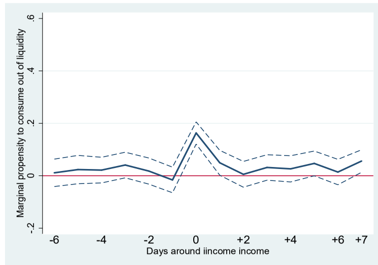
(A) All-Spending



(B) Non-Recurring All-Spending



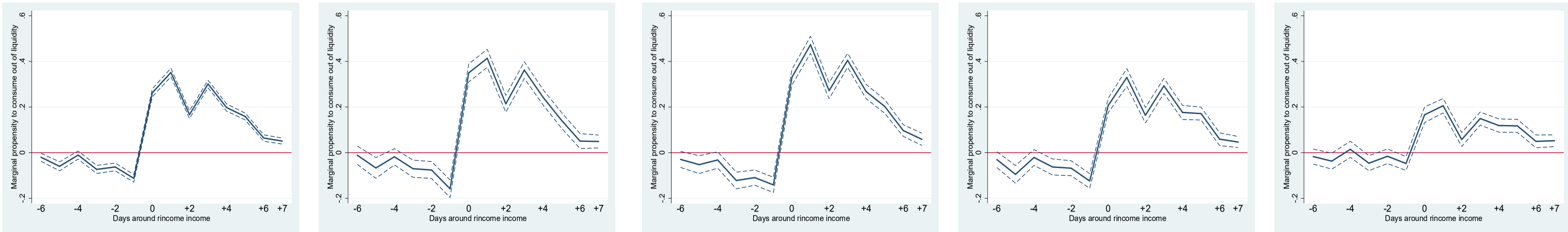
(C) Non-Recurring Discretionary



(D) Non-Recurring Necessary

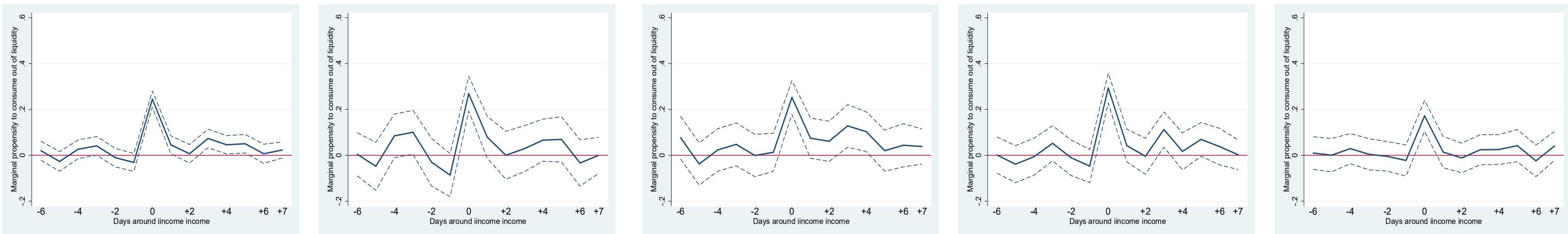
Note: 1) The horizontal axis displays two weeks around paydays. 2) The vertical axis shows the estimated MPCL for each day 3) The dashed line shows 95% confidence interval.

Figure 2.25: Payday Effects of MPCL around Regular Income Payments on Non-Recurring All-Spending



(A) All income group (B) Income level 1 (C) Income level 2 (D) Income level 3 (E) Income level 4

Figure 2.26: Payday Effects of MPCL around Irregular Income Payments on Non-Recurring All-Spending

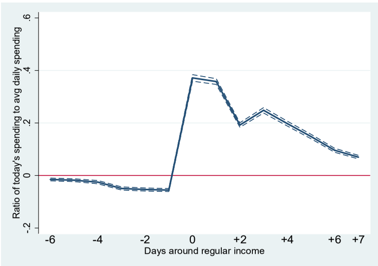


(A) All income group (B) Income level 1 (C) Income level 2 (D) Income level 3 (E) Income level 4

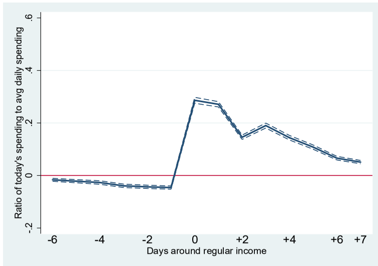
Note: 1) The horizontal axis displays two weeks around paydays. 2) The vertical axis shows the estimated MPCL for each day 3) The dashed line shows 95% confidence interval.

2.9.10 Payday Effects: 1st-50th Biggest Income Payments in a Year

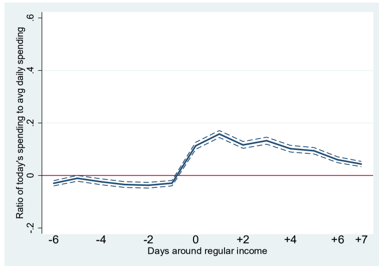
Figure 2.27: Payday Effects of Regular Income Payments on Consumption Items



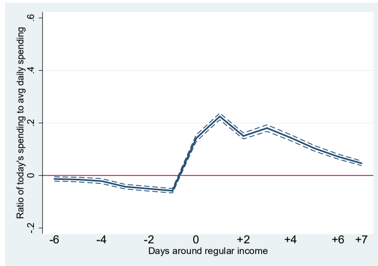
(A) All-Spending



(B) Non-Recurring All-Spending

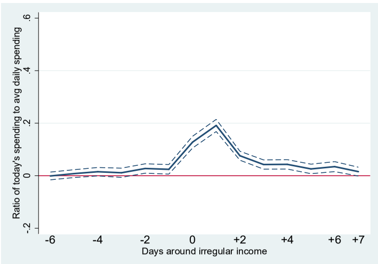


(C) Non-Recurring Discretionary

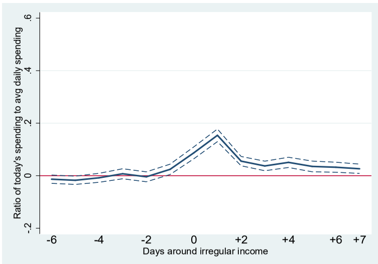


(D) Non-Recurring Necessary

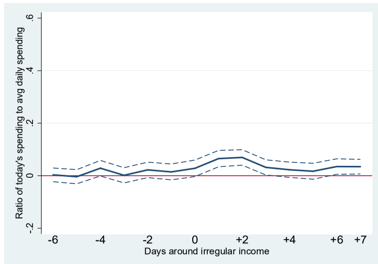
Figure 2.28: Payday Effects of Irregular Income Payments on Consumption Items



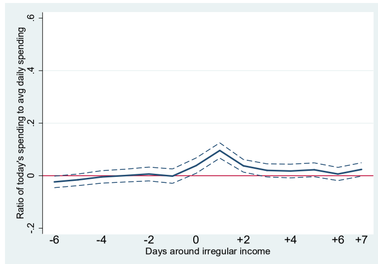
(A) All-Spending



(B) Non-Recurring All-Spending



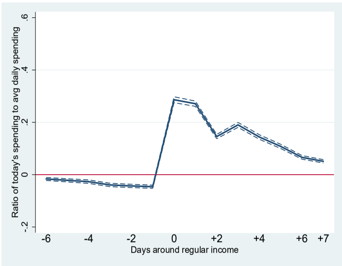
(C) Non-Recurring Discretionary



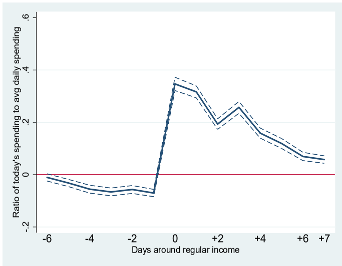
(D) Non-Recurring Necessary

Note: 1) The horizontal axis displays two weeks around paydays. 2) The vertical axis shows the estimated coefficients of payday effect: the fraction by which individual spending deviates from average daily spending in the days around an income arrival. 3) The dashed line shows 95% confidence interval. 4) The estimation is based on the first-to-fiftieth biggest income payments in a year.

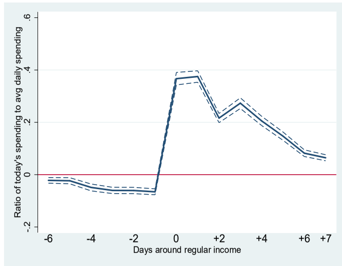
Figure 2.29: Payday Effects of Regular Income Payments by Income Levels: Non-Recurring All-Spending



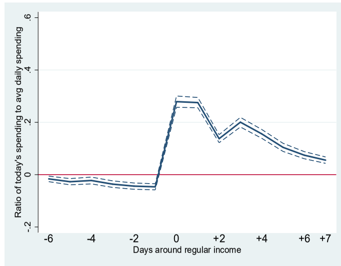
(A) All income group



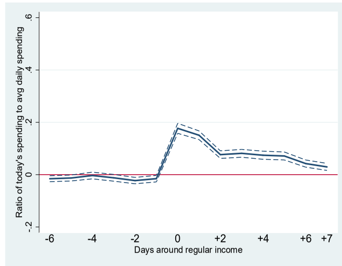
(B) Income level 1



(C) Income level 2

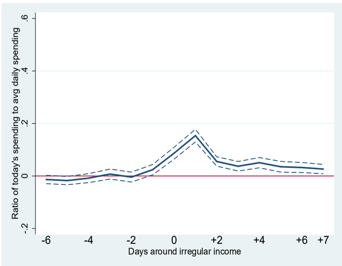


(D) Income level 3

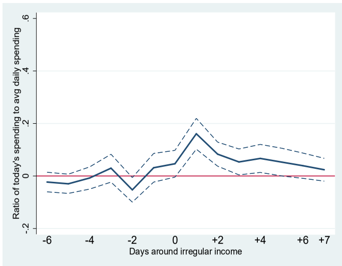


(E) Income level 4

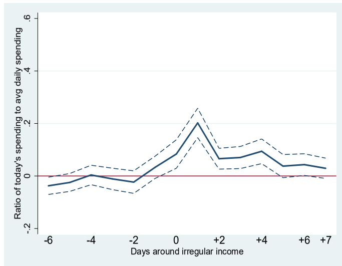
Figure 2.30: Payday Effects of Irregular Income Payments by Income Levels: Non-Recurring All-Spending



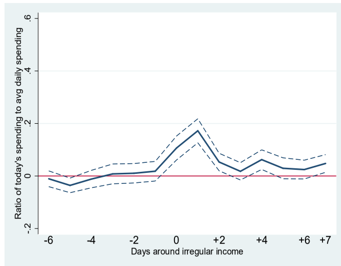
(A) All income group



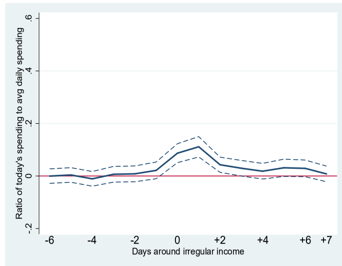
(B) Income level 1



(C) Income level 2



(D) Income level 3



(E) Income level 4

Note: 1) The horizontal axis displays two weeks around paydays. 2) The vertical axis shows the estimated coefficients of payday effect: the fraction by which individual spending deviates from average daily spending in the days around an income arrival. 3) The dashed line shows 95% confidence interval. 4) The estimation is based on the first-to-fiftieth biggest income payments in a year.

Chapter 3

Reference Effect on Consumption Choices: Evidence from Highly Disaggregate Spending Data

3.1 Introduction

What determines consumption expenditure has been a research question of great interest in the history of economics. Typical answers are focused on the individual-level relationship between income and consumption (MPC), the relation between liquidity level and consumption (MPCL) and the effect of debt or credit amounts on consumption. From the perspective of policy prescriptions, researchers have investigated the effect of disposable income or interest rates on consumption expenditure according to government spending, tax rates and monetary policy. However, all these works impose strong assumptions on the consumption utility function such as time separability and cross-section independence. Classical consumption theory only tells us stories within its boundary of assumptions. In the well-known consumption Euler equation, rational consumption choices are made under the condition wherein the relative marginal utility across two periods equals the relation between the market interest rate and subjective discount rate. However, it is more realistic if we think an individual's actual consumption choices are affected by her neighbours or friends (cross-section dependence) and her spending in the past (habits). Although we have recently begun to see the availability of highly disaggregate data, papers incorporating cross-section dependence into consumption behaviour are rare. This paper fills this gap by employing transaction-level spending data to compare the reference effects of one item to those of other items. I further study the relative importance of reference group spending variables[1] in explaining each consumption item's reference effects.

Following recent literature works in which the dynamic panel model in time and space is widely employed, I show that an individual's global MPC elasticity[2] (hereinafter,

[1]Reference group spending variables are vectors of each individual's peer members' average spending except each individual. In terms of matrix multiplication, an NxN weighting matrix of N individuals is applied to the dependent variable (spending) to make a reference group spending variable.

[2]I use MPC elasticity and income elasticity of demand interchangeably.

global MPC) can be decomposed into direct MPC, and indirect MPC, which can be understood as the reference effect. Furthermore, the associated long-run MPC can be further obtained by taking lagged dependent variables (habitual spending) into account. Herein, I apply this framework to a balanced panel of 5,424 individuals[3] who have a regular income and spending history for 36 months from the UK's financial management application **MDB**. In this paper, the use of raw data extends to social interactions across cross-section dimension. The time dimension is set to a monthly frequency, and C_{it} is constructed as aggregate, broad category, and sub-category levels.

First, I define five reference groups. Four of them (age, gender, income and region) are easily identified from the MDB, which has detailed information on age, gender, derived income and the four-digit UK postcodes. More interestingly, I identify individuals' spending patterns with expenditure elasticity across three consumption items within the Almost Ideal Demand System (Deaton and Muellbauer, 1980). I call these spending patterns as 'individual preference'. I assume that an individual's preference of spending is determined by prices of and expenditures on three sub-category items: recreational activity, eating-at-home and eating-out.[4] Using the restrictions implied by the AID system, I capture eight (2^3) consumer's preference groups with combinations of higher and lower than average elasticities in each item. Intuitively, each individual can fall into a specific group with their own consumption composition depending on the prices of items and total expenditure under the conditions of the demand system.[5]

Second, I set up an extensive and general dynamic network panel model to identify the reference effect. Following Manski (1993) and Bramoullé et al. (2009), I employ **endogenous** (reference effect on outcome: spending), **exogenous** (reference effect on reference characteristics: income) and **correlated effects** (network fixed effects) as the baseline specification. In addition, I add **common factors** to transform the data in terms of deviation from time-specific averages to control cross-sectional, time-varying factors motivated by Sarafidis and Robertson (2009).

With all these estimated reference group variable coefficients, reference effects can be computed.[6] In the short-run, I basically have the direct MPC, and the indirect

[3]I restrict the samples into a balanced panel of 5,424 users to have only economically active consumers.

[4]The reasons for selecting these items are that recreational activity and eating-out represent discretionary items whereas eating-at-home stands for necessary items. Also these items have the associated UK ONS consumer price index (CPI).

[5]Since the transaction-level spending data can be aggregated into any aggregation level, applying the AID system framework into this data enables me to identify consumers' preferences in a more sophisticated way than any other aggregate database approach and this is one of the empirical contributions of this paper.

[6]One way to identify the reference effect is to compare the coefficients of reference group spending variables. One caveat of this interpretation of coefficients has been suggested by recent spatial econometrics literature in that coefficients from a "network autoregressive model" can not necessarily represent a network marginal effect since it should be calculated from the total (global) effects reflecting individual

MPC (the remaining part of the global MPC). In the long-run, where I take habitual spending into account, I have the direct MPC with the habit effect (scaled up by lagged dependent variables) and the indirect MPC with habit (scaled up by habit and reference variables). Then, I can calculate the relative size between the indirect and global MPC (indirect MPC/global MPC) to identify which items are more likely to be affected by the reference effect (indirect MPC) instead of an individual's own decision (direct MPC).

Third, the estimation results are as follows. The global MPC elasticities computed from various reference group spending variable coefficients categorise consumption items into normal/luxury/inferior goods as suggested by microeconomic theory. The indirect effects computed from the difference of global and direct MPC elasticities show that discretionary, visible items generate the greatest reference effects whereas necessary type spending items are less affected by the reference groups. Additionally, I find that the income reference group spending variable tends to be the main driver in most consumption items, whereas preference reference is the strongest factor in discretionary spending. Necessary type spending items are more driven by habitual factors rather than reference effects.

I further explore robustness check exercises in which I split samples by gender and construct corresponding weighting matrices for each gender group. This exercise has two purposes: checking whether the weighting matrices are suitably constructed and studying if there are differences in the reference effect between the genders. The gender sample restriction confirms that the weighting matrices are well constructed. The indirect MPC of females is bigger than that of males in the case of all-spending. In the other items, the sizes of the reference effects between females and males are mixed.

Last but not least, I exercise indirect effect estimation based on a single matrix in which I set up a more parsimonious specification instead of five reference group variables. Assuming that the estimation results of indirect effects with five separate weighting matrices are true, I calculate the RMSE of each single matrix specification across consumption items. The results show that the restricted single weighting matrix structure based on three important reference groups replicates the baseline (assumed to be true) indirect effects better than just a single weighting matrix structure based on a simple average of five reference groups.

My results have significant implications. How to exploit high-frequency data to understand consumption decisions has been relatively well dealt with in the recent literature. However, the size of the reference effects in numerous consumption items is rarely investigated. My results provide exercises that can reveal the consumption item's characteristics as well as individuals' affectability to their reference groups. From a theoretical perspective, analysis of an individual's consumption decisions should incorporate cross-section dependence and time non-separability if we want the

network relations in the weighting matrix.

consumption theory to reflect realistic individual choices. Otherwise, we will end up overestimating the direct MPC with toy models.

The limitations of this paper are in line with the dataset. Even though the MDB data allows me to use very fine data of 5,424 individuals across the UK, I am not able to be sure that they have actual relationships such as friendship or acquaintanceship. This is why I say reference effect instead of peer effect, with which other papers focused more on restricted samples with close peer relationships.[7] In addition to that, if I were allowed to have a more balanced panel quite larger than 5,424 individuals, it would be possible to investigate the consumption reference or peer effect on specific brands (e.g. Deliveroo) rather than category-level spending.

This paper is related to the literature on the peer group identification problem. Due to the seminal work of Manski (1993, 2000), it is widely known that the linear-in-means model has the reflection problem if we do not impose a proper identification strategy. Manski argues that even when there is no problem in separating social effects from correlated effects, simultaneous interaction across individuals and their peers still renders perfect collinearity between peer outcomes and peer characteristics.[8] Bramoullé et al. (2009) generalises necessary and sufficient conditions for identifying the endogenous and exogenous effects under incomplete relation based network interactions, which means that not all individuals are interlinked. Herein, I mainly follow their contribution in that I construct weighting matrices that satisfy the condition of interaction matrix: $G \neq G^2$. Lin (2015) uses the extensive spatial econometrics model with endogenous, contextual and group fixed effects to identify peer effects in adolescents. Lin only uses one weighting matrix and interpret peer variable coefficients as peer effects, whereas I further use several network structures and compute indirect effects from weighting matrices. The closest paper in terms of the identification strategy is that of Bridges and Lee (2016), in which they study wage determination in the presence of reference effects whereas my question lies in consumption behaviour.

This paper is also part of the recent literature regarding estimation strategy, taking weak and strong cross-section dependence into account. Peer effects are generally considered as weak cross-section dependence, whereas the factor model is an example of capturing strong cross-section dependence (Pesaran, 2006; Chudik et al., 2011). It is generally considered that peer effects are not strong enough for forecasting purposes compared to factor models; however, they are still useful for explaining indirect effects across interlinked individuals. While factors are regarded as nuisance variables, the network model focuses on modelling interactions in detail (Ertur and Musolesi, 2017).

[7] For example, Agarwal et al. (2020) deal with networks within the same residential building, and Patacchini and Venanzoni (2014) uses detailed friendships in neighbourhood.

[8] Endogenous social effects capture the effects of a reference group's outcome on an individual's outcome. Exogenous social effects (contextual effects) grasp the effects of a reference group's characteristics.

Bridges and Lee (2016) also emphasize the role of unobserved common factors in dynamic panel system GMM estimation, motivated by Sarafidis and Robertson (2009). A similar approach of common factors in the dynamic panel model is explicitly employed by Cicarrelli and Elhorst (2018), who study the spatial diffusion of cigarette consumption expenditure. Here, I follow their discussions on the role of common factors in the model selection process.

My paper contributes to the overall literature on consumption peer effects. The subject of studying peer effects has mainly focused only on public spending (Foucault et al., 2008), aggregate state spending (Korniotis, 2010) or specific consumption item (Ciccarelli and Elhorst, 2018), restrictive housing demands in a small group of areas (Patacchini and Venanzoni, 2014). More recently, it was documented that individuals' consumption choices depend on their peer groups (Boneva, 2013). Agarwal et al. (2020) use detailed data on residents in the same building to show that consumption choices are affected by peers and more pronounced for women who are sensitive to their peer groups. De Giorgi et al. (2019) employs the Danish administrative tax record and matched employer-employee data to examine peer groups in the workplace. However, my paper focuses on individual consumption expenditure and selective consumption sub-categories (necessary, discretionary and visible spending). I also assume that those who are in the same group of characteristics tend to refer to their group members without detailed peer relations.

One interesting sub-category is visible spending (conspicuous consumption). Roth (2015) employs an experimental approach to examine peer effects in conspicuous items and he finds that peer effects are high in conspicuous items especially in the low levels of social activity groups. Currid-Halkett et al. (2019) show that visible spending is more sensitive to urban characteristics than inconspicuous items.

Research on imposing restrictions on weighting matrices is at an early stage. Recently, researchers have been interested in estimating proper weighting matrices in network modelling (Manresa, 2016; Lam and Souza, 2019; De Paula et al., 2019). In many cases of spatial econometrics literature, a weighting matrix is constructed based on geographic proximity, whereas cases in the labour economics literature (Bridges and Lee, 2016) use several weighting matrices to construct multiple peer group variables. However, I impose simple restrictions based on the relative strength of reference groups to make a parsimonious model in terms of a single weighting matrix.

The use of the AID system is very abundant in the literature. Since Deaton and Muellbauer (1980), demand elasticities can be estimated with price, demand quantities across several consumption items at the same time. Next generation of classical AID system is the quadratic AID system by Banks, Blundell and Lewbel (1997). Since this paper's purpose is not about rigorous estimation of AID system but constructing weighting matrix for individual's unobserved preference and I am more focused on empirical application.[9]

The rest of this paper proceeds as follows. Section 3.2 describes the econometric strategy. Section 3.3 provides data overview and reference group illustration. Section 3.4 describes the model choice procedure. Section 3.5 illustrates the main estimation results. Section 3.6 focuses on the use of single weighting matrices. Section 3.7 concludes.

3.2 Econometric Strategy

3.2.1 MPC Elasticity with Cross-Section Dependence

In microeconomic theory, it is widely known that characteristics of consumption items are classified as normal, luxurious and inferior goods depending on their degree of income elasticity of demand. Generally, the income elasticity of demand is defined as an individual's responsiveness of the consumption demanded (quantities) for a certain good to an income change.[10] We call consumption items as normal goods when the elasticity falls between zero and one and some examples are necessary goods such as food and water. Luxurious goods such as jewellery are identified when the elasticity is bigger than one. Inferior goods are known to have negative elasticity, and an associated example is low-quality food. Although the income elasticity of demand (or MPC) is a classic concept, investigation on MPC with dynamics in time and network has been rare even in the household finance literature. In this paper, I incorporate cross-section dependence (network relations) and time dynamics (time lags) into the MPC elasticity estimation to examine the role of reference effects on consumption choices.

3.2.2 Identification within the Network Interaction Framework

Using social interaction in understanding consumer behaviour dates back to Manski (1993), who points out that social interactions can be conceptually decomposed into endogenous effects (one's behaviour is affected by the behaviour of the group), exogenous effects (one's behaviour is affected by the characteristics of the group) and correlated effects (individual characteristics or similar institutional environments). However, the usual linear-in-means model causes identification failure due to the collinearity of group behaviours and group characteristics. This is widely known as the 'reflection problem'. Although some literature works employing the linear-in-means model detour this problem by choosing either endogenous effects or exogenous effects

[9] I refer to STATA's user-written command 'QUAIDS' for the quadratic AID system written by Poi (2012).

[10] As a mirror image of item characteristics, the concept of MPC is frequently used to illustrate an individual's consumption patterns. In this paper, I will use two terms interchangeably. I use income elasticity of demand when it comes to consumption item characteristics whereas I use the MPC in cases of describing an individual's consumption patterns.

(Lin, 2015), this is not the ideal identification strategy. Recently, Bramoullé et al. (2009) propose a network model of social interaction in which the network structures in weighting matrices across individuals are used to identify endogenous, exogenous and correlated effects as a whole. Specifically, it is required for the interaction matrices G, G^2 and G^3, which are all linearly independent to identify the extensive social interaction model.[11] The proposed network structure (Bramoullé et al. [2009]) can be illustrated as below.

$$
\begin{aligned}
W_{i,j} =& \frac{1}{N_g - 1} \; if \quad i \neq j \\
=& \;\; 0 \qquad if \quad i = j \\
& where\ N_g = Number\ of\ individuals\ in\ the\ g^{th}\ group \\
& \qquad i,\ j \in N\ (5,424\ individuals)
\end{aligned}
\tag{3.1}
$$

where $W_{i,j}$ represents components of i^{th} row and j^{th} column in the N x N weighting matrix. Following the discussion of Manski (1993, 2000) and Bramoullé et al. (2009), the baseline specification is as below[12]:

$$
\begin{aligned}
C_{i,t} =& \alpha_i + \sum_{s=1}^{S=4} \rho_s C_{i,t-s} + \beta_{Direct} Y_{i,t} + \sum_{k=1}^{K=4} \theta_k X_{i,t}^k + \sum_{j=0}^{J=4} \lambda_j \overline{C}_{t-j} \\
& + \sum_{r=1}^{R=5} (\sum_{g=1}^{Gr} \mu_{rg} f_i^{rg} + \delta^r \widetilde{C}_{i,t}^r + \gamma^r \widetilde{Y}_{i,t}^r) + \epsilon_{i,t} \\
& where \quad i = 1, \ldots, N \quad t = 1, \ldots, T
\end{aligned}
\tag{3.2}
$$

$C_{i,t}$ is individual i's consumption expenditure (All-spending or sub-category spending) at time t;

α_i is the unobserved individual heterogeneity;

ρ_s is the coefficient of the s_{th} lagged consumption $C_{i,t-s}$[13];

β_{Direct} is the usual direct MPC elasticity that is of interest; $Y_{i,t}$ is individual monthly income;

θ_k is the coefficients of the k^{th} explanatory variables $X_{i,t}^k$ such as monthly net liquidity, borrowing, repaying and saving amounts other than $Y_{i,t}$ in this specification.

λ_j is the j^{th} lagged coefficients of the common factors $\overline{C}_{t-j}$ that are constructed with the mean value of dependent variable $C_{i,t-j}$ at the time of $t - j$ period;

μ_{rg} represents network fixed effects coefficients of the g^{th} group of r^{th} network;

[11] Intuitively G=G^2=G^3 (linear dependent) means that every individuals' behaviour is simultaneously reflected in the group's behaviour. (Bridges and Lee, 2016)

[12] All variables are log transformed.

[13] At this moment, I allow lagged variables (time dynamics) only for consumption time dynamics for easier representation.

δ^r is the coefficient of r^{th} endogenous reference group spending variable $\widetilde{C}^r_{i,t}$[14];

γ^r is the coefficient of r^{th} exogenous (contextual) reference group income variable $\widetilde{Y}^{\gamma}_{i,t}$[15];

$\epsilon_{i,t}$ is an independently and identically distributed disturbance that can be correlated with the α_i.

One important caveat in this specification is that we cannot interpret δ^r and γ^r as reference effects since they do not represent the marginal effect of independent reference group variables (Elhorst, 2014; Cicarreli and Elhorst, 2018). Coefficients will affect reference effects but marginal effects can only be obtained when considering all diagonal and off-diagonal parts of an interaction matrix, by which we can figure out cross-section dependence. Therefore, if we want to identify the marginal reference effects, it is required to invert all consumption-related variables ($C_{i,t-s}$, $\widetilde{C}^r_{i,t}$, $\overline{C}_{t-j}$) in equation (3.2) to the left-hand side. Then, we have the global MPC elasticity which also has direct MPC elasticity. In terms of matrix notation, we have

$$C_t = \left[I - G\right]^{-1}\alpha + \underbrace{\left[I - G\right]^{-1}(\beta_{Direct} I_N + \sum_{r=1}^{R=5} \gamma^r W^r)}_{\beta_{Global} = \frac{1}{N^2} D' G(1) D \beta_{Direct}} Y_t + \ldots + \left[I - G\right]^{-1}\epsilon_t \quad t = 1, \ldots, T \tag{3.3}$$

where

$$G(L) = \Big[\sum_{s=1}^{S=4} \rho_s L^s I_N + \sum_{j=0}^{J=4} \lambda_j L^j M + \sum_{r=1}^{R=5} \delta^r W^r \Big] \tag{3.4}$$

also, where L^s is the s^{th} lag indicator, M is the 5,424x5,424 identity matrix multiplied by $\frac{1}{5{,}424}$ and W^r is r^{th} 5,424x5,424 weighting matrix. Thus, we have

$$\beta_{Global} = \frac{1}{N^2} D' G(1) D \beta_{Direct} = \frac{1}{N^2} D' \begin{bmatrix} \frac{\partial C_{1,t}}{\partial Y_{1,t}} & \frac{\partial C_{1,t}}{\partial Y_{2,t}} & \cdots & \cdots & \frac{\partial C_{1,t}}{\partial Y_{N,t}} \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \frac{\partial C_{N,t}}{\partial Y_{1,t}} & \frac{\partial C_{N,t}}{\partial Y_{2,t}} & \cdots & \cdots & \frac{\partial C_{N,t}}{\partial Y_{N,t}} \end{bmatrix} D \tag{3.5}$$

From equation (3.3), $\left[I - G\right]^{-1}(\beta_{Direct} I_N + \sum_{r=1}^{R=5} \gamma^r W^r)$ is the global MPC elasticity. Since $\beta_{Direct} I_N$ represents the direct effect of each individual which is estimated in

[14] $\widetilde{C}^r_{i,t}$ vector can be obtained by applying W^r (5,424 x 5,424 matrix) to $C_{i,t}$ vector. r can be any of reference groups such as income, preference, region, age, gender.

[15] $\widetilde{Y}^r_{i,t}$ vector can be obtained by applying W^r (5,424 x 5,424 matrix) to $Y_{i,t}$ vector. r can be any of reference groups such as income, preference, region, age, gender.

equation (3.2), we can draw the indirect effect by computing $\beta_{Global} - \beta_{Direct}$[16].

One crucial condition for drawing conclusions in this framework is the stationarity condition for matrix inversion. As we can see from equations (3.3), (3.4) and (3.5), in terms of matrix inversion to get the indirect effects, the sum of the lagged spending coefficients ($\rho_1 + \rho_2 + \rho_3 + \rho_4$), the common factor coefficients ($\lambda_0 + \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4$) and the endogenous reference group coefficients ($\delta^1 + \delta^2 + \delta^3 + \delta^4 + \delta^5$) in $G(L)$ should not be close enough to be one. If the sum of these coefficients is close to one[17], the parameter of interest (here, global MPC = β / [1-ρ s - λ s -δ s]) will be infinite, which will render interpretations too difficult to comprehend. In this paper, I report on this condition with the associated significance levels and do not interpret the global MPC coefficients in the case of non-stationarity.

3.2.3 Estimation of Dynamic Network Panel Model

In the dynamic network panel model, network lagged vectors are constructed by applying a network weighting matrix to a dependent variable vector, which makes it challenging for researchers to obtain a consistent estimator. First, the simple pooled OLS estimation of equation (3.2) is inconsistent due to the existence of unobserved individual heterogeneity α_i, since this is correlated with any explanatory variable. Then, the within-group estimation can be employed by subtracting individual means to eliminate the unobserved heterogeneity. However, according to Nickell (1981), we still have the problem of correlation between transformed lagged dependent variables and transformed error, which will not disappear as N increases in the finite dynamic panel model (Bridges and Lee, 2016). To tackle this problem, especially in the dynamic panel model, the system GMM has been proposed to use numerous instruments for both cross-section level data and differenced time-series data. Recently, Sarafidis and Robertson (2009) argue that the presence of unobserved common factors in linear panel models can lead to inconsistent estimation when using system GMM. Thus, they suggest that we should include common factors that are constructed as time-specific, cross-sectional average in the specification. Bridges and Lee (2016) illustrate these empirical challenges in detail, and I follow their approach herein.

