FOOD INSECURITY, RACE and MARKET DEMAND

by

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Abstract

This dissertation includes three essays related to the analysis of the food market from both the consumers' end and the producers' end. On the consumption side, I look into the association between food insecurity and liquidity constraint. Further, I investigate this association focusing on black households. On the production side, I estimate the effect of generic advertising on market demand using the Autoregressive Distributive Lag Model.

In chapter 1, I investigate the association between food insecurity and financial liquidity constraints. I use a survey data obtained from the Qualtrics panel on the residents of Alabama and estimate the association using Linear Probability Model. In my study, liquidity constrained is defined as the inadequate cash in hand of the respondents. My estimation suggests that adequate cash in hand will act as a cushion for food insecurity. My results underscore that short-term cash on hand can be a solution to smoothen out consumption during a sudden disruption in income to restore food security. To check the robustness of my results, I controlled for the respondents living in the urban areas and incorporated the census tract data obtained from the Food Research Atlas to gauge the association between liquidity constraint and the food insecurity if the households are in the food deserts. We find that our estimates are robust. In addition to this, I find that, the association between financial liquidity constraint and food insecurity varies over race. For example, in the sample as a whole liquidity constraint increases the probability of a household being food insecure by 0.22. For white households the probability increases to 0.26, and for black households it decreases to 0.052.

The next chapter focuses on why the correlation between food insecurity and financial liquidity constraint is so much weaker for the black households. In this chapter, the analysis proceeds by focusing on a subset of the original sample identified as black households. For the

estimation, I use Linear Probability Model. Surprisingly, I find no significant association between food insecurity and liquidity constraints among the black households. To see whether specification error might explain the result, I explore the influence of different factors that include employment status, ability to obtain money from informal sources, participation of Supplemental Nutrition Assistance Program (SNAP), method of payment for grocery bills, frequency of visits to the grocery stores, distance of grocery stores, time to reach the grocery stores and the choice of visiting the grocery stores. Among these variables the only one to have a significant effect on results was informal sources for obtaining money. In this instance, all else equal the lack of such sources increases the probability of a black household being food insecure by 0.20. The inclusion of the variable caused the liquidity constraint variable to become significant with an estimated coefficient of 0.22. Overall, results suggest black households can mitigate food insecurity and the effect of liquidity constraints on food insecurity if they are able to borrow money from informal sources.

The third chapter explores the impact of generic advertising on market demand in the Norwegian whitefish industry using Autoregressive Distributive Lag (ADL) Model. Despite being a "workhorse" for dynamic single-equation regressions the ADL model and attendant methods of testing for cointegration have not been applied in empirical studies of generic advertising. The advantages of the autoregressive distributed lag (ADL) model for estimating the effects of generic advertising on market demand are evaluated by applying the model and attendant methods to data used in a recent study of Norway's export promotion program for whitefish. The dynamic specification differed greatly depending on model selection criteria (Akaike Information, Hannan-Quin, Schwarz, and Adjusted R2). Despite this there was little to choose between the specifications in terms of the estimated long-run demand elasticities. The estimated short-run elasticities differed among the specifications, with the model selected by the Hannan-Quin criterion indicating a more elastic response to income than the model selected by the Schwarz criterion. The bounds test for cointegration, a special feature of the ADL approach, proved useful in distinguishing between the appropriateness of quantity- and price-dependent specifications of the demand equation. Tests for weak exogeneity of the regressors indicated adjustments in quantity are 5.5 times more important than adjustments in price in resolving dynamic disequilibria caused by random (monthly) shocks to long-run demand.

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List of Abbreviations

ADL	Autoregressive Distributive Lagged
AIC	Akaike Information Criteria
ECM	Error Correction Model
ECT	Error Correction Term
HQ	Hannan Quin
LPM	Linear Probability Model
LR	Long Run
OLS	Ordinary Least Squares
SC	Schwartz Criteria
VECM	Vector Error Correction Model

Chapter 1

Food Insecurity and Financial Liquidity Constraints[1]

Introduction

Food insecurity, a households' limited accessibility of adequate quantity or quality of food (Mook et al. 2020) due to insufficient household resources and money (Nord et al. 2008; Coleman-Jensen et al. 2012) is associated with an array of detrimental health outcomes including mental health outcomes, higher risks of certain birth defects, and diabetes (Gundersen and Ziliak 2018). Forty million Americans (12.5 percent of the population) belong to food insecure households in 2017 (Coleman-Jensen et al. 2018). In 2020, owing to COVID-19, the levels of food insecurity have increased sharply compared to that in 2018 (Gundersen et al. 2021). Lack of access to adequate food due to insufficient purchasing power contributes to one of the elements of food insecurity. As income generation is vital for food security, unexpected shocks to household's income and budget makes them susceptible to food insecurity (Gundersen and Gruber 2001) and destabilizes the sustainable livelihoods. Households experiencing negative income shocks can avert the disruption in the pattern of consumption if they have sufficient savings[2] and liquid cash in hand. With enough cash in hand, an unanticipated change in the monthly income may not disturb food consumption.

In this study, we ask whether scarcity of cash in hand is related with household food insecurity, independent of income. The literature on food security has established socioeconomic and demographic factors like income, unemployment (Loopstra and Tarasuk 2013), race, household composition, marital status, education, and age (Nord 2012; Coleman-Jensen et al.

[1] Authors: Abhipsita Das, Dr. Joel Cuffey and Dr. Shuoli Zhao
[2] Here savings refer to liquid savings (Gundersen and Gruber 2001).

2012) that are associated with food insecurity. In addition to this, Americans have difficulty in consumption smoothing due to liquidity constraints (Ganong and Noel 2019; Ganong et al. 2020). Still studies about the association of food insecurity with liquidity constraints are scant. In this study, we try to fill the gap studying the impact of financial liquidity constraints on food insecurity.

Prior literature has established that food security is related to liquidity constraints captured through measures of assets. Assets in the literature include savings, money market funds, certificates of deposit, interest-earning checking accounts, government securities, bonds, stocks, mutual funds, treasury bills (Chang et al. 2014; Gundersen and Gruber 2001; Zeldes 1989). A few studies have also explored the association between food security and household assets like non-housing net worth, non-pension financial asset, vehicle ownership, and home ownership (Chang et al. 2014; Guo 2011). Most of the studies focused on their level of savings and risky assets, household debt burden and measures of household financial ratios (Olson et al. 1996, West and Prince 1976, Chang et al. 2014) apart from income to capture liquidity constraint. Leete and Bania (2010) do not have a proper definition of liquidity constrained status of households, but they consider, the inadequate combination of their income, assets, and the ability to borrow against future income to finance their optimal level of consumption that would maximize their utility in the absence of borrowing constraints to explain liquidity constrained. They test the importance of stable and transitory income components to determine food insufficiency. Using a logistic regression model, the study found that level of income as well as negative income shocks affect the predicted probabilities of food insufficiency, on the other hand, positive income shock do not affect them. Gundersen and Gruber (2001) focused beyond the current economic status of the households because only current income does not reflect the dynamic nature of the consumption decision of the households. They found that food insufficient households usually belong to the lower average incomes and are prone to income shocks and are less able to combat these shocks through their savings or borrowings. According to Ribar and Hamrick (2003), low levels of income derived from assets is an indicator of a household's ability to allocate the costs of consumption over time. The study also finds an association between low levels of asset income and food insufficiency problems. Our study looks beyond savings, capability of borrowing income, asset incomes, and focus on cash in hand. Inadequate cash in hand is an indicator of liquidity constrained of the households.

Our measurement of liquidity constrained does not require us to measure assets. Assets are also subject to substantial reporting. So, we use a measure of liquidity constrained that does not require us to measure assets and also capture non-asset sources of liquidity. We leverage a survey of Alabama residents from the online Qualtrics panel. We measure liquidity constraint by asking the respondents directly about their ability to obtain money immediately. Importantly the survey captured the level of difficulty that the respondents would face in immediately obtaining substantial sums of money. The cash in hand can be a non-formal method to smooth out consumption.

Our study tries to answer the following research questions. Is the scarcity of cash in hand related with household food insecurity, independent of income? Does the relationship between scarcity of cash in hand and household food insecurity vary over race, time, and income? To answer these research questions, we estimate linear probability model for our estimation and control for a range of demographic factors.