In spatial econometrics literature, especially regarding the dynamic network panel model, it is widely known that maximum likelihood (ML) and IV/GMM are mainly employed to solve the endogeneity problem (Elhorst et al. 2018). If we assume explanatory variables other than spatial or network variables are exogenous, ML is used (Elhorst,

[16]Theoretically, we can guess the idea of analytical solution of the inverse matrix in detail so that we could exploit the delta method to calculate the statistical significance of the global effect with a large matrix. However, it is practically beyond the current machine capacity. Even the MATLAB package is unable to proceed with the matrix inversion of analytical representation in a 30x30 matrix, whereas this paper needs a 5,424x5,424 matrix.

[17]We can rewrite this in terms of a hypothesis test. Null hypothesis: Sum of coefficients - 1 = 0

2005) whereas system GMM tends to be employed when variables are more likely to be endogenously determined. (Kukenova and Monteiro, 2009). Taking these discussions into account, I use the system GMM estimation throughout this paper.

3.3 Data Overview and Reference Group Description

3.3.1 Data Source, Sample Periods, Variable Construction

This paper employs a rich dataset from UK financial aggregator **MDB** which has data from January 2012 to February 2018. Sample periods are cut to make a balanced panel of 5,424[18] individuals between January 2015 and December 2017. From the transaction-level raw data, I construct monthly variables for each individual. To be specific, there are monthly all-spending, necessary, discretionary, visible, eating-at-home and eating-out spending and monthly income for the main analysis. Additionally, the monthly net liquidity, borrowing amount and repaying amounts serve as a set of control variables in the specification. In the case of indicator variables, there are reference groups such as income, preference, region, age and gender. In order to have time dummies, I construct yearly and monthly dummies to control time-specific effects. Finally, common factor variables are made by taking the average of 5,424 individuals' spending on specific items at each time period.

3.3.2 Reference Groups

From the MDB data, I could identify the income, region, age and gender for 5,424 individuals during a 36 month period. Income reference group is constructed based on 'tagnames' that encompasses paycheck, salaries or similar amounts of money arrivals on a regular basis. Then, I classify each individual's average monthly income level into a decile. Regional groups are constructed based on 12 UK areas.[19] The age reference group has 19 groups with those born in 1968-1985 in order to restrict only to those who are active economic agents. Naturally, the gender group has male and female.

The advantage of this MDB dataset is that there are granular spending histories of each individual. By exploiting the broad CPI[20] level in mid-aggregate consumption items and spending amounts in this data, I could compute the price elasticity and expenditure elasticity across a set of consumption items according to Deaton and Muellbauer (1980). In this section, I follow Banks, Blundell and Lewbel (1997) and Poi

[18]This number of individuals was constructed by choosing those who existed in the designated period of 36 months and had both proper monthly spending and income amounts.

[19]12 areas: Scotland, Nothern Ireland, Wales, North East, North West, Yorkshire and the Humber, West Midlands, East Midlands, South West, South East, East of England, Greater London

[20]ONS CPI INDEX: recreational activity (09 RECREATION & CULTURE 2015=100), eating-at-home (CPI INDEX 01.1: FOOD 2015=100), eating-out (11.1.1: RESTAURANTS & CAFES 2015=100)

(2012)'s applied work and then construct a consumer's demand for a set of k goods within m amounts of income.[21] Due to the availability of price indices only in the form of broad consumption items, k goods are categorised with broad items.

With this AID system framework, I use the price and spending amount of the 'eating-at-home', 'eating-out' and 'recreational activity' categories to estimate expenditure elasticities. After estimation, I split each category's elasticity into two groups (H: higher than average; L: lower than average). As a result, I make eight (2^3) groups according to the high and low groups for three categories that are used to construct the 'spending preference' weighting matrix in the following estimation (Section 3.4).

3.3.3 Restriction Imposed Weighting Matrices

The most important part in this paper is the weighting matrix construction. The generalised reference group components in the baseline specification (3.2) are as below:

$$\sum_{r=1}^{R=5}\sum_{g=1}^{Gr}(\mu_{rg}f_i^{rg} + \delta^r\widetilde{C}_{i,t}^r + \gamma^r\widetilde{Y}_{i,t}^r) \quad where \quad i = 1, ..., N \quad t = 1, ..., T \tag{3.6}$$

To explain equation (3.6) in detail, if I make a specification with five reference groups (five endogenous and five exogenous reference group variables), I would have a set of endogenous reference group spending variables like below:

$$\delta^{Income}\widetilde{C}_{i,t}^{Income} + \delta^{Preference}\widetilde{C}_{i,t}^{Preference} + \delta^{Region}\widetilde{C}_{i,t}^{Region} + \delta^{Age}\widetilde{C}_{i,t}^{Age} + \delta^{Gender}\widetilde{C}_{i,t}^{Gender}$$
$$where \quad i = 1, ..., N \quad t = 1, ..., T \tag{3.7}$$

However, as I have endogenous and exogenous reference group variables in each of the reference groups, I might lose the degree of freedom due to the increased number of estimates. In addition, the spatial econometrics literature simply uses distance or proximity with one weighting matrix. Analogously, even in this case of reference effects, we can think of a single matrix in which the distances between reference groups are incorporated. If we make a single weighting matrix with information from five reference group spending variables in equation (3.2), we have a weighting matrix with a linear combination of five weighting matrices.

$$W_{Average5W} = \frac{1}{5}W_{Income} + \frac{1}{5}W_{Preference} + \frac{1}{5}W_{Region} + \frac{1}{5}W_{Age} + \frac{1}{5}W_{Gender} \tag{3.8}$$

[21] Here I set k=3 for recreational spending, eating-at-home and eating-out.

If we make one weighting matrix with information from estimation coefficients of the five reference group spending variables, we have a more sophisticated version like below

$$
\begin{aligned}
W_{Estimation5W} = & \left[\frac{\delta^{Income}}{\delta^{Income}+\delta^{Preference}+\delta^{Region}+\delta^{Age}+\delta^{Gender}}\right] W_{Income} \\
& + \left[\frac{\delta^{Preference}}{\delta^{Income}+\delta^{Preference}+\delta^{Region}+\delta^{Age}+\delta^{Gender}}\right] W_{Preference} \\
& + \left[\frac{\delta^{Region}}{\delta^{Income}+\delta^{Preference}+\delta^{Region}+\delta^{Age}+\delta^{Gender}}\right] W_{Region} \\
& + \left[\frac{\delta^{Age}}{\delta^{Income}+\delta^{Preference}+\delta^{Region}+\delta^{Age}+\delta^{Gender}}\right] W_{Age} \\
& + \left[\frac{\delta^{Gender}}{\delta^{Income}+\delta^{Preference}+\delta^{Region}+\delta^{Age}+\delta^{Gender}}\right] W_{Gender}
\end{aligned} \tag{3.9}
$$

If we make just one weighting matrix with information from the biggest three reference group spending variables, we have

$$
W_{Biggest3W} = \frac{1}{3} W_{1^{st}\ biggest\ reference} + \frac{1}{3} W_{2^{nd}\ biggest\ reference} + \frac{1}{3} W_{3^{rd}\ biggest\ reference} \tag{3.10}
$$

I use equation (3.7) in the main results in Section 3.5 and use equations (3.8)-(3.10) in the robustness check in Section 3.6.

3.4 Preliminary Diagnosis for Model Choice

3.4.1 Dynamics in Network and Time: System-GMM with Common Factors

Baltagi et al. (2014, 2019) explain the need for dynamics both in space (network) and time in the panel model. In light of this chapter's research question, their discussions imply that the existence of time lags and network weighting matrices can be interpreted as wanting the dependent variable to be explained by the network (reference group) diffusion that takes place over time (habit). In this section, I compare several basic specifications as well as estimation methods to obtain consistent estimators, then, I proceed with the system GMM estimation.[22]

To start, I compare a few preliminary estimation results of pooled OLS, panel within-group and system GMM. Table 3.4 shows the different candidate estimation results. Initially, as a baseline estimation, I estimate OLS specifications with and without

[22] I use the STATA's user-written command 'XTABOND2' made by Roodman(2009).

reference group spending variables. Column (1) generates 0.475 MPC coefficient without any reference effects. Columns (2) and (3) also produce the same MPC coefficients with reference group spending variables. The next estimation method is the panel within-group estimation to control unobserved heterogeneity. Columns (4)-(6) generate about 0.345 MPC coefficients regardless of whether reference group variables are included or not. However, it is well known that estimation results are severely biased if dependent variables and independent variables are determined at the same time. Additionally, due to the structure of the dynamic panel, there is a remaining correlation between the transformed lagged dependent variable and error terms (Nickell bias). In this reference effect specification, the reference group spending variables are constructed by applying the respective reference weighting matrix into the dependent variables (spending variables in this paper). One way to detour this simultaneity problem is to use the system GMM approach in which we can use a set of variables from the past to tackle endogeneity. Finally, the chosen system GMM with reference effects generates MPC coefficient that shrinks to around 0.166 compared to that without reference effects (0.378). I could confirm that this specification satisfies the autocorrelation condition with Arellano–Bond tests as well as the Hansen test of proper IV conditions in all estimation cases. From this set of estimation results, we could say that the system GMM approach is the most proper estimation method among all three candidates.

3.4.2 Tests of Cross-Section Dependence and Panel Unit Root

Even given the chosen estimation methodology of system GMM, there remain some issues. Sarafidis and Robertson (2009) found that when we encounter error structures in the dynamic panel model, we should consider that time dummies cannot rule out unobserved cross-section dependence. More recently, Elhorst et al. (2018, ECB WP) propose a series of test procedures regarding cross-section dependence as well as the panel unit root test. In their following empirical study, Cicarrelli and Elhorst (2018) use a set of test results and show that inclusion of common factors in addition to control variables can mitigate the stationarity problem in the dynamic spatial panel model. They use the CD-test of Pesaran (2015a)[23], and the exponential α test of Bailey et al. (2016a) to confirm the need for common factor inclusion. Following this approach, I explore candidate specifications with these tests and include common factors in the following section 3.4.3.

It is also important to examine whether a dependent variable has a panel unit root or not.[24] Here I use the Im-Pesaran-Shin test and the associated null hypothesis of the

[23]In STATA, I use the command 'XTCDF'.

[24]Stata has 'XTUNITROOT' to test stationarity in panel datasets. The null hypothesis: all the panels contain a unit root.

panel unit root is rejected.[25] Another type of test is the cross-section augmented panel unit root test (Pesaran, 2007)[26] and in the following specification search, I set up the chosen specification passed by this test result. The test results are reported in each set of estimation results.

Table 3.1: Specification Search with Common Factors

	M1	M2	M3	M4	M5	M6	M7	M8
All-spending(-1)	-0.06	0.18***	0.11	0.09***	0.38***	0.28***	0.23***	0.21***
All-spending(-2)	0.12***	0.17***	0.19***	0.08***	0.06***	0.22***	0.15***	0.14***
All-spending(-3)	0.16***	0.15***	0.21***	0.10***	0.05**	0.04**	0.17***	0.15***
All-spending(-4)	0.11***	0.08***	0.06	0.13***	0.08***	0.06***	0.04**	0.08**
Common factor(0)			0.79***	-1.70***	-1.17***	-1.16***	-1.19***	-1.24***
Common factor(-1)			-0.09		-0.39***	-0.28***	-0.22***	-0.20***
Common factor(-2)			-0.17***			-0.21***	-0.14***	-0.13***
Common factor(-3)			-0.22***				-0.20***	-0.17***
Common factor(-4)			-0.01					-0.05
Income(0)	0.38***	0.18***	0.17***	0.28***	0.22***	0.19***	0.17***	0.17***
Endog Income reference(0)		0.43***		0.60***	0.57***	0.61***	0.63***	0.64***
Endog Preference reference(0)		0.23***		0.49***	0.39***	0.39***	0.42***	0.42***
Endog Regional reference(0)		0.31***		0.52***	0.41***	0.43***	0.44***	0.46***
Endog Age reference(0)		0.08		0.56***	0.43***	0.42***	0.43***	0.44***
Endog Gender reference(0)		-0.13		0.16*	0.10	0.09	0.08	0.09
Exog Income reference(0)		-0.07*		-0.06	-0.06*	-0.07*	-0.06*	-0.06
Exog Preference reference(0)		-0.05		-0.10**	-0.08*	-0.08*	-0.07	-0.07
Exog Regional reference(0)		-0.07*		-0.08**	-0.04	-0.04	-0.04	-0.04
Exog Age reference(0)		-0.03		-0.11**	-0.03	-0.02	-0.02	-0.02
Exog Gender reference(0)		0.21***		0.22***	0.16**	0.17**	0.19***	0.19
AR(2) test p-value	0.00	0.02	0.19	0.09	0.06	0.00	0.73	0.67
Hansen test p-value	0.15	0.99	1.00	0.84	1.00	1.00	1.00	1.00
Network FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	No	No	No	No	No
Common factors	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Reference variables	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Stationarity coefficients	-0.68***	0.50***	-0.15***	0.01***	-0.09***	-0.12***	-0.15***	-0.16***
S.E of stationarity coeff	0.04	0.06	0.03	0.03	0.03	0.03	0.03	0.03
CD-test(residual)	18.5	5.92	1.26	38.5	7.33	2.77	-0.18	-0.15
CD-test p-value(residual)	0.00	0.00	0.21	0.00	0.00	0.01	0.86	0.88
Alpha test(residual)	0.57	0.50	0.23	0.60	0.56	0.61	0.62	0.51
S.E of Alpha test(residual)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Pesaran CADF test t-bar	-2.80	-3.28	-3.54	-2.75	-3.05	-3.26	-3.56	-3.47

Note: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Null hypothesis of CD-test: Residuals have only weakly cross-section dependence. 3) α =1 means strong cross-section dependence whereas [1/2,3/4] indicates weakly cross-sectional dependence. 4) Pesaran CADF test (2007) is based on the mean of individual ADF t-statistics of each unit in the panel. Null hypothesis: all series are non-stationary.

[25] In each variable from panel data with 5,424 panels and 36 months, all tests reject the null hypothesis of "All panels contain unit roots". Test results can be provided upon request.

[26] In STATA, I use the command 'PESCADF'.

3.4.3 Model Choice

In Table 3.1, I report eight versions of system GMM estimations and compare the results of these tests and statistical significance of the null hypothesis '[sum of (ρs, λs and δs) -1] =0'. Among these candidates, M8 is the most preferred specification since it satisfies all the required tests including the AR(2)[Arellano-Bond] test, Hansen test, stationarity condition, CD-test and α-test. First, M1 and M2 had to be dropped due to the lack of lags in terms of Arellano–Bond tests. M3 looks proper in terms of all tests, but there are no reference group spending variables in which I am interested.[27] Moreover, the M4-M6 models are not proper due to the CD-test which rejects its null hypothesis of 'No strong cross-section dependence'; these test results indicate that we should include more common factor variables to control potential strong cross-section dependence. Finally, M7-M8 satisfy with the required tests. However, I prefer the M8 due to its lag length being consistent with the M3 model. Therefore, I choose four lagged dependent variables, five common factors including a contemporaneous one and four lags, one contemporaneous income and five reference group variables in terms of both endogenous and exogenous reference effects.[28]

3.5 Main Estimation Results

3.5.1 Size of Reference Effects on Consumption Items

This subsection displays the estimation results of the question: 'What kinds of consumption items are pronounced in terms of reference effects?'. Since this specification employs five reference group weighting matrices of W_{Income}, $W_{Preference}$, W_{Region}, W_{Age} and W_{Gender} at the same time, I could only compare five coefficients of the reference group spending variables to capture the relative strength of those variables. However, as spatial literature points out that coefficients cannot necessarily be interpreted as marginal reference effects, I compute the indirect effects of each consumption item with these estimated coefficients. The regression specification in equation (3.2) is estimated without time dummies since I include common factors.

First, I compare the estimated coefficients in each consumption item (Table 3.2). All-spending and necessary spending have δ^{income} of 0.64 and 0.55, respectively, followed by δ^{region} of 0.46 and 0.38 respectively. Discretionary spending has the preference reference as the highest coefficient (0.81) followed by income reference (0.77). Visible spending has income reference (0.71) and age reference (0.70) as the two biggest coefficients. Overall,

[27]This M3 will be the baseline specification if we want to exercise simulations for the omitted variable bias from reference variables.

[28]In the case of further sample restrictions or different consumption item estimations, I apply this chosen model to compare results with the same specifications although some sub-sample estimations do not satisfy all the tests suggested in this section.

the observed patterns from this estimation are consistent with common sense. The income reference group spending variable tends to be strongest in most cases; however, discretionary spending is affected by the preference reference. Visible and eating-out spending are affected by the age reference group right after the income reference group. Again, the caveat to this intuition is that we cannot interpret coefficients as marginal reference effects. However, we can practically get the idea of the relative strength of reference group spending variables.

Table 3.2: Estimation Results: Indirect Effects of W(Full Reference Group Information)

	All-spending	Discretionary	Necessary	Visible	Eating-at-home	Eating-out
δ_0^{Income}	0.64***	0.77***	0.55***	0.71***	0.60***	0.77 ***
$\delta_0^{Preference}$	0.42***	0.81***	0.36***	0.63***	0.58***	0.64***
δ_0^{Region}	0.46***	0.70***	0.38***	0.69***	0.63***	0.56***
δ_0^{Age}	0.44***	0.66***	0.36***	0.70***	0.63***	0.73***
δ_0^{Gender}	0.09	0.50***	0.05	0.27	0.30***	0.75***
AR(2) test p-value	0.67	0.73	0.88	0.32	0.31	0.16
Hansen test p-value	1.00	1.00	1.00	1.00	1.00	1.00
Stationarity coefficient - 1	-0.16***	-0.06**	-0.08**	-0.05**	-0.06	-0.01
Stationarity standard error	0.03	0.03	0.04	0.03	0.10	0.04
CD-test(residual)_test	-0.15	-1.97	0.28	-1.73	0.14	-1.66
CD-test(residual)_p-value	0.88	0.05	0.78	0.08	0.89	0.10
alpha-test statistic	0.51	0.43	0.68	0.57	0.40	-0.40
alpha-test standard error	0.01	0.01	0.01	0.01	0.02	-
LR ρ sum(habit)	0.59***	0.59***	0.70***	0.69***	0.69***	0.58***
LR $\lambda + \delta$ sum(reference)	0.26***	0.36 ***	0.22***	0.26***	0.25**	0.41***
LR habit + reference sum	0.84***	0.94 ***	0.92***	0.95***	0.94***	0.99***
LR habit/reference ratio(%)	69.5	62.0	76.4	73.0	73.1	58.5
LR β sum(MPC)	0.17***	0.11***	0.09***	0.09***	0.05	0.10*
LR γ sum	0.00	-0.01	-0.06**	0.00	-0.11**	-0.05
LR $\beta + \gamma$	0.16***	0.10**	0.03	0.09	-0.06	0.05
Total_SR	0.86	1.65	0.25	0.82	-0.80	1.87
Direct_SR	0.17	0.11	0.09	0.09	0.05	0.10
Indirect_SR	0.70	1.54	0.17	0.73	-0.85	1.77
Direct_SR ratio (%)	19.2	6.7	33.8	11.4	5.5	5.4
Indirect_SR ratio (%)	80.8	93.3	66.2	88.6	94.5	94.6
Total_LR	1.03	1.82	0.33	1.23	-0.99	3.75
Direct_LR	0.40	0.26	0.29	0.31	0.16	0.24
Indirect_LR	0.63	1.55	0.04	0.93	-1.15	3.51
Direct_LR ratio (%)	38.8	14.6	86.8	24.8	12.1	6.4
Indirect_LR ratio (%)	61.2	85.4	13.2	75.2	87.9	93.6

Note: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Stationarity coefficients condition: (ρs+λs+δs)-1. 3) "-" indicates that estimation results are under non-stationary condition of inverse matrix.

Second, I compute a long-run habit/reference ratio[29] to examine the relative strength between lagged consumption items and reference group variable coefficients. I find that necessary type items (necessary and eating-at-home) show higher ratio (76.4

[29] Ratio = $\frac{Habit}{Habit+Reference}$ X 100%

% and 73.1%, respectively) of habits compared to the corresponding discretionary type (discretionary (62.0%), visible (73.0%) and eating-out (58.5%)) spending. We can interpret that necessary type spending is more driven by habitual factors than reference groups in the long-run.

Third, the total income elasticity of demand in the short-run show that discretionary and eating-out items are characterised as luxury (elasticity>1) while all-spending, necessary and visible items fall under the normal goods category (0<elasticity<1). Eating-at-home (spending at supermarkets) is shown to be inferior goods (elasticity<0).

Last but not least, I pay attention to the size of indirect effects to compare one item with another. If we want to assess reference effects, we should take indirect effects into account by taking the direct MPC out from the global MPC. In Table 3.2, the all-spending item shows the indirect effects of 80.8% in the short-run and 61.2% in the long-run. Once we narrow down our attention to sub-categories, initial guesses on indirect effects in consumption items say that necessary type (necessary, eating-at-home) spending will have smaller indirect effects than discretionary type (discretionary, visible, eating-out) spending. My estimation results of the indirect effect ratio out of global MPC elasticity are consistent with this initial guess. Discretionary spending (SR: 93.3%, LR: 85.4%) generates the biggest indirect effects, followed by visible spending (SR: 88.6%, LR: 75.2%) and necessary spending (SR: 66.2%, LR: 13.2%). When we examine sub-category consumption items, the reference effect of eating-out (discretionary type, SR: 94.6%, LR: 93.6%) is stronger than eating-at-home (necessary type, SR: 94.5%, LR: 87.9%). From these exercises, we can conclude the necessary spending type items are less affected by reference group.

3.5.2 Specification without Contextual Reference Effects

To further investigate the role of reference effects from the reference group characteristics, I perform another exercise without contextual (exogenous) reference effects (which affect coefficients γ^r=0 in equation 3.2). Table 3.5 compares results with and without contextual reference. All-spending and any other discretionary type items (discretionary, visible, eating-out) show similar stationarity coefficient and associated MPC elasticities between two specifications. However, the necessary type (necessary item and eating-at-home spending) items are very sensitive to the existence of contextual reference effects. I believe this is partly due to the fact that the omitted variable bias can occur in the case of ignoring contextual reference variables despite their existence. In the necessary spending item estimation of Table 3.5, $\beta+\gamma$ sum of extensive specification and the one without contextual effect (exogenous) are 0.03 and 0.07, respectively. This is mainly because the γ sum of -0.06 (significance level 95%) is a coefficient of contextual effect.[30] We can see that omitting exogenous variables causes an overestimated indirect effect (endogenous + exogenous: 66.2%, endogenous only: 88.1%) in the short-run. Although the interpretation of negative coefficients of reference group variables is not easy, we need to incorporate contextual (exogenous) reference group variables in the specification. Thus, I suggest we should use an extensive specification strategy with contextual (exogenous) reference group variables.

3.5.3 Reference Effects on Consumption Items: Sample Split by Gender

As a robustness check, I split the balanced panel into a female group of 2,084 individuals and a male group of 3,340 of individuals. Since weighting matrices are constructed based on different samples, this is a good way to test the sensitivity of estimations based on the weighting matrices executed in this paper. Another purpose of this exercise is to answer the question: 'Any heterogeneities in reference effects between genders?'. The below specification is the one used in this subsection.

$$\begin{aligned} C_{i,t} =& \alpha_i + \sum_{s=1}^{S=4} \rho_s C_{i,t-s} + \beta Y_{i,t} + \sum_{k=1}^{K=4} \theta_k X_{i,t}^k + \sum_{j=0}^{J=4} \lambda_j \overline{C}_{t-j} \\ &+ \sum_{r=1}^{R=4} (\sum_{g=1}^{Gr} \mu_{rg} f_i^{rg} + \delta^r \widetilde{C}_{i,t}^r + \gamma^r \widetilde{Y}_{i,t}^r) + \epsilon_{i,t} \\ & where \quad i = 1, ..., N \quad (N = 2,084 \quad if \quad female, \quad N = 3,340 \quad if \quad male) \quad t = 1, ..., T \end{aligned} \tag{3.11}$$

Table 3.6 suggests the results. First, we compare the estimated coefficients in each consumption item between the female and male groups. The majority of the female reference group spending variable coefficients (δ^{Income}, $\delta^{Preference}$, δ^{Region} and δ^{Age}) are larger than those of the male group. Again, the income reference group is the most important driver, followed by the regional reference. However, the preference reference group is the third driver in males whereas females are more affected by the age reference group instead of the preference group.

Second, the indirect ratio (ratio of reference effect) of discretionary and visible items are shown to be larger than that of necessary items regardless of gender sample split, which confirms that weighting matrices are well constructed as in equation (3.2). In the case of all-spending item, females (SR: 81.9%, LR: 69.9%) tend to show a higher indirect MPC ratio than males (SR: 78.0%, LR: 66.9%). Basically we can conclude that

[30] It is understood that negative spatial autocorrelation tends to appear when competition between agents outweighs cooperation power. Spatial Regression: The Curious Case of Negative Spatial Dependence, Kao and Bera (2013)

females' reference effects are bigger than males'.

However, in all other consumption sub-category items, the relative size of indirect effects across gender are mixed. This is mainly due to the γ coefficient of contextual effect (exogenous reference group effect) as mentioned in Section 3.5.2. Females tend to spend less (negative γs) on discretionary, necessary, visible items when reference group income (characteristics) increases, while males tend to spend less (negative γs) on food when reference groups' income increases. This can be interpreted as men taking social competition between reference group members into account more when spending on food items. Women tend to compete with reference groups by spending less on necessary spending item when they encounter their reference group's income increases.

3.5.4 Discussion

From this section's exercises, we spot some patterns of reference effects in each consumption item. First, income reference groups tend to be pronounced in most consumption items. Secondly, preference reference groups from the AID system are effective in discretionary spending, whereas age groups are relatively strong in visible spending. We can interpret these as unobserved preferences or tendencies to consume can be captured by the AID system and this preference weighting matrix can identify additional layers of reference relations given a situation where there is no explicit qualitative relation between individuals.[31] Finally, from the perspective of consumption items, discretionary type items show bigger indirect effects in both short-run and long-run MPC elasticities, whereas necessary type items have bigger direct effects. Also, the sub-category (eating-at-home and eating-out) consumption items' indirect effects are consistent with these findings. In sum, we can conclude that reference effects have an important role in understanding what are the characteristics of consumption items and consumers' actual spending behaviours.

3.6 Restricted Single Weighting Matrix

3.6.1 Motivation for a Single Weighting Matrix

Until previous sections, I exercise with a specification in which all individual reference group variables are included at the same time as in equation (3.2). From the practical point of view, it is an interesting question whether a single weighting matrix can replicate the indirect effect estimation with multiple reference group variables all

[31] One motivation for this paper was to examine whether unobserved preference can be a strong reference group in consumption and this is a very supportive finding.

at once. In the spatial econometrics literature, a weighting matrix is constructed with geographic information, and the best way to construct a weighting matrix is still controversial. Lee (2008) shows that if an interaction matrix is under-specified/over-specified, the spatial autoregressive parameter is biased downward/overestimated respectively. Debarsy and Ertur (2019) argue that the consequences of the under-specification of the interaction matrix bring more serious problems than the cases of over-specification regarding both bias and RMSE. Basically, the exercise in this section has two purposes. First, I study whether alternative single weighting matrices provide robust estimation results of relative indirect effects across consumption items. Second, I investigate whether there is any evidence of biased reference group spending/income coefficients due to under-specified weighting matrices. In this paper, which uses reference groups rather than geographic proximity, the research question turns out to be 'what is proper weights across reference groups?'. Maybe we can say the income group weighting matrix should be heavily taken into account whereas the gender matrix should be ignored in terms of 'human proximity criteria' if we want to construct a single weighting matrix similar to the spatial weighting matrix. In this section, I assume that my estimation based on equation (3.2) is a true representation of reference effects since this encompasses all reference group spending/income variables available in the data set. Then the question in this section is whether a restricted version of the single weighting matrix (and corresponding endogenous and exogenous reference variables) replicates the true reference effect better than any other weighting matrix based estimation.

3.6.2 Imposed Restrictions

This subsection displays results of using a single weighting matrix to make a more parsimonious specification. Then, we will check whether these alternative weighting matrices generate similar relative sizes of reference effects across consumption items. The difference from the previous specification is that we now have $\sum_{r=1}^{R=1}(\delta^r \widetilde{C}^r_{i,t} + \gamma^r \widetilde{Y}^r_{i,t})$ rather than five endogenous reference and five exogenous reference group variables like below.

$$\begin{aligned} C_{i,t} =& \alpha_i + \sum_{s=1}^{S=4} \rho_s C_{i,t-s} + \beta Y_{i,t} + \sum_{k=1}^{K=4} \theta_k X^k_{i,t} + \sum_{j=0}^{J=4} \lambda_j \overline{C}_{t-j} \\ &+ \sum_{r=1}^{R=5}(\sum_{g=1}^{Gr} \mu_{rg} f^{rg}_i) + \sum_{r=1}^{R=1}(\delta^r \widetilde{C}^r_{i,t} + \gamma^r \widetilde{Y}^r_{i,t})+)\epsilon_{i,t} \\ & where \quad i = 1, ..., N \quad t = 1, ..., T \end{aligned} \tag{3.12}$$

I set weighting matrices W_{Income}, $W_{Preference}$, W_{Region}, W_{Age} and W_{Gender} and finally construct the multi-layer matrix with each of individual matrices. Thus, I use equation (3.12) to examine this question. Candidate 'single' weighting matrices are constructed based on the i) simple average of five reference group weighting matrices: W(Average5W)[3.8], ii) estimation based reference groups weighting matrices: W(Coefficients5W)[3.9] and iii) average of the three (biggest coefficients) reference group weighting matrices: W(Biggest3W)[3.10]. In order to assess which weighting matrix replicates reference effects of equation (3.2) better, I compute the RMSE of indirect effect ratios in each weighting matrix specification across consumption items. In this subsection, I compare the indirect effects of these three newly constructed weighting matrices.

The results are presented in the last column of Table 3.7. First, the alternative weighting matrices seemingly provide similar indirect effect ratios across consumption items and these are robust to the results in the main section. Despite the fact that we can see some changes in the indirect effect numbers, the relative sizes of indirect effects across consumption items show that the reference effects of discretionary spending are the biggest, followed by those of visible and necessary spending. Second, the indirect effects of necessary spending and eating-at-home spending look volatile compared to any other consumption items. As we saw in Section 3.5.2, necessary type items (necessary, and eating-at-home) show sensitive indirect effects across candidate weighting matrices. In the case of necessary spending, it varies from 1.1% to 40.5%. This is due to the bigger and negative coefficients of contextual reference group income variables (γs). I suspect that introducing a single weighting matrix might pose an omitted variable bias in estimating reference effects. The implication from this exercise is that we should employ properly extended specification in order to estimate robust reference effects at the cost of the degree of freedom. Last, the weighting matrices of W(Biggest3) show a lower RMSE than any other restricted weighting matrix. Even though it is still arguable which combinations of candidate weighting matrices are the best, at least we can say that if we construct weighting matrices based on three strong reference effects groups, this selection process of constructing matrices is meaningful rather than just simply averaging weighting matrices away.

3.7 Conclusion

This paper investigates the existence of reference effects on consumption behaviour with high-frequency consumer data. Despite the lack of detailed (randomly assigned) peer relations across consumers, I set up unobserved spending preferences within the AID system as well as observed reference groups such as income, region, age and gender. Then, I construct an extensive specification that has endogenous reference effects (outcome of references), exogenous reference effects (characteristics of references), correlated effects with network fixed effects and common factors. After constructing a well-defined dynamic network panel model, this paper measures the direct and indirect impacts of income on various consumption items. By applying this econometric methodology, I find out what kind of consumption items and network group relationships show the most pronounced reference effects.

It is clearly documented that discretionary type items tend to show bigger indirect effects whereas necessary type items have less indirect effects. Based on the reference group spending variable coefficient comparisons, the income group reference is an important driver in most consumption items and the preference reference for discretionary spending, the region for necessary spending and the age for visible spending are shown as the next most important reference variables. When I split gender groups, the results are robust and females tend to be affected more by their reference groups than males in the all-spending item. Then, I construct a single weighting matrix reflecting specification with all reference group variables to make a parsimonious model. Assuming that our specification with all reference group spending/income variables (weighting matrices) is true, I calculate the RMSE of each candidate single weighting matrix across all spending items. The results indicate that 'W(Biggest3W)' replicates the indirect effects of my baseline regression (equation 3.2) better than W(Average5W), which just takes the simple average of reference weighting matrices away.

Still, there are many issues to be solved in future research. First, one limitation of this work is the data quality. Even though the data is really granular, there is no proper further information on how the individuals are related to each other (regarding genuine peer relations). In reality, maybe more detailed administrative data such as taxes or firm levels would be more helpful to answer this research question. Second, even though I investigate potential reference effects in the all-spending category and sub-categories (necessary, discretionary and visible), it is possible that spending on specific firm, such as Amazon and Deliveroo could be examined if we had more individuals with longer time-series data. Then, we might be able to ask whether specific IT or delivery-based firm items are severely affected by one of the reference groups. Third, in this paper's exercises, sometimes the stationarity conditions of long-run MPC elasticity are not satisfied with some candidate specifications. How to meet this stationarity condition is still not fully solved within this paper's discussion. Fourth, one future work could be about statistical inference on short-run and long-run MPC elasticities in each of the consumption items.[32] Finally, the proper construction of a single weighting matrix in which individual reference information is included is still unclear. It might employ machine learning approach, but this topic is beyond this chapter's scope.

[32] I run a simulation exercise to generate the small sample property of these elasticities; however, about 40% of the simulation is out of the stationary condition for matrix inversion which did not allow me to make a proper inference.

Table 3.3: Components in the Reference Effect Identification Strategy

Classification	Variable name	Description	Notation
Social interaction	Endogenous reference (outcome)	Effects of reference outcome on individual outcome (Social multiplier)	$\widetilde{C}_{i,t}^{r}$: r^{th} reference based behaviour
	Exogenous reference (contextual, characteristics)	Effects of reference characteristics on individual outcome (No social multiplier)	$\widetilde{Y}_{i,t}^{r}$: r^{th} reference based characteristics
Correlated effects	Selective association	Birds of a feather flock together	Network FE f_i^{rg}
	Common environment	Happens even in case of no social interaction due to circumstances	Time FE Common factor $\overline{C}_t$

Note: 1) Sources: Manski (1993), Lin (2015)

Table 3.4: Estimation Results: Preliminary Model Comparison

	Dependent variable: Monthly Consumption Expenditure									
	Pooled	Pooled w/ Endog Reference	Pooled w/ Endog&Exog Reference	FE	FE w/ Endog Reference	FE w/ Endog&Exog Reference	SysGMM with no CF	SysGMM with CF	SysGMM w/ Endog&CF	SysGMM w/ Endog&Exog Reference, CF
	(1) lmconsume_a b/se	(2) lmconsume_a b/se	(3) lmconsume_a b/se	(4) lmconsume_a b/se	(5) lmconsume_a b/se	(6) lmconsume_a b/se	(7) lmconsume_a b/se	(8) lmconsume_a b/se	(9) lmconsume_a b/se	(10) lmconsume_a b/se
Consumption(-1)							-0.063	0.106	0.286***	0.213***
							(0.042)	(0.072)	(0.047)	(0.038)
Consumption(-2)							0.117***	0.192***	0.170***	0.143***
							(0.030)	(0.062)	(0.044)	(0.035)
Consumption(-3)							0.156***	0.206***	0.116***	0.154***
							(0.033)	(0.056)	(0.044)	(0.035)
Consumption(-4)							0.115***	0.056	0.050	0.076**
							(0.032)	(0.049)	(0.037)	(0.031)
Common factor(0)								0.787***	-1.066***	-1.238***
								(0.035)	(0.188)	(0.153)
Common factor(-1)								-0.092	-0.271***	-0.203***
								(0.073)	(0.050)	(0.042)
Common factor(-2)								-0.175***	-0.162***	-0.127***
								(0.064)	(0.047)	(0.039)
Common factor(-3)								-0.219***	-0.134***	-0.174***
								(0.059)	(0.048)	(0.040)
Common factor(-4)								-0.009	-0.016	-0.052
								(0.053)	(0.042)	(0.037)
Income(0)	0.475***	0.475***	0.475***	0.345***	0.344***	0.344***	0.378***	0.173***	0.152***	0.166***
	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)	(0.008)	(0.030)	(0.028)	(0.022)	(0.021)
Income Peer[Endog](0)		-0.003	-0.030		0.130**	0.128**			0.619***	0.639***
		(0.055)	(0.056)		(0.058)	(0.059)			(0.080)	(0.070)
Preference Peer[Endog](0)		-0.205***	-0.289***		-0.156**	-0.200***			0.284***	0.424***
		(0.072)	(0.075)		(0.073)	(0.075)			(0.110)	(0.073)
Region Peer[Endog](0)		-0.107	-0.104		0.092	0.101			0.392***	0.461***
		(0.066)	(0.063)		(0.059)	(0.061)			(0.082)	(0.064)
Age Peer[Endog](0)		-0.249***	-0.272***		0.081	0.081			0.358***	0.440***
		(0.052)	(0.052)		(0.051)	(0.051)			(0.095)	(0.079)
Gender Peer[Endog](0)		0.869***	1.027***		0.506***	0.547***			0.230***	0.088
		(0.088)	(0.096)		(0.091)	(0.097)			(0.065)	(0.083)
Income Peer[Exog](0)			0.023			-0.001				-0.061
			(0.036)			(0.037)				(0.038)
Preference Peer[Exog](0)			0.094**			0.059				-0.067
			(0.039)			(0.038)				(0.046)
Region Peer[Exog](0)			-0.015			-0.017				-0.041
			(0.034)			(0.029)				(0.039)
Age Peer[Exog](0)			0.021			-0.001				-0.024
			(0.023)			(0.023)				(0.041)
Gender Peer[Exog](0)			-0.250***			-0.064				0.189***
			(0.062)			(0.060)				(0.069)
Net Liquidity(0)	-0.072***	-0.072***	-0.072***	-0.058***	-0.058***	-0.058***	-0.093***	-0.039***	-0.032***	-0.031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.004)	(0.004)
Borrowing(0)	0.052***	0.051***	0.051***	0.035***	0.035***	0.035***	0.019***	0.013***	0.015***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.004)	(0.003)	(0.003)
Repaying(0)	-0.017***	-0.017***	-0.017***	-0.011***	-0.011***	-0.011***	-0.037***	-0.021***	-0.010**	-0.007
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.007)	(0.005)	(0.005)
R-Squared	0.58	0.58	0.58	0.30	0.30	0.30				
Observations	195,264	195,264	195,264	195,264	195,264	195,264	173,568	173,568	173,568	173,568
Number of ID				5,424	5,424	5,424	5,424	5,424	5,424	5,424
Number of Instruments							516	561	851	1,112
AR(1) tests(p-value)							0.00	0.00	0.00	0.00
AR(2)tests(p-value)							0.00	0.19	0.52	0.67
Sargan(p-value)							0.00	0.00	0.00	0.02
Hansen(p-value)							0.15	1.00	1.00	1.00
Sigma				0.49	0.46	0.46	0.29	0.28	0.30	0.29
Network Group FE	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Common Factor	No	No	No	No	No	No	No	Yes	Ye s	Yes

Notes: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Network group FE: Income group (10), Preference group (8), Regional group (12), Age group (19), Gender (2).

Table 3.5: Estimation Results: Alternative Specifications with Contextual Effects

	All-spending		Discretionary		Necessary		Visible		Eating-at-home		Eating-out	
	Endog+Exog	Endog	Endog+Exog	Endog	Endog+Exog	Endog	Endog+Exog	Endog	Endog+Exog	Endog	Endog+Exog	Endog
δ_0^{Income}	0.64***	0.62***	0.77***	0.68***	0.55***	0.58***	0.71***	0.64***	0.60***	0.51***	0.77***	0.53***
$\delta_0^{Preference}$	0.42***	0.28***	0.81***	0.79***	0.36***	0.19***	0.63***	0.75***	0.58***	0.64***	0.64***	0.59***
δ_0^{Region}	0.46***	0.39***	0.70***	0.73***	0.38***	0.34***	0.69***	0.58***	0.63***	0.61***	0.56***	0.42***
δ_0^{Age}	0.44***	0.36***	0.66***	0.71***	0.36***	0.25***	0.70***	0.73***	0.63***	0.56***	0.73***	0.65***
δ_0^{Gender}	0.09	0.23***	0.50***	0.48***	0.05	0.20**	0.27**	0.42***	0.30***	0.31***	0.75***	0.74***
AR(2) test p-value	0.67	0.52	0.73	0.56	0.88	0.87	0.32	0.27	0.31	0.84	0.16	0.31
Hansen test p-value	1.00	1.00	1.00	1.00	1.00	0.98	1.00	1.00	1.00	1.00	1.00	1.00
Stationarity coefficient	-0.16***	-0.14***	-0.06**	-0.05**	-0.01	-0.13***	-0.05	-0.06***	-0.06	-0.20**	-0.13	-0.02
Stationarity standard error	0.03	0.02	0.03	0.02	0.04	0.03	0.03	0.02	0.10	0.08	0.04	0.03
CD-test(residual)_test	-0.15	-0.56	-1.97	-2.24	0.28	-0.27	-1.73	-2.15	0.14	0.20	-1.66	-1.67
CD-test(residual)_pvalue	0.88	0.57	0.05	0.03	0.78	0.79	0.08	0.03	0.89	0.84	0.10	0.10
alpha-test statistic	0.52	051	0.43	0.49	0.68	0.57	0.55	0.50	0.43	0.55	-0.40	-0.11
alpha-test standard error	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	=	=
LR ρ sum(habit)	0.59***	0.62***	0.59***	0.62***	0.70***	0.72***	0.69***	0.71***	0.69***	0.71***	0.58***	0.61***
LR $\lambda + \delta$ sum(reference)	0.26***	0.23***	0.36***	0.32***	0.22***	0.15***	0.26***	0.23 ***	0.25**	0.08	0.41***	0.37***
LR habit + reference sum	0.84***	0.86***	0.94***	0.95***	0.92***	0.87***	0.95***	0.94 ***	0.94***	0.79***	0.99***	0.98***
LR habit/reference ratio(%)	69.5	72.8	62.0	65.8	76.4	83.0	73.0	75.5	73.1	89.3	58.5	62.3
LR β sum(MPC)	0.17***	0.15***	0.11***	0.09***	0.09***	0.07 ***	0.09***	0.08***	0.05	0.02	0.10**	0.08
LR γ sum	0.00	0.00	-0.01	0.00	-0.06**	0.00	-0.03	0.00	-0.11**	0.00	-0.05	0.00
LR $\beta + \gamma$	0.16***	0.15***	0.10**	0.09***	0.03	0.07 ***	0.06	0.08***	-0.06	0.02	0.05	0.08
Total_SR	0.86	0.83	1.65	1.60	0.25	0.56	0.82	1.16	-0.80	0.22	1.87	2.09
Direct_SR	0.17	0.15	0.11	0.09	0.09	0.07	0.09	0.08	0.05	0.02	0.10	0.08
Indirect_SR	0.70	0.68	1.54	1.50	0.17	0.49	0.73	1.08	-0.85	0.19	1.77	2.01
Direct_SR ratio (%)	19.2	18.4	6.7	5.9	33.8	11.9	11.4	7.3	5.5	11.0	5.4	3.7
Indirect_SR ratio (%)	80.8	81.6	93.3	94.1	66.2	88.1	88.6	92.7	94.6	89.0	94.6	96.3
Total_LR	1.03	1.05	1.82	1.78	0.33	0.50	1.23	1.39	-0.99	0.12	3.75	4.03
Direct_LR	0.40	0.40	0.26	0.25	0.29	0.24	0.31	0.29	0.16	0.08	0.24	0.20
Indirect_LR	0.63	0.65	1.55	1.53	0.04	0.26	0.93	1.10	-1.15	0.03	3.51	3.83
Direct_LR ratio (%)	38.8	38.3	14.6	13.9	86.8	47.3	24.8	20.9	12.1	70.8	6.4	4.9
Indirect_LR ratio (%)	61.2	61.7	85.4	86.1	13.2	52.7	75.2	79.1	87.9	29.2	93.6	95.1

Note: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Stationarity coefficients condition: ($\rho s+\lambda s+\delta s$)-1. 3) "-" indicates that estimation results are under non-stationary condition of inverse matrix. 4) SR: Short-run, LR: Long-run. 5) "=" indicates that test results are not available.

Table 3.6: Estimation Results: Gender Heterogeneity

	All-spending			Discretionary			Necessary			Visible			Eating-at-home			Eating-out		
	All	female	male	All	female	male	All	female	male	All	female	male	All	female	male	All	female	male
δ_0^{Income}	0.64***	0.60***	0.56***	0.77***	0.90***	0.70***	0.55***	0.60***	0.52***	0.71***	0.80***	0.63***	0.60***	0.65***	0.61***	0.77***	0.79***	0.87***
$\delta_0^{Preference}$	0.42***	0.45***	0.41***	0.81***	0.78***	0.70***	0.36***	0.46***	0.45***	0.63***	0.63***	0.70***	0.58***	0.68***	0.54***	0.64***	0.73***	0.73***
δ_0^{Region}	0.46***	0.62***	0.55***	0.70***	0.83***	0.72***	0.38***	0.51***	0.45***	0.69***	0.74***	0.60***	0.63 ***	0.60***	0.66***	0.56***	0.74***	0.67***
δ_0^{Age}	0.44***	0.60***	0.37***	0.66***	0.77***	0.62***	0.36***	0.50***	0.33***	0.70***	0.72***	0.62***	0.63***	0.58***	0.55***	0.73***	0.82***	0.80***
δ_0^{Gender}	0.09			0.50***			0.05			0.27**			0.30 ***			0.75***		
AR(2) test p-value	0.67	0.37	0.67	0.73	0.43	0.97	0.88	0.85	0.57	0.32	0.69	0.75	0.31	0.65	0.73	0.16	0.02	0.74
Hansen test p-value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Stationarity coefficient -1	-0.16***	-0.15***	-0.14***	-0.06**	-0.01	-0.06*	-0.08**	-0.08	-0.05	-0.05**	-0.05	-0.03	-0.06	0.02	-0.17*	-0.01	0.03	-0.03
Stationarity standard error	0.03	0.05	0.03	0.03	0.04	0.03	0.04	0.06	0.04	0.03	0.04	0.03	0.10	0.12	0.10	0.04	0.06	0.05
CD-test(residual)_test	-0.15	-0.80	0.59	-1.97	-2.78	-2.71	0.28	-2.49	1.50	-1.73	-2.21	-1.33	0.14	-1.88	-1.04	-1.66	-3.24	-2.02
CD-test(residual)_pvalue	0.88	0.43	0.55	0.05	0.01	0.01	0.78	0.01	0.13	0.08	0.03	0.18	0.89	0.06	0.30	0.10	0.00	0.04
alpha-test statistic	0.52	0.41	0.59	0.43	0.21	0.53	0.68	0.35	0.54	0.55	0.63	0.42	0.43	-0.26	0.52	-0.40	-3.45	-0.29
alpha-test standard error	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.02	=	0.01	=	=	=
LR ρ sum(habit)	0.59***	0.55***	0.51***	0.59***	0.48***	0.58***	0.70***	0.60***	0.70***	0.69***	0.65***	0.67***	0.69***	0.59***	0.72***	0.58***	0.48***	0.48***
LR $\lambda + \delta$ sum(reference)	0.26***	0.30***	0.35***	0.36***	0.51***	0.36***	0.22***	0.32***	0.25***	0.26***	0.30***	0.30***	0.25**	0.43***	0.11	0.41***	0.55***	0.49***
LR habit + reference sum	0.84***	0.85***	0.86***	0.94***	0.99***	0.94***	0.92***	0.92***	0.95***	0.95***	0.95***	0.97***	0.94***	1.02***	0.83***	0.99***	1.03***	0.97***
LR habit/reference ratio(%)	69.5	64.5	59.2	62.0	48.6	61.8	76.4	65.7	73.3	73.0	68.3	69.2	73.1	57.9	86.4	58.5	46.9	49.2
LR β sum(MPC)	0.17***	0.17***	0.18***	0.11***	0.16***	0.15***	0.09***	0.13***	0.07***	0.09***	0.18***	0.10***	0.05	0.02	0.11**	0.10*	0.05	0.19***
LR γ sum	0.00	0.02	-0.02	-0.01	-0.12	-0.04	-0.06**	-0.11**	-0.04	-0.03	-0.08	-0.06	-0.11**	-0.03	-0.12*	-0.05	-0.04	-0.10
LR $\beta + \gamma$	0.16***	0.19***	0.16***	0.10**	0.04	0.11*	0.03	0.02	0.03	0.06	0.10	0.04	-0.06	-0.01	-0.01	0.05	0.01	0.09
Total_SR	0.86	0.96	0.81	1.65	0.74	1.56	0.25	0.21	0.19	0.82	0.78	0.45	-0.80	-0.25	-0.07	1.87	0.75	2.21
Direct_SR	0.17	0.17	0.18	0.11	0.16	0.15	0.09	0.13	0.07	0.09	0.18	0.10	0.05	0.02	0.11	0.10	0.05	0.19
Indirect_SR	0.70	0.79	0.63	1.54	0.58	1.41	0.17	0.07	0.13	0.73	0.60	0.35	-0.85	-0.27	-0.18	1.77	0.70	2.02
Direct_SR ratio (%)	19.2	18.1	22.0	6.7	21.4	9.5	33.8	64.2	34.0	11.4	23.2	22.5	5.5	7.6	38.0	5.4	7.0	8.6
Indirect_SR ratio (%)	80.8	81.9	78.0	93.3	78.6	90.5	66.2	35.8	66.0	88.6	76.8	77.5	94.5	92.4	62.0	94.6	93.0	91.4
Total_LR	1.03	1.28	1.09	1.82	3.07	1.80	0.33	0.30	0.56	1.23	1.95	1.13	-0.99	0.38	-0.05	3.75	-0.56	2.67
Direct_LR	0.40	0.39	0.36	0.26	0.31	0.35	0.29	0.34	0.22	0.31	0.51	0.31	0.16	0.05	0.38	0.24	0.10	0.36
Indirect_LR	0.63	0.90	0.73	1.55	2.76	1.45	0.04	-0.04	0.35	0.93	1.43	0.82	-1.15	0.32	-0.43	3.51	-0.66	2.30
Direct_LR ratio (%)	38.8	30.1	33.1	14.6	10.0	19.7	86.8	89.3	38.6	24.8	26.4	27.1	12.1	-	47.2	6.4	-	13.6
Indirect_LR ratio (%)	61.2	69.9	66.9	85.4	90.0	80.3	13.2	10.7	61.4	75.2	73.6	72.9	87.9	-	52.8	93.6	-	86.4

Note: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Stationarity coefficients condition: (ρs+λs+δs)-1. 3) "-" indicates that estimation results are under non-stationary condition of inverse matrix. 4) SR: Short-run, LR: Long-run. 5) "=" indicates that test results are not available.

Table 3.7: Indirect Effect Ratios with Alternative Weighting Matrices

	Weighting matrices	All-spending (%)	Discretionary (%)	Necessary (%)	Visible (%)	Eating-at- home (%)	Eating-out (%)	RMSE(1W vs. 5W)
Short-run Elasticity	W(Income)	80.7	92.7	77.9	88.2	92.1	87.4	0.22
	W(preference)	80.7	91.0	49.8	86.9	94.3	87.7	0.28
	W(Region)	81.7	88.9	3.0	84.1	94.1	85.1	1.00
	W(Age)	81.4	92.8	68.4	89.1	93.7	91.5	0.06
	W(Gender)	81.8	90.3	63.5	88.6	92.1	92.2	0.08
	W(Average5W)	80.3	95.0	69.8	89.7	85.8	76.8	0.89
	W(Estimation5W)	80.4	95.2	67.5	90.4	85.2	74.0	1.00
	W(Biggest3W)	80.6	94.0	62.2	89.7	89.3	87.6	0.42
	W(I) + W(P)+W(R)+W(A)+W(G)	80.8	93.3	66.2	88.6	94.5	94.6	=
Long-run Elasticity	W(Income)	68.3	83.3	23.3	74.6	89.1	94.7	0.41
	W(preference)	69.4	80.3	17.2	73.3	81.0	92.3	0.42
	W(Region)	66.6	77.5	40.5	66.5	89.8	96.0	1.00
	W(Age)	68.6	82.6	5.2	75.3	84.7	88.7	0.42
	W(Gender)	62.7	79.6	20.4	70.9	84.0	-	0.40
	W(Average5W)	60.9	83.1	1.1	70.9	68.3	-	1.00
	W(Estimation5W)	61.5	83.9	6.7	74.1	68.4	-	0.88
	W(Biggest3W)	63.7	83.8	8.0	74.1	79.6	86.9	0.48
	W(I) + W(P)+W(R)+W(A)+W(G)	61.2	85.4	13.2	75.2	87.9	93.6	=
Habit ratio(%)	W(Income)	63.7	62.9	75.7	72.7	73.4	63.8	0.75
	W(preference)	65.2	59.6	73.3	70.6	75.9	53.0	0.82
	W(Region)	67.5	63.4	74.8	73.0	75.1	60.1	0.36
	W(Age)	66.3	64.8	74.6	73.2	77.3	64.4	0.80
	W(Gender)	73.6	62.8	78.9	74.8	78.4	66.2	1.00
	W(Average5W)	73.0	69.9	78.5	77.3	83.0	61.9	1.00
	W(Estimation5W)	72.6	69.7	78.6	77.1	82.1	62.6	0.95
	W(Biggest3W)	71.4	65.2	76.7	75.5	78.5	66.6	0.75
	W(I) + W(P)+W(R)+W(A)+W(G)	69.5	62.0	76.4	73.0	73.1	58.5	=

Note: 1) Indirect effects ratio (%) = (Indirect effect coefficient / Global effect coefficient). 2) $W(I) + W(P) + W(R) + W(A) + W(G)$ means each reference group variables are included in the estimation specification. 3) “-” indicates that estimation results are under non-stationary condition of inverse matrix. 4) “=” indicates that RMSE is not available because weighting matrix itself is the baseline specification.

Table 3.8: Estimation Results: Indirect Effects of W(Income)

	All-spending	Discretionary	Necessary	Visible	Eating-at-home	Eating-out
AR(2) test p-value	0.49	0.82	0.85	0.26	0.86	0.09
Hansen test p-value	1.00	1.00	1.00	1.00	1.00	1.00
Stationarity coefficients -1	-0.14***	-0.06	-0.11	-0.05	-0.03	-0.01
Stationarity standard error	0.03	0.03	0.04	0.03	0.11	0.04
CD-test(residual)_test	0.98	-1.64	-0.16	-1.65	2.38	0.74
CD-test(residual)_pvalue	0.33	0.10	0.88	0.10	0.02	0.46
alpha-test statistic	0.43	0.49	0.49	0.47	0.22	=
alpha-test se	0.01	0.01	0.01	0.01	0.02	=
LR ρ sum(habit)	0.55***	0.59***	0.67***	0.69***	0.71***	0.63***
LR $\lambda + \delta$ sum(reference)	0.31***	0.35***	0.22***	0.26***	0.26**	0.36***
LR habit + reference sum	0.86***	0.94***	0.89***	0.95***	0.97***	0.99***
LR habit/reference ratio(%)	63.7	62.9	75.7	72.7	73.4	63.8
LR β sum(MPC)	0.15***	0.14***	0.08***	0.11***	0.05	0.09
LR γ sum	0.00	-0.02	-0.04	-0.05	-0.08	-0.05
LR $\beta + \gamma$	0.15***	0.13**	0.03	0.07	-0.03	0.04
Total_SR	0.79	1.98	0.36	0.95	-0.53	0.71
Direct_SR	0.15	0.14	0.08	0.11	0.05	0.09
Indirect_SR	0.64	1.83	0.28	0.83	-0.58	0.62
Direct_SR ratio (%)	19.3	7.3	22.1	11.8	7.9	12.6
Indirect_SR ratio (%)	80.7	92.7	77.9	88.2	92.1	87.4
Total_LR	1.07	2.12	0.32	1.44	-1.23	4.53
Direct_LR	0.34	0.35	0.24	0.37	0.17	0.24
Indirect_LR	0.73	1.76	0.07	1.07	-1.41	4.29
Direct_LR ratio (%)	31.7	16.7	76.7	25.4	10.9	5.3
Indirect_LR ratio (%)	68.3	83.3	23.3	74.6	89.1	94.7

Note: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. 2) Stationarity coefficients condition: (ρs+λs+δs)-1. 3) “-” indicates that estimation results are under non-stationary condition of inverse matrix. 4) SR: Short-run, LR: Long-run. 5) “=” indicates that test results are not available.

Table 3.9: Estimation Results: Indirect Effects of W(Preference)

	All-spending	Discretionary	Necessary	Visible	Eating-at-home	Eating-out
AR(2) test p-value	0.35	0.58	0.55	0.34	0.39	0.20
Hansen test p-value	1.00	1.00	1.00	1.00	1.00	1.00
Stationarity coefficient -1	-0.14***	-0.07***	-0.09**	-0.06**	-0.08	-0.02
Stationarity standard error	0.03	0.03	0.04	0.03	0.11	0.04
CD-test(residual)_test	1.77	-1.72	1.77	-1.10	-0.59	-0.70
CD-test(residual)_pvalue	0.08	0.09	0.08	0.27	0.56	0.48
alpha-test statistic	0.42	0.24	0.50	0.50	0.35	-0.12
alpha-test se	0.01	0.01	0.01	0.01	0.02	=
LR ρ sum(habit)	0.56***	0.55***	0.66***	0.66***	0.70***	0.52***
LR $\lambda + \delta$ sum(reference)	0.30***	0.38***	0.24***	0.28***	0.22*	0.46***
LR habit + reference sum	0.86***	0.93***	0.91***	0.94***	0.92**	0.98***
LR habit/reference ratio(%)	65.2	59.6	73.3	70.6	75.9	53.0
LR β sum(MPC)	0.16***	0.15***	0.09***	0.12***	0.05	0.10
LR γ sum	0.01	-0.03	-0.07**	-0.04	-0.10	-0.05
LR $\beta + \gamma$	0.17***	0.12 **	0.02	0.08*	-0.05	0.05
Total_SR	0.83	1.69	0.18	0.91	-0.85	0.81
Direct_SR	0.16	0.15	0.09	0.12	0.05	0.10
Indirect_SR	0.67	1.54	0.09	0.79	-0.90	0.71
Direct_SR ratio (%)	19.3	9.0	50.2	13.1	5.7	12.3
Indirect_SR ratio (%)	80.7	91.0	49.8	86.9	94.3	87.7
Total_LR	1.19	1.73	0.22	1.33	-0.59	2.69
Direct_LR	0.36	0.34	0.28	0.36	0.18	0.21
Indirect_LR	0.82	1.39	-0.06	0.98	-0.77	2.48
Direct_LR ratio (%)	30.6	19.7	82.8	26.7	19.0	7.7
Indirect_LR ratio (%)	69.4	80.3	17.2	73.3	81.0	92.3

Note: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01.2) Stationarity coefficients condition: (ρs+λs+δs)-1. 3) "-" indicates that estimation results are under non-stationary condition of inverse matrix. 4) SR: Short-run, LR: Long-run. 5) "=" indicates that test results are not available.

Table 3.10: Estimation Results: Indirect Effects of W(Region)

	All-spending	Discretionary	Necessary	Visible	Eating-at-home	Eating-out
AR(2) test p-value	0.27	0.72	0.60	0.15	0.63	0.20
Hansen test p-value	1.00	1.00	1.00	1.00	1.00	1.00
Stationarity coefficient -1	-0.16***	-0.07**	-0.09**	-0.05*	-0.03	-0.01
Stationarity standard error	0.03	0.03	0.04	0.03	0.12	0.05
CD-test(residual)_test	0.87	-1.76	0.77	-1.60	2.38	0.69
CD-test(residual)_pvalue	0.39	0.08	0.44	0.11	0.02	0.49
alpha-test statistic	0.41	0.32	0.58	0.29	0.47	0.12
alpha-test se	0.01	0.01	0.01	0.01	0.02	0.06
LR ρ sum(habit)	0.57***	0.59***	0.68***	0.69***	0.73***	0.60***
LR $\lambda + \delta$ sum(reference)	0.27***	0.34***	0.23***	0.26***	0.24**	0.40***
LR habit + reference sum	0.84***	0.93***	0.91***	0.95***	0.97***	0.99***
LR habit/reference ratio(%)	67.5	63.4	74.8	73.0	75.1	60.1
LR β sum(MPC)	0.16***	0.16***	0.09***	0.12***	0.03	0.08
LR γ sum	0.02	-0.04	-0.09***	-0.06	-0.06	-0.05
LR $\beta + \gamma$	0.17***	0.12**	0.01	0.06	-0.03	0.03
Total_SR	0.85	1.42	0.09	0.74	-0.50	0.53
Direct_SR	0.16	0.16	0.09	0.12	0.03	0.08
Indirect_SR	0.70	1.26	0.00	0.62	-0.54	0.45
Direct_SR ratio (%)	18.3	11.1	97.0	15.9	5.9	14.9
Indirect_SR ratio (%)	81.7	88.9	3.0	84.1	94.1	85.1
Total_LR	1.08	1.71	0.09	1.13	-0.98	4.86
Direct_LR	0.36	0.38	0.29	0.38	0.13	0.20
Indirect_LR	0.72	1.32	-0.20	0.75	-1.11	4.66
Direct_LR ratio (%)	33.4	22.5	59.5	33.5	10.2	4.0
Indirect_LR ratio (%)	66.6	77.5	40.5	66.5	89.8	96.0

Note: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01.2) Stationarity coefficients condition: (ρs+λs+δs)-1. 3) "-" indicates that estimation results are under non-stationary condition of inverse matrix. 4) SR: Short-run, LR: Long-run. 5) "=" indicates that test results are not available.

Table 3.11: Estimation Results: Indirect Effects of W(Age)

	All-spending	Discretionary	Necessary	Visible	Eating-at-home	Eating-out
AR(2) test p-value	0.18	0.74	0.87	0.27	0.64	0.14
Hansen test p-value	1.00	1.00	1.00	1.00	1.00	1.00
Stationarity coefficient -1	-0.15***	-0.07**	-0.09**	-0.05**	-0.05	-0.03
Stationarity standard error	0.03	0.03	0.04	0.03	0.12	0.04
CD-test(residual)_test	1.10	-1.68	0.91	-1.73	1.64	0.53
CD-test(residual)_pvalue	0.27	0.09	0.36	0.08	0.10	0.60
alpha-test statistic	0.48	0.40	0.56	=	0.31	-0.14
alpha-test se	0.01	0.01	0.01	=	0.03	=
LR ρ sum(habit)	0.56***	0.60***	0.68***	0.69***	0.74***	0.63***
LR $\lambda + \delta$ sum(reference)	0.29***	0.33***	0.23***	0.25***	0.22*	0.35***
LR habit + reference sum	0.85***	0.93***	0.91***	0.95***	0.95***	0.97***
LR habit/reference ratio(%)	66.3	64.8	74.6	73.2	77.3	64.4
LR β sum(MPC)	0.16***	0.14***	0.10***	0.12***	0.05	0.09
LR γ sum	0.02	0.00	-0.07**	-0.03	-0.09	-0.03
LR $\beta + \gamma$	0.17***	0.15**	0.03	0.08**	-0.04	0.06
Total_SR	0.85	1.97	0.31	1.06	-0.71	1.09
Direct_SR	0.16	0.14	0.10	0.12	0.05	0.09
Indirect_SR	0.69	1.83	0.21	0.94	-0.76	1.00
Direct_SR ratio (%)	18.6	7.2	31.6	10.9	6.3	8.5
Indirect_SR ratio (%)	81.4	92.8	68.4	89.1	93.7	91.5
Total_LR	1.15	2.03	0.32	1.52	-0.88	2.19
Direct_LR	0.36	0.35	0.30	0.38	0.19	0.25
Indirect_LR	0.79	1.68	0.02	1.15	-1.08	1.94
Direct_LR ratio (%)	31.4	17.4	94.8	24.7	15.3	11.3
Indirect_LR ratio (%)	68.6	82.6	5.2	75.3	84.7	88.7

Note: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01.2) Stationarity coefficients condition: (ρs+λs+δs)-1. 3) "-" indicates that estimation results are under non-stationary condition of inverse matrix. 4) SR: Short-run, LR: Long-run. 5) "=" indicates that test results are not available.