Using the survey data, we estimated linear probability models. using OLS. We find that, households are 22 percent (Table 1.2, Panel A, Column 2) more likely to be food insecure if they are financial liquidity constrained. Our results underscore that short-term cash on hand can be a solution to smoothen out consumption during a sudden disruption in income to restore food security; in other words, adequate cash in hand will act as a cushion for food insecurity. In addition, we find that, the association between financial liquidity constraint and food insecurity varies over race. We compared the marginal effects generated by LPM with those of nonlinear model, Probit and found they are very similar to each other. Following Occam's razor, we prefer LPM over Probit model in our analysis. To check the robustness of our results, we controlled for the respondents living in the urban areas and incorporated the census tract data obtained from the Food Research Atlas to gauge the association between liquidity constraint and the food insecurity if the households are in the food deserts. We find that our estimates are robust.

In the next section, our study explains the data and summary statistics, followed by empirical methods, and threats to identification. After that, our study explains the results, robustness checks, heterogeneity of the results of the baseline model across time, income and race and conclude along with the policy implications.

Data and Summary Statistics

We leverage an online survey of Alabama residents from the online Qualtrics panel. The project is based on a USDA grant to explore the willingness to pay for the organics of Alabama, thus it is restricted to Alabama. The online survey was launched in August 2020, the pilot survey was introduced in July 2020. The objective of the pilot survey is to make sure everyone understood the questions of the survey. The survey is conducted it online through mobile phones or computer. After the pilot survey, Qualtrics have sent invitations to a set of people to take the survey for some amount of money. If the participants have clicked yes to the invitations, they took the survey. But not a particular group of people was targeted in our survey. The age group of the respondents ranged between 19 to 70, and we tried to match the age distribution of Alabama. We did not target any specific race or income. We have used convenient sampling for the respondents. Data were collected for 1938 individuals. Initially the sample size was 2038, since we have not considered the sample collected during the pilot survey, the final sample size is 1938. The reason for this sample size is based on the amount of money we could provide participants to take the survey.

To assess a respondent's liquidity constraints, hypothetical scenarios were given to the respondents. Each scenario describes a financial problem that participants might experience. The scenarios are: "An emergency requires of you an immediate $3000 expense. How difficult would it be for you to come up with this amount of money on a very short notice?" and "An emergency requires of you an immediate $100 expense. How difficult would it be for you to come up with this amount of money on a very short notice?" These scenarios, by touching monetary issues, are meant to gauge their difficulty levels of obtaining the money right then, reflecting their short-term cash in hand constraint. Based on the amounts of money, the respondents are asked to obtain, we defined the scenarios as hard and easy. Following the works of Mani et al. (2013), the respondents were randomly assigned either to a "hard" condition, in which the scenario also involved higher costs that are $3000 for both car specific and any general problem; or to an "easy" condition, in which the scenarios involved lower costs that are $100. Respondents were given a hypothetical situation, asking how difficult for them to obtain either $100 or $3000 right then. We classified households as liquidity constraint if they answer, "very difficult" or "difficult". On the other hand, they are not liquidity unconstrained if their responses are either "easy" or "very easy" or "neither difficult nor easy". Liquidity constraint is a binary variable which is equal to one if the respondent is liquidity constrained and zero if the respondent is liquidity unconstrained.

The outcome variable is a binary indicator denoting whether the household is food insecure. We have constructed the outcome variable as a binary variable which is equal to one if households are categorized as food insecure, and equal to zero if households are food secure. To gauge food insecurity in our study, we used the situations: “The food that we bought just didn’t last and we didn’t have money to get more”; and “We couldn’t afford to eat balanced meals”. The affirmative responses of the households, “often true” and “sometimes true” categorized them as food insecure households. On the other hand, the households responding “never true” are classified as food secure households. All the questions asked to measure food insecurity relate to the financial constraints of the households in meeting food needs. The situations given in the survey fall under the category of marginal food security and food insecure without hunger according to USDA. In 2006, USDA has extended the classifications for food security and food insecurity that include High Food Security (HFS), Marginal Food Security (MFS), Low Food Security (LFS) and Very Low Food Security (VLFS) (Encinger et al. 2020). USDA defines marginal food secure households are those who experience problems at times or anxious about accessing sufficient food, but the quality, variety and quantity of their food are not significantly reduced. Studies of Ziliak and Gundersen (2016) have underscored marginal food security to explain entry and exit models. Encinger et al. (2020) also pointed out that labeling Marginal Food Secure households as “food secure” may underestimate their negative impacts. Coleman-Jensen (2010) finds that quality of life of Marginal food secure households more closely features that of food insecure households. Blumberg et al. (1999) also finds that food insecurity occurs “with and without” hunger and both the conditions render serious long-term health consequences.

We also asked them about their sources of borrowing in an emergency. An array of their sources includes banks, loans either from banks or families, credit cards, savings and checking accounts, and paychecks. The data contains a pool of information at the individual and household level. In the survey, we have asked about their nature of employment, income of the households, age, relationship status (married or unmarried), composition of households that include the number of adults and children, race, gender, and their educational attainment; they have attended schools and graduated from there, they have graduate degree or any other special skills for work, time of receiving paychecks.

Table 1.1 presents the summary statistics of the sample we use from the survey for our analysis. We have divided our sample according to the financial liquidity constraints of the respondents. From our sample, almost 29 percent of the liquidity unconstrained respondents are food insecure, while the percentage increased to 70 percent of being food insecure when the respondents are liquidity constrained. 18 percent of the financial liquidity unconstrained respondents belong to black households, on the other hand, 77 percent of the liquidity unconstrained respondents come from the white households. In the scenario of liquidity constraint, 21 percent of the respondents belong to black households and 73 percent of them come from white households. We divided our sample according to two races, white and black to compare the differences in the association between food insecurity and liquidity constrained. We do not show the percentage of food insecurity of other races (Hispanic and others) as there are not enough data points. Percentage of respondents belonging to the black households in our sample is 19. Comparing the percentage of black households with the census, which is 26.8 percent[3], black households are underrepresented. Our sample is non-representative of Alabama Representativeness is a worry if we want to have an external validity that is extrapolating our results with another sample. Our sample does not look like population of Alabama, so we cannot extrapolate our results to the population of Alabama or the entire population of US. For robustness

[3] The source of the census data: https://www.census.gov/quickfacts/AL

checks, the sample size shrinks to 1243 when we control for LILA along with the other controls. We dropped observations for respondents who could not be verified as living in Alabama. We merged the survey data with the food desert data using the latitude and longitude of the survey data, there some observations are dropped coming to 1243.

Empirical Strategy and Threats to Identification

Baseline Model

We model food insecurity as a function of whether the household is liquidity-constrained, controlling for socio demographic characteristics previously found to be related with food insecurity (Coleman-Jensen et al. 2012; Bartfeld and Dunifon 2006), and other attributes of the households, like time of receiving checks, difficulty of obtaining which amount more. To investigate the statistical relationship between food insecurity and financial liquidity constraint, the racial heterogeneity, and robustness of our results, we estimate a baseline model and interaction models. In all the models, our variable of interest that is financial liquidity constraint and dependent variable, food insecurity is binary. In the baseline model, we estimate the relationship using linear probability model (LPM) and Probit. The empirical relationship between food insecurity and financial liquidity constraint is expressed as:

1) $Pr(food\ insecurity|x, Z, T, \theta) = \alpha + \beta_1 x + \beta_2 Z + \beta_3 T + \epsilon$

2) $Pr(food\ insecurity = 1|x, Z, T, \theta) = \Phi(\alpha + \tau_1 x + \tau_2 Z + \tau_3 T)$

where $food\ insecurity$ is our outcome variable measuring household food insecurity, x measures financial liquidity constraint, Z is the vector of socio-demographic variables, T is the vector of specific control variables, θ is a vector of coefficients (β_1, β_2 and β_3, τ_1 , τ_2 and τ_3) to be estimated. ϵ is the random error with mean zero. The independent variable, x captures liquidity constrained. We treat equation (1) as linear probability model (LPM). On the other hand, equation (2) is treated as a probit model. Φ is the cumulative standard normal distribution function.