Table 3.12: Estimation Results: Indirect Effects of W(Gender)

	All-spending	Discretionary	Necessary	Visible	Eating-at-home	Eating-out
AR(2) test p-value	0.27	0.94	0.84	0.23	0.63	0.08
Hansen test p-value	1.00	1.00	1.00	1.00	1.00	1.00
Stationarity coefficient -1	-0.17***	-0.08**	-0.11**	-0.07**	-0.05	0.01
Stationarity standard error	0.03	0.03	0.04	0.03	0.13	0.05
CD-test(residual)_test	0.08	-1.77	0.53	-1.88	1.90	1.18
CD-test(residual)_pvalue	0.94	0.08	0.60	0.06	0.06	0.24
alpha-test statistic	0.48	0.44	0.43	0.43	0.42	0.09
alpha-test se	0.01	0.01	0.01	0.01	0.03	0.01
LR ρ sum(habit)	0.61***	0.58***	0.70***	0.70***	0.74***	0.67***
LR $\lambda + \delta$ sum(reference)	0.22***	0.34***	0.19***	0.23***	0.21	0.34***
LR habit + reference sum	0.83***	0.92***	0.89***	0.93***	0.95***	1.01***
LR habit/reference ratio(%)	73.6	62.8	78.9	74.8	78.4	66.2
LR β sum(MPC)	0.17***	0.15***	0.09***	0.12***	0.03	0.05
LR γ sum	0.03	-0.01	-0.06	-0.02	-0.06	-0.07
LR $\beta + \gamma$	0.19***	0.13**	0.02	0.09**	-0.03	-0.02
Total_SR	0.91	1.53	0.24	1.04	-0.36	-0.56
Direct_SR	0.17	0.15	0.09	0.12	0.03	0.05
Indirect_SR	0.74	1.38	0.15	0.92	-0.39	-0.61
Direct_SR ratio (%)	18.2	9.7	36.5	11.4	7.9	7.8
Indirect_SR ratio (%)	81.8	90.3	63.5	88.6	92.1	92.2
Total_LR	1.14	1.73	0.22	1.34	-0.56	1.83
Direct_LR	0.42	0.35	0.29	0.39	0.13	0.16
Indirect_LR	0.71	1.37	-0.08	0.95	-0.69	1.68
Direct_LR ratio (%)	37.3	20.4	79.6	29.1	16.0	8.5
Indirect_LR ratio (%)	62.7	79.6	20.4	70.9	84.0	-

Note: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01.2) Stationarity coefficients condition: (ρs+λs+δs)-1. 3) "-" indicates that estimation results are under non-stationary condition of inverse matrix. 4) SR: Short-run, LR: Long-run. 5) "=" indicates that test results are not available.

Table 3.13: Estimation Results: Indirect Effects of W(Average5W)

	All-spending	Discretionary	Necessary	Visible	Eating-at-home	Eating-out
AR(2) test p-value	0.86	0.54	0.83	0.26	0.65	0.21
Hansen test p-value	1.00	1.00	0.95	1.00	0.99	1.00
Stationarity coefficient -1	-0.18***	-0.07**	-0.08**	-0.06**	-0.10	0.01
Stationarity standard error	0.03	0.03	0.04	0.03	0.10	0.04
CD-test(residual)_test	0.48	-2.36	0.17	-2.22	-0.22	-1.79
CD-test(residual)_pvalue	0.63	0.02	0.86	0.03	0.83	0.07
alpha-test statistic	0.56	0.43	0.67	0.43	0.54	-0.14
alpha-test se	0.01	0.01	0.01	0.01	0.02	=
LR ρ sum(habit)	0.60***	0.65***	0.72***	0.73***	0.75***	0.62***
LR $\lambda + \delta$ sum(reference)	0.22***	0.28***	0.20***	0.21***	0.15	0.38***
LR habit + reference sum	0.82***	0.93***	0.92	0.94***	0.90***	1.01***
LR habit/reference ratio(%)	73.0	69.9	78.5	77.3	83.0	61.9
LR β sum(MPC)	0.17 ***	0.11***	0.07***	0.10***	0.06	0.10
LR γ sum	0.02	0.01	-0.05	-0.03	-0.09	-0.07
LR $\beta + \gamma$	0.19***	0.12**	0.02	0.07	-0.03	0.02
Total_SR	0.84	2.11	0.23	0.93	-0.30	0.42
Direct_SR	0.17	0.11	0.07	0.10	0.06	0.10
Indirect_SR	0.68	2.00	0.16	0.84	-0.36	0.32
Direct_SR ratio (%)	19.7	5.0	30.2	10.3	14.2	23.2
Indirect_SR ratio (%)	80.3	95.0	69.8	89.7	85.8	76.8
Total_LR	1.06	1.79	0.25	1.23	-0.28	-3.43
Direct_LR	0.41	0.30	0.25	0.36	0.24	0.26
Indirect_LR	0.65	1.49	0.00	0.87	-0.52	-3.68
Direct_LR ratio (%)	39.1	16.9	98.9	29.1	31.7	6.5
Indirect_LR ratio (%)	60.9	83.1	1.1	70.9	68.3	-

Note: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01.2) Stationarity coefficients condition: (ρs+λs+δs)-1. 3) “-” indicates that estimation results are under non-stationary condition of inverse matrix. 4) SR: Short-run, LR: Long-run. 5) “=” indicates that test results are not available.

Table 3.14: Estimation Results: Indirect Effects of W(Estimation5W)

	All-spending	Discretionary	Necessary	Visible	Eating-at-home	Eating-out
AR(2) test p-value	0.81	0.55	0.87	0.28	0.66	0.20
Hansen test p-value	1.00	1.00	0.98	1.00	0.99	1.00
Stationarity coefficient -1	-0.17***	-0.06	-0.08**	-0.05*	-0.09	0.00
Stationarity standard error	0.03	0.03	0.04	0.03	0.10	0.04
CD-test(residual)_test	0.13	-2.37	-0.25	-2.26	-0.26	-1.78
CD-test(residual)_pvalue	0.90	0.02	0.80	0.02	0.80	0.08
alpha-test statistic	0.52	0.49	0.66	0.42	0.38	-0.26
alpha-test se	0.01	0.01	0.01	0.01	0.02	=
LR ρ sum(habit)	0.60***	0.65**	0.72***	0.73***	0.75***	0.63***
LR $\lambda + \delta$ sum(reference)	0.23***	0.28***	0.20***	0.22***	0.16	0.38***
LR habit + reference sum	0.83***	0.94***	0.92***	0.95***	0.91***	1.00***
LR habit/reference ratio(%)	72.6	69.7	78.6	77.1	82.1	62.6
LR β sum(MPC)	0.16***	0.11***	0.07***	0.10***	0.06	0.10
LR γ sum	0.02	0.01	-0.05	-0.03	-0.08	-0.07
LR $\beta + \gamma$	0.18***	0.12**	0.02	0.07	-0.02	0.02
Total_SR	0.83	2.20	0.22	1.00	-0.28	0.37
Direct_SR	0.16	0.11	0.07	0.10	0.06	0.10
Indirect_SR	0.67	2.10	0.15	0.90	-0.34	0.27
Direct_SR ratio (%)	19.6	4.8	32.5	9.6	14.8	26.0
Indirect_SR ratio (%)	80.4	95.2	67.5	90.4	85.2	74.0
Total_LR	1.06	1.91	0.23	1.39	-0.28	-3.26
Direct_LR	0.41	0.31	0.25	0.36	0.24	0.26
Indirect_LR	0.65	1.60	-0.02	1.03	-0.51	-3.52
Direct_LR ratio (%)	38.5	16.1	93.3	25.9	31.6	6.8
Indirect_LR ratio (%)	61.5	83.9	6.7	74.1	68.4	-

Note: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01.2) Stationarity coefficients condition: (ρs+λs+δs)-1. 3) "-" indicates that estimation results are under non-stationary condition of inverse matrix. 4) SR: Short-run, LR: Long-run. 5) "=" indicates that test results are not available.

Table 3.15: Estimation Results: Indirect Effects of W(Biggest3W)

	All-spending	Discretionary	Necessary	Visible	Eating-at-home	Eating-out
AR(2) test p-value	0.51	0.65	0.88	0.32	0.77	0.14
Hansen test p-value	1.00	1.00	1.00	1.00	0.99	1.00
Stationarity coefficient -1	-0.17***	-0.05*	-0.09**	-0.04	-0.04	-0.02
Stationarity standard error	0.03	0.30	0.04	0.03	0.11	0.04
CD-test(residual)_test	0.00	-2.21	0.14	-2.19	1.80	-0.09
CD-test(residual)_pvalue	1.00	0.03	0.89	0.03	0.07	0.93
alpha-test statistic	0.38	0.48	0.60	0.58	0.47	0.29
alpha-test se	0.01	0.01	0.01	0.01	0.02	0.02
LR ρ sum(habit)	0.59***	0.62***	0.70***	0.72 ***	0.75 ***	0.65***
LR $\lambda + \delta$ sum(reference)	0.24***	0.33***	0.21***	0.23***	0.21*	0.33***
LR habit + reference sum	0.83***	0.95***	0.91***	0.96 ***	0.96***	0.98***
LR habit/reference ratio(%)	71.4	65.2	76.7	75.5	78.5	66.6
LR β sum(MPC)	0.16***	0.12***	0.08***	0.10 ***	0.06	0.11
LR γ sum	0.02	-0.02	-0.06	-0.04	-0.09	-0.05
LR $\beta + \gamma$	0.18***	0.10*	0.02	0.06	-0.03	0.06
Total_SR	0.83	2.01	0.21	0.95	-0.45	0.85
Direct_SR	0.16	0.12	0.08	0.10	0.06	0.11
Indirect_SR	0.67	1.89	0.13	0.85	-0.51	0.75
Direct_SR ratio (%)	19.4	6.0	37.8	10.3	10.7	12.4
Indirect_SR ratio (%)	80.6	94.0	62.2	89.7	89.3	87.6
Total_LR	1.09	1.96	0.25	1.36	-0.72	2.30
Direct_LR	0.40	0.32	0.27	0.35	0.25	0.30
Indirect_LR	0.70	1.64	-0.02	1.01	-0.97	2.00
Direct_LR ratio (%)	36.3	16.2	92.0	25.9	20.4	13.1
Indirect_LR ratio (%)	63.7	83.8	8.0	74.1	79.6	86.9

Note: 1) * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01.2) Stationarity coefficients condition: (ρs+λs+δs)-1. 3) “-” indicates that estimation results are under non-stationary condition of inverse matrix. 4) SR: Short-run, LR: Long-run. 5) “=” indicates that test results are not available.

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3.8 Appendix

3.8.1 Almost Ideal Demand System (Quardratic)

This section is mainly based on Poi (2012). The quadratic AID system can be represented by

$$\ln V(p, m) = \left[\left\{ \frac{\ln m - \ln a(p)}{b(p)} \right\}^{-1} + \lambda(p) \right]^{-1} \tag{3.13}$$

where $\ln a(p)$ is the transcendental logarithm function

$$\ln a(p) = a_0 + \sum_{i=1}^{k} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{k} \sum_{j=1}^{k} \gamma_{ij} \ln p_i \ln p_k \tag{3.14}$$

where p_i is the price of good i for i=1,....,k; $b(p)$ is the Cobb-Douglas price aggregator

$$b(p) = \prod_{i=1}^{k} {p_i}^{\beta_i} \tag{3.15}$$

and

$$\lambda(p) = \sum_{i=1}^{k} \lambda_i \ln p_i \tag{3.16}$$

Deaton and Muellbauer (1980) and Banks et al. (1997) set α_0 to be slightly less than the lowest value of $\ln m$ observed in the data.

By adding up, we impose homogeneity and slutsky symmetry condition

$$\sum_{i=1}^{k} \alpha_i = 1, \qquad \sum_{i=1}^{k} \beta_i = 0, \qquad \sum_{j=1}^{k} \gamma_{ij} = 0, \qquad \sum_{i=1}^{k} \lambda_i = 0, \qquad and \qquad \gamma_{ij} = \gamma_{ji} \tag{3.17}$$

In order to show the AID system, we define q_i which is the quantity of good i consumed by an individual and define the expenditure share for good i as $w_i = p_i q_i / m_i$. Then we have the expenditure share equation for good i :

$$w_i = \alpha_i + \sum_{i=1}^{k} \gamma_{ij} \ln p_j + \beta_i \ln \left\{ \frac{m}{a(p)} \right\} + \frac{\lambda_i}{b(p)} \left[\ln \left\{ \frac{m}{a(p)} \right\} \right]^2, i = 1, ..., k \tag{3.18}$$

When λ_i=0 for all i, we can get back to the original AID system suggested by Deaton and Muellbauer (1980).

3.8.2 Derivation of Global MPC Elasticity

$$\begin{aligned} C_{i,t} =& \alpha_i + \sum_{s=1}^{S=4} \rho_s C_{i,t-s} + \beta Y_{i,t} + \sum_{k=1}^{K=4} \theta_k X_{i,t} + \sum_{j=0}^{J=4} \lambda_j \overline{C}_{t-j} \\ &+ \sum_{r=1}^{R=5} (\sum_{g=1}^{Gr} \mu_{rg} f_i^{rg} + \delta^r \widetilde{C}_{i,t}^r + \gamma^r \widetilde{Y}_{i,t}^r) + \epsilon_{i,t} \\ & where \quad i = 1, \ldots, N \quad t = 1, \ldots, T \end{aligned} \tag{3.19}$$

$$\begin{aligned} \Big[I - \sum_{s=1}^{S=4} \rho_s L^s I_N - \sum_{j=0}^{J=4} \lambda_j L^j M - \sum_{r=1}^{R=5} \delta^r W^r \Big] C_{i,t} =& \alpha_i + (\beta I_N + \sum_{r=1}^{R=5} \gamma^r W^r) Y_{i,t} + \ldots + \epsilon_{i,t} \\ & i = 1, \ldots, N \quad t = 1, \ldots, T \end{aligned} \tag{3.20}$$

$$\begin{aligned} C_{i,t} =& \big[I - G\big]^{-1} \alpha_i + \big[I - G\big]^{-1} (\beta I_N + \sum_{r=1}^{R=5} \gamma^r W^r) Y_{i,t} + \ldots + \big[I - G\big]^{-1} \epsilon_{i,t} \\ & where \quad i = 1, \ldots, N \quad t = 1, \ldots, T \\ G =& \sum_{s=1}^{S=4} \rho_s L^s I_N + \sum_{j=0}^{J=4} \lambda_j M + \sum_{r=1}^{R=5} \delta^r W^r \end{aligned} \tag{3.21}$$

$$\beta_{Global} = \frac{1}{N^2} D' G(1) D \beta = \frac{1}{N^2} D' \begin{bmatrix} \frac{\partial C_{1,t}}{\partial Y_{1,t}} & \frac{\partial C_{1,t}}{\partial Y_{2,t}} & \cdots & \cdots & \frac{\partial C_{1,t}}{\partial Y_{N,t}} \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \frac{\partial C_{N,t}}{\partial Y_{1,t}} & \frac{\partial C_{N,t}}{\partial Y_{2,t}} & \cdots & \cdots & \frac{\partial C_{N,t}}{\partial Y_{N,t}} \end{bmatrix} D \tag{3.22}$$

3.8.3 General Method of Moment

This paper mainly employs the system GMM estimation. The core idea of method of moment can be described as below. Let us consider a random variable X and assume that associated expectation of X is known as θ_0 in population. Then our target moment condition is as below equation[33].

$$\begin{aligned} E(X - \theta o) = 0 \quad (Moment \quad condition) \\ X - \theta o : \text{moment function} \end{aligned} \tag{3.23}$$

[33]This discussion is mainly referred from "Chirok Han (2016) *Lectures on panel data econometrics*"

Then we can say the true value θo is the one which make population mean of moment function to be zero. Given this known true condition, method of moment estimates $\widehat{\theta o}$ in the sample counterpart from below condition.

$$\frac{1}{n}\sum g(X_i - \widehat{\theta o}) = 0 \quad given\, sample \quad X_1, X_2, ...X_n \tag{3.24}$$

Furthermore, this can be extended to the General Method of Moment (GMM) especially when we have multiple random variables for one parameter. For example, given two random variables X and Y, suppose their expectations are known to be E(X) = E(Y) = θo in the population.

$$\begin{gathered} g(X, Y, \theta 0) = (X - \theta o, \text{Y-}\theta o)' \quad \text{(Moment condition)} \\ where \quad X - \theta o \quad \text{and} \quad \text{Y-}\ \theta o \ \text{are two moment functions} \end{gathered} \tag{3.25}$$

In the sample counterpart of the above is expressed as below

$$\overline{g}(\theta) = \frac{1}{n} \sum g(X_i, Y_i, \widehat{\theta}) \neq 0 \tag{3.26}$$

Due to this condition of inequality, what we need to is to find the minimum of Euclidean distance of the above eqation, which means the distance of $\overline{g}(\theta)$ from zero. Since we have q elements in $\overline{g}(\theta)$, our target of minimisation is $[\overline{g}(\theta)'\overline{g}(\theta)]^{1/2}$.

Chapter 4

The Value of Local Information in Portfolio Decisions: Exploiting High-Frequency Transaction Data in the Retail Sector

4.1 Introduction

Achieving excess return in financial markets has always been of great interest in the fields of economics and applied finance. The stock market is characterised as a place where individuals and institutional investors compete for profits with each other with frequently updated information in a real-time manner. Examples of predictors in the stock market are dividend yields, macroeconomic variables, news, and Google trends. Existing research papers usually provide forecasting exercises based on low frequency (yearly, quarterly and monthly) aggregate data and their contributions enlighten relations between stock returns and predictors including macroeconomic and financial aggregates. In the case of real-time forecasting exercises, analysis is more focused on the mixed-frequency model with the baseline specification of low-frequency variables. Especially in the marketing field, existing studies employing detailed data use firms' historical sales to make sophisticated predictions of which items customers will buy in the future. However, the majority of this approach is restricted to only the cases of a few stores or a limited number of customers.

The advent of high-frequency disaggregate data has changed these old-fashioned studies into a way in which firms can directly use consumer data to maximise rents from stock markets. As more consumers use electronic payments instead of cash, individual spending is easily recorded and tracked by big datasets, which allows researchers to obtain nation-level samples. This means that consumer data represent the spending behaviours of populations, and it is expected that implications from consumer data can explain the movement of macro variables including stock prices. Although we are able to approach granular consumer datasets, we are not yet certain how to exploit data at the micro-level in portfolio investment. In this chapter, I fill this gap by setting up an investment strategy in which portfolios are paired to a set of predictors from UK financial management application MDB.

To be specific, I set up a weekly investment portfolio tracked by consumer predictors constructed from the MDB data and ask what kind of investment strategy can achieve stock profitability. I show that consumer transaction-level data allows investors to achieve economic profits and investigate further on how predictors of varied aggregation levels can be matched to candidate portfolios to secure economic profits. I use weekly predictors aggregated from 13,173 individuals' spending. The aggregation levels of spending are all-spending, broad-category, sub-category and firm-level spending.

In line with the recent advances in the decision-based evaluation of forecasts, this paper employs an illustrative investment scenario where an investor chooses weights between two stocks or sector indices. The investor is assumed to buy portfolio allocation at time T and hold until T+H periods, and her utility is determined by the standard constant relative risk aversion (CRRA) power utility function in order to reflect the risk an investor encounters. To incorporate stochastic uncertainty in an individual's economic decisions, the density forecast framework is used through simulation exercises. Following Garratt and Lee (2010), I evaluate alternative predictive densities based on the Vector-autoregression (VAR) model depending on consumer data predictors. I find an optimal weight w^* that maximises the expected utility obtained from 300 repetitions for each forecast horizon. By averaging the maximised utility across the number of recursions (26 weeks) associated with the optimal weight w^* for each forecast horizon H, and risk aversion A, I derive an estimate of realised utility suggested by predictive densities. Since we are unsure of the true probability density function of utility improvements, we can compute the ratio of utility with an MDB predictor to the utility without one in practice. If the ratio is significantly different from unity, we can conclude that the MDB predictor is useful. The statistical significance of utility improvements is calculated based on the simple Diebold-Mariano test of equal predictive accuracy.

Although the model specification (maximum five-variable VAR) is simple, the variables in the model are deliberately chosen. All stock price variables are transformed to excess return version variables, which are computed as (weekly stock return − weekly risk-free asset return). Oil price as a baseline predictor is transformed as the growth rate of the weekly oil price. Candidate predictors of interest are constructed as a ratio of (100+weekly growth rate of spending amount on A) to (100+weekly growth rate of spending amount on B) from which I could draw many combinations of A and B according to the firm, category and macro level.

The main research question is closely related to how to set up a portfolio and associated predictors in terms of the aggregation level: If stocks in the portfolio lie in the intra(or inter)-aggregation level[1], would a predictor constructed from spending amounts in the corresponding intra(or inter)-aggregation level be a good match for the portfolio? The expected intuition is that we need to use well-matched predictors depending upon the aggregation level of the portfolio components if we want to exploit consumer data in achieving profitability.

Table 4.1: Forecasts and Predictors According to Aggregation Level

Forecast A	Forecast B	Portfolio relation	Ideal Predictors
Firm (disaggregate)	Firm (disaggregate)	Intra-aggregate	Firm level
Firm (disaggregate)	Sector (mid-disaggregate)	Inter-aggregate	Firm & Category level
Firm (disaggregate)	Index (aggregate)	Inter-aggregate	Category& Macro level
Sector (mid-disaggregate)	Sector (mid-disaggregate)	Intra-aggregate	Firm level
Sector (mid-disaggregate)	Index (aggregate)	Inter-aggregate	Category& Macro level

The main lessons of this paper are that portfolio pairs are recommended to be in the intra-aggregation level and that associated predictors should be constructed as a ratio of spending amounts on two specific firms. In the case of inter-aggregation level portfolios, category-level predictors relatively perform better than firm-specific level predictors. Furthermore, when it comes to the portfolio between a highly disaggregate firm and a highly aggregate FTSE350 composite index (i.e. an extreme case of inter-aggregation portfolios), MDB predictors are shown to be weak.

To sum up, the information gain from consumers' detailed spending data is pronounced when we can keep track of the sales of specific firms. Then, consumer spending data can fill the information gap between portfolio components and benchmark predictors better if portfolios and the associated predictors are made within the intra-aggregation level. Intuitively, highly aggregated stock indices are more likely to have complicated factors other than just sales information. Thus, if we invest in an intra-aggregation level portfolio, unidentified important factors other than sales information can be assumed to be dealt with the macro factor such as the oil price.

I also study the role of a second MDB predictor on top of a single MDB predictor. Basically, the combination of two strong predictors tends to beat a single predictor. However, adding one extra predictor does not necessarily improve economic profits.

This paper is closely linked to the literature on the decision-based evaluation of forecasts. Barberis (2000) investigates the role of parameter uncertainty in the long-run investment between a risk-free asset and risky asset and find that predictability makes investors invest more in risky assets with longer horizons. Garratt and Lee (2010) followed Barberis' framework but stress the merits of economic evaluation criteria in

[1] i) Intra-aggregation level: [firm vs. firm] or [sector vs. sector]; ii) Inter-aggregation level: [firm vs. sector] or [sector vs. index] or [firm vs. index])

the context of portfolio allocation to domestic and foreign assets. Sirichand and Hall (2016) also employ decision-based forecast evaluation in terms of portfolio decisions between long and short bond returns. I follow and extend these papers but my paper is different in that I focus on how to match MDB predictors to portfolio components and compare the relative performance of investment strategies.

The idea to use disaggregate data in forecasting aggregates is not new even though we only recently began to encounter detailed big data sets. Van Garderen et al. (2000) argue that disaggregate information should be exploited when the main objective is aggregate variables especially when parameter heterogeneity exists among micro-units. Wilcox (2007) shows that survey information about components of consumption improves the forecast accuracy of aggregate consumption. Hendry and Hubrich (2011) document theoretically and empirically that using disaggregate information for forecasting aggregates is better than combining disaggregate information. They also confirm that selective variables from disaggregate information improve forecast accuracy. Very recently, Agarwal et al. (2020) use transaction-level spending data to predict firms' stock prices. They find that consumer-oriented firms show strong predictability. My paper is similar to their research questions and data sources; however, my work is different in that I use a time-series VAR model while they use panel regression estimation. Broadly, my paper is similar to all these intuitions in that we exercise prediction with disaggregate firm sales as well as aggregate (combined) sector sales to examine relative forecast accuracy.

This paper is also related to the recently growing literature on real-time forecasting. Most studies in real-time prediction involve handling mixed-frequency data. This is because these studies are motivated to use high-frequency data as an extra layer to predict low-frequency macro variables. For example, Garratt and Vahey (2006) document that preliminary real-side indicators are not powerful in predicting UK macroeconomic data. Galbraith and Tkacz (2007) use electronic transaction data as high-frequency indicators of economic activity and find that real-time debit card data can lower forecast errors for both GDP and non-durable consumption. Exploiting transaction data to have more information on spending in real-time appears similar to my work; however, my focus is different in that I set forecasts as a weekly frequency to be free from mixed frequency problem. Then, I ask a different question regarding the aggregation levels between portfolios and predictors.

Constructing valuable predictors is at the heart of forecasting literature. Pesaran and Timmermann (2000) classify sets of predictors for stock returns as core, focal and potential according to their importance. Lettau and Ludvigson (2001) suggest the consumption-wealth ratio as a strong predictor by showing that this predictor is better than any dividend-yield or dividend pay-out ratio. Santos and Veronesi (2006) theoretically introduce the role of labour income in the predictability of stock returns with empirical evidence. Goyal and Welch (2008) argue that no dominant predictors exist since the performances were poor in both in-sample and out-of-sample. Nevertheless, Campbell and Thompson (2008) point out that even though out-of-sample power is small, predictors are helpful once simple theoretical sign restrictions are imposed.

When it comes to research with large datasets, factors extracted from sets of potential predictors have been used for forecasting. For example, Rapach et al. (2011) use the principal components method to deal with large datasets and confirm improvements in forecasting for both out-of-sample and economic significance. Vosen and Schmidt (2011) show that factors extracted from the Google trend indicator outperform the survey based forecasts in forecasting private consumption. Martinesen et al. (2014) use factors extracted from disaggregate (regional and sectoral) survey data to predict macroeconomic variables. However, I do not use factor variables in order to focus on aggregation-level relations between a portfolio and predictor.

From the theoretical point of view, Elliott et al. (2013) study the best subset of many predictors in forecasting theoretically and conclude that subset regressions with 2, 3 and 4 predictors generate the lowest out-of-sample MSE out of 12 potential predictors. I question whether extra predictors can necessarily help forecasting with this intuition.

The rest of this paper proceeds as follows. Section 4.2 describes the forecast evaluation framework. Section 4.3 presents modeling strategies. Section 4.4 illustrates data descriptions and variable constructions. Section 4.5 lays out the main results of baseline simulation. Section 4.6 tests the robustness of this paper's main results with alternative settings. Section 4.7 concludes.

4.2 Optimal Portfolio Choice Using Stock Excess Return Forecasts

4.2.1 Statistical Criteria of Forecast Evaluation

The usual statistical process of evaluating out-of-sample forecasting is calculating the Root Mean Squared Error (RMSE) which means dispersion from the actually realised target forecast.

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} e_{t+h,t}^{2}} \tag{4.1}$$

where $e_{t+h,t}$ is the h-step forecast error at time t. Garratt and Lee (2010) argue that the statistical evaluation of the model based on in-sample fit or diagnostic tests can mislead investment decisions. From the perspective of an investor who takes risk aversion into account, it is highly likely that the real utility from investment may be far from what we expect only from the lowest RMSE results of the model. In addition, even though the object is to forecast only one stock excess return, portfolio decisions ultimately should consider the alternative stock's forecasting task as well. Thus, it is controversial whether we should consider target stock's RMSE only or both stocks' RMSE as a whole.

Taking all this into account, Garratt and Lee (2010) show that economic profit can be an alternative forecasting model evaluation criterion in that an investor's profits might be worse if they follow statistical criteria only. This paper uses the economic criteria in evaluating forecast, motivated by their findings.

4.2.2 Economic Criteria of Forecast Evaluation

Following Garratt and Lee (2010), let us consider a stock investor who wants to buy a stock portfolio at time T and hold it for H period (investment horizon) without dynamic rebalancing. This investor wants to allocate her portfolio into stock A with weight $(1-\omega)$ and stock B with weight ω . Therefore, this investor will make a decision of proportion between stocks A and B at time T and achieve excess return at the $T+H$ period. The end-of-period wealth can be described as:

$$W_{T+H}(\omega) = (1-\omega)exp(\sum_{h=0}^{H} ER(A)_{T+h}) + (\omega)exp(\sum_{h=0}^{H} ER(B)_{T+h}) \tag{4.2}$$

where $ER(i)$ denotes the end-of-period excess return from stock i investment and ω denotes a fraction of the portfolio in a share where ω=0,1,2, ... ,100%.

As Barberis (2000) and Garratt and Lee (2010) mentioned, the non-linearity of (4.2) means that the investor needs to evaluate the entire joint probability of the forecast values of $ER(i)_{T+h}$, h= 1, ..., H. to evaluate $E(W_{T+H}|\Omega_T)$. In addition, the investor's risk aversion can be accommodated into this framework by applying the standard CRRA power utility function.

$$v(W_{T+H}) = \frac{W_{T+H}^{1-A}}{1-A} \tag{4.3}$$

where A is the degree of risk aversion. Thus, the investor's problem at time T can be described as

$$\max_{\omega} E[v(W_{T+H}(\omega))|\Omega_T] \tag{4.4}$$

Then, optimal weights ω^* can be generated from this portfolio decision problem in which the investor maximises the expected utility across all 101 candidate portfolio weights. Specifically, we compute the sample counterpart of expected utility over R (=300) simulation exercises given risk aversion A, forecasting horizon H and weight ω^*

at time T. The sample expected utility is defined as below

$$v^*(W_{T+H}(\omega^*, A)) = \frac{1}{R}\sum_{r=1}^{R} v(W_{T+H}(r, \omega^*, A)) \tag{4.5}$$

4.2.3 Testing the Null Hypothesis of Equal Accuracy

Now, the focus is whether one forecast measured in the suggested loss function is more accurate than another. In this paper, I use the Diebold-Mariano test to examine the performance of predictors.[2] The usual null hypothesis of equal accuracy is

$$H_o : E(L(e^a_{t+h,t})) = E(L(e^b_{t+h,t})) \tag{4.6}$$

against the alternative

$$H_1 : E(L(e^a_{t+h,t})) \neq E(L(e^b_{t+h,t})) \tag{4.7}$$

where $e_{t+h,t}$ is the h-step forecast error at time t and L(.) is the assumed loss function. The specific loss function in this paper's exercise is the utility ratio of VAR with a predictor to VAR without the predictor.

$$H_o : E(L(U^{MDB}_{t+h,t})) = E(L(U^{NoMDB}_{t+h,t})) \tag{4.8}$$

The null hypothesis is that two utility levels based on different VAR specifications have the same accuracy in a statistical sense. If the utility ratio is higher than the unity, VAR with the MDB predictor is shown to improve economic profit compared to VAR without predictor. The related significance level shows how significant this difference is significant in the statistical sense, and I assess utility improvements in each of the significance levels of 10%, 20% and 30%.

Pesaran and Skouras (2002) provide the idea of a decision based criterion function as below:

$$\psi_H = E_p[v^*(W_{T+H}(\omega^*, A))|\Omega_T] \tag{4.9}$$

where $v^*(W_{T+H}(\omega^*, A))$ is from (4.5). We can calculate associated sample statistics computed as the average over the number of recursions (N=26,...,15) for each of $H = 1, \ldots, 12$ periods[3]

$$\widehat{\psi}_H = \frac{1}{N}\sum_{n=1}^{N}[v^*(W^{MDB}_{T+H}(n, \omega^*, A))] \tag{4.10}$$

However, we do not know the true probability density function of forecast variables in practice. We can then calculate the ratio of two economic profits with optimal weights

[2] In STATA, I use the command 'DMARIANO' made by Christopher F Baum.

[3] Forecasting horizons (H) and associated recursion numbers (N) : H=1 (N=26),...,H=12 (N=15).

for each of T,H and A like below:

$$Ratio_{T,H,A}^{\frac{MDB}{NoMDB}} = \frac{v^*(W_{T+H}^{MDB}(\omega^*, A))}{v^*(W_{T+H}^{NoMDB}(\omega^*, A))} \tag{4.11}$$

If the null hypothesis of (4.8) is true, the ratio in (4.11) will have unity, which means the MDB predictors are not useful in achieving stock profitability; otherwise, the ratio will statistically have non-unity, which allows us to conclude that MDB predictors are helpful.

4.2.4 Mean-Variance Investor's Portfolio

According to the mean-variance investment theory (Markowitz, 1952) in which one imposes weight on risk against expected return, if one stock performs better in terms of both expected profit and volatility, it is considered that this stock dominates over another stock in portfolio choice. In this case, rational (mean-variance) investors would not choose dominated stock and always invest in dominating stock. Among the stocks and indices in my candidate portfolio objects in this chapter, the dominating-dominated matches are less likely to be helpful in displaying clear predictability of consumer data. Thus, I investigate all combinations of candidate portfolio pairs and focus only on rational (neither dominating nor dominated pairs) portfolio combinations. For example, in Table 4.2, if we compare Morrisons and Sainsbury in portfolio decisions, the expected return of Morrisons is higher than that of Sainsbury, whereas the variance of Morrisons is lower than that of Sainsbury. As we perform a simulation exercise, the simulation suggests that we should buy and hold Morrisons, which is dominating instead of dominated stock. Thus there is no point in doing this exercise.[4] Consequently, I believe we should only focus on a 'rational' combination of portfolios in order to distinguish good predictors from poor ones.

4.3 Modelling Strategy

First, I set up a few candidate predictors of interest. Then, I start forecasting with the benchmark model of VAR (Vector Autoregressions) without candidate MDB predictors. Among the out-of-sample period of the first 26 weeks of 2018, I focus on forecast horizon h=1 to 12, which can be understood as that 'buy and hold for h period'

[4]As we can see in Table 4.2, Tesco stock is dominated by the FTSE350 index in terms of both mean and variance, simulation generates one as a utility ratio, which indicates that it is always better to invest in FTSE350 100% . In Section 4.6.2, this will be illustrated as a robustness check.

Table 4.2: Rational Combinations of Portfolio Components

Excess return	Mean	Std dev	FTSE350 Composite	FTSE350 retail	FTSE350 Food&Drug	Morrisons	Greggs	Sainsbury	Tesco	Ocado
FTSE350 composite	-0.0051	0.0180		Dominated	Rational	Rational	Rational	Dominated	Dominated	Rational
FTSE350 retail	-0.0071	0.0195	Dominated		Rational	Rational	Rational	Rational	Rational	Rational
FTSE Food&Drug	**-0.0052**	**0.0313**	**Rational**	**Rational**		**Rational**	**Rational**	**Dominated**	**Dominated**	**Rational**
Morrisons	**-0.0044**	**0.0349**	**Rational**	**Rational**	**Rational**		**Rational**	**Dominated**	**Dominated**	**Rational**
Greggs	-0.0016	0.0371	Rational	Rational	Rational	Rational		Dominated	Dominated	Dominated
Sainsbury	-0.0057	0.0373	Dominated	Rational	Dominated	Dominated	Dominated		Rational	Rational
Tesco	-0.0054	0.0414	Dominated	Rational	Dominated	Dominated	Dominated	Rational		Rational
Ocado	**-0.0042**	**0.0711**	**Rational**	**Rational**	**Rational**	**Rational**	**Dominated**	**Rational**	**Rational**	

Note: 1) "Rational" means two stocks are not dominated to each other in the context of mean and variance of excess return. "Dominated" means one stock dominates over another stock in terms of the mean and standard deviation of excess return.

strategy. I perform this series of forecast with the rolling-window scheme.[5] Then I could compare the actual profits obtained from portfolio-predictor pairs for each of the forecast horizons h, so that I could find which predictor beats the others. The notations and discussions on simulation technique are mainly based on Garratt et al. (2006)[6]

4.3.1 Vector Autoregressions

Here, following Barberis (2000) and Garratt and Lee (2010), I employ the conventional VAR based density forecasts framework to explore additional information gain from real-time consumer data. The idea behind using the VAR framework is that if the errors in the VAR are assumed to follow the normal distribution, the associated density function of h-step ahead forecast will be normally distributed. Usually, the case of non-normality can be dealt with Monte Carlo methods or bootstrap techniques (Garratt et al., 2006). I employ rolling estimation to consider time-variation in parameters with the normal distribution.[7] I will describe the steps involved in the density forecasts based on VAR following Garratt et al. (2006):

$$y_t = c + A_1 y_{t-1} + \ldots + A_p y_{t-p} + \epsilon_t, \quad t = 1, 2, \ldots, T \tag{4.12}$$

where y_t is an m x 1 vector containing observations on m time-series variables (m=3 w/o MDB predictor, m=4 or 5 with MDB predictor) for t=1,...,T. ϵ_t is a m x 1 vector of errors and is assumed to be a serially uncorrelated i.i.d vector of shocks with zero means and a positive definite covariance matrix, $\sum_\epsilon$. c is a m x 1 vector of intercepts. A_i are m x m coefficients matrices. The vector of errors is assumed as i.i.d N(0,σ). Equation

[5]However, Rapach et al. (2011), Goyal and Welch (2008) and Elliot et al. (2013) adopt the recursively expanding estimation scheme.

[6]I also refer to the associated lecture slides: Garratt. A., *Forecasting economic and financial time series* (Warwick Business School, 2019); Lee. K. C. *Financial and Macro Econometrics* (Nottingham School of Economics, 2019).

[7]For the time-variation in the variance of the error term, we could consider ARCH and GARCH specification. Since my data have at best 150 weekly observations, it does not seem to be possible to employ GARCH specification, so I focus on the rolling window VAR framework.

(4.12) can be re-written as:

$$y_t = c + \sum_{i=1}^{p} A_i y_{t-p} + \epsilon_t, \quad t = 1, 2, ..., T \tag{4.13}$$

4.3.2 General-to-Specific Specification Search

In this forecasting exercise, I use the VAR framework with the so-called 'general to specific' specification search process. This process is supported by a theorem by White (1990), which implies that only the true specification will survive from a stringent enough set of tests at least asymptotically (Hoover and Perez, 1999). The specification search strategy is summarised as follows in practice: for each of the VAR equations, start checking the p-value of the longest lags of variables. Once we cannot reject the null hypothesis of the zero coefficient, reduce the number of lags until we have at least one lag for each variable. In the case that we have a significant coefficient, then remaining lags will survive in the equation. For each movement of rolling windows, we revise this specification search with a newly updated information set. As a result, this VAR framework has at least one lag of each variable while it can have a maximum of four lags with significant p-values.

4.3.3 Stochastic Uncertainty and Simulated Errors

Following Garratt et al. (2006), the h-step ahead point forecasts of the y_{T+h} conditional on information set I_T can be obtained recursively as below

$$y_{T+h} = \widehat{c} + \sum_{i=1}^{p} \widehat{A}_i y_{T+h-i}, \quad h = 1, 2, ..., H \tag{4.14}$$

where the initial values, y_T, y_{T-1},..., y_{T-p+1} are given and $\widehat{A}_i$, $\widehat{c}$ and $\widehat{\sum_\epsilon}$ are estimates of A_i, c and σ_ϵ in (4.13), respectively. Then, we can simulate with stochastic uncertainty to get the density forecast

$$y^{(r)}_{T+h} = \widehat{c} + \sum_{i=1}^{p} \widehat{A}_i y^{(r)}_{T+h-i} + \eta^{(r)}_{T+h}, \quad r = 1, 2, ..., R \tag{4.15}$$

where superscript (r) refers to the r^{th} replication of the simulation algorithm. The $\eta^{(r)}_{T+h}$ can be drawn either by parametric or non-parametric methods (Garratt et al., 2006). The core part of this simulation exercise is to generate proper errors in different equations of VAR. We need to estimate in-sample errors in each equation and future errors such as $\eta^{(r)}_{T+h}$ to take contemporaneous correlations into account from the viewpoint of shocks in the simulation.[8] The parametric approach considers that the errors are

[8]For example, $\eta^{(r)}_{T+h} \quad i = 1, 2, ..., h; r = 1, 2, ..., R$ computed as $\eta^{(r)}_{T+h} = \widehat{P}\epsilon^{(r)}_{T+h}$ with $\widehat{P}$ being the lower

drawn from an assumed probability distribution function, whereas the non-parametric approach generates simulated errors from taking random draws from the in-sample residual vectors with replacement. It is worth doing the non-parametric approach to obtain the same distribution without any distributional assumptions and covariance structures in the original sample; however, it can be exposed to serial dependence especially at longer horizons. Garratt et al. (2006) suggest that the parametric approach is better for longer horizon forecasting exercises. In this paper, I follow the parametric approach of generating simulated error with the normal distribution assumption.

4.4 Data

4.4.1 Data Sources

This paper uses a rich dataset from UK financial aggregator MDB covering the period from January 2012 to February 2018. Here, I use the same data source as in Chapter 2 and Chapter 3, and I cut only a balanced panel of 13,173 individuals for this chapter, as can be seen in Table 4.3.

Table 4.3: Summary Statistics of the Balanced Panel

	N	mean	min	25%	50%	75%	max
Age (years old)	13,173	31	19	25	29	35	52
Gender (1 if female)	13,173	0.44	0	0	0	1	1
Annual income(pounds)	13,173	28,250	1,001	14,317	22,547	34,845	168,613
Income quartiles	13,173	3	1	2	3	4	4

Note: 1) This 13,173 panel is cut to make balanced panel over 39 periods from Jan.2015 to Feb.2018. 2) Income quartiles: 1(lowest) to 4(highest)

Stock market data were retrieved from these sources: *Yahoo finance*, *Bloomberg* and *Investing.com*. The stock prices and trading volume, constituents in each index refer to these sources. The **composite index type** (FTSE350[FTLC]), **sector type** (FTSE Food&Drug Retailer Index [FTNMX5330][9], FTSE General Retailer index [FTNMX5370][10]) and **firm type** (Tesco[TSCO], Sainsbury[SBRY], Ocado[OCDO], Morrisons[MRW] and Greggs[GRG]) are mainly used in this chapter.

triangular Cholesky factor of $\widehat{\sum_{\epsilon}}$. This approach is based on the textbook '*Global and National Macroeconomic Modelling: A Long-Run Structural Approach*' by Garratt et al. (2006).

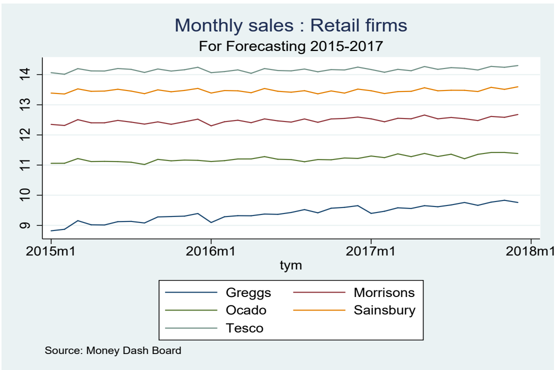
[9]Constituents: Tesco, Morrisons, Sainsbury, Greggs, Ocado.

[10]Constituents: AO World, B&M, Card Factory, Dixons, Dunelm, Halfords, JD Sports, JD Williams, Jacamo, Just Eat, Marks and Spencer, Next, Pets at Home, Saga, Screwfix, Simply Be, Sports Direct, WH Smith.

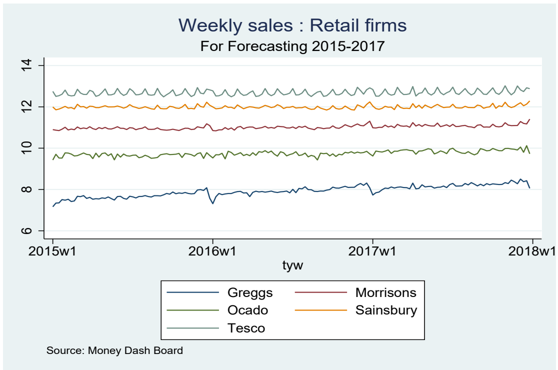
4.4.2 Sample Periods

Sample periods were cut to make a balanced panel between 2015w1 and 2017w52 as the in-sample period. The forecast evaluation is based on the out-of-sample period: 2018w1-2018w26. I assume that investors buy and hold for a 1-week to 12-week period ($h1$ to $h12$).

Figure 4.1: Monthly and Weekly Constructed Retailers' Sales



(A) Monthly Sales of retailers



(B) Weekly Sales of retailers

Note: 1) Source: Yahoo finance, MDB

4.4.3 Data Cleaning and Diagnostic Tests

Seasonal & Calendar Effects

Since this analysis is based on weekly data, it could be argued that seasonality exists in non-financial variables. Thus, I adjust the seasonality by regressing the monthly dummy (M1-M12) and the weekly (of each month) dummy (W1-W4) on the targeted retailers' sales figure following Choi and Min (2016).

$$S_t = \beta Trend_t + \sum_{i=2}^{12} \phi_i MD_{it} + \sum_{i=2}^{4} \phi_i WD_{it} + \sum_{i=1}^{c} \delta_i CD_{it} + \epsilon_t \tag{4.16}$$

where S_t is the weekly sales variable, MD_{it} is the monthly dummy for 12 months, WD_{it} is the weekly dummy for each week of the month and CD_{it} is the calendar dummy for the Easter and Christmas weeks. A trend term is included for any potential trend effect during the three-year period. In this weekly frequency data, the potential seasonality could be adjusted as in the below procedure. From the above equation (4.16), first we regress the dependent variables S_t on trend only to get residuals in which error term and seasonality are included. As the next step, I regress the residual in the first step on monthly, weekly and calendar dummies. Then, the second residual was obtained as a real residual after excluding seasonality. In the third step, once the second residual and fitted trend are gained, these will be the seasonally adjusted variables. Figure 4.7 presents the results of the seasonal adjustment.

Unit Root Test

After adjusting the seasonality in the variables, I perform unit root tests (Tables 4.22-4.25). In the in-sample period from 2015w1 to 2017w52, I test the stationarity of the variables with the Augmented Dickey-Fuller (ADF) test to determine whether the variables are an I(0) or I(1) process, and then proceed the estimation of VAR with only stationary variables.[11]

4.4.4 Variable Construction

Variables for the candidate predictors are constructed based on a weekly frequency.

Forecasts: Stock Excess Return

I construct variables of stock excess return by computing the continuously compounded return on the target stock (without dividends) minus the three-month UK government bond yield. In the case of a buy-and-hold for more than one week, I compute the h-week return from the stock price at time T and stock price at time $T + h$. Then, the stock excess return for h-week is defined as the 'weekly return on target stock for h-week - weekly return on risk-free asset for h-week'.

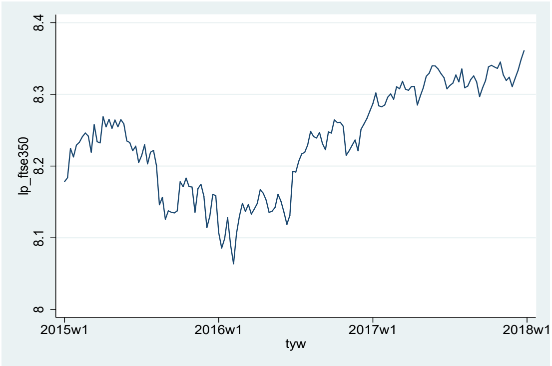
Benchmark Predictor: Oil Price

Choosing the benchmark predictor is not a simple task since there is no dominating theory. Especially when it comes to stock excess return forecasting, financial predictors such as the dividend-yield ratio[12] are widely known to be powerful predictors. However, I deal with weekly frequency investment, so it is not suitable for me to use low-frequency type data. However, the crude oil price is announced on a weekly basis (and even daily) and is considered to reflect economic growth or macro shocks in the economy. Numerous forecasting literature works have used oil prices as the predictors (Narayan et al. 2015). Considering the purpose of a benchmark predictor as a reflection of macro factors, I chose the weekly oil price as the benchmark predictor.

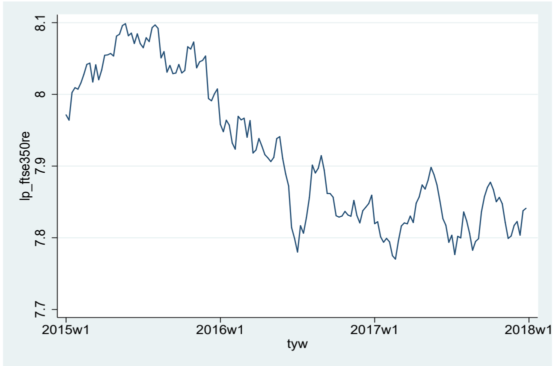
[11]Except for oil price, forecast objects (stock excess return) and predictors are stationary by construction(Details are introduced in Subsection 4.4.4). Thus, I take first difference of the oil price and move on to forecasting exercises.

[12]Dividend-yield is normally computed based on the 'ratio of yield paid over the last 12 months to current stock prices'. However, some firms of interest in this paper have no dividend over two years.

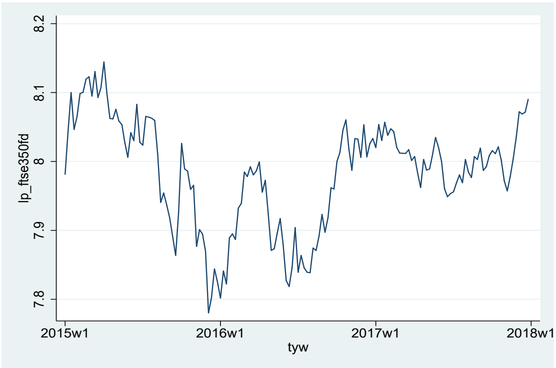
Figure 4.2: Stock Market Variables



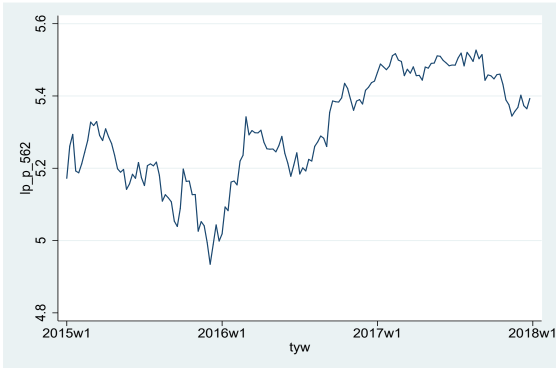
(A) FTSE350 Composite Index



(B) FTSE General Retailer Sector Index



(C) FTSE Food&Drug Retailer Sector Index



(D) Morrisons Firm Stock

Note: 1) Source: Yahoo finance. 2) Stock prices are log-transformed.

MDB Predictors: Macro-level, Category-level, Retail sector-level & Firm-level

The benchmark VAR consists of the i) target forecast, ii) alternative index and iii) oil price. Candidate MDB predictors are based on weekly aggregated variables computed from the balanced panel of 13,173 individuals. I consider four groups of MDB predictors: i) macro-level ii) category-level, iii) retail-sector-level and iv) firm-level.

The **macro-level predictor** is $\widehat{\frac{C}{Y}}$= the ratio predictor of the weekly growth of the aggregate spending to the aggregate income arrivals of the balanced panel.

The **category-level predictors** are constructed by computing (100 + weekly growth rate of one category sales) /(100 + weekly growth rate of the aggregate spending of the balanced panel). Examples of category level predictors are: predictor $\widehat{\frac{N}{C}}$ = the ratio predictor of the weekly growth of the necessary spending to the aggregate spending of the balanced panel, predictor $\widehat{\frac{D}{C}}$ = the ratio predictor of the weekly growth of the discretionary spending to the aggregate spending of the balanced panel.

If I narrow down to sub-categories, I can construct the **retail-sector-level predictor** of $\widehat{\frac{EH}{C}}$ = the ratio predictor of the weekly growth of the eating-at-home spending to the aggregate spending of the balanced panel and the predictor $\widehat{\frac{EO}{C}}$= the ratio predictor of the weekly growth of the eating-out spending to the aggregate spending of the balanced panel.

Finally, the **firm-level predictors** are constructed as follows: for any two firm stocks or indices, I make a ratio of two sales figures from the 13,173 balanced panels. Specifically, predictor $\frac{\widehat{v_A}}{\widehat{v_B}}$ = the ratio predictor of the weekly growth of individual firm A's sales to that of firm B's. This is computed as (100 + weekly growth rate of firm A sales) /(100 + weekly growth rate of firm B sales). Another similar but cost-augmented predictor is $\frac{\widehat{v_1}^{perstore}}{\widehat{v_2}^{perstore}}$= the ratio predictor of the weekly growth of individual firm A's sales per store to that of firm B's. This is obtained by calculation (100 + weekly growth rate of firm A sales per number of stores) /(100 + weekly growth rate of firm B sales per number of stores).

Portfolio Construction: Intra-Aggregation and Inter-Aggregation Level

The constructed MDB predictors in the previous subsection are closely related to the portfolio strategy in order to achieve profitability. I introduce an **intra-aggregation level portfolio**, which means two portfolio components are from the same aggregation levels (i.e. [firm stock-firm stock] or [sector index-sector index]). However, an **inter-aggregation level portfolio** indicates that two portfolio components are from different aggregation levels (i.e. [firm-sector index], [firm-composite index], [sector-composite index]). Below, Table 4.4 summarises this strategy.

Table 4.4: Investment Strategy: Intra & Inter Aggregation Level Portfolio and Predictors

Subset	Portfolio	Stock A	Stock B	Predictor_Baseline	Predictor_MDB
FF	Firm - Firm (Intra)	Firm1	Firm2	Oil	$\frac{\widehat{v_1}}{\widehat{v_2}}, \frac{\widehat{v_1}^{perstore}}{\widehat{v_2}^{perstore}}$
FS	Firm - Sector (Inter)	Firm1	Sector	Oil	$\frac{\widehat{v}}{\widehat{V}}, \frac{\widehat{v}^{perstore}}{\widehat{V}}, \frac{\widehat{N}}{\widehat{C}}, \frac{\widehat{D}}{\widehat{C}}, \frac{\widehat{EH}}{\widehat{C}}, \frac{\widehat{EO}}{\widehat{C}}, \frac{\widehat{C}}{\widehat{Y}}$
FI	Firm - Index (Inter)	Firm1	Index	Oil	$\frac{\widehat{v}}{\widehat{V}}, \frac{\widehat{v}^{perstore}}{\widehat{V}}, \frac{\widehat{N}}{\widehat{C}}, \frac{\widehat{D}}{\widehat{C}}, \frac{\widehat{EH}}{\widehat{C}}, \frac{\widehat{EO}}{\widehat{C}}, \frac{\widehat{C}}{\widehat{Y}}$
SS	Sector - Sector (Intra)	Sector1	Sector2	Oil	$\frac{\widehat{v_1}}{\widehat{v_2}}, \frac{\widehat{N}}{\widehat{C}}, \frac{\widehat{D}}{\widehat{C}}, \frac{\widehat{EH}}{\widehat{C}}, \frac{\widehat{EO}}{\widehat{C}}, \frac{\widehat{C}}{\widehat{Y}}$
SI	Sector - Index (Inter)	Sector1	Index	Oil	$\frac{\widehat{v}}{\widehat{V}}, \frac{\widehat{N}}{\widehat{C}}, \frac{\widehat{D}}{\widehat{C}}, \frac{\widehat{EH}}{\widehat{C}}, \frac{\widehat{EO}}{\widehat{C}}, \frac{\widehat{C}}{\widehat{Y}}$

Note: 1) $\frac{\widehat{V_1}}{\widehat{V_2}} = \frac{100+\dot{V_1}}{100+\dot{V_2}}$ where lowercase "$\dot{v}$" is weekly growth rate of individual firm or sector sales variable and the uppercase "$\dot{V}$" is weekly growth rate of aggregate category sales variable.

4.5 Investigating Real-Time Value of MDB Predictors

I report forecasting performances of each pair of portfolio-predictors based on different risk aversions $A(= 2, 5, 10)$, one to three months ahead horizons (out of 1 to 12 week ahead forecasting horizons) and 10%, 20% and 30% significance levels. In each month, I compute the net proportion (%p) of utility improved horizons.[13] (hereinafter, referred to as, UIHs). The benchmark VAR consists of i) first stock or index, ii) second stock or index and iii) oil price. The candidate MDB predictors are $\frac{\widehat{v_1}}{\widehat{v_2}}$: firm-level sales ratio, $\frac{\widehat{N}}{\widehat{C}}$: necessary spending ratio, $\frac{\widehat{D}}{\widehat{C}}$: discretionary spending ratio, $\frac{\widehat{EH}}{\widehat{C}}$: eating-at-home spending ratio, $\frac{\widehat{EO}}{\widehat{C}}$: eating-out spending ratio and $\frac{\widehat{C}}{\widehat{Y}}$: macro spending ratio.

4.5.1 Forecasting Sector Excess Return

Forecasting Sector: When the Alternative Choice is Another Sector

In Table 4.6, we deal with an investment problem between two intra-aggregation level sectors of Food&Drug retailer (5 firms) and General Retailer (13 firms). Here I focus on firm-level predictors (ratio of the growth rate of sales between two sectors). This is because there are specific constituents in each sector, so I expect that firm-level predictors can be effective in portfolio decisions in the short-run. Another prediction is that we can consider the Food&Drug retailer sales to represent the necessary item spending and eating-at-home item spending while the General Retailer sales reflect the discretionary item spending. Then, we might guess that category-level predictors can be helpful in this intra-aggregation portfolio.

The results are consistent with these predictions. Table 4.6 shows the net proportion (%p) of utility improved horizons. The $\frac{\widehat{D}}{\widehat{C}}$ (category-level predictors) and $\frac{\widehat{EH}}{\widehat{C}}$ (eating-at-home predictor) are pronounced, and $\frac{\widehat{fd}}{\widehat{ge}}$ (firm-level predictor) is less powerful but the improvements are still significant. Considering that the "eating-at-home predictor" reflects its retail-sector-level spending, it makes sense that sub-category spending well tracks its corresponding portfolio stock movements. Since the targets in this portfolio are sector aggregates, we can conclude that category-level and retail-level predictors can be helpful in achieving higher economic profits, especially in one to two month periods.

Forecasting Sector: When the Alternative Choice is a Composite Index

This combination of forecasts can be defined as the inter-aggregation level portfolio since the sector and composite indices are from different aggregation levels.

[13]Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons)

Table 4.7 shows the percentage points (%p) of the net UIHs for each of one-month to three-month forecasting horizons. When investing in portfolios between the FTSE Food&Drug sector and FTSE 350 composite index, category-level predictors such as $\frac{\widehat{N}}{\widehat{C}}$ (necessary spending ratio) and $\frac{\widehat{D}}{\widehat{C}}$ (discretionary spending ratio) are powerful in both a one-month period and the total period. However, $\frac{\widehat{C}}{\widehat{Y}}$ (macro-level predictor) does not seem to provide extra information gain on top of the oil price. Therefore, we can conclude that category-level variables well predict sector-index portfolios; specifically, the $\frac{\widehat{N}}{\widehat{C}}$ (necessary spending ratio) predictor performs best in investing in the Food&Drug sector and composite index. It looks convincing since the FTSE Food&Drug sector represents necessary goods rather than discretionary spending.

4.5.2 Forecasting Firm Excess Return

Similar to the exercises in Section 4.5.1, firm forecasts use the same predictors as well as cost-augmented firm-level predictors.

Forecasting Firms: When the Alternative Choice is Another Firm

In Table 4.8, we now deal with a firm-firm portfolio exercise. I choose portfolio decisions over two firms: Morrisons and Greggs, which are in the FTSE Food&Drug sector index. My initial prediction suggests that firm-level predictors and cost-augmented firm-level predictors will be the most powerful among the candidate predictors. This is because firm-level predictors represent the relative changes in each firm's spending. The simulation exercises confirm that these firm-level predictors are the strongest predictors. In this exercise, cost-augmented firm-level predictors achieve higher economic profits than pure firm-level predictors even in the one-month period as well as 10% significance level. In the case of the Morrisons and Ocado exercise (Table 4.9), the results are consistent with the Morrisons and Greggs case.

The examples of firm-firm portfolio results are even stronger in Table 4.10 in that the firm-level predictors tend to be more powerful than macro-level predictors $\frac{\widehat{C}}{\widehat{Y}}$ regardless of the portfolio component pairs.

Forecasting Firms: When the Alternative Choice is a Sector Index

In this subsection, a portfolio between firm and sector indices is simulated. In Table 4.11, the firm/sector predictors and retail-sector level predictors are powerful, whereas the category level predictors are weak in all periods. Due to the fact that the Food&Drug sector index has five firms including Morrisons, it is expected that firm/sector predictor($\frac{\widehat{m}}{\widehat{fd}}$) should be powerful, and the results are consistent with this prediction.

In Table 4.12, the net proportions of UIHs are pronounced when Morrisons is invested in a pair with the General Retailer sector. Since Morrisons is a big constituent in the Food&Drug sector, it can represent the eating-at-home or necessary items. The FTSE General Retailer represents the discretionary and eating-out spending. Thus, I expect $\frac{\widehat{m}}{\widehat{ge}}$, $\frac{\widehat{EH}}{\widehat{C}}$ and $\frac{\widehat{D}}{\widehat{C}}$ would be good predictors. The results are somewhat mixed up. In a one-month period, the $\frac{\widehat{EH}}{\widehat{C}}$ and $\frac{\widehat{D}}{\widehat{C}}$ predictors are consistent with my predictions on performance.

Forecasting Firms: When Alternative Choice is a Composite Index

In Table 4.13, we now pay attention to portfolio decisions between a highly disaggregate individual firm and a highly aggregate composite index. The results of firm-level predictors look disappointing in that the net proportions of the UIH in the total period are almost negative in the one-month and two-month periods. Even though there are some improvements in the three-month periods, we cannot be sure that the firm-level predictors here are helpful in portfolio decisions because we focus on short-term predictability. Firm-level predictors are poor in forecasting firm-index level portfolios. I suspect that the predictors constructed from the firm-level and macro-level are not an ideal pair to allow good information gain due to the serious gap in aggregation level for both the forecasts and predictors. Instead, category-level predictors ($\frac{\widehat{N}}{\widehat{C}}$ and $\frac{\widehat{D}}{\widehat{C}}$) are somewhat better than the firm-level predictors.

4.5.3 Two MDB Predictors Exercises

One potential question is whether forecasting performance can be improved if we employ more than a single MDB predictor. In this section, I perform exercises with five variable VAR specifications. Instead of just one predictor from MDB, I include two strong predictors from the firm/category/macro-level predictors separately. Then, I compare the forecasting performance between a four-variable VAR and five-variable VAR.

Adding Extra Predictors in the Sector Forecasting

In the four-variable VAR exercise, the sector-index portfolio achieves the highest prediction when it uses category level predictor ($\frac{\widehat{N}}{\widehat{C}}$) as well as firm-level predictor ($\frac{\widehat{fd}}{\widehat{C}}$). As in Table 4.14, the five-variable VAR exercise shows that there are significant improvements in the forecasting performance when we include the two best predictors are included.

Another sector-sector portfolio achieves the highest prediction when it uses firm-level predictor ($\frac{\widehat{m}}{\widehat{g}}$) as well as macro-level predictor ($\frac{\widehat{C}}{\widehat{Y}}$). From Table 4.15, the five-variable VAR exercise shows that there are significant utility improvements when the two best predictors are included.

Adding Extra Predictors in the Firm Forecasting

The results are similar to those of the sector forecasting exercises. If the existing MDB predictor is poor, the power of another strong predictor is limited as the fourth columns in Table 4.16-4.17 suggest. However, we can still say that an extra predictor contributes to forecasting performances to a certain degree, especially in a one-month period (1-4 weeks ahead).