The main advantage of the LPM is the estimates are easy to interpret and the parameter estimates reliably represent mean marginal effects (Angrist and Pischke 2008). We have used robust standard errors to mitigate the problem of heteroskedasticity. Prior literature has investigated the tradeoffs between estimating a LPM model versus a nonlinear model like the probit model when the outcome variable is binary (Deke 2014, Greene 2003). One of the main disadvantages of LPM over nonlinear models, is that the predicted probabilities generated by the LPM can fall outside of the range zero and one. In Probit model, the predicted probabilities are always within the range of zero and one, while the disadvantage is that they are not easy to interpret. The limitation of the probit model is that it requires normal distributions of all unobserved components (Train 2003). In linear models, marginal effects are assumed to be linear, while non-linear marginal effects are not assumed to be linear and follow a different functional form. Both of those are just assumptions and often linear marginal effects are sufficient for approximation. But probit model is preferred by some researchers (Lien and Rearden (1990), thus we estimate our baseline model that is equation 2 using probit model[4].

Our coefficient of interests are β_1 and τ_1 ,which measure the correlation between our variable of interest, liquidity constraint (x) and the outcome variable, food insecurity of the households (food insecurity). We include eighteen control variables in the vector Z: gender (binary variable, male=1 or equal to 0), race, relationship status of the households which is a binary variable, equal

[4] The correct way to approach things is probably to estimate all the linear and non-linear models (Bellamere, blog "A Rant on Estimation with Binary Dependent Variables (Technical)", 2015 http://marcfbellemare.com/wordpress/8951).

to one if the respondent is married, zero if not, households with children and household size (number of adults, whether the households have children), age of the respondents, educational qualification of the respondents, nature of their employment, and household income. We also controlled for whether the household was asked about obtaining $100 or $3000, and whether the household was asked a general emergency or car repair specifically and the time of receiving their paychecks.

Threats to identification

Sources of threats to identification can be categorized into three broad sources of endogeneity: i) reverse causality, ii) unobserved heterogeneity, and iii) measurement error. There lies a possibility that financial liquidity constraint is caused by food insecurity. Kirkpatrick and Tarasuk (2008) and McIntyre et al. (2003) note that food insecure households are more likely to have adults who are nutrition deficient. These adults are also more probably suffer from cognitive problems (Heflin, Siefert and Williams 2005), depression (Whitaker et al. 2006), prolonged physical health problems (Tarasuk 2001) and diabetes (Seligman et al. 2007). The health problems have negative consequences on productivity of the adults. Brown et al. (1997), using a panel data set of 1992 from SIPP, found that even 37.5% of the food insufficient households despite being above the poverty level, have lost their jobs. Similarly, Rose (1999) also found that, comparing food insufficient and food sufficient individuals, the former are more likely to suffer from unemployment or losing food stamps that make them budget constraint. With our survey data, we find that food insecure households are 19 percent (Table 1.4) more likely to be liquidity constrained and thus we cannot rule out the existence of reverse causality. Moreover, the situation of food insecurity becomes more challenging for children. Study of Lueng et al. (2020) found an association between this stress and rise in the household food insecurity.

We cannot rule out the possibility of unobserved heterogeneity. It is likely that food insecurity and constraints are jointly determined that means they are jointly affected by a common set of confounders. Our data do not capture omitted variables that include prices, disability. Lastly in the case of measurement error, there is a chance of misreporting in our survey data.

Results

Impact of financial liquidity constraints on food insecurity

We estimated model 1 treating it as LPM, and the results are presented in Panels A, B and C of Table 1.2. The dependent variable, $food\ insecurity$ represents the household food insecurity taking the value 1 if the household is food insecure and 0 if food secure. The coefficients obtained are the marginal effects. The independent variable, x indicates the financial liquidity constraint and In the LPM model, we find a positive and statistically significant relationship between food insecurity and financial liquidity constraint. Households are 22 percent more likely to be food insecure if they are liquidity constrained. Consistent with the literature (Leete and Bania 2010; Gundersen and Gruber 2001), households with liquidity constraints are more likely to be food insecure than liquidity unconstraint ones and assets act as a cushion against food insecurity (Ribar and Hamrick 2003). In our estimation of the baseline model and the robustness check controlling urban, the sample size is dropped from 1938 to 1712 because there are missing values in the food insecurity where respondents skipped either of the questions.

The average marginal effects of the probit model are presented in Panel D of Table 1.2 (Column 2). We find the marginal effect of liquidity constrained on household food insecurity is positive and significant which indicates that households are almost 21 percent more likely to be food insecure if they are liquidity constrained. The marginal effects of probit model are almost the same as those estimated by LPM in terms of significance and magnitude. However, empirical literature which compare the estimates of LPM with those of nonlinear acknowledge the shortcomings of LPM, they also make the argument that the average estimates yielded by both the LPM, and nonlinear model are the same (Deke 2014). Consistent with Deke (2014), our estimates yielded by LPM, and probit model are also the same.

We continue to observe this relationship between food insecurity and financial liquidity constraint varying over races. The results for the white sample (Table 1.2, Panel B, column 2) mirror those from the entire sample. The white households are almost 26 percent to be food insecure if they are food insecure. On the other hand, the estimates of the black respondents indicate a significant association between the liquidity constraint and food insecurity of the black respondents (Panel C, column 3 of Table 1.2), the financial liquidity constrained households are 5.2 percent more likely to be food insecure which is much smaller than that of the white respondents. Despite the percentage of black households are less financially liquidity unconstrained compared to the white counterparts, the results across the races are quite surprising and suggest an existence of racial heterogeneity in our study. To check for the robustness of our estimates, we ran the model based on the access to food in food desert areas.

Robustness Checks

The marginal effects yielded by LPM, and Probit are the same, we focus on LPM in this section. To check the robustness of our estimates, we add controls for whether the respondent took the survey in a food desert and whether the respondent took the survey in an urban area. Food insecurity is a intricated public health issue influenced by socio-economic conditions, available resources, and infrastructure, which differs by location (JR and MD 2014). Economic opportunities came to a standstill in rural areas when compared to urban areas even before the pandemic. In rural areas, lower population growth restricted the growth of supermarkets. On the other hand, supermarket redlining in urban areas, exacerbated the access to affordable healthy food, and also scant vehicle facilities inhibits the accessibility to healthy food both in rural and urban areas (Garasky et al. 2006, Zhang and Ghosh 2016, Baek 2016). We therefore also control for whether the respondent took the survey in a food desert tract.

To obtain this spatial information, we merged our survey data with census tract identifiers using latitudes and longitudes given by Qualtrics. The census tract data obtained is then merged with the data obtained from food desert atlas of US matching their geographic identifiers[5] that are geoids. Food deserts are defined as geographical areas, particularly composed of lower income households characterized by a limited access of affordable and nutritious food according to the 2008 US Farm Bill.

The result presented in Table 1.2 (Column 2) is positive and significant which supports our main result (Table 1.2, Column 2). Households are 21 percent more likely to be food insecure if they are liquidity constrained. Controlling for low-income households with low accessibility (LILA) to healthy foods that is they are quite far away from supermarkets[6], 22 percent (Table 1.2, Column 2) more likely to be food insecure if they are financial liquidity constraint. Controlling both urban and LILA, we get almost the same results as our main results.

Heterogeneity of main results over time, income, and race

Based on the marginal effects generated by both LPM and Probit model, we use LPM for our estimation here. In addition to this, we also do a joint f test of the interaction terms to explore if

[5] Geographic identifiers are numeric codes that are assigned to every state and counties that uniquely identify all administrative/legal and statistical geographic areas for which the Census Bureau tabulates data. Geoids are different for each county among every state. They are important for interpreting geographic and demographic data and understanding their relationships with each other.

[6] Low access is measured as the distance from the supermarkets, where half a mile is used for urban areas and 10 miles for rural areas.

they are different from zero. Food consumption pattern can vary across the month. At the beginning of the month, cash in hand is often more than the end of the month as people usually receive their paychecks at the beginning of the month. The cash in hand tends to diminish towards the end of the month and impacts the consumption pattern of the households. We estimate the association between food insecurity and liquidity constrained of the households based on the beginning of the month. Thus, we estimate the interaction model:

3) $Pr(food\ insecurity|x, beginning, Z, T, \theta) = \alpha + \gamma_1 x + \gamma_2 beginning + \gamma_3 x * beginning + \gamma_4 Z + \gamma_5 T + \epsilon$

where $food\ insecurity$ is our outcome variable measuring household food insecurity, x measures financial liquidity constrained, Z and T are the vector of socio-demographic controls and specific control variables included in the baseline model, equation 1, θ is a vector of coefficients (γ_1, γ_2, γ_3, γ_4 and γ_5) to be estimated. ϵ is the random error with mean zero.

We have constructed the variable, $beginning$ as a binary variable according to the time of the survey taken by the respondents. The binary variable is equal to one if the respondents have taken the survey at the beginning of the month, starting from 1st of August till 14th of August and is equal to zero if the survey is taken on 15th August or sometime before or on 31st July 2020. The coefficient of the interaction term is γ_3 which will help us to estimate the association between food insecurity and liquidity constrained allowing the time to vary treating equation 2 as LPM.

From the significant coefficient of the interaction term (Table 1.3, Panel A, Column 2), we find that when the respondents took the survey at the beginning of the month, the association between the food insecurity and liquidity constrained is more than that when the survey is taken at the end of the month. Liquidity constrained households are 30 percent more likely to be food insecure at the beginning of the month, while they are 19 percent more likely to be food insecure at the end of the month. This estimate yields a heterogeneity in the results of the baseline model 1. The total effects (0.30 in Table 1.3) compared with the different time of the month suggests that there must be other factors that influence the association between food insecurity and liquidity constrained of the households like low income and different races. We performed a joint F test to estimate the impact of the interaction terms. The null hypothesis for the F test is H_0: γ_1+γ_3=0. Based on the p value (0.0263), we reject the null hypothesis.

Food insecurity of the households are different across the various strata of income. Income impacts the food insecurity of households significantly (Birkenmaier et al. 2016). The likelihood of being food insecure is high for the households experiencing income volatility (Leete and Bania 2010). We explain the heterogeneity of the estimates of the baseline model 1 based on the comparison of low income and high-income households using the LPM:

4) $Pr((food\ insecurity|x, low\ income, Z, T, \theta) = \alpha + \omega_1 x + \omega_2 low\ income + \omega_3 x *$
$low\ income + \omega_4 Z + \omega_5 T + \epsilon$

where $food\ insecurity$ is our outcome variable measuring household food insecurity, x measures financial liquidity constrained, Z and T are the vector of socio-demographic controls and specific control variables included in the baseline model, equation 1, θ is a vector of coefficients (ω_1, ω_2, ω_3, ω_4 and ω_5) to be estimated. ϵ is the random error with mean zero.

The variable, $low\ income$ is a binary variable which is coded as one if the annual income of the respondents is less than or equal to \$35000 and is equal to zero if the income is more than \$35000. Like the other estimated equations, we treat equation 3 as LPM and estimate it using OLS. The coefficient of the interaction term is ω_3 which will help us to estimate the association between food insecurity and liquidity constrained across the income of the households. Comparing low income and high-income households, we find the interaction term, ω_3 presented in Table 1.3 of

Panel B (Column 2) is statistically insignificant. This insignificant interaction coefficient suggests that the association between food insecurity and liquidity constrained do not depend on the variation on the income of the respondents. The total effect is statistically insignificant, and we fail to reject the null hypothesis.

Food insecurity varies across the races. In US food insecurity African Americans, Hispanics, and American Indians disproportionately (Kamdar et al. 2018). Moreover, the strategies adopted to reduce the effects of food insecurity are also influenced by race. In terms of financial assets, black households are more constrained and own less assets than white households to use when required to meet some unprecedented disruptions in the expenditure as they have just $1 in wealth for each $20 owned by the whites (Ruetschlin and Asante-Muhammad 2013). Thus, to explore how the association among food insecurity and liquidity constrained varies across races, we compare black households vs households of other race. In our survey, majority of other race consists of white households, there are hardly 29 data points for Hispanics and others, thus we consider only black and white households for our comparison. In equation 2, we estimate the association of food insecurity and liquidity constrained vary across black and white households:

5) $Pr(food\ insecurity|x, black, Z, T, \theta) = \alpha + \rho_1 x + \rho_2 black + \rho_3 x * black + \rho_4 Z + \rho_5 T + \epsilon$

where $food\ insecurity$ is our outcome variable measuring household food insecurity, x measures financial liquidity constrained and are same as included in equation 1, Z and T are the vector of socio-demographic controls and specific control variables included in the baseline model, equation 1, θ is a vector of coefficients (ρ_1, ρ_2, ρ_3, ρ_4 and ρ_5) to be estimated. ϵ is the random error with mean zero. Here also, equation 4 is treated as LPM and the coefficients are estimated using OLS.

The variable $black$ is a binary variable which is constructed as one if the respondents belong to black households and zero if they belong to white households. The results are presented in Table 1.3 in Panel C (Column 2). The coefficient of interaction term, ρ_3 is negative and statistically significant. When the white households are liquidity constrained, they are more 26 percent more likely to be food insecure. However, black households are 5.2 percent more likely to be food insecure if they are liquidity constrained. Our results find a major difference between the likelihood of being food insecure among the liquidity constrained households of the two races. From the joint f test of the interaction coefficients, we find that the sum of the coefficients of black and white households are not equal to zero, as we reject the null hypothesis ($p=0.0003<0.05$). Black households have financial liquid assets, not only less than that of their white counterparts despite being equal in age, education, employment and education (Despard et al. 2018). Despite the percentage of black households are less financially liquidity unconstrained compared to the white counterparts. Our result does not support that food insecurity is higher for black households than their white counterparts. One of the reasons might be the strong social networking they have, which help them to avert food insecurities despite having inadequate cash on hand. In the literature of food insecurity, African American households use food banks (Zekeri 2007; Barnidge et al. 2017). About 38 percent of black households are more likely to have a member involved in a social or civic organization (Martin et al. 2004). Social networks, through sharing of food or borrowing from friends, play a crucial role for the black households to diminish food insecurity (Parket et al. 2010). The estimates yield a racial heterogeneity, and we provide explanation behind the racial heterogeneity in chapter 2.

Conclusion

This chapter documents the methods of consumption smoothing during a sudden disruption in income using survey data. Our estimates suggest that the cash in hand will help in smoothing consumption pattern. Households are 22 percent more likely to be food insecure if they are liquidity constrained. Consistent with the literature (Leete and Bania 2010; Gundersen and Gruber 2001), households without liquidity constraints are more likely to be food insecure than liquidity unconstraint ones and assets act as a cushion against food insecurity (Ribar and Hamrick 2003). We suggest that cash in hand can be a support not only for poor people, also for others to maintain the same standard of living and consumption pattern at the end of the month as it was at the beginning of the month. Our results also explore a heterogeneity across time, income, and race in the path of consumption response and short-term cash in hand.

In our study, we highlight directions for future research. Future work can be carried on different samples to investigate if our results are consistent in the sample of other states. The extension of unemployment insurance and the benefits from the insurance can be effective in states like Alabama whose average monthly income is lower than that of New York. Our data could not capture the unemployment insurance benefits and the pattern of consumption spending during a temporary income disruption. The extension of this insurance is more beneficial than raising the insurance benefits (Ganong et al. 2019). The benefits given to the financially liquidity constrained households might help them to diminish food insecurity and smoothen out their consumption. The study of Ganong et al. (2019) also documents that liquidity constraints fail to address the reason behind the failure of the households to save when a fall in income is anticipated. To explain this failure, we propose income volatility may be studied and how it affects the savings of the households. The type of liquidity constrained we document in our study, explains the importance of cash on hand, but without savings, the cash on hand will not be sufficient to meet the demand of food at the time of the unprecedented economic shock. The pattern of spending of consumers varies in different states if they receive the insurance benefits. From policy perspective, savings scheme is important along with the financial literacy.