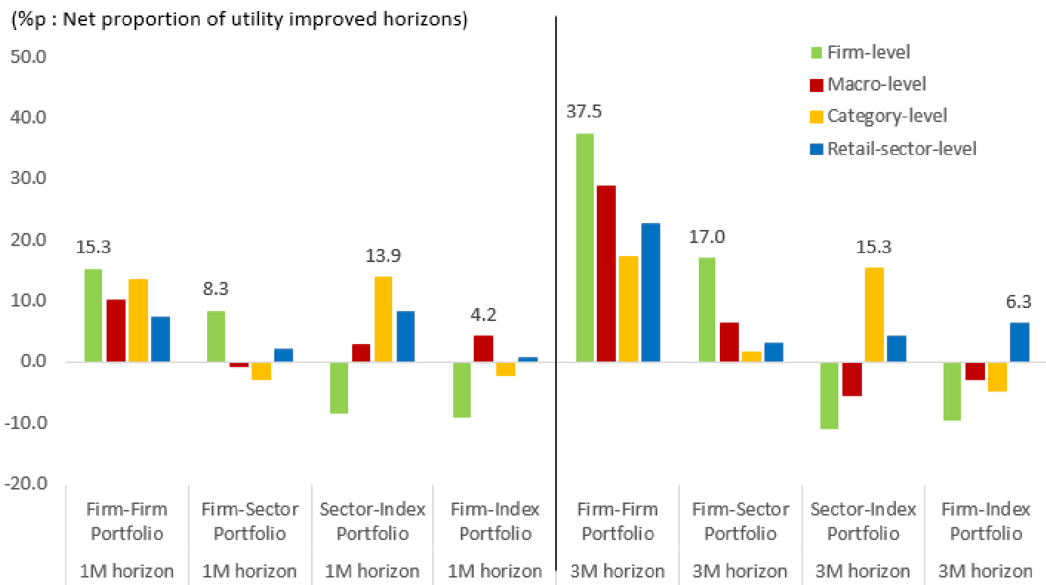
4.5.4 Discussion: Performances of MDB Predictors

Since the MDB data are very detailed disaggregate information, it is natural to investigate what kind of aggregation level from individual transaction-level spending data is needed in order to achieve stock profitability. After confirming that MDB predictors contribute to predictability in the financial market, a corresponding assessment is performed at each of 10% 20%, and 30% significance levels. If we want to use sales figures information from highly disaggregate data, the first thing to consider is to choose portfolio stocks that are consistent with the 'mean-variance' investment theory. It is not reasonable to invest in between dominating-dominated portfolios if we want to use high-frequency sales information. In terms of how to use consumer data in portfolio decisions, we can conclude that we should use specific firm-level sales data in the portfolios of similarly aggregated stocks (Intra-aggregation level). When it comes to sector-index portfolios, category-level predictors perform relatively well. However, consumer data are not helpful in the portfolio of a highly disaggregate firm and highly aggregate index in this paper's exercises. Thus, if we are to use consumer real-time data in achieving higher profits in the short-run, in which we do not have enough financial market data, employing specifically identified firms' sales data will allow us to achieve higher economic profits in the case of investing in two similar aggregate level stocks.

The overall pattern is summarised in Figure 4.3. Firm-firm investment and firm-sector investment perform best with firm-level predictors. Sector-index investment performs better with category-level predictors. However, firm-index was the worst in exploiting consumer data in stock profitability.

Additionally, even though more predictors do not necessarily generate higher profits, it is suggested that it is better to include combinations of powerful predictors only if computing capabilities are allowed.[14]

Figure 4.3: Summary of Net Proportions (%p) of Utility Improved Horizons



Note: 1) Net utility improvements are computed as average over the same portfolio groups: Firm-Firm (Food&Drug-General Retailer, Morrisons-Greggs, Morrisons-Ocado), Firm-Sector (Morrisons-Food&Drug, Morrisons-General Retailer, Ocado-Food&Drug, Ocado-General Retailer), Sector-Index (Food&Drug-FTSE 350 Composite Index , Firm-Index (Morrisons-FTSE 350 Composite Index, Ocado-FTSE 350 Composite Index)

[14]This is consistent with the theoretical approach (Elliott et al. 2013) in that many predictors do not necessarily provide forecasting power.

Table 4.5: Variables Construction and Candidate Combinations of Predictors

		Firms	Sectors	Aggregate spending
Components		$\widehat{m}$:morrisons $\widehat{o}$:ocado $\widehat{g}$:greggs $\widehat{t}$:tesco $\widehat{s}$:sainsbury	$\widehat{fd}$:FTSE Food&Drug retailers $\widehat{ge}$: FTSE General retilers	$\widehat{C}$:All type spending $\widehat{N}$: Necessary spending $\widehat{D}$:Discretionary spending $\widehat{EH}$:Eating-at-home spending $\widehat{EO}$:Eating-out spending $\widehat{Y}$:Income arrivals
Predictors	Firms	$\frac{\widehat{Firm1}}{\widehat{Firm2}}$	-	-
	Sectors	$\frac{\widehat{Firm}}{\widehat{Sector}}$	$\frac{\widehat{Sector1}}{\widehat{Sector2}}$	-
	Aggregate	$\frac{\widehat{Firm}}{\widehat{Aggregate}}$	$\frac{\widehat{Sector}}{\widehat{Aggregate}}$	$\frac{\widehat{Aggregate1}}{\widehat{Aggregate2}}$

Note: 1) $\frac{\widehat{V_1}}{\widehat{V_2}} = \frac{100+\dot{V_1}}{100+\dot{V_2}}$ where $\dot{v}$ = weekly growth rate of individual firm or sector sales variable and $\dot{V}$ = weekly growth rate of aggregate category sales variable.

Table 4.6: Performance: FTSE Food&Drug Retailer Vs. FTSE General Retailer

Positive-Negative (%p)		Firm-level $\frac{\widehat{fd}}{\widehat{ge}}$	Firm-level $\frac{\widehat{fd}^{perstore}}{\widehat{ge}^{perstore}}$	Macro $\frac{\widehat{C}}{\widehat{Y}}$	Category-level $\frac{\widehat{N}}{\widehat{C}}$	Category-level $\frac{\widehat{D}}{\widehat{C}}$	Retail-level $\frac{\widehat{EH}}{\widehat{C}}$	Retail-level $\frac{\widehat{EO}}{\widehat{C}}$
Total	p0.10	30.6	-	22.2	33.3	41.7	55.6	41.7
	p0.20	36.1	-	33.3	27.8	44.4	61.1	44.4
	p0.30	27.8	-	38.9	38.9	50.0	55.6	52.8
1-4 ahead	p0.10	22.2	-	16.7	19.4	33.3	33.3	16.7
	p0.20	27.8	-	16.7	22.2	33.3	33.3	16.7
	p0.30	27.8	-	16.7	22.2	33.3	33.3	16.7
5-8 ahead	p0.10	11.1	-	8.3	13.9	-8.3	16.7	11.1
	p0.20	8.3	-	11.1	0.0	-11.1	16.7	11.1
	p0.30	0.0	-	5.6	0.0	-16.7	5.6	8.3
9-12 ahead	p0.10	-2.8	-	-2.8	0.0	16.7	5.6	13.9
	p0.20	0.0	-	5.6	5.6	22.2	11.1	16.7
	p0.30	0.0	-	16.7	16.7	33.3	16.7	27.8

Note: 1) p0.10 indicates significance at 10%. 2) Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

Table 4.7: Performance: FTSE Food&Drug Retailer Vs. FTSE 350 Index

Positive-Negative (%p)		Firm-level $\frac{\widehat{fd}}{\widehat{C}}$	Firm-level $\frac{\widehat{fd}^{perstore}}{\widehat{C}}$	Macro $\frac{\widehat{C}}{\widehat{Y}}$	Category-level $\frac{\widehat{N}}{\widehat{C}}$	Category-level $\frac{\widehat{D}}{\widehat{C}}$	Retail-level $\frac{\widehat{EH}}{\widehat{C}}$	Retail-level $\frac{\widehat{EO}}{\widehat{C}}$
Total	p0.10	-11.1	-	-5.6	11.1	19.4	11.1	-2.8
	p0.20	27.8	-	16.7	41.7	36.1	11.1	8.3
	p0.30	25.0	-	38.9	63.9	33.3	25.0	13.9
1-4 ahead	p0.10	-8.3	-	2.8	16.7	11.1	11.1	5.6
	p0.20	16.7	-	16.7	33.3	27.8	2.8	16.7
	p0.30	16.7	-	16.7	33.3	27.8	11.1	16.7
5-8 ahead	p0.10	-2.8	-	-8.3	-5.6	8.3	0.0	-8.3
	p0.20	2.8	-	0.0	8.3	8.3	8.3	-8.3
	p0.30	2.8	-	16.7	16.7	8.3	16.7	-8.3
9-12 ahead	p0.10	0.0	-	0.0	0.0	0.0	0.0	0.0
	p0.20	8.3	-	0.0	0.0	0.0	0.0	0.0
	p0.30	5.6	-	5.6	13.9	-2.8	-2.8	5.6

Note: 1) p0.10 indicates significance at 10%. 2) Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

Table 4.8: Performance: Morrisons Vs. Greggs

Positive-Negative (%p)		Firm-level $\frac{\widehat{m}}{\widehat{g}}$	$\frac{\widehat{m}^{perstore}}{\widehat{g}^{perstore}}$	Macro $\frac{\widehat{C}}{\widehat{Y}}$	Category-level $\frac{\widehat{N}}{\widehat{C}}$	$\frac{\widehat{D}}{\widehat{C}}$	Retail-level $\frac{\widehat{EH}}{\widehat{C}}$	$\frac{\widehat{EO}}{\widehat{C}}$
Total	p0.10	61.1	69.4	41.7	41.7	-2.8	30.6	16.7
	p0.20	69.4	88.9	44.4	61.1	19.4	50.0	63.9
	p0.30	77.8	88.9	36.1	61.1	25.0	55.6	69.4
1-4 ahead	p0.10	22.2	30.6	19.4	22.2	11.1	22.2	5.6
	p0.20	27.8	33.3	22.2	27.8	22.2	22.2	16.7
	p0.30	27.8	33.3	22.2	27.8	22.2	22.2	16.7
5-8 ahead	p0.10	13.9	25.0	13.9	2.8	-16.7	5.6	8.3
	p0.20	16.7	33.3	22.2	0.0	-16.7	13.9	22.2
	p0.30	16.7	33.3	22.2	0.0	-16.7	11.1	22.2
9-12 ahead	p0.10	25.0	13.9	8.3	16.7	2.8	2.8	2.8
	p0.20	25.0	22.2	0.0	33.3	13.9	13.9	25.0
	p0.30	33.3	22.2	-8.3	33.3	19.4	22.2	30.6

Note: 1) p0.10 indicates significance at 10%. 2) Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

Table 4.9: Performance: Morrisons Vs. Ocado

Positive-Negative (%p)		Firm-level $\frac{\widehat{m}}{\widehat{o}}$	$\frac{\widehat{m}^{perstore}}{\widehat{o}^{perstore}}$	Macro $\frac{\widehat{C}}{\widehat{Y}}$	Category-level $\frac{\widehat{N}}{\widehat{C}}$	$\frac{\widehat{D}}{\widehat{C}}$	Retail-level $\frac{\widehat{EH}}{\widehat{C}}$	$\frac{\widehat{EO}}{\widehat{C}}$
Total	p0.10	38.9	25.0	22.2	0.0	-11.1	-22.2	13.9
	p0.20	58.3	22.2	50.0	27.8	-8.3	-13.9	22.2
	p0.30	55.6	22.2	55.6	25.0	-11.1	-16.7	22.2
1-4 ahead	p0.10	16.7	0.0	-5.6	8.3	-13.9	-33.3	0.0
	p0.20	16.7	0.0	0.0	16.7	-5.6	-33.3	0.0
	p0.30	16.7	0.0	0.0	16.7	-5.6	-33.3	0.0
5-8 ahead	p0.10	22.2	8.3	25.0	-11.1	-2.8	-13.9	11.1
	p0.20	19.4	11.1	33.3	-8.3	2.8	-13.9	11.1
	p0.30	16.7	11.1	33.3	-11.1	0.0	-16.7	11.1
9-12 ahead	p0.10	0.0	16.7	2.8	2.8	5.6	25.0	2.8
	p0.20	22.2	11.1	16.7	19.4	-5.6	33.3	11.1
	p0.30	22.2	11.1	22.2	19.4	-5.6	33.3	11.1

Note: 1) p0.10 indicates significance at 10%. 2)Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

Table 4.10: Performance: Firm Portfolios Comparison

Positive-Negative (%p)		Morrisons-Greggs			Morrisons-Ocado			Ocado-Tesco			Ocado-Sainsbury		
		$\frac{\widehat{m}}{\widehat{g}}$	$\frac{\widehat{m}^{perstore}}{\widehat{g}^{perstore}}$	$\frac{\widehat{C}}{\widehat{Y}}$	$\frac{\widehat{m}}{\widehat{o}}$	$\frac{\widehat{m}^{perstore}}{\widehat{o}^{perstore}}$	$\frac{\widehat{C}}{\widehat{Y}}$	$\frac{\widehat{o}}{\widehat{t}}$	$\frac{\widehat{o}^{perstore}}{\widehat{t}^{perstore}}$	$\frac{\widehat{C}}{\widehat{Y}}$	$\frac{\widehat{o}}{\widehat{s}}$	$\frac{\widehat{o}^{perstore}}{\widehat{s}^{perstore}}$	$\frac{\widehat{C}}{\widehat{Y}}$
Total	p0.10	61.1	69.4	41.7	38.9	25.0	22.2	33.3	47.2	-2.8	33.3	36.1	-5.6
	p0.20	69.4	88.9	44.4	58.3	22.2	50.0	61.1	55.6	-16.7	66.7	66.7	2.8
	p0.30	77.8	88.9	36.1	55.6	22.2	55.6	63.9	55.6	-16.7	66.7	66.7	5.6
1-4 ahead	p0.10	22.2	30.6	19.4	16.7	0.0	-5.6	11.1	25.0	19.4	8.3	25.0	-16.7
	p0.20	27.8	33.3	22.2	16.7	0.0	0.0	16.7	25.0	16.7	16.7	25.0	-16.7
	p0.30	27.8	33.3	22.2	16.7	0.0	0.0	16.7	25.0	16.7	16.7	25.0	-16.7
5-8 ahead	p0.10	13.9	25.0	13.9	22.2	8.3	25.0	13.9	16.7	-13.9	11.1	0.0	-13.9
	p0.20	16.7	33.3	22.2	19.4	11.1	33.3	27.8	16.7	-16.7	33.3	8.3	-11.1
	p0.30	16.7	33.3	22.2	16.7	11.1	33.3	30.6	16.7	-16.7	33.3	8.3	-11.1
9-12 ahead	p0.30	25.0	13.9	8.3	0.0	16.7	2.8	8.3	5.6	-8.3	13.9	11.1	25.0
	p0.50	25.0	22.2	0.0	22.2	11.1	16.7	16.7	13.9	-16.7	16.7	33.3	30.6
	p1.00	33.3	22.2	-8.3	22.2	11.1	22.2	16.7	13.9	-16.7	16.7	33.3	33.3

Note: 1) p0.10 indicates significance at 10%. 2) Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

Table 4.11: Performance: Morrisons Vs. FTSE Food&Drug Retailer

Positive-Negative (%p)		Firm-level		Macro	Category-level		Retail-level	
		$\frac{\widehat{m}}{\widehat{fd}}$	$\frac{\widehat{m}^{perstore}}{\widehat{fd}}$	$\frac{\widehat{C}}{\widehat{Y}}$	$\frac{\widehat{N}}{\widehat{C}}$	$\frac{\widehat{D}}{\widehat{C}}$	$\frac{\widehat{EH}}{\widehat{C}}$	$\frac{\widehat{EO}}{\widehat{C}}$
Total	p0.10	11.1	11.1	2.8	-11.1	-25.0	8.3	-11.1
	p0.20	30.6	8.3	11.1	-13.9	-27.8	27.8	-5.6
	p0.30	27.8	0.0	11.1	-8.3	-25.0	27.8	2.8
1-4 ahead	p0.10	8.3	8.3	8.3	-5.6	-16.7	8.3	5.6
	p0.20	5.6	11.1	8.3	-2.8	-16.7	16.7	5.6
	p0.30	5.6	11.1	5.6	-5.6	-16.7	16.7	5.6
5-8 ahead	p0.10	2.8	-8.3	0.0	-5.6	-2.8	-5.6	-11.1
	p0.20	19.4	-13.9	11.1	-13.9	0.0	-8.3	-8.3
	p0.30	16.7	-22.2	13.9	-5.6	2.8	-8.3	0.0
9-12 ahead	p0.10	0.0	11.1	-5.6	0.0	-5.6	5.6	-5.6
	p0.20	5.6	11.1	-8.3	2.8	-11.1	19.4	-2.8
	p0.30	5.6	11.1	-8.3	2.8	-11.1	19.4	-2.8

Note: 1) p0.10 indicates significance at 10%. 2) Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

Table 4.12: Performance: Morrisons Vs. FTSE General Retailer

Positive-Negative (%p)		Firm-level		Macro	Category-level		Retail-level	
		$\frac{\widehat{m}}{\widehat{ge}}$	$\frac{\widehat{m}^{perstore}}{\widehat{ge}}$	$\frac{\widehat{C}}{\widehat{Y}}$	$\frac{\widehat{N}}{\widehat{C}}$	$\frac{\widehat{D}}{\widehat{C}}$	$\frac{\widehat{EH}}{\widehat{C}}$	$\frac{\widehat{EO}}{\widehat{C}}$
Total	p0.10	2.8	-5.6	-5.6	-5.6	22.2	2.8	-8.3
	p0.20	0.0	-8.3	-5.6	-13.9	19.4	2.8	-19.4
	p0.30	2.8	-5.6	-2.8	-11.1	19.4	0.0	-22.2
1-4 ahead	p0.10	2.8	-8.3	-5.6	-8.3	19.4	5.6	-5.6
	p0.20	5.6	-11.1	0.0	-2.8	27.8	11.1	-11.1
	p0.30	5.6	-11.1	0.0	0.0	27.8	11.1	-11.1
5-8 ahead	p0.10	-2.8	0.0	-2.8	0.0	0.0	-5.6	-2.8
	p0.20	-8.3	0.0	-8.3	-13.9	-8.3	-8.3	-5.6
	p0.30	-5.6	2.8	-5.6	-13.9	-8.3	-11.1	-8.3
9-12 ahead	p0.10	2.8	2.8	2.8	2.8	2.8	2.8	0.0
	p0.20	2.8	2.8	2.8	2.8	0.0	0.0	-2.8
	p0.30	2.8	2.8	2.8	2.8	0.0	0.0	-2.8

Note: 1) p0.10 indicates significance at 10%. 2) Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

Table 4.13: Performance: Morrisons Vs. FTSE 350 Index

Positive-Negative (%p)		Firm-level		Macro	Category-level		Retail-level	
		$\frac{\widehat{m}}{\widehat{C}}$	$\frac{\widehat{m}^{perstore}}{\widehat{C}}$	$\frac{\widehat{C}}{\widehat{Y}}$	$\frac{\widehat{N}}{\widehat{C}}$	$\frac{\widehat{D}}{\widehat{C}}$	$\frac{\widehat{EH}}{\widehat{C}}$	$\frac{\widehat{EO}}{\widehat{C}}$
Total	p0.10	-22.2	-16.7	-22.2	19.4	30.6	5.6	8.3
	p0.20	-27.8	-5.6	-27.8	5.6	38.9	5.6	0.0
	p0.30	-27.8	-5.6	-27.8	5.6	38.9	5.6	0.0
1-4 ahead	p0.10	-16.7	-5.6	5.6	16.7	16.7	0.0	16.7
	p0.20	-16.7	-5.6	5.6	16.7	16.7	0.0	16.7
	p0.30	-16.7	-5.6	5.6	16.7	16.7	0.0	16.7
5-8 ahead	p0.10	-19.4	-5.6	-8.3	0.0	5.6	8.3	-16.7
	p0.20	-16.7	0.0	-13.9	-5.6	11.1	8.3	-16.7
	p0.30	-16.7	0.0	-16.7	-5.6	11.1	5.6	-16.7
9-12 ahead	p0.10	13.9	-5.6	-19.4	2.8	8.3	-2.8	8.3
	p0.20	5.6	0.0	-19.4	-5.6	11.1	-2.8	0.0
	p0.30	5.6	0.0	-16.7	-5.6	11.1	0.0	0.0

Note: 1) p0.10 indicates significance at 10%. 2) Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

Table 4.14: Extra predictor: FTSE Food&Drug Vs. FTSE 350 Index

Positive-Negative (%p)		$\frac{\widehat{fd}}{\widehat{C}}$	$\frac{\widehat{N}}{\widehat{C}}$	$\frac{\widehat{C}}{\widehat{Y}}$	$\frac{\widehat{N}}{\widehat{C}}+\frac{\widehat{fd}}{\widehat{C}}$	$\frac{\widehat{C}}{\widehat{Y}}+\frac{\widehat{fd}}{\widehat{C}}$
Total	p0.10	-11.1	11.1	-5.6	30.6	-5.6
	p0.20	27.8	41.7	16.7	36.1	-8.3
	p0.30	25.0	63.9	38.9	38.9	-11.1
1-4 ahead	p0.10	-8.3	16.7	2.8	30.6	-2.8
	p0.20	16.7	33.3	16.7	33.3	0.0
	p0.30	16.7	33.3	16.7	33.3	0.0
5-8 ahead	p0.10	-2.8	-5.6	-8.3	0.0	-2.8
	p0.20	2.8	8.3	0.0	2.8	-8.3
	p0.30	2.8	16.7	16.7	8.3	-8.3
9-12 ahead	p0.10	0.0	0.0	0.0	0.0	0.0
	p0.20	8.3	0.0	0.0	0.0	0.0
	p0.30	5.6	13.9	5.6	-2.8	-2.8

Note: 1) p0.10 indicates significance at 10%. 2) Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

Table 4.15: Extra predictor: FTSE Food&Drug Vs. FTSE General Retailers

Positive-Negative (%p)		$\frac{\widehat{fd}}{\widehat{C}}$	$\frac{\widehat{N}}{\widehat{C}}$	$\frac{\widehat{C}}{\widehat{Y}}$	$\frac{\widehat{N}}{\widehat{C}}+\frac{\widehat{fd}}{\widehat{C}}$	$\frac{\widehat{C}}{\widehat{Y}}+\frac{\widehat{fd}}{\widehat{C}}$
Total	p0.10	30.6	-0.3	22.2	-19.4	41.7
	p0.20	36.1	-0.1	33.3	-27.8	52.8
	p0.30	27.8	-1.0	38.9	-33.3	55.6
1-4 ahead	p0.10	22.2	-1.0	16.7	2.8	27.8
	p0.20	27.8	-0.2	16.7	0.0	27.8
	p0.30	27.8	-0.1	16.7	0.0	27.8
5-8 ahead	p0.10	11.1	-0.1	8.3	-5.6	0.0
	p0.20	8.3	-1.0	11.1	-11.1	2.8
	p0.30	0.0	-0.3	5.6	-16.7	0.0
9-12 ahead	p0.10	-2.8	-0.2	-2.8	-16.7	13.9
	p0.20	0.0	-0.1	5.6	-16.7	22.2
	p0.30	0.0	-1.0	16.7	-16.7	27.8

Note: 1) p0.10 indicates significance at 10%. 2) Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

Table 4.16: Extra predictor: Morrisons Vs. FTSE 350 Index

Positive-Negative (%p)		$\frac{\widehat{fd}}{\widehat{C}}$	$\frac{\widehat{N}}{\widehat{C}}$	$\frac{\widehat{C}}{\widehat{Y}}$	$\frac{\widehat{N}}{\widehat{C}}+\frac{\widehat{fd}}{\widehat{C}}$	$\frac{\widehat{C}}{\widehat{Y}}+\frac{\widehat{fd}}{\widehat{C}}$
Total	p0.10	-22.2	19.4	-22.2	-13.9	8.3
	p0.20	-27.8	5.6	-27.8	-19.4	5.6
	p0.30	-27.8	5.6	-27.8	-22.2	5.6
1-4 ahead	p0.10	-16.7	16.7	5.6	-33.3	19.4
	p0.20	-16.7	16.7	5.6	-33.3	22.2
	p0.30	-16.7	16.7	5.6	-33.3	22.2
5-8 ahead	p0.10	-19.4	0.0	-8.3	-2.8	-5.6
	p0.20	-16.7	-5.6	-13.9	-5.6	-5.6
	p0.30	-16.7	-5.6	-16.7	-5.6	-5.6
9-12 ahead	p0.10	13.9	2.8	-19.4	19.4	-5.6
	p0.20	5.6	-5.6	-19.4	19.4	-11.1
	p0.30	5.6	-5.6	-16.7	16.7	-11.1

Note: 1) p0.10 indicates significance at 10%. 2) Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

Table 4.17: Extra predictor: Morrisons Vs. FTSE Food&Drug Retailer

Positive-Negative (%p)		$\frac{\widehat{fd}}{\widehat{C}}$	$\frac{\widehat{N}}{\widehat{C}}$	$\frac{\widehat{C}}{\widehat{Y}}$	$\frac{\widehat{N}}{\widehat{C}}+\frac{\widehat{fd}}{\widehat{C}}$	$\frac{\widehat{C}}{\widehat{Y}}+\frac{\widehat{fd}}{\widehat{C}}$
Total	p0.10	11.1	-11.1	2.8	-25.0	2.8
	p0.20	30.6	-13.9	11.1	-47.2	13.9
	p0.30	27.8	-8.3	11.1	-44.4	16.7
1-4 ahead	p0.10	8.3	-5.6	8.3	-13.9	5.6
	p0.20	5.6	-2.8	8.3	-19.4	11.1
	p0.30	5.6	-5.6	5.6	-22.2	11.1
5-8 ahead	p0.10	2.8	-5.6	0.0	-5.6	2.8
	p0.20	19.4	-13.9	11.1	-16.7	13.9
	p0.30	16.7	-5.6	13.9	-11.1	16.7
9-12 ahead	p0.10	0.0	0.0	-5.6	-5.6	-5.6
	p0.20	5.6	2.8	-8.3	-11.1	-11.1
	p0.30	5.6	2.8	-8.3	-11.1	-11.1

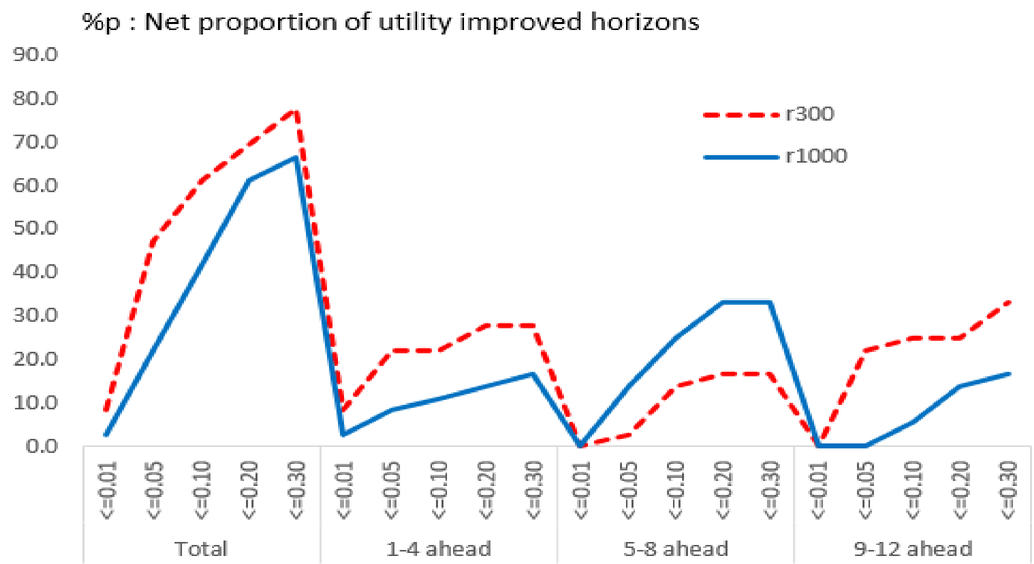
Note: 1) p0.10 indicates significance at 10%. 2) Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

4.6 Robustness Check

4.6.1 Robustness Check: Number of Repetitions to 1,000

It is widely suggested that more than 1,000 repetitions be performed in simulation exercises. However, as I performed simulations of many combinations of portfolios and corresponding predictors, I set 300 repetitions in each of the simulation exercises due to time restriction. Thus, in this sub-section, I report one pair of simulation exercises to examine whether exercises with 300 repetitions are similar to ones with 1,000 repetitions. As we can see in Figure 4.4 (Table 4.18), the forecasting performances based on the two repetition numbers are similar. Thus, we can say that the 1,000 repetition simulation results will be similar to the current intuitions drawn from this paper.

Figure 4.4: Summary of Net Proportions (%p) of Utility Improved Horizons: Repetition Number Comparison



Note: 1) Source: MDB. 2) **r300**: 300 repetition, **r1000**: 1000 repetition.

4.6.2 Robustness Check: Dominating-Dominated Portfolio

In order to check whether my simulation is consistent with the theoretical prediction of mean-variance, I choose a dominating-dominated pair of stocks. The Tesco individual stock had a lower mean and higher variance of excess return compared to the highly aggregate FTSE 350 composite index (Table 4.19). In the below table, I report 300 repetition and 1,000 repetition cases. As I invest in longer-week periods, the simulation results suggest that I would be better off investing in FTSE 350 composite index (0.0% indicates that investing in FTSE 350 composite index=100.0% whereas in

Table 4.18: Economic Criteria: Morrisons Vs. Greggs (Repetition Number Comparison)

			Morrisons Vs. Greggs ($\frac{\widehat{m}}{g}$ with r300)					Morrisons Vs. Greggs ($\frac{\widehat{m}}{g}$ with r1000)				
A	h	recursion	Utility Ratio	MDB predictor	BM	P-value	Sig	Utility Ratio	MDB predictor	BM	P-value	Sig
2	1	26	1.0143	63.2	52.0	0.05	**	1.0009	57.2	32.3	0.03	**
	2	25	1.0029	34.0	34.2	0.02	**	1.0059	51.2	41.2	0.02	**
	3	24	0.9992	51.5	52.0	0.01	**	1.0007	28.5	29.5	0.04	**
	4	23	1.0064	54.0	14.9	0.04	**	0.9981	44.2	27.7	0.07	*
	5	22	1.0050	28.7	4.5	0.11	++	1.0019	28.9	21.8	0.05	**
	6	21	1.0146	63.5	9.8	0.08	*	1.0102	56.0	16.6	0.09	*
	7	20	1.0000	48.5	40.1	0.06	*	1.0050	40.0	29.5	0.11	++
	8	19	0.9996	24.6	22.2	0.09	*	1.0090	48.5	15.8	0.10	++
	9	18	1.0019	20.7	11.6	0.05	**	1.0075	29.2	0.3	0.09	*
	10	17	1.0019	13.5	4.0	0.02	**	1.0010	35.3	29.4	0.28	+
	11	16	1.0129	54.7	0.0	0.05	**	1.0087	36.0	0.0	0.14	++
	12	15	1.0039	20.0	0.0	0.23	+	0.9970	20.0	26.7	0.15	++
5	1	26	1.0376	57.5	49.7	0.00	***	1.0116	54.8	41.8	0.02	**
	2	25	1.0092	40.3	36.0	0.02	**	1.0125	51.6	41.2	0.08	*
	3	24	1.0068	55.2	44.0	0.01	***	0.9959	34.3	36.9	0.02	**
	4	23	1.0264	56.9	19.8	0.05	**	0.9995	48.3	27.5	0.03	**
	5	22	1.0218	32.4	7.3	0.08	*	1.0137	33.3	22.3	0.02	**
	6	21	1.0572	62.3	11.7	0.08	*	1.0366	58.4	19.0	0.08	*
	7	20	1.0004	48.3	42.2	0.04	**	1.0179	44.7	29.0	0.08	*
	8	19	0.9956	23.7	25.6	0.07	*	1.0394	53.8	16.4	0.10	++
	9	18	1.0073	20.9	12.8	0.04	**	1.0257	29.7	5.2	0.08	*
	10	17	1.0110	19.2	7.2	0.03	**	1.0044	35.6	30.1	0.18	++
	11	16	1.0521	53.8	0.5	0.05	**	1.0364	36.7	0.0	0.14	++
	12	15	1.0146	18.7	0.0	0.22	+	0.9900	19.4	24.7	0.14	++
10	1	26	1.0652	56.0	49.5	0.11	++	1.0296	55.4	47.7	0.14	++
	2	25	1.0260	46.5	39.0	0.16	++	1.0245	51.7	44.4	0.24	+
	3	24	1.0222	55.8	41.9	0.05	**	1.0025	43.3	41.0	0.10	*
	4	23	1.0435	58.1	31.5	0.01	***	1.0040	49.2	32.2	0.00	***
	5	22	1.0417	37.1	15.5	0.06	*	1.0201	42.3	34.0	0.02	**
	6	21	1.1001	58.7	21.6	0.08	*	1.0510	54.7	21.9	0.01	**
	7	20	1.0123	51.9	42.1	0.05	**	1.0224	45.9	32.9	0.02	**
	8	19	0.9918	24.7	27.7	0.03	**	1.0809	56.5	17.7	0.08	*
	9	18	1.0154	23.2	15.2	0.03	**	1.0456	31.7	10.9	0.03	**
	10	17	1.0219	24.6	13.2	0.10	*	1.0135	36.8	30.8	0.16	++
	11	16	1.1022	51.9	5.8	0.05	**	1.0853	39.8	2.6	0.13	++
	12	15	1.0317	18.1	0.3	0.21	+	0.9727	18.4	26.9	0.05	**

Note: Superscript ***, ** and * indicate significance at 1%, 5% and 10% levels respectively. Superscript ++ and + indicate significance at the 20% and 30% levels.