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Table 1.1. Summary Statistics

Variables	Liquidity Unconstrained	Liquidity Constrained	Total
Food Insecurity	0.289 (0.453)	0.708 (0.455)	0.452 (0.498)
Gender	0.404 (0.491)	0.192 (0.394)	0.320 (0.467)
Black	0.175 (0.380)	0.214 (0.411)	0.190 (0.393)
White	0.771 (0.421)	0.737 (0.440)	0.757 (0.429)
Hispanic	0.0145 (0.120)	0.0157 (0.124)	0.0150 (0.121)
Other Race	0.0401 (0.196)	0.0327 (0.178)	0.0372 (0.189)
Relationship	0.590 (0.492)	0.322 (0.467)	0.484 (0.500)
Household with Children	0.316 (0.465)	0.399 (0.490)	0.349 (0.477)
Household Size	2.677 (1.405)	2.956 (1.544)	2.787 (1.467)
Education	0.969 (0.173)	0.901 (0.299)	0.942 (0.233)
Employment	0.517 (0.500)	0.417 (0.493)	0.477 (0.500)
Age (Young, Mid-aged & old)	2.633 (1.046)	2.048 (0.892)	2.402 (1.028)
Poverty Ratio	3.278 (1.941)	1.658 (1.234)	2.638 (1.873)
Specific financial shocks	0.516 (0.500)	0.461 (0.499)	0.493 (0.500)
Amount	0.614 (0.487)	0.325 (0.469)	0.500 (0.500)
Paycheck Time	0.222 (0.416)	0.233 (0.423)	0.226 (0.418)

Note: The standard deviations are in parenthesis. Food insecurity is an outcome variable which is binary, equal to one if the households are food insecure and zero if they are food secure. Households are categorized based on their affirmative responses of the situations: "The food that we bought just didn't last and we didn't have money to get more"; and "We couldn't afford to eat balanced meals". The affirmative responses of the households, "often true" and "sometimes true" categorized them as food insecure households. On the other hand, the households responding "never true" are classified as food secure households. The sample size is 1938 and is summarized according to the liquidity constrained of the respondents of the survey.

Table 1.2. Relationship between food insecurity and liquidity constraint and the robustness checks of the estimates

Variables	Marginal Effects
Panel A: Full Sample	
Liquidity Constrained	0.216*** (7.70)
Sample	1712
Panel B: Robustness Checks (Controlling Urban)	
Liquidity Constrained	0.217*** (7.72)
Sample	1712
Panel C: Robustness Checks (Controlling Food Access)	
Liquidity Constrained	0.224*** (6.70)
Sample	1243
Panel D: Probit Model	
Liquidity Constrained	0.208*** (7.56)
Sample	1700

Note: T statistics are in parenthesis. *, **, *** indicate statistical significance at 5%, 1% and 10% level. Other coefficients are omitted for brevity. A full set of results containing the controls is presented in appendix Table A1.1. The dependent variable food insecurity is binary, equal to one if the households are food insecure and zero if they are food secure. We have controlled for urban and Food access, results presented in Panel B and Panel C. Urban is constructed based on the areas categorized as urban based on population. Food Access is measured by LILA. LILA denotes low income and low access households, low-income households living in urban areas that are more than one mile and rural areas that are more than ten miles from the supermarket. Other coefficients are not shown for brevity. Table A1.1, Table A1.2 and Table A1.4 represent the full set of coefficients. Coefficients are the marginal effects of LPM estimated by OLS. Panel D represents the marginal effects rendered by Probit Model.

Table 1.3. Relationship between food insecurity and liquidity constraint and the heterogeneity across time, income and race

Variables	Marginal Effects
Panel A: Interaction Model with Beginning of the month	
Liquidity Constrained	0.190*** (6.32)
Beginning	-0.0293 (-0.94)
Liquidity Constrained*Beginning	0.110* (2.22)
Total Effect at the beginning of the month	0.30* (p=0.0263) (2.22)
Panel B: Interaction Model with Low Income	
Liquidity Constrained	0.201*** (5.00)
Low Income	0.00620 (0.11)
Liquidity Constrained*Low Income	0.0273 (0.52)
Total Effect at Low Income level	0.23 (p=0.621) (0.51)
Panel C: Interaction Model with Black Households	
Liquidity Constrained	0.259*** (8.46)
Black Households	0.126** (3.10)
Liquidity Constrained*Black Households	-0.207*** (-3.64)
Total Effect of Black Households	0.052**(p=0.0003) (3.64)
Sample	1712

Note: T statistics are in parenthesis. *, **, *** indicate statistical significance at 5%, 1% and 10% level. Other coefficients are omitted for brevity. A full set of results containing the controls is presented in appendix Table A1.1. Time is the beginning of the month that is the survey taken at from 1st to 14th August. The dependent variable food insecurity is binary, equal to one if the households are food insecure and zero if they are food secure. Other coefficients are not shown for simplicity. Table A1.2, Table A1.3 and Table A1.4 represent the full set of coefficients. Coefficients are the marginal effects of LPM estimated by OLS. P values in brackets after coefficients of total effects are generated from the joint F tests.

Table 1.4. Reverse Causality

Variables	Marginal Effects
Food Insecurity	0.193*** (7.61)
Constant	0.71*** (8.85)
Sample	1712

Note: T statistics are in parenthesis. *, **, *** indicate statistical significance at 5%, 1% and 10% level. Here the dependent variable is food insecurity.

Appendix

Table A1.1. Association of food insecurity and liquidity constraints (Baseline Model), Robustness Check controlling urban

Variables	(1)	(2)
	Marginal Effects	
Liquidity Constrained	0.216***	0.217***
	(7.70)	(7.72)
Male	-0.0216	-0.0215
	(-0.94)	(-0.94)
Black Households	-0.00840	-0.00774
	(-0.14)	(-0.13)
White Households	-0.0388	-0.0360
	(-0.68)	(-0.63)
Hispanic Households	-0.0428	-0.0419
	(-0.46)	(-0.45)
Married	-0.0842**	-0.0835**
	(-3.17)	(-3.14)
Household with children	0.107**	0.108**
	(3.07)	(3.09)
Household (2 members)	0.0199	0.0202
	(0.55)	(0.56)
Household (3 members)	0.00791	0.00761
	(0.18)	(0.17)
Household (4 members)	-0.0405	-0.0408
	(-0.79)	(-0.80)
Household (5 members)	-0.0273	-0.0267
	(-0.46)	(-0.45)
Household (6 members)	-0.0572	-0.0571
	(-0.71)	(-0.71)
Household (7 members)	0.00783	0.00800
	(0.08)	(0.08)
Household (8 members)	0.164**	0.165**
	(2.65)	(2.64)
Household (9 members)	-0.657***	-0.662***
	(-9.13)	(-9.17)
Household (10 members)	0.284*	0.287*
	(2.03)	(2.04)
Education	-0.0893*	-0.0896*
	(-2.07)	(-2.07)

Employment	-0.00270 (-0.12)	-0.00299 (-0.13)
Age (>30 & <=50)	0.0320 (1.04)	0.0330 (1.07)
Age (>50 & <=65)	-0.0888* (-2.50)	-0.0871* (-2.44)
Age (>65)	-0.180*** (-4.47)	-0.178*** (-4.41)
Poverty (>=200% &<300%)	-0.135*** (-3.97)	-0.135*** (-3.97)
Poverty (>=300% &<400%)	-0.273*** (-7.14)	-0.275*** (-7.18)
Poverty (>=400% &<500%)	-0.279*** (-6.32)	-0.279*** (-6.31)
Poverty (>=500% &<600%)	-0.328*** (-7.06)	-0.329*** (-7.09)
Poverty (>=600% &<700%)	-0.317*** (-8.03)	-0.320*** (-8.10)
Poverty (>=700% &<800%)	-0.332 (-1.92)	-0.330 (-1.93)
Poverty (>=800% &<900%)	-0.399*** (-5.10)	-0.399*** (-5.05)
Poverty (>=900% &<1000%)	-0.361*** (-4.16)	-0.363*** (-4.19)
Financial Shock	-0.0107 (-0.53)	-0.0111 (-0.55)
Amount to obtain	0.0534** (2.60)	0.0540** (2.62)
Time of Paycheck	0.0174 (0.71)	0.0169 (0.69)
Urban		0.0146 (0.71)
Constant	0.672*** (8.19)	0.660*** (7.84)
Sample	1712	1712

Note: T statistics are in parenthesis. *, **, *** indicate statistical significance at 5%, 1% and 10% level.
Financial shock refers to sudden requirement of money for repairing car. Amount to obtain is ability to obtain either $100 or $3000.
Time of payment refers to the beginning of the month when usually respondents receive paychecks.

Table A1.2. Association of food insecurity and liquidity constraints (Baseline Model), Robustness Check controlling Food Access

Variables	(1)
	Marginal Effects
Liquidity Constrained	0.224*** (6.70)
Male	-0.0504 (-1.92)
Black Households	-0.0228 (-0.33)
White Households	-0.0737 (-1.17)
Hispanic Households	-0.0197 (-0.17)
Married	-0.112*** (-3.46)
Household with children	0.0912* (2.17)
Household (2 members)	0.0654 (1.48)
Household (3 members)	0.0424 (0.79)
Household (4 members)	0.0347 (0.56)
Household (5 members)	0.0291 (0.42)
Household (6 members)	0.0779 (0.84)
Household (7 members)	0.107 (0.96)
Household (8 members)	0.270*** (3.66)
Household (9 members)	-0.544*** (-6.18)
Education	-0.128* (-2.22)

Employment	0.0122 (0.48)
Age (>30 & <=50)	0.0392 (1.02)
Age (>65)	-0.0720 (-1.67)
Poverty (>=200% &<300%)	-0.134*** (-3.31)
Poverty (>=300% &<400%)	-0.277*** (-6.36)
Poverty (>=400% &<500%)	-0.310*** (-6.15)
Poverty (>=500% &<600%)	-0.331*** (-6.48)
Poverty (>=600% &<700%)	-0.305*** (-6.80)
Poverty (>=700% &<800%)	-0.280 (-1.32)
Poverty (>=800% &<900%)	-0.324*** (-3.42)
Poverty (>=900% &<1000%)	-0.362*** (-4.20)
Financial Shock	-0.0179 (-0.76)
Amount to obtain	0.0539* (2.25)
Time of Paycheck	0.00726 (0.26)
LILATracts_1And10	0.0118 (0.37)
Constant	0.672*** (6.56)
Sample	1243

Note: T statistics are in parenthesis. *, **, *** indicate statistical significance at 5%, 1% and 10% level. LILATracts_1And10 is the low income and low access areas where rural households and urban households have their grocery stores more than ten miles and one mile. Financial shock refers to sudden requirement of money for repairing car. Amount to obtain is ability to obtain either $100 or $3000. Time of payment refers to the beginning of the month when usually respondents receive paychecks.

Table A1.3. Association of food insecurity and liquidity constraints (Baseline Model), Robustness Check using Probit Model

Variables	(1)
Liquidity Constrained	0.660*** (7.93)
Male	-0.0922 (-1.17)
Black Households	0.0197 (0.10)
White Households	-0.0808 (-0.45)
Hispanic Households	-0.0553 (-0.17)
Married	-0.271** (-3.14)
Household with children	0.341** (3.13)
Household (2 members)	0.0255 (0.22)
Household (3 members)	-0.0122 (-0.09)
Household (4 members)	-0.157 (-0.98)
Household (5 members)	-0.124 (-0.70)
Household (6 members)	-0.227 (-0.91)
Household (7 members)	0.00636 (0.02)
Education	-0.331* (-2.04)
Employment	-0.00281 (-0.04)
Age (>30 & <=50)	0.128 (1.32)
Age (>50 & <=65)	-0.248* (-2.21)

Age (>65)	-0.645*** (-4.56)
Poverty (>=200% &<300%)	-0.368*** (-3.79)
Poverty (>=300% &<400%)	-0.765*** (-6.42)
Poverty (>=400% &<500%)	-0.785*** (-5.39)
Poverty (>=500% &<600%)	-0.967*** (-6.13)
Poverty (>=600% &<700%)	-1.082*** (-6.16)
Poverty (>=700% &<800%)	-0.984 (-1.45)
Poverty (>=8200% &<900%)	-1.480* (-2.48)
Poverty (>=900% &<1000%)	-1.163** (-2.77)
Financial Shocks	-0.0308 (-0.44)
Amount to obtain	0.204** (2.70)
Time for Paycheck	0.0594 (0.71)
Constant	0.504 (1.87)
	Marginal Effects
	0.208*** (7.56)
Sample	1700

Note: T statistics are in parenthesis. *, **, *** indicate statistical significance at 5%, 1% and 10% level. Financial shock refers to sudden requirement of money for repairing car. Amount to obtain is ability to obtain either $100 or $3000. Time of payment refers to the beginning of the month when usually respondents receive paychecks.

Table A1.4. Heterogeneity of the main results (Baseline Model) over time, income and race

Variables	(1)	(2)	(3)
		Marginal Effects	
Liquidity Constrained	0.190***	0.201***	0.259***
	(6.32)	(5.00)	(8.46)
Beginning	-0.0293		
	(-0.94)		
Liquidity Constrained*Beginning	0.110*		
	(2.22)		
Time for Paycheck		0.0178	0.0148
		(0.73)	(0.61)
Male	-0.0241	-0.0216	-0.0200
	(-1.05)	(-0.94)	(-0.88)
Black Households	-0.00648	-0.0107	
	(-0.11)	(-0.17)	
White Households	-0.0378	-0.0411	
	(-0.67)	(-0.72)	
Hispanic Households	-0.0439	-0.0480	
	(-0.48)	(-0.51)	
Married	-0.0843**	-0.0838**	-0.0774**
	(-3.18)	(-3.15)	(-2.92)
Household with children	0.106**	0.106**	0.0995**
	(3.06)	(3.02)	(2.83)
Household (2 members)	0.0182	0.0200	0.0145
	(0.51)	(0.55)	(0.41)
Household (3 members)	0.00901	0.0108	0.00741
	(0.20)	(0.24)	(0.17)
Household (4 members)	-0.0393	-0.0367	-0.0341
	(-0.77)	(-0.70)	(-0.66)
Household (5 members)	-0.0246	-0.0216	-0.0240
	(-0.42)	(-0.36)	(-0.41)
Household (6 members)	-0.0545	-0.0488	-0.0548
	(-0.68)	(-0.58)	(-0.69)
Household (7 members)	0.0139	0.0137	0.0107
	(0.15)	(0.14)	(0.11)
Household (8 members)	0.170**	0.172*	0.154*
	(2.86)	(2.51)	(2.57)
Household (9 members)	-0.620***	-0.642***	-0.734***
	(-8.43)	(-7.17)	(-9.97)
Household (10 members)	0.282*	0.287*	0.262
	(2.10)	(2.04)	(1.73)
Education	-0.0879*	-0.0869*	-0.0910*
	(-2.03)	(-2.01)	(-2.16)

Employment	-0.0000731 (-0.00)	-0.00230 (-0.10)	-0.00520 (-0.23)
Age (>30 & <=50)	0.0342 (1.11)	0.0318 (1.03)	0.0305 (1.00)
Age (>50 & <=65)	-0.0890* (-2.51)	-0.0894* (-2.51)	-0.0901* (-2.56)
Age (>65)	-0.178*** (-4.43)	-0.181*** (-4.50)	-0.177*** (-4.45)
Poverty (>=200% &<300%)	-0.137*** (-4.03)	-0.121** (-2.79)	-0.139*** (-4.11)
Poverty (>=300% &<400%)	-0.273*** (-7.14)	-0.257*** (-4.55)	-0.271*** (-7.11)
Poverty (>=400% &<500%)	-0.280*** (-6.38)	-0.264*** (-4.31)	-0.276*** (-6.24)
Poverty (>=500% &<600%)	-0.329*** (-7.11)	-0.313*** (-4.95)	-0.325*** (-6.98)
Poverty (>=600% &<700%)	-0.315*** (-7.96)	-0.302*** (-5.06)	-0.307*** (-7.81)
Poverty (>=700% &<800%)	-0.338* (-1.98)	-0.314 (-1.76)	-0.344* (-2.15)
Poverty (>=800% &<900%)	-0.398*** (-5.04)	-0.382*** (-4.13)	-0.381*** (-4.72)
Poverty (>=2900% &<1000%)	-0.368*** (-4.37)	-0.345*** (-3.46)	-0.356*** (-3.92)
Financial Shocks	-0.0100 (-0.50)	-0.0109 (-0.54)	-0.00906 (-0.45)
Amount to obtain	0.0532** (2.59)	0.0532* (2.58)	0.0539** (2.63)
Low Income		0.00620 (0.11)	
Liquidity Constrained*Low Income		0.0273 (0.52)	
Blacks Households (Comparison)			0.126** (3.10)
Liquidity Constrained*Blacks Households (Comparison)			-0.207*** (-3.64)
Constant	0.678*** (8.25)	0.658*** (6.75)	0.618*** (10.06)
Sample	1712	1712	1712

Note: T statistics are in parenthesis. *, **, *** indicate statistical significance at 5%, 1% and 10% level. Blacks Households (Comparison) is the dummy variable which is equal to one if the respondents belong to black households and zero if they belong to white households. Beginning is equal to one if the survey taken between 1st August to 14th August 2020, and zero if it is taken on 15th August. Low Income is coded as one if the annual income of respondents is less than equal to $35000, and zero if the income is greater than $35000. Financial shock refers to sudden requirement of money for repairing car. Amount to obtain is ability to obtain either $100 or $3000. Time of payment refers to the beginning of the month when usually respondents receive paychecks.