Tesco=0.0%) instead of individual stocks with a low mean and high variance. As I increase the simulation repetition, this tendency becomes clearer. This exercise confirms that we need to rule out dominating-dominated cases in the context of mean-variance investment theory in order to obtain clear results.

Table 4.19: Economic Criteria: Tesco Vs. FTSE 350 Index

			Tesco Vs. FTSE 350 ($\frac{\widehat{L}}{C}$ with r300)					Tesco Vs. FTSE 350 ($\frac{\widehat{L}}{C}$ with r1000)				
A	h	recursion	Utility Ratio	MDB predictor	BM	P-value	Sig	Utility Ratio	MDB predictor	BM	P-value	Sig
2	1	26	1.0023	16.4	10.4	0.03	**	1.0002	11.4	8.2	0.09	*
	2	25	0.9971	8.2	26.7	0.13	++	1.0010	11.8	3.0	0.20	++
	3	24	1.0005	7.9	2.3	0.17	++	1.0003	11.5	0.0	0.18	++
	4	23	1.0000	1.3	0.0	0.22	+	1.0000	0.0	0.0	.	.
	5	22	1.0000	0.8	1.9	0.17	++	1.0000	0.0	0.0	.	.
	6	21	1.0000	0.0	0.0	.	.	1.0000	0.0	5.6	0.20	+
	7	20	1.0006	12.7	0.0	0.06	*	1.0000	0.0	0.0	.	.
	8	19	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
	9	18	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
	10	17	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
	11	16	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
	12	15	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
5	1	26	1.0025	7.9	4.1	0.01	**	0.9999	5.7	3.0	0.07	*
	2	25	0.9894	3.6	15.2	0.16	++	1.0007	6.4	1.3	0.10	++
	3	24	1.0007	3.4	0.9	0.16	++	1.0006	5.1	0.0	0.20	++
	4	23	1.0000	0.5	0.0	0.22	+	1.0000	0.0	0.0	.	.
	5	22	1.0001	0.2	0.5	0.20	++	1.0000	0.0	0.0	.	.
	6	21	1.0000	0.0	0.0	.	.	1.0000	0.0	2.1	0.20	+
	7	20	1.0013	8.8	0.0	0.13	++	1.0000	0.0	0.0	.	.
	8	19	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
	9	18	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
	10	17	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
	11	16	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
	12	15	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
10	1	26	1.0030	3.7	2.0	0.03	**	0.9995	2.4	1.3	0.01	***
	2	25	0.9876	2.1	7.8	0.17	++	1.0009	3.3	0.8	0.10	++
	3	24	1.0005	1.7	0.5	0.16	++	1.0010	3.2	0.0	0.21	+
	4	23	1.0001	0.3	0.0	0.22	+	1.0000	0.0	0.0	.	.
	5	22	1.0001	0.0	0.1	0.20	++	1.0000	0.0	0.0	.	.
	6	21	1.0000	0.0	0.0	.	.	0.9999	0.0	1.0	0.20	+
	7	20	1.0016	4.9	0.0	0.11	++	1.0000	0.0	0.0	.	.
	8	19	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
	9	18	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
	10	17	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
	11	16	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.
	12	15	1.0000	0.0	0.0	.	.	1.0000	0.0	0.0	.	.

Note: Superscript ***, ** and * indicate significance at 1%, 5% and 10% levels respectively. Superscript ++ and + indicate significance at the 20% and 30% levels.

4.6.3 Robustness Check: Ocado Forecasting

Ocado stock cases are very similar to the Morrisons stock results in that firm-level predictors perform best in the case of intra-aggregation portfolio (Table 4.10).

Table 4.20: Performance: Ocado Vs. FSTE 350 Index

Positive-Negative (%p)		Firm-level		Macro	Category-level		Retail-level	
		$\frac{\widehat{m}}{\widehat{C}}$	$\frac{\widehat{m}^{perstore}}{\widehat{C}}$	$\frac{\widehat{C}}{\widehat{Y}}$	$\frac{\widehat{N}}{\widehat{C}}$	$\frac{\widehat{D}}{\widehat{C}}$	$\frac{\widehat{EH}}{\widehat{C}}$	$\frac{\widehat{EO}}{\widehat{C}}$
Total	p0.10	11.1	-11.1	16.7	-27.8	-41.7	-11.1	22.2
	p0.20	-27.8	-16.7	38.9	-16.7	-61.1	-41.7	22.2
	p0.30	-33.3	-11.1	38.9	-27.8	-61.1	-50.0	5.6
1-4 ahead	p0.10	8.3	-22.2	2.8	-16.7	-25.0	-11.1	-2.8
	p0.20	0.0	-16.7	11.1	0.0	-33.3	-16.7	-11.1
	p0.30	0.0	-16.7	11.1	0.0	-33.3	-16.7	-11.1
5-8 ahead	p0.10	2.8	8.3	-2.8	-2.8	-8.3	0.0	19.4
	p0.20	-16.7	0.0	11.1	-2.8	-8.3	-16.7	33.3
	p0.30	-16.7	0.0	11.1	-5.6	0.0	-16.7	33.3
9-12 ahead	p0.10	0.0	2.8	16.7	-8.3	-8.3	0.0	5.6
	p0.20	-11.1	0.0	16.7	-13.9	-19.4	-8.3	0.0
	p0.30	-16.7	5.6	16.7	-22.2	-27.8	-16.7	-16.7

Note: 1) p0.10 indicates significance at 10%. 2) Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

Table 4.21: Performance: Ocado Vs. FSTE Food&Drug Retailer

Positive-Negative (%p)		Firm-level		Macro	Category-level		Retail-level	
		$\frac{\widehat{m}}{\widehat{fd}}$	$\frac{\widehat{m}^{perstore}}{\widehat{fd}}$	$\frac{\widehat{C}}{\widehat{Y}}$	$\frac{\widehat{N}}{\widehat{C}}$	$\frac{\widehat{D}}{\widehat{C}}$	$\frac{\widehat{EH}}{\widehat{C}}$	$\frac{\widehat{EO}}{\widehat{C}}$
Total	p0.10	33.3	41.7	5.6	-2.8	8.3	2.8	55.6
	p0.20	11.1	63.9	0.0	-11.1	0.0	5.6	55.6
	p0.30	11.1	61.1	0.0	-11.1	0.0	5.6	55.6
1-4 ahead	p0.10	5.6	22.2	-16.7	-8.3	-19.4	-13.9	27.8
	p0.20	0.0	27.8	-16.7	-11.1	-16.7	-11.1	27.8
	p0.30	0.0	27.8	-16.7	-11.1	-16.7	-11.1	27.8
5-8 ahead	p0.10	8.3	0.0	-2.8	8.3	13.9	-2.8	16.7
	p0.20	0.0	16.7	0.0	16.7	16.7	0.0	16.7
	p0.30	0.0	16.7	0.0	16.7	16.7	0.0	16.7
9-12 ahead	p0.10	19.4	19.4	25.0	-2.8	13.9	19.4	11.1
	p0.20	11.1	19.4	16.7	-16.7	0.0	16.7	11.1
	p0.30	11.1	16.7	16.7	-16.7	0.0	16.7	11.1

Note: 1) p0.10 indicates significance at 10%. 2) Net proportion (%p) of utility improved horizons = (proportion(%) of utility improved horizons - proportion(%) of utility deteriorated horizons) .

4.7 Conclusion

This paper investigates the potential usefulness of highly disaggregate consumer transaction information in achieving excess return in the UK stock market.

Using the general-to-specific specification search method, I generate simulated optimal portfolio choices between two candidate stocks to assess the contribution of predictors extracted from the consumer data in the context of economic decision making. First, the predictors constructed from actual spending data are helpful in achieving higher economic profits. Second, firm-level predictors are useful when investing in the firm-level and firm-sector portfolios. Third, the category-level predictors are more powerful than the firm-level predictor when it comes to the sector-index portfolio decisions. Fourth, the predictors from consumer data are weak in the firm-index portfolio decisions. In terms of how to use consumer data in portfolio decisions, we can conclude that portfolio pairs are recommended to be in the same aggregation level as well as the associated predictors are to be constructed as a ratio of spending amounts on two specific firms or sectors. Consumer data are not helpful in the portfolio of a highly disaggregate firm and highly aggregate index in this paper's exercises. Thus, if we were to use real-time consumer data in achieving higher profits in the short-run, in which we do not have enough financial market data, employing specifically identified firms' sales data would allow us to achieve higher economic profits in the case of investing in two similar aggregate level stocks. Finally, I also study the role of a second MDB predictor on top of a single MDB predictor. It is advised that it is better to include combinations of powerful predictors only. However, adding one extra predictor does not necessarily improve economic profits.

There are some limitations in this research. First, the balanced panel of 13,173 individuals might not have been enough to track and forecast stock aggregates. Thus, if I were allowed to have more individuals with a longer duration, the results would have been clearer than my conclusions. Second, some predictors extracted from sample restrictions with characteristics such as income and liquidity groups might be able to closely track stock returns. For example, we could work on whether a balanced panel of the rich or the poor helps us to achieve stock profitability better. Third, it is possible to extend the number of lags in VAR or to increase predictors in the specification as long as computing abilities are allowed. In this chapter, I restrict the specification with four-week lags due to the machine capacity. Fourth, although I adjusted the seasonality on the weekly data, how to clean weekly data in a big dataset is still controversial. Finally, this study only employs the time-series econometrics approach and only deals with linear relationships rather than fully exploiting the data structure. Perhaps we could use a machine learning approach in forecasting; however, that is beyond the scope of the research question in this paper. These issues are left to future research.

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4.8 Appendix: Preliminary Diagnosis

Table 4.22: Unit Root Tests : Stocks & Indices

Forecasts	Difference	ADF specification	obs	ADF lags	DF test stat	MacKinnon p-value
FTSE350 Index	No	constant term	150	4	-5.10	0.00
	No	drift term	150	4	-5.10	0.00
	No	trend term	150	4	-5.55	0.00
FTSE350 General Retailer	No	constant term	150	4	-5.49	0.00
	No	drift term	150	4	-5.49	0.00
	No	trend term	150	4	-5.55	0.00
FTSE350 Food&Drug Retailer	No	constant term	150	4	-5.10	0.00
	No	drift term	150	4	-5.10	0.00
	No	trend term	150	4	-5.37	0.00
Tesco	No	constant term	150	4	-5.21	0.00
	No	drift term	150	4	-5.21	0.00
	No	trend term	150	4	-5.45	0.00
Sainsbury	No	constant term	150	4	-5.79	0.00
	No	drift term	150	4	-5.79	0.00
	No	trend term	150	4	-5.78	0.00
Morrisons	No	constant term	150	4	-4.76	0.00
	No	drift term	150	4	-4.76	0.00
	No	trend term	150	4	-4.75	0.00
Ocado	No	constant term	150	4	-5.29	0.00
	No	drift term	150	4	-5.29	0.00
	No	trend term	150	4	-5.51	0.00
Greggs	No	constant term	150	4	-5.36	0.00
	No	drift term	150	4	-5.36	0.00
	No	trend term	150	4	-5.35	0.00

Note: All stocks and indices are weekly growth rate basis.

Table 4.23: Unit Root Tests : Non Firm-Specific Predictors

Predictor	Difference	ADF specification	obs	ADF lags	DF test stat	MacKinnon p-value
Oil price(lp_oil)	No	constant term	151	4	-1.34	0.61
	No	drift term	151	4	-1.34	0.09
	No	trend term	151	4	-1.49	0.83
	Yes	constant term	150	4	-4.9	0.0
	Yes	drift term	150	4	-4.9	0.0
	Yes	trend term	150	4	-5.0	0.0
$\frac{\widehat{N}}{\widehat{C}}$	No	constant term	146	4	-6.95	0.00
	No	drift term	146	4	-6.95	0.00
	No	trend term	146	4	-6.93	0.00
$\frac{\widehat{D}}{\widehat{C}}$	No	constant term	146	4	-6.83	0.00
	No	drift term	146	4	-6.83	0.00
	No	trend term	146	4	-6.81	0.00
$\frac{\widehat{EH}}{\widehat{C}}$	No	constant term	146	4	-6.56	0.00
	No	drift term	146	4	-6.56	0.00
	No	trend term	146	4	-6.52	0.00
$\frac{\widehat{EO}}{\widehat{C}}$	No	constant term	146	4	-6.04	0.00
	No	drift term	146	4	-6.04	0.00
	No	trend term	146	4	-6.02	0.00
$\frac{\widehat{C}}{\widehat{Y}}$	No	constant term	146	4	-10.41	0.00
	No	drift term	146	4	-10.41	0.00
	No	trend term	146	4	-10.38	0.00

Note: 1) $\frac{\widehat{V_1}}{\widehat{V_2}} = \frac{100+\dot{V}_1}{100+\dot{V}_2}$ where lowercase "$\dot{v}$" is weekly growth rate of individual firm or sector sales variable and the uppercase "$\dot{V}$" is weekly growth rate of aggregate category sales variable.

Table 4.24: Unit Root Tests : Sector-Specific Predictors

Sector predictor	Difference	ADF specification	obs	ADF lags	DF test stat	MacKinnon p-value
$\frac{\widehat{fd}}{\widehat{C}}$	No	constant term	146	4	-7.11	0.00
	No	drift term	146	4	-7.11	0.00
	No	trend term	146	4	-7.08	0.00
$\frac{\widehat{ge}}{\widehat{C}}$	No	constant term	146	4	-8.08	0.00
	No	drift term	146	4	-8.08	0.00
	No	trend term	146	4	-8.05	0.00
$\frac{\widehat{fd}}{\widehat{ge}}$	No	constant term	146	4	-10.73	0.00
	No	drift term	146	4	-10.73	0.00
	No	trend term	146	4	-10.71	0.00

Note: 1) $\frac{\widehat{V_1}}{\widehat{V_2}} = \frac{100+\dot{V}_1}{100+\dot{V}_2}$ where lowercase "$\dot{v}$" is weekly growth rate of individual firm or sector sales variable and the uppercase "$\dot{V}$" is weekly growth rate of aggregate category sales variable.

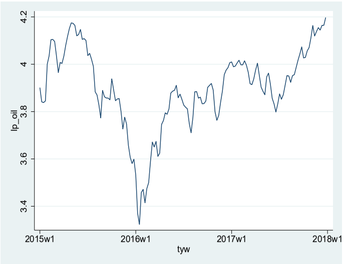
Table 4.25: Unit Root Tests : Firm-Specific Predictors

Firm predictor	Difference	ADF specification	obs	ADF lags	DF test stat	MacKinnon p-value
$\frac{\widehat{m}}{\widehat{g}}$	No	constant term	146	4	-7.36	0.00
$\frac{\widehat{m}}{\widehat{g}}$	No	drift term	146	4	-7.36	0.00
$\frac{\widehat{m}}{\widehat{g}}$	No	trend term	146	4	-7.42	0.00
$\frac{\widehat{m}^{perstore}}{\widehat{g}^{perstore}}$	No	constant term	146	4	-7.39	0.00
$\frac{\widehat{m}^{perstore}}{\widehat{g}^{perstore}}$	No	drift term	146	4	-7.39	0.00
$\frac{\widehat{m}^{perstore}}{\widehat{g}^{perstore}}$	No	trend term	146	4	-7.39	0.00
$\frac{\widehat{m}}{\widehat{o}}$	No	constant term	146	4	-8.30	0.00
$\frac{\widehat{m}}{\widehat{o}}$	No	drift term	146	4	-8.30	0.00
$\frac{\widehat{m}}{\widehat{o}}$	No	trend term	146	4	-8.24	0.00
$\frac{\widehat{m}^{perstore}}{\widehat{o}^{perstore}}$	No	constant term	146	4	-8.25	0.00
$\frac{\widehat{m}^{perstore}}{\widehat{o}^{perstore}}$	No	drift term	146	4	-8.25	0.00
$\frac{\widehat{m}^{perstore}}{\widehat{o}^{perstore}}$	No	trend term	146	4	-8.23	0.00
$\frac{\widehat{t}}{\widehat{o}}$	No	constant term	146	4	-7.57	0.00
$\frac{\widehat{t}}{\widehat{o}}$	No	drift term	146	4	-7.57	0.00
$\frac{\widehat{t}}{\widehat{o}}$	No	trend term	146	4	-7.57	0.00
$\frac{\widehat{t}^{perstore}}{\widehat{o}^{perstore}}$	No	constant term	146	4	-7.57	0.00
$\frac{\widehat{t}^{perstore}}{\widehat{o}^{perstore}}$	No	drift term	146	4	-7.57	0.00
$\frac{\widehat{t}^{perstore}}{\widehat{o}^{perstore}}$	No	trend term	146	4	-7.58	0.00
$\frac{\widehat{s}}{\widehat{o}}$	No	constant term	146	4	-8.94	0.00
$\frac{\widehat{s}}{\widehat{o}}$	No	drift term	146	4	-8.94	0.00
$\frac{\widehat{s}}{\widehat{o}}$	No	trend term	146	4	-8.89	0.00
$\frac{\widehat{s}^{perstore}}{\widehat{o}^{perstore}}$	No	constant term	146	4	-8.95	0.00
$\frac{\widehat{s}^{perstore}}{\widehat{o}^{perstore}}$	No	drift term	146	4	-8.95	0.00
$\frac{\widehat{s}^{perstore}}{\widehat{o}^{perstore}}$	No	trend term	146	4	-8.91	0.00
$\frac{\widehat{o}}{\widehat{g}}$	No	constant term	146	4	-8.13	0.00
$\frac{\widehat{o}}{\widehat{g}}$	No	drift term	146	4	-8.13	0.00
$\frac{\widehat{o}}{\widehat{g}}$	No	trend term	146	4	-8.10	0.00
$\frac{\widehat{o}^{perstore}}{\widehat{g}^{perstore}}$	No	constant term	146	4	-8.13	0.00
$\frac{\widehat{o}^{perstore}}{\widehat{g}^{perstore}}$	No	drift term	146	4	-8.13	0.00
$\frac{\widehat{o}^{perstore}}{\widehat{g}^{perstore}}$	No	trend term	146	4	-8.10	0.00

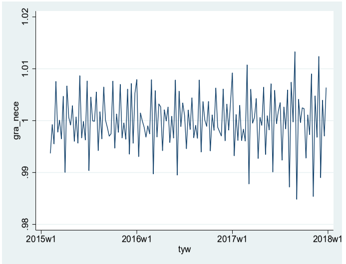
Note: 1) **Ratio of weekly sales growth rate between Firm A & Firm B**= (100 + growth rate of Firm A sales) /(100 + growth rate of Firm B sales), 2) **Ratio of weekly per store sales growth rate between Firm A & Firm B**= (100 + growth rate of Firm A sales per number of stores) /(100 + growth rate of Firm B sales per number of stores)

4.8.1 Variables Before & After Difference

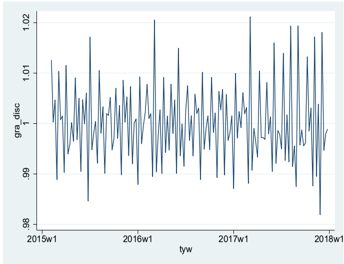
Figure 4.5: Variables before Difference



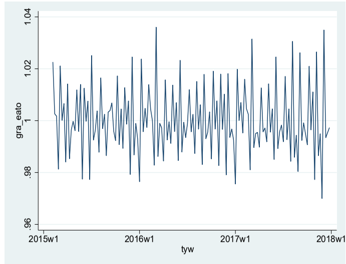
(A) Log oil price



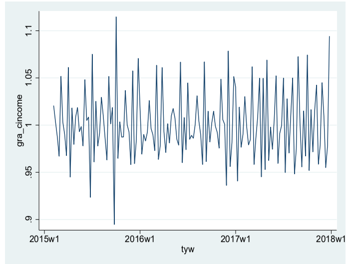
(B) Necessary spending ratio



(C) Discretionary spending ratio

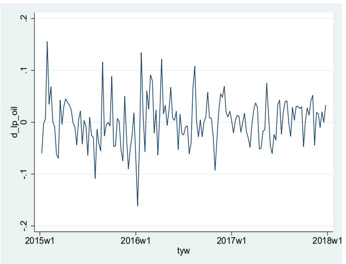


(D) Eating-out spending ratio

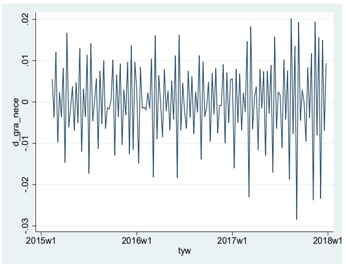


(E) Spending/income ratio

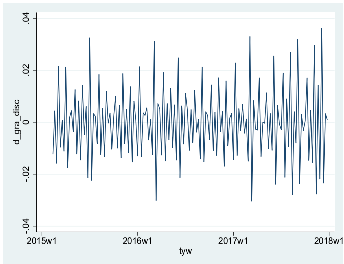
Figure 4.6: Variables after First Difference



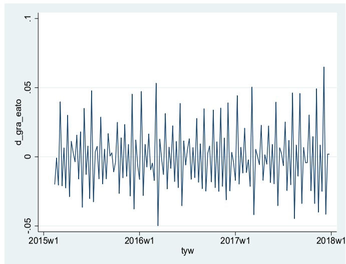
(A) Log oil Price



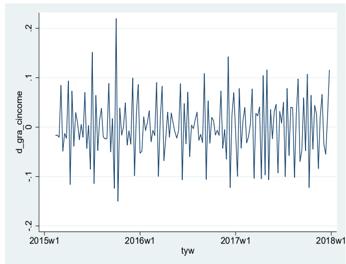
(B) Necessary spending ratio



(C) Discretionary spending ratio



(D) Eating-out spending ratio

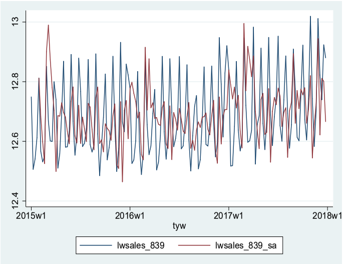


(E) Spending/income ratio

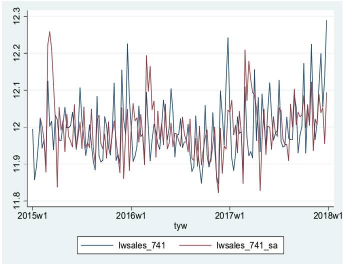
Note: 1) **lpoil** = log transformed weekly oil price, 2) **Necessary spending ratio**=(100 + weekly growth rate of Necessary spending) /(100 + weekly growth rate of the all types of spending) , 3) **Discretionary spending ratio**=(100 + weekly growth rate of Discretionary spending) /(100 + weekly growth rate of the all-spending), 4) **Eating-out spending ratio**=(100 + weekly growth rate of Eating-out spending) /(100 + weekly growth rate of the all-spending) , 5) **Spending/Income ratio**=(100 + weekly growth rate of all spending) /(100 + weekly growth rate of all income)

4.8.2 Firms Sales & Associated Predictors

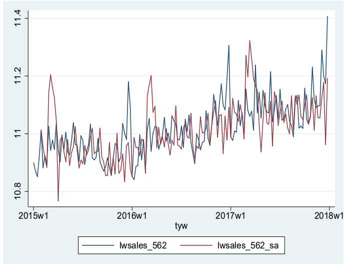
Figure 4.7: Firm Sales after Seasonal Adjustment



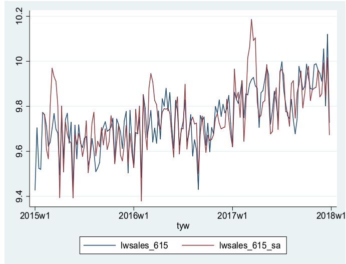
(A) Sales Figure (Tesco)



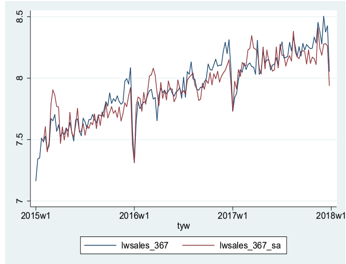
(B) Sales Figure (Sainsbury)



(C) Sales Figure (Morrisons)

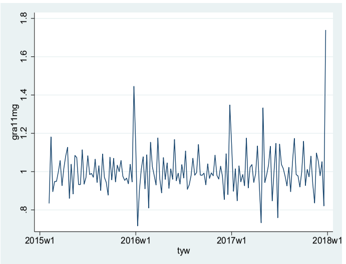


(D) Sales Figure (Ocado)

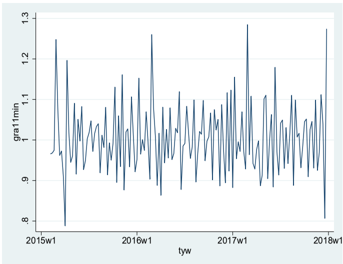


(E) Sales Figure (Greggs)

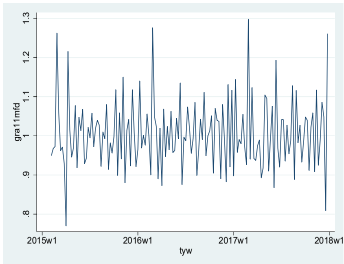
Figure 4.8: Ratio Predictors



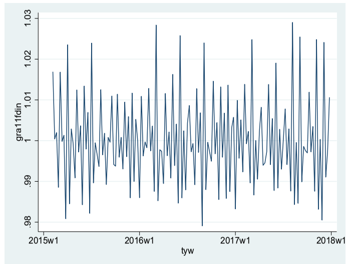
(A) Morrisons & Greggs



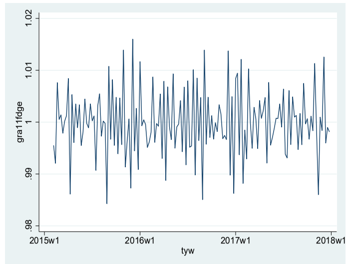
(B) Morrisons & FTSE350 Index



(C) Morrisons & FTSE350 Food&Drugs



(D) FTSE350 Food&Drugs & FTSE350 Index



(E) FTSE350 Food&Drugs & FTSE350 General Retailer

Note: 1) **Ratio of weekly sales growth rate between specific category or index**= (100 + weekly growth rate of category sales) /(100 + weekly growth rate of the alternative index sales)

Chapter 5

Conclusion

This thesis studies the way in which we can exploit highly disaggregate consumer datasets in understanding individuals' financial decisions and forecasting the financial market. The main findings are below:

In Chapter 2 (consumption payday effects), I document the payday effects of UK consumers. I find the payday effects appear regardless of any consumption items including non-recurring discretionary and necessary items. Heterogeneities of income, liquidity, spending patterns (MPC) and income uncertainty are introduced to examine the relative strength of the payday effects.

In Chapter 3 (consumption reference effects), I explore the role of reference effects on consumption choices. My results show that consumption items aggregated from transaction-level data are clearly characterized as normal, luxury and inferior goods, as suggested by the microeconomic theory. I find that consumption reference effects exist, the sizes of which depend on item category and consumer sample split. It is shown that the reference effects of discretionary and visible items are pronounced and that the income reference group is the main driver of reference effects in most consumption items.

In Chapter 4 (forecasting financial markets), spending data on each type of consumption item or specific firm are employed to construct predictors for achieving stock profitability. Evaluated by predictive density, I find that portfolio pairs are advised to be in the same aggregation level and that associated predictors are to be constructed as a ratio of the spending amounts on two specific firms or sectors. Information gain from consumers' detailed spending data is pronounced when we can keep track of the sales of specific firms or at least the sales figures of all constituents in the case of dealing with specific sectors.

This thesis attempts to deal with consumer big data. In some sense, how to deal with data cleaning is an implicit research question in that MDB data are used throughout three chapters. In terms of the consumer behaviour chapters (Ch.2 and Ch.3), I clean and make a self-contained dataset, which means I constructed the majority of variables only from raw data. For example, I derive an individual's income arrivals only with regularly received credit transactions[1].

This thesis also uses various data frequency and estimation strategies since it is constructed flexibly based on transaction-level data. In Chapter 2 (payday effects), I construct daily frequency variables and then apply panel within-group estimation on the unbalanced panel of 14,881 individuals to secure as many N (consumers) and T (daily observations) as possible. The heterogeneity analysis is based on sample split because the characteristics of individual heterogeneity are identified as time-invariant. In Chapter 3 (reference effects), the analysis is based on monthly frequency in order to focus on the MPC estimation in the context of reference effects. One crucial consideration in this chapter is that it is necessary to construct an interaction matrix between 5,424 individuals, which requires a balanced panel. Due to the endogeneity issue in dealing with network lags as explanatory variables, the system GMM estimation method is employed. In Chapter 4 (forecasting), weekly frequency is employed to guarantee a large enough number of observations of a balanced panel for time series analysis. Samples are cut for observations of three years to make a balanced panel of 13,173 individuals from those who are observed continuously in the data. Classic vector autoregression is used to perform the forecasting exercises.

This thesis focused on documenting results arising from different aggregation levels of consumption items in order to mainly exploit the advantage of the transaction-level dataset. However, I mainly restrict my analysis to broad-category consumption items such as necessary and discretionary items rather than specific brands due to the limited number of individuals in the sample as well as the machine capacity. I believe that the analysis would have been more convincing if I could have used more consumers with longer sample periods. To be specific, it would be possible to investigate the MPC on individual spending items to characterise consumer types in detail.

Another aspect is more qualitative information from banks and financial companies. The MDB data can be understood as a 'spending diary' that records everybody's debit and credit transactions automatically. Although I admit that I could take advantage of this automatically recorded spending history, the lack of information on debts, overdrafts, balances at the regular frequency made me just focus on the restricted part of the research. In Chapter 4, I only deal with forecasting the retail sector due to the fact that spending in the retail sector is easily observable and identifiable compared to other sectors. However, extended coverage to other merchants and spending items would be fruitful if possible. On top of that, the use of recent advances in data science could be a promising option. All these topics are left to future research.

[1]Even though how to clean transaction-level data is relatively masked by the importance of the main research questions in this thesis, I believe the step-by-step data cleaning procedure is also one contribution of this thesis.

5.1 Appendix for Econometric Methodology

In this appendix, I provide a more complete set of details on the methods I used in this thesis and suggest some alternative econometric methodology in each chapter. Regarding Chapter 2, I compare the within-group OLS estimation to the Tobit model in terms of consistency. When it comes to Chapter 3, I describe the ways until the final choice of the system GMM in the presence of reference effects. Regarding Chapter 4, I explain why I chose VAR rather than VECM or GARCH model in the stock market forecasting.[2]

5.1.1 The Choice of Within-group Estimation over Tobit Model in Chapter 2

It is well known that the within-group estimation in the static panel set-up is a very basic approach in which we consider individual unobserved heterogeneity. However, it could be argued that OLS regression can be inconsistent when we have lots of zero spending amounts as dependent variable observations. Thus, I compare the within-group estimation and the Tobit model and discuss the actual application to the Money DashBoard data.