Chapter 2

Race and the association between food insecurity and financial liquidity constraints[1]

Introduction

In US the financial assets owned by black households are less than that of their white counterparts despite being equal in age, education, employment and education (Despard et al. 2018). When required to meet some unprecedented changes in the expenditure black households have just $1 in wealth for each $20 owned by the whites (Ruetschlin and Asante-Muhammad 2013). Black households are twice likely to have insufficient liquid assets as whites to meet necessary expenses of three months (Haveman and Wolff 2005) and have liquid savings equivalent to an average of 5 days of income; however, white households have savings equivalent to average of 31 days of income (Pew Charitable Trusts 2015). Ganong et al. (2020), using a statistical model of consumption and income, calculates the welfare gain of protecting a household from a transient income volatility. They found the welfare gain for the black households to be 46 percent higher than those of white households, suggesting larger differences in consumption elasticities lead to larger gap in welfare gaps.

In US, black households are significantly more food insecure compared to other races (Myers and Painter 2017). Despite black households having less financial assets than other races, it is important to focus on how insufficient cash in hand impact their consumption pattern. In this chapter, we aim to answer two research questions: Does inadequate cash in hand or liquidity constraints impact food insecurity among black households? What are the explanations behind this relationship? To answer the research questions, we leverage a survey of Alabama residents from

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the online Qualtrics panel. We obtain data from the survey taken by the respondents and restricted our sample only to black sample as we are interested in the association between food insecurity and liquidity constraints among the black households.

We estimated the survey data using linear probability model (LPM). We find no significant association between financial liquidity constraint and food insecurity among black households. Furthermore, our results indicate that the financial liquidity constrained households are less likely to be food insecure when they are able to obtain money from informal sources. In the next section, our study explains the data and summary statistics, followed by empirical methods, the explanations for racial heterogeneity and conclude along with the policy implications.

Data and summary statistics

In this chapter, to explain the reasons behind the association between food insecurity and liquidity constrained among the black households, our sample is only restricted to the black respondents of the survey. We leverage an online survey of Alabama residents from the online Qualtrics panel. In our survey, first, we sampled the Qualtrics respondents in Alabama to match Alabama's age distribution. Data were collected for 1938 individuals.

To capture household financial liquidity constraints, respondents are asked a scenario. The scenarios are: "An emergency requires of you an immediate $3000 expense. How difficult would it be for you to come up with this amount of money on a very short notice?" and "An emergency requires of you an immediate $100 expense. How difficult would it be for you to come up with this amount of money on a very short notice?" These scenarios, by touching monetary issues, are meant to gauge their difficulty levels of obtaining the money right then, reflecting their short-term cash in hand constraint. We classified households as liquidity constrained if they answer, "very difficult" or "difficult". On the other hand, they are not liquidity unconstrained if their responses are either “easy” or “very easy” or “neither difficult nor easy”. The variable of interest capturing liquidity constraints is a binary variable.

The outcome variable is a binary indicator denoting whether the household is food insecure. To gauge food insecurity in our study, we used the situations: “The food that we bought just didn’t last and we didn’t have money to get more”; and “We couldn’t afford to eat balanced meals”. The affirmative responses of the households, “often true” and “sometimes true” categorized them as food insecure households. On the other hand, the households responding “never true” are classified as food secure households. All the questions asked to measure food insecurity relate to the financial constraints of the households in meeting food needs.

We also asked them about their sources of borrowing in an emergency. An array of their sources includes banks, loans either from banks or families, credit cards, savings and checking accounts, and paychecks. In the survey, we have asked about their nature of employment, income of the households, age, composition of households that include the number of adults and children, race, gender, and their educational attainment; they have attended schools and graduated from there, they have graduate degree or any other special skills for work. In addition to obtaining the socio demographic factors, some people are asked how difficult it will be for them to obtain $100 or $3000 immediately for financial shocks[2] like car repair, and the questions were randomized to reduce biased responses with closed-ended answers.

In our survey, to capture the shopping behavior, we have asked the respondents how many times they visit grocery stores in a month: at least once a month, once in two weeks, once in a month and less than once in a month, as the geographic location of the grocery stores affect the

[2] It is likely that financial shocks like car repair may disrupt the finances of the households making them financially insecure (Despard et al. 2018).

shopping pattern of the individuals. To estimate the distance of the grocery stores from their places, we ask how much time required to reach there: less than five minutes, five to ten minutes, ten to twenty minutes, twenty to forty minutes, or more than forty minutes. Lack of transportation hinders the visits to the grocery stores, especially for low-income households (Clifton 2004; Bader et al. 2010; Widener et al. 2011). Thus, we have asked their modes of transportation, whether they have used their own car, someone has given their rides, or they order online. Moreover, prior literature (Hendrickson et al. 2006; Disantis et al. 2016; Alkon et al. 2013) suggests that prices of the grocery items is the key factor of the shopping behavior. Therefore, we asked the reason behind choosing their grocery stores. The respondents were also asked about their modes of payments, credit cards or debit cards for the groceries as well. The survey also asked if the respondents have participated in Supplemental Nutrition Assistance Program (SNAP). Responses are coded 1 as yes and 0 as no.

Table 2.1 presents the summary statistics of the black sample we use from the survey for our analysis. We have divided our sample according to the financial liquidity constraints of the respondents. From our sample, 49.7 percent of the liquidity unconstrained respondents belonging to the black households are food insecure. The percentage of being food insecure increased to 70 percent under the scenario of liquidity constrained for the black respondents. Only 45.7 percent of the liquidity constrained black respondents are employed, while we find the percentage of the unconstrained respondents employed is very close to 65. The percentage of respondents borrowing money from informal sources that include friends, family, partners for liquidity constrained and unconstrained situations do not differ much, 70 and 68.8. 33 (32.7) percent of the liquidity constrained respondents participate in Supplemental Nutrition Assistance Program (SNAP), however, 26 percent of the unconstrained respondents participate in SNAP. Our sample shows that almost 18 percent of the liquidity constrained respondents use credit cards for grocery bills, surprisingly the percentage of the unconstrained ones using credit cards for the same purpose are more, close to 30 (29.6 percent). The determinants of the shopping behavior include number of visits to the grocery stores, distance of grocery stores from their places and whether they use their own car to travel to the grocery stores. For liquidity constrained respondents, the percentage (72.6) of them visiting grocery stores atleast once in a month or once in two weeks are less than that of unconstrained counterparts (80 percent). This suggests that inadequate cash in hand makes them difficult to buy grocery frequently. From the sample, 62 percent of the liquidity constrained respondents live in places which is within five minutes and five to ten minutes from the grocery stores. 57 percent of the unconstrained respondents live within five to ten minutes distance from the grocery stores. Thus, less percentage of better off respondents live nearby grocery stores in our sample. Almost 70 percent (69.6 percent precisely) of the respondents who are liquidity constrained use their own or family vehicle to reach the grocery stores, the percentage of respondents using own cars increase to 75 when they are better off in liquidity. 22 percent of the liquidity constrained respondents choose grocery stores where low-priced food items are available, the percentage does not change by much, 20 percent when they are unconstrained. Though the actual sample size is 314, in some estimations it shrinks because of missing variables in the survey data.

Empirical Strategy

Baseline Model

To study the association between food insecurity and liquidity constrained among the black households, we estimate the equation:

1) $Pr(food\ insecurity|x, Z, T, \theta) = \alpha + \beta_1 x + \beta_2 Z + \beta_3 T + \varepsilon$

In the equation 1, $food\ insecurity$ is the outcome variable and x represents the liquidity constraints of the black households. θ is a vector of coefficients (β_1 , β_2 , β_3) to be estimated. ε is the random error that has mean zero. The outcome variable is a binary variable, constructed as one if the households are food insecure and as zero if they are food secure. In addition to this, the independent variable, x is also binary, which is equal to one if the respondents are liquidity constrained and equal to zero if they are liquidity constrained. The coefficient of interest is β_1 which measures the association of food insecurity and liquidity constraints of the black sample. In the baseline model (equation 1), the three sources of threats to identification that include reverse causality, unobserved heterogeneity and measurement error, contribute to the reasons behind our coefficient of interest, β_1 cannot capture causality, and it reflects only the association.

We treat equation 1 as linear probability model and estimate the model using OLS. The reason for using LPM is the coefficients generated by the model are easy to comprehend and they represent marginal effects. In our estimates, we checked heteroskedasticity using robust standard errors. We estimated equation 1 using only black sample. The results for the baseline model are presented in Table 2.2. Our estimates find no significant association between the food insecurity and liquidity constraints of the black households, which is surprising. To explain the insignificant association in the estimates yielded in the baseline model, we present different models, interacting certain factors, employment status, borrowing from informal sources, shopping behavior of the households, availability of low-priced food items, participation in Supplemental Nutrition Assistance Program (SNAP), payment of grocery bills through credit cards.

Explanations behind the relationship between food insecurity and liquidity constraints

Influence of employment status

For our estimation of the LPM models explaining racial heterogeneity through interaction terms, we take the subset of the sample containing the information for only black households. We also conducted f tests on the interaction terms to check if the sum of the coefficients of the interaction terms is different from zero. The nature of employment as well as the status of employment influences

2) $Pr(food\ insecurity|x, employed, Z, T, \theta) = \alpha + \gamma_1 x + \gamma_2 employed + \gamma_3 x * employed + \gamma_4 Z + \gamma_5 T + \varepsilon$

Here, we construct $employed$, a binary variable which is equal to one if the respondents are employed and equal to zero if they are not. This variable captures the employment status of the respondents. The other variables remain the same as equation 1. γ_1 and γ_3 are the coefficients of interest measuring the effect of liquidity constraint on the food insecurity relative to their status of employment. θ is a vector of coefficients (γ_1 , γ_2 , γ_3, γ_4 , γ_5) to be estimated. ε is the random error that has mean zero. We estimate equation (2) using OLS. For the f test in all the interaction models, the null hypothesis H_0: $\gamma_1 + \gamma_3 = 0$.

In the interaction model presented in equation (2), the estimate of the interaction terms (Panel A of Table 2.3), liquidity constraint (x) and employment status of the black households ($employed$) is found to be insignificant (γ_3=0.177). The insignificant coefficient of the interaction term indicates that the association between food insecurity and liquidity constrained do not depend on the employment status of the black households, they might depend on the nature of the jobs, and the strong social networking they have to mitigate food insecurity. Studies have underscored social networks as well as social support systems as mediums to maintain the supplied of food for households (Young 1998, Martin et al. 2004). Fitchen coined the sharing of food among households "an informal security of networks" (Fitchen 1987). While being employed, black household is 15 percent more likely to be food insecure if financially unconstrained. Besides income, negative psychosocial factors such as less perception on healthy food choices serve as a barrier to the purchase and consumption of healthy food and fresh produce (Vedovato et al. 2016).

Influence of ability of obtaining money from informal sources

Nearly 10 million of the American population are unbanked that they lack access to formal financial institutions[3] (Birkenmaier et al. 2016). Barr (2012) also found, controlling for education, employment and income, African Americans are more likely to be unbanked compared to their non-American counterparts. 56 percent of low income[4] banked population are more likely to maintain only a checking account, on the other hand, 53 percent of the banked black report of having a savings account (Brobeck 2008; Burhouse 2012). Formal borrowing indicates that banked status of the households. In our study, we estimate the effect of financial constraint of the black households on their food insecurities based on their borrowing money from informal sources, treating the following equation as LPM model.

3) $Pr(food\ insecurity|x, informal, Z, T, \theta) = \alpha + \delta_1 x + \delta_2 informal + \delta_3 x * informal + \delta_4 Z + \delta_5 T + \varepsilon$

Here, we construct a binary variable informal, equal to one if the respondents cannot have the accessibility to the formal institutions and sources, that include banks, loans, savings, checking

[3] Household financial access is defined as the inaccessibility of savings or checking (Ardic et al. 2013; FDIC 2012a; US. Department of the Treasury, 2011).
[4] Low income indicates income up to $30000 annually.

accounts, and paychecks to obtain money and equal to zero if they can borrow money from these formal sources. The other variables remain the same as equation 1. δ_1 and δ_3 are the coefficients of interest measuring the effect of liquidity constraint on the food insecurity varying on borrowing money from formal sources. θ is a vector of coefficients (δ_1, δ_2, δ_3, δ_4 and δ_5) to be estimated. ε is the random error that has mean zero.

The marginal and total effects from equation (3) are shown in Table 2.3. We find the coefficient (Panel B, Table 2.3) of interaction term of liquidity constraint and borrowing from informal sources of the black households varying on their ability to access credit from informal sources negative and statistically significant (δ_3 = -0.260) at 5 percent level of significant. This implies that black households are 23 percent more likely to be food insecure if they are liquidity constrained and are incapable of obtaining \$100 or \$3000 even from the informal sources. The total effect, -0.034 suggests of the situation when the liquidity constrained black households are able to borrow money from informal sources, they are 3.4 percent less likely to be food insecure. We cannot reject the null hypothesis of the f test of joint significance. An African American household, also of smaller size may suffer less financial insecurity than a low-income household, making banked status less associated with their hardships of food. The black households can reduce their food insecurity through social networks or borrowing from other families or social organizations. Certain strategies adopted by the black households to combat food insecurity are use of food stamps, food pantries, social networking through meal-sharing with extended family, nutrition-related like reduction in portion size of intakes and nonpayment of bills to purchase food (Chilton et al. 2013).

Influence of the participation of SNAP and mode of payment for grocery bills

Prior studies on food insecurity found a positive association between participation of Supplemental Nutrition Assistance and the less healthy consumption pattern of black households especially at the starting and end of the benefit cycle (Meyerhoefer and Yang 2011; Kharmats et al. 2014), and these federal food assistance programs play an important role in mitigating food insecurity (Leung and Villamor 2011; Leung et al. 2014). We explore the association of liquidity constraint and food insecurity of the black households on the basis of their participation of the Supplemental Nutrition Assistance Program (SNAP) through the LPM model:

4) $Pr(food\ insecurity|x, SNAP,\ Z, T, \theta) = \alpha + \omega_1 x + \omega_2 SNAP + \omega_3 x * SNAP + \omega_4 Z + \omega_5 T + \varepsilon$

In the above model, SNAP is constructed as a binary variable, equal to one if the respondents participated in the program and equal to zero if they have not participated in the program. The model contains all the variables, other than SNAP same as model 1. ω_1 and ω_3 are the coefficients of interest measuring the association between food insecurity and financial liquidity constraint of the black households based on their participation on SNAP. θ is a vector of coefficients (ω_1, ω_2, ω_3, ω_4 and ω_5) to be estimated. ε is the random error that has mean zero.

Another important factor that determines the shopping pattern of the black households is their mode of payment, whether they depend on credit card to pay for their grocery bills. Other studies have found that, under tumultuous economic conditions many African American households depend on credit to fulfill their basic needs (Ruetschlin and Muhammad 2013). Thus, the role played by the credit in the financial securities of the black households is substantial. We investigate the impact of liquidity constraint condition of the black households on their food insecurities when they use their credit cards to pay their grocery bills.

5) $Pr(food\ insecurity|x, credit, Z, T, \theta) = \alpha + \tau_1 x + \tau_2 credit + \tau_3 x * credit + \tau_4 Z + \tau_5 T + \varepsilon$

This model (equation 7) also contains all the variables, other than credit same as model 1. τ_1 and τ_3 are the coefficients of interest measuring the effect of liquidity constraint on the food insecurity based on their payments for groceries. We have constructed the variable, credit as a binary, equal to one if the respondents use their credit cards for their grocery expenses and zero if they use other mediums, like debit cards, cash, EBT (Electronic Benefits Transfer