Description of Within-group Estimation

A panel data model can be described as below

$$\begin{aligned} y_{i,t} =& \beta_0 + \beta_1 x_{i,t} + u_i + \epsilon_{i,t} \\ & where \quad i = 1, \ldots, N \quad t = 1, \ldots, T \\ & \epsilon_{i,t} \sim N(0, \sigma_\epsilon^2), \quad u_i \sim N(0, \sigma_u^2) \end{aligned} \tag{5.1}$$

$\epsilon_{i,t}$ is the idiosyncratic random error which vary with individual i and time t. u_i indicates the individual unobserved heterogeneity. Estimation depends on the assumptions on the relation between regressors and individual unobserved heterogeneity. The random effect model assumes that

$$Cov(x'_{i,t}, u_i) = E(x'_{i,t}, u_i) = 0 \tag{5.2}$$

where individual unobserved heterogeneity u_i is assumed to be uncorrelated with the regressor $x_{i,t}$. In this case, the model is known to be best estimated with the Generalized Least Squares (GLS). However, when this assumption does not hold,

[2] In this section, I referred to various textbooks and lecture notes. Details are provided in the bibliography section.

$$Cov(x'_{i,t}, u_i) = E(x'_{i,t}, u_i) \neq \quad 0 \tag{5.3}$$

then, the usual pooled OLS estimator will be inconsistent due to individual unobserved heterogeneity. Thus, we estimate the model with OLS by transforming the data in terms of deviations from the individual mean which takes this fixed effect into account.

$$(y_{i,t} - \overline{y}_i) = \beta_1(x_{i,t} - \overline{x}_i) + (\epsilon_{i,t} - \overline{\epsilon}_i) \tag{5.4}$$

Basically, we get the same result if we include individual dummies in the original specification and this is known as Least Squares Dummy Variable (LSDV) model. An alternative way to rule out individual unobserved heterogeneity is to first-difference the original specification as below.

$$(y_{i,t} - y_{i,t-1}) = \beta_1(x_{i,t} - x_{i,t-1}) + (\epsilon_{i,t} - \epsilon_{i,t-1}) \tag{5.5}$$

It is widely understood that this within-group estimation generates a consistent estimator in the static panel data set-up. One caveat is that this transformation eliminates all time-invariant variables so that we split the sample according to these time-invariant characteristics once we are interested in the role of heterogeneous fixed effects. [3]

Description of Tobit Model

The Tobit model is widely used when we have a large number of observations of dependent variables as limiting values. It is known that the usual OLS estimation can generate an inconsistent estimator especially due to many missing values or zeros. Examples are infrequent medical expenses in a year period or dividend payments to shareholders. These examples mean that if the actual observations are censored(and observed as limiting values), the slope of OLS might not be properly estimated. Also, if we drop zero observations of dependent variables, the employed dependent variables will not represent the actual population. Thus, it is better to take the ways of censoring process into account when we estimate our target specification. Let's consider the following model.

$$y_i = x'_i\beta + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2) \tag{5.6}$$

[3] In Chapter 2, I split the sample in order to estimate heterogeneous payday effects because of this elimination of all time-invariant variables.

The setting of Tobit model assumes that the dependent variables can be differentiated from one with the limiting observation (y=0) and the non-limiting observations (y>0). In terms of the modeling process, the limit observations (y=0) are generated from the normal probability density function with the mean $x_t'\beta$ and the variance σ^2. This is the one we use in the probit model and its probability of obtaining a limit observation is as below

$$Pr(y_i = 0|x) = 1 - Pr(y_i > 0|x) = 1 - \Phi(\frac{x_i'\beta}{\sigma}) \tag{5.7}$$

where the probability distribution function of the standard normal variable is as below.

$$\Phi(z) = \int_{-\infty}^{z} \phi(w)dw \quad with \quad \phi(z) = \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}z^2} \tag{5.8}$$

However, in the case of non-limiting observations (y>0), we use a linear regression function with normally distributed errors.

The Tobit model introduces the concept of the latent variable in which we cannot directly observe but affects the actual response variable. A latent variable y_i^* can be defined as below.

$$y_i^* = x_i'\beta + \epsilon_i, \; \epsilon_i \sim N(0, \sigma^2) \tag{5.9}$$

This is a linear function of the regressor vector x_i, parameter vector β and a normally distributed error term ϵ. Thus, we can have the relationship between actual response variables and latent variables.

$$y_i = \begin{cases} y_i^* \; if \; y_i^* \; > \; 0 \\ 0 \; if \; y_i^* \; \leq \; 0 \end{cases} \tag{5.10}$$

One thing that we need to consider is that the Tobit model imposes strong assumptions on the conditional distribution of data and functional form. For example, zero observations and positive values are generated based on the same stochastic mechanism. To be specific, Tobit MLE estimation is widely used based on the set-up in which regression errors are homoscedastic and follow the normal distribution which is quite strict assumptions. [4]

[4] Diagnosis tests are required to convince the use of this model.

Discussion: Application to My Work

I understand that the Tobit model can handle specific cases where lots of zero daily spending exist especially due to the information loss characterized by the censoring process. In terms of my data, I think if my variables of interest lie in very specific items: such as 'car purchase', 'medical expenditure'[5], it can be reasonable that we need more information beyond zeros. In this case, many zero observations of the dependent variables can be a serious problem. Since censored samples cannot represent the population, OLS regression generates inconsistent estimation. I believe this application of the Tobit model can be useful if we try to estimate the payday effect in each specific item or highly disaggregate spending items. However, I construct All-spending, Necessary, Discretionary spending which are highly/mid aggregated spending in Chapter 2. As I aggregate spending items into a higher aggregation level, it is less likely to have zero spendings in a day. As a result, I don't see many cases of zero spending.[6] Still with the highly-aggregated or mid-aggregated spending category, within-group estimation is widely used to estimate payday effects very well. This is because zero spendings cannot be understood as a loss of information in the context of mid-aggregate spending items (necessary and discretionary) and aggregate all-spending items. Furthermore, this estimation result is consistent to existing literature (Olafsson and Pagel, 2018).

On top of that, I performed a series of data cleaning processes to use within-group estimation for payday effects. I cleaned the data by excluding individuals with irrational (non-reasonable) monthly spending amounts and income arrivals which are inconsistent with the UK ONS data. I focus on those who have enough non-zero observations of spending from the perspective of monthly spending amounts. This can be justified that I investigate only economically active consumers. [7]

Finally, the currently available panel Tobit estimation in the STATA is 'xttobit' which employs random effect assumption in the panel model. The application of the fixed effect Tobit is not recommended due to the incidental parameter problem in which the fixed effect model has too many intercepts in the panel set-up according to Greene (2004).

[5]Individuals can be asked to answer how much money were spent higher than 100 pounds in a month especially in case of medical expenditure survey. However, MDB data is not based on the survey method.

[6]Even in these cases, in the main specification, we can allow zero spending if it is real and these are not poorly observed cases. I believe that zero aggregate spending itself is meaningful since this MDB data is tracked and restored based on transaction-level automatically. In the robustness check exercises, also this is log-transformed, so I add all the daily spending with ten pounds before I take logarithms.

[7]Although I did exclude those who rarely spend or earn money in terms of a monthly basis. I did not exclude transactions with zero spendings in the within-group estimation.

Random Effect and Fixed Effect

In the within-group estimation, Random Effect (RE) and Fixed Effect (FE) should be distinguished. If the unobserved individual heterogeneity is correlated with explanatory variables in the regression, it is widely known that we should use the FE model instead of the RE model. I use the Hausman test to determine whether I should choose one of them in practice. The related hypothesis test is based on below

H_o = Regressors and Unobserved individual heterogeneity are uncorrelated

H_1 = Not H_o

Then the Hausman test statistics is as below.

$$\begin{aligned} H =& (\hat{\beta_{FE}} - \hat{\beta_{RE}})' V^{-1} (\hat{\beta_{FE}} - \hat{\beta_{RE}}) \\ & where\ V = Var(\beta_{FE}) - VAR(\beta_{RE}) \end{aligned} \tag{5.11}$$

In my dataset, the null hypothesis is statistically rejected so I actually used FE model throughout this thesis.

5.1.2 The Choice of System GMM in the Presence of Reference Effect in Chapter 3

Endogeneity Problem in Terms of Time and Spatial Dynamics

In Chapter 3, I use the usual dynamic panel data model in which the dependent variable is spending amount on the mid-aggregate item categories. A dynamic panel model in Chapter 3 can be simplified as

$$\begin{aligned} y_{i,t} =& \alpha y_{i,t-1} + \beta x_{i,t} + u_i + \epsilon_{i,t} \\ & where \quad i = 1, ..., N \quad t = 1, ..., T \end{aligned} \tag{5.12}$$

where u_i are the individual unobserved heterogeneity and $\epsilon_{i,t}$ are serially uncorrelated errors. In general, we assume that most cases in dynamic panel data are characterized by large N (individuals) and a small number of T (time periods) and this is consistent with my balanced data set up. In addition, if we allow for the reference effect with network matrix W, $Wy_{i,t}$ (reference effect variable) can be included in the above specification. Thus, we should consider how endogeneity from reference effect variables can be dealt with as well as time dynamics in the context of estimation methodology.

Pooled OLS, Within-group Estimation

In the static panel data model, we overcome the inconsistency of pooled OLS by controlling individual unobserved heterogeneity u_i in (5.12). From the perspective of empirical studies, the choice of the Random Effect model and Fixed Effect model ends up choosing Fixed Effect model since we cannot guarantee the zero correlation between the regressors and individual unobserved heterogeneity. However, in the context of dynamic panel models, the within-group estimator cannot be the consistent estimator unless the number of time periods is large. [8] This is because if we perform the within-group estimation, still individual sample mean of $y_{i,t-1}$ and sample mean of error term are correlated (Han, 2017).

$$y_{i,t} - \frac{1}{T}\sum_{s=1}^{T} y_{i,s} = \alpha(y_{i,t-1} - \frac{1}{T}\sum_{s=1}^{T} y_{i,s-1}) + \beta(x_{i,t} - \frac{1}{T}\sum_{s=1}^{T} x_{i,s}) + (\epsilon_{i,t} - \frac{1}{T}\sum_{s=1}^{T} \epsilon_{i,s}) \tag{5.13}$$

[8] In my dataset, I set up with N=5,424 individuals and T=36 months. It could be argued that whether this 36 months period is long enough or not. Basically, I follow the existing literature in which assumes a relatively small number of periods (T) compared to many units (N). Nickell (1981) measured this bias and the bias converges to zero as T increases. However, Judson and Owen (1999) show that this bias is similar to 20% of the true value of the coefficient of interest even when the time dimension T=30.

If we take a difference of the above model specification in order to eliminate u_i

$$\begin{gathered} y_{i,t} - y_{i,t-1} = \alpha(y_{i,t-1} - y_{i,t-2}) + \beta(x_{i,t} - x_{i,t-1}) + (\epsilon_{i,t} - \epsilon_{i,t-1}) \\ where \quad i = 1, \ldots, N \quad t = 1, \ldots, T \end{gathered} \tag{5.14}$$

Then, we can eliminate the individual unobserved heterogeneity u_i, though, we come across a new problem. If we assume that error term has no serial correlation, then the explanatory variable $\Delta y_{i,t-1}$ and the error $\Delta\epsilon_{i,t}$ are correlated. This is because $y_{i,t-1}$ and $\epsilon_{i,t-1}$ are correlated. Then, several trials related to the GMM approach to guarantee consistent estimators have been performed in the context of the dynamic panel model.

IV Approach

Motivated by the discussion in the previous sub-section, Anderson and Hsiao (1981) suggest that it is possible to use instrumental variables (IV) after eliminating individual unobserved heterogeneity. Since the error term is constructed as $(\epsilon_{i,t} - \epsilon_{i,t-1})$ in the equation (5.14), the proper IV for the $(y_{i,t-1} - y_{i,t-2})$ would be $y_{i,t-2}$ since this IV is not correlated with any of $\epsilon_{i,t}$ and $\epsilon_{i,t-1}$. In case of $(x_{i,t} - x_{i,t-1})$, there are three cases depending on the concept of endogeneity.[9] If $X_{i,t}^{exog}$ is strictly exogenous variable, this will not be correlated with $\epsilon_{i,t} - \epsilon_{i,t-1}$. If $X_{i,t}^{pred}$ is the predetermined variable, this will be correlated with $\epsilon_{i,t-1}$. Thus $(x_{i,t}^{pred} - x_{i,t-1}^{pred})$ has the endogeneity problem again. Possible IV for this is $x_{i,t-1}^{pred}$ since this is uncorrelated with $\epsilon_{i,t} - \epsilon_{i,t-1}$. If the contemporaneously endogeneous explanatory variable is correlated with the error term in the same period. Thus, $x_{i,t-2}^{endog}$ can be IV for $(x_{i,t}^{endog} - x_{i,t-1}^{endog})(Han, 2017)$.

Difference GMM

In the previous subsection, Anderson and Hsiao (1981) exploit only one IV for each regressor. However, we can think of more IVs which are uncorrelated with the error term $(\epsilon_{i,t} - \epsilon_{i,t-1})$. Arellano and Bond (1991) introduce the GMM method in which we can exploit all available linear moment conditions. To be more specific, if the assumption that $\epsilon_{i,t}$ are serially uncorrelated holds, the longer lags of dependent variables can instrument the endogenous regressor in the first-differenced model. For example, in the case of equation (5.14), we can have several vaild IVs since below IVs are all uncorrelated with $(\epsilon_{i,t} - \epsilon_{i,t-1})$.

[9] The definition of endogeneity in panel data context : 1. Strictly exogeneous: $E(\epsilon_t|x_1, \ldots, x_T) = 0$, 2. *Weakly exogeneous (predetermined)* : $E(\epsilon_t|x_1, \ldots, x_t) = 0$, 3. *Contemporaneously endogeneous* : $E(\epsilon, x) \neq 0$.

- For IVs for the exogenous variable : we can use $X_{i,1}^{exog}$, $X_{i,2}^{exog}$,...,$X_{i,T}^{exog}$.

- For IVs for the predetermined variable : we can use $X_{i,1}^{pred}$, $X_{i,2}^{pred}$,...,$X_{i,T-1}^{pred}$.

- For IVs for the endogenous variable : we can use $X_{i,1}^{endog}$, $X_{i,2}^{endog}$,...,$X_{i,T-2}^{endog}$.

- For IVs for the lagged difference variable : we can use $y_{i,0}$, $y_{i,1}$,...,$y_{i,t-2}$.

Also, it is worthwhile to note that the number of IVs are different according to time periods in the Difference GMM compared to the IV approach of Anderson and Hsiao (1981).

System GMM

The motivation for the system GMM is that the correlation between the endogenous variable and their IVs can be weak if the dependent variable is highly persistent, which means close to the unit root. Thus, the difference GMM can suffer from this weak IV problem mainly due to the fact that differenced variables and the instrument variables can be less correlated. Arellano and Bover (1995), Blundell and Bond (1998) propose the idea of the level GMM and system GMM approach. This can be illustrated as below equations

$$\begin{aligned} \Delta y_{i,t} &= \alpha \Delta y_{i,t-1} + \beta \Delta x_{i,t} + \Delta \epsilon_{i,t} \\ y_{i,t} &= \alpha y_{i,t-1} + \beta x_{i,t} + u_i + \epsilon_{i,t} \\ & where \quad i = 1, \ldots, N \quad t = 1, \ldots, T \end{aligned} \tag{5.15}$$

The first equation in (5.15) is the differenced GMM estimation. The second equation in (5.15) is the level equation in which we use $\Delta y_{i,t-1}$ as an instrument for $y_{i,t-1}$. Intuitively, we can use the lagged first differences as IVs for the level equation, whereas the lagged level variables as IVs for the differenced equation. As a result, we are able to get a consistent and more efficient estimator with system GMM than difference GMM. One caveat is that we exploit more IVs for both difference and level equations so that we might have too many IVs which restricts results due to machine capacity.[10]

[10] I also restrict the number of IVs in the Chapter 3 estimation.

Common Factor in System GMM

Sarafidis and Robertson (2009) consider the first-order autoregressive panel data model as below [11]

$$
\begin{aligned}
y_{i,t} =& \lambda y_{i,t-1} + u_i + \epsilon_{i,t} \\
\epsilon_{i,t} =& \sum_{m=1}^{M} \phi_{m,i} f_{m,i} + \eta_{i,t} = \phi_i' f_t + \eta_{i,t} \\
& where \quad i = 1, \ldots, N \quad t = 1, \ldots, T
\end{aligned} \tag{5.16}
$$

where $y_{i,t}$ is the observation of the dependent variable of the ith individual at time t and λ is the unknown parameter of interest. u_i is individual unobserved heterogenetiy. $\epsilon_{i,t}$ is a multi-factor structure, where $f_t = (f_{1,t}, \ldots., f_{M,t})'$ denotes an Mx1 vector of individual-invariant time-specific unobserved effects. $\phi_i = \phi_{1,i}, \ldots., \phi_{M,i}'$ is an Mx1 vector of factor loadings and $\eta_{i,t}$ is a purely idiosyncratic component with zero mean and constant finite variance (Sarafidis and Robertson (2009)).

Their paper contributes by providing the way of how to reduce the bias of IV and GMM from error cross-section dependence in the dynamic panel. It is suggested that we should transform the data in terms of deviations from time-specific averages. From the above set-up, if we average the equation (5.16) over individual i and subtract the average variable, we obtain

$$
(y_{i,t} - \overline{y}_t) = (u_i - \overline{u}) + \lambda(y_{i,t-1} - \overline{y}_{t-1}) + (\phi_{i,t} - \overline{\phi}) f_t + (\eta_{i,t} - \overline{\eta}_t) \tag{5.17}
$$

where $\overline{y}_t = \sum_{i=1}^{N} y_{i,t}$ and same constructions are applied to other mean variables. They take first-differences the above equation,

$$
\begin{aligned}
\Delta(y_{i,t} - \overline{y}_t) =& \lambda \Delta(y_{i,t-1} - \overline{y}_{t-1}) + (\phi_{i,t} - \overline{\phi}) \Delta f_t + \Delta(\eta_{i,t} - \overline{\eta}_t) \\
=& \lambda \Delta(y_{i,t-1} - \overline{y}_{t-1}) + \Delta(\epsilon_{i,t} - \overline{\epsilon}_t)
\end{aligned} \tag{5.18}
$$

This equation tells us that the mean value of the factor loading is eliminated and the error term is mean zero. Sarafidis and Robertson (2009) show that the asymptotic bias from the time-specific demeaned data will be lower than that from the original model in terms of the ratio of relative biases. In Chapter 3, I apply this paper's intuition so that I include time-specific common factor instead of time dummies.[12]

[11] Notations and derivations are from Sarafidis and Robertson (2009)

[12] Cicarelli and Elhorst (2018) use the common factor in the spatial diffusion model in order to guarantee stationarity of the model. I believe Cicarelli and Elhorst (2018) and Sarafidis and Robertson (2009) raise the same issue of potential misspecification problem.

Reflection Problem with the Linear-in-means Model

Let us consider the standard linear-in-mean model [13]

$$\begin{aligned} c_i =& \alpha + \beta y_i + \delta c^e_{i,g} + \gamma y^e_{i,g} + \epsilon_i \\ & \textit{where each individual } i \textit{ is the member of group } g. \end{aligned} \tag{5.19}$$

where c_i is individual i's spending (behaviour), y_i is individual income (characteristics). $c^e_{i,g}$ is average spending behaviour of g^{th} group and this represents the endogenous peer effects. $y^e_{i,g}$ is average income characteristics of g^{th} group and this represents the exogenous (contextual) peer effects. If we take expectation on the equation (5.19), we have

$$E(c_i) = \alpha + \beta E(y_i) + \delta E(c^e_{i,g}) + \gamma E(y^e_{i,g}) \tag{5.20}$$

then, we have

$$c_g = \frac{\alpha + (\beta + \gamma) y_g}{1 - \delta} \tag{5.21}$$

which means that the expected average peer group behavior is a linear function of the expected average group characteristics. To confirm that the separation of peer behaviour and peer characteristics are not feasible, we put the derived c_g (5.21) into (5.20)

$$\begin{aligned} c_i &= \alpha + \beta y_i + \delta(\frac{\alpha + (\beta + \gamma) y_g}{1 - \delta}) + \gamma y_g \\ &= \alpha(1 + \frac{\delta}{1 - \delta}) + \beta y_i + \delta(\frac{(\beta + \gamma) y_g}{1 - \delta} + \gamma) y_g \end{aligned} \tag{5.22}$$

As we can see from the above equation, since the group mean behavior is linear dependent on the group mean of characteristics, we need to detour this reflection problem to identify peer (reference) effects in a more sophisticated way.

[13]Notations and derivations are from Nikolov (2012).

Spatial Model of Interaction Matrix

The chosen system GMM estimation with the below specification will find parameters of regression that minimize the correlation between IVs and error terms. The time dynamics characteristics will be dealt with in the dynamic panel model with the usual specification of difference GMM and system GMM. However, the main contribution of this paper is including the reference effect variables. In this subsection, I describe how the reference effect variables are constructed and employed by introducing the spatial model of Bramoullé et al. (2009) approach.

The simplest version of specification of interest is

$$\begin{aligned} y_{i,t} =& \delta W y_{i,t} + \alpha y_{i,t-1} + \beta x_{i,t} + u_i + \epsilon_{i,t} \\ & where \quad i = 1, \ldots, N \quad t = 1, \ldots, T \end{aligned} \tag{5.23}$$

where W is n x n individual interaction matrix. In practice, let us suppose that we have six consumers in two groups of three members. Then, we can construct the interaction matrix as below $W_{reference\ group\ same\ size}$. The example below is constructed based on six consumers with the same number of members in each group. Consumer 1 refers to her own group members' spending amounts when she decides her own spending. Note that consumer 1 should exclude herself when she refers to other members' behaviour. The associated weighting matrix (interaction) is below.

$$W_{reference\ group\ same\ size} = \begin{array}{c} \\ row_1 \\ row_2 \\ row_3 \\ row_4 \\ row_5 \\ row_6 \\ \\ \end{array} \begin{array}{c} \begin{array}{cccccc} col_1 & col_2 & col_3 & col_4 & col_5 & col_6 \end{array} \\ \left(\begin{array}{ccc|ccc} 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} & 0 & 0 & 0 \\ \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} \\ 0 & 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 \end{array}\right) \\ \begin{array}{cccccc} col_1 & col_2 & col_3 & col_4 & col_5 & col_6 \end{array} \end{array} \begin{array}{c} \\ row_1 \\ row_2 \\ row_3 \\ row_4 \\ row_5 \\ row_6 \\ \\ \end{array}$$

One another condition for the reference effect identification is that we should construct the interaction matrix with at least two groups of different sizes. In Chapter 3, this condition holds for each reference group.[14] The example below is the one simply constructed based on seven consumers with two groups (three consumers and four consumers for each group, respectively).

[14]In Chapter 3, we have 10 Income groups, 8 Preference groups, 12 Regional groups, 19 Age groups, 2 Gender groups.

$$
W_{reference\ group\ different\ size} = \begin{array}{c} \\ row_1 \\ row_2 \\ row_3 \\ row_4 \\ row_5 \\ row_6 \\ row_7 \\ \\ \end{array} \begin{array}{c} \begin{array}{ccccccc} col_1 & col_2 & col_3 & col_4 & col_5 & col_6 & col_7 \end{array} \\ \left(\begin{array}{ccc|cccc} 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} & 0 & 0 & 0 & 0 \\ \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ 0 & 0 & 0 & \frac{1}{3} & 0 & \frac{1}{3} & \frac{1}{3} \\ 0 & 0 & 0 & \frac{1}{3} & \frac{1}{3} & 0 & \frac{1}{3} \\ 0 & 0 & 0 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 \end{array}\right) \\ \begin{array}{ccccccc} col_1 & col_2 & col_3 & col_4 & col_5 & col_6 & col_7 \end{array} \end{array} \begin{array}{c} \\ row_1 \\ row_2 \\ row_3 \\ row_4 \\ row_5 \\ row_6 \\ row_7 \\ \\ \end{array}
$$

With this type of matrix construction, I apply this concept to 5,424 individuals with several reference groups of different sizes. The intuition of this matrix construction is that, the contemporaneously endogenous reference variables ($WC_{i,t}$) can be included in the specification under the linearly independent (I≠W≠W^2) condition with the dependent variable ($C_{i,t}$, aggregate spending variable). By adding these reference group variables into the list of IVs, system GMM will care more about the cross-section dependence on top of the time dynamics especially due to linearly independent interaction variables with aggregate spending variables.

MLE vs. GMM vs. OLS based on Interaction Matrix

This discussion on the consistency condition for spatial & Global VAR (GVAR) is based on Elhorst et al. (2018). It is standard that the spatial econometrics literature assumes that spatially lagged terms as endogenous variables and use the MLE/GMM estimation, whereas GVAR assumes the foreign variables as weakly exogenous so that use OLS estimation. [15] Elhorst et al. (2018) summarise the relationship between the connectivity (interaction relations) matrix and conditions for satisfying consistent estimator in their paper. In this subsection, I refer to the main conditions and explain whether my interaction matrices are consistent with this discussion.

[Conditions for the choice of GMM/ML over OLS]

1. [Condition A: Boundness] The row and column sums of the non-normalised [16] matrix W are uniformly upper-bounded in absolute value K as N goes to infinity (Kelejian and Prucha (1999), Elhorst et al. (2018)).

[15] Spillovers in space and time: where spatial econometrics and Global VAR models meet, El horst et al. (2018)

[16] In this paper, I deal with the non-spatial matrix with the condition : each $W_{i,j} = 1$.

$$0 < \lim_{N \to +\infty} \sum_{j=1}^{N} |\omega_{i,j}| < K \tag{5.24}$$

Intuitively, it is understood that as we increase the number of consumers N, $\omega_{i,k} = 1$ is not always added up to the row sum.

2. [Condition B: Weak Divergence] The row and column sums of the non-normalized W diverge to infinity at a rate slower than N (Lee (2004), Elhorst et al. (2018)).

$$\lim_{N \to +\infty} \frac{\sum_{j=1}^{N} \omega_{i,j}}{N} = 0 \tag{5.25}$$

Intuitively, as the number of N increases (which means we add more cross-section relations), the connectivity across individuals becomes weaker.

3. [Condition C: Strong Divergence] The row and column sums of the non-normalised W diverge to infinity at a rate faster than $\sqrt{N}$ (Elhorst et al. (2018)).

$$\lim_{N \to +\infty} \frac{\sum_{j=1}^{N} \omega_{i,j}}{\sqrt{N}} = \infty \tag{5.26}$$

This condition means that each additional cross-section unit has so-called weak bilateral interaction, however, when they are aggregated, there is a significant aggregate effect.

Furthermore, Elhorst et al. (2018) summarise these above conditions to use MLE/GMM in the case of spatial econometrics whereas the OLS estimation is proper when GVAR framework in which a matrix of dense bilateral connections is characterized by small and equally distributed cross-section connectivity. [17]

[Choice between MLE and GMM]

Elhorst et al. (2018) suggest that spatial econometrics usually exploit IV/GMM or MLE and show that the choice of econometric methodology depends on the sparsity of the weighting matrix. [18] However, when it comes to the choice between ML and GMM. It is known that the system GMM can correct for the endogeneity of the spatial lag

[17] Elhorst et al. (2018) provide further conditions for consistency of OLS estimation in GVAR in their paper.

[18] OLS is used in the case of a dense interaction matrix (GVAR).

and lagged dependent variables as well as other potentially endogenous explanatory variables (Kukenova et al. 2009). GMM allows for the general identification without strong assumptions on error distribution. Since GMM estimates are from the set of moments that satisfies the target data and moment information. It is, however, known that GMM estimates are not statistically significant due to the lack of distribution assumptions. MLE usually assumes exogenous covariates and the ML procedure sidesteps the weak-IV-related issues (Xu, 2015).

Discussion: Application to My Work

All things considered, I choose the system GMM estimation with the common factors for the reference effect estimation in this Chapter 3. In terms of time dynamics, it is well described that the system GMM will care about the endogeneity with the exploitation of IVs. In terms of spatial (network) dynamics, if we include the network lag variables, we are exposed to the endogeneity from these network lags. However, GMM will care more about reference effects with the available moment condition, and the structure of weighting matrices ($I \neq W \neq W^2$) will allow us to use more IVs related to these reference effect variables as proper IVs in the system GMM estimation. In the choice of MLE and GMM, GMM is more likely to deal with the endogeneity from both time and spatial dynamics. MLE should impose a strong assumption on the normal distribution of error terms. Thus, I choose the system GMM approach. Of course, I believe that the MLE approach also can be employed in an attempt to compare two estimation methods in future research.

5.1.3 The choice of VAR and VECM, GARCH in Chapter 4

VAR vs. VECM, GARCH

[Reduced VAR. Recursive VAR, Structrual VAR]

The usual exploitation of the time-series model is the Vector Autoregression (VAR).

$$y_t = a + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t \tag{5.27}$$

where E(u$_t$) = 0, $E(u_t u_t')$ =Σ for all t=s and E(u$_t u_s'$) $= 0\ for\ all\ t \neq$ s, and y_t is a vector of k variables with p lags. u_t is vector of random distrubances.

Reduced VAR assumes that error terms are characterized by contemporaneous correlation. In the case of the recursive VAR, the model imposes identifying restrictions in which the previous error term only affects the following error components in an orderly manner. Structural VAR also imposes more strong restrictions based on theoretical background for macroeconomic forecasting. In Chapter 4, I use the reduced VAR approach since the target forecasting exercise is set up in a simplified way.

[Vector Error Correction Model : VECM]

VECM can be understood as an extension of the basic VAR model. If variables in the model are non-stationary, what we usually do is differencing the level variable to make it stationary. However, Granger and Engle (1987) suggest that two or more integrated nonstationary time series variables can be cointegrated. Their finding is that we might lose the long-run relationship if we just difference the time series variables to secure stationarity. The below equation is VECM specification.

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + u_t \tag{5.28}$$

where Δy_t is the differenced variable vector (k x 1), Γ_i and Π are k x k coefficient matrix. Π is the long-run equation matrix in which we can identify long-run relationship between variables. According to Granger representation theorem, if $r \leq k - 1$, which means the number of ranks in Π (r) is not higher than the number of integrated variables (k), there exists (k x k) matrix α and β where $\Pi = \alpha \times \beta$ and $\beta' X_t$ are all stationary. Then the above equation can be rephrased as below

$$\Delta y_t = \alpha\beta' i y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + u_t \tag{5.29}$$

Here, α can be interpreted as the speed of adjustment from the deviation from the long-run relationship. Intuitively, if variables are shown to be move together in the long run, it is better to use the extended model of VECM rather than VAR. However, I believe that my variables of interests are constructed as stationary[19] so that I chose a simple VAR model.

[ARCH and GARCH]

One alternative methodology is to use the conditional variance of time series data for forecasting. This is mainly motivated by the stylized facts of stock's variance clustering (Engle, 1982) in the stock market especially when we are allowed to use high-frequency data. In many cases of high-frequency data including daily stock forecasting, GARCH is exploited in the time-series forecasting literature. Below we can illustrate the GARCH(1,1) model which is the alternative representation of the ARCH(∞). The mean equation of the GARCH(1,1) is

$$Y_t = \mu_t + u_t \quad u_t = \sqrt{h_t}\epsilon_t \tag{5.30}$$

Then, additaionlly, we have variance equation part.

$$h_t = a_0 + a_1 u_{t-1}^2 + b_1 h_{t-1} \tag{5.31}$$

If we generalise the above variance equation of GARCH(1,1) into GARCH(p,q), we get

$$h_t = a_0 + \sum_{i=1}^{p} a_i u_{t-i}^2 + \sum_{i=1}^{q} b_i h_{t-i}^2 \tag{5.32}$$

The main motivation for this GARCH is that we observe daily stock volatility in high-frequency data. Many papers use daily stock prices for as long as ten years. However, my in-sample forecasting period is relatively short (three years with weekly data = 150 weeks) whereas the majority of the GARCH approach is characterized by longer time periods and more observations. Thus I employed the simple VAR approach in answering my research question.

[19] Since these are mainly excess return, ratio predictor of firms' sales growth variables.

Simulated Error and Cholesky Decomposition

In this paper, I am interested in simulating potential forecasts based on the error term of normal distribution. Thus, what I needed to do is decomposing $E(u_t u_t') = \Sigma$ with the Cholesky decomposition. This can be obtained by finding a matrix P which satisfies the below condition.

$$\Sigma = PDP' \tag{5.33}$$

where D is a positive diagonal matrix. Then, we can identify the structure of correlated random variables so that we are able to impose normal shock in each VAR equation. And these shocks will propagate in each VAR equation. Finally, we can make the distribution of forecasts of interest.

Discussion: Application to My Work

As I consider the available time-series econometric methodology, I chose simple VAR rather than VECM nor GARCH model. Since this Chapter 4 is restricted in terms of the time period (three years with weekly frequency), I believe that ARCH-type estimation could be exploited if we are more interested in daily stock forecasting or if we have long time series. VECM model is too general to implement and my variables tend to be stationary by construction. Thus, I did not use this model. While the econometric methodology is relatively simple, I focus on the research question related to various aggregation levels of variables and possible combinations of several firms and indices in Chapter 4. Still, I believe that future studies can employ alternative econometric methodology or models if we are allowed to use longer time series in a different set-up.

5.1.4 Summary of the Appendix

In this appendix, I provide reasons and limitations of my preferred estimators and models. Obviously, my main contribution is how to exploit high-frequency consumer information. Since my data is characterized by transaction-level, it is interesting to question whether the different levels of aggregation can provide new stylized facts. I tried to answer these research questions with consistent econometric methodology across constructed variables according to different aggregation levels. Although I believe my choices in my thesis fit the research questions within the available methods, it will be fruitful for me to study alternative methodology with extended datasets and research questions in future research.

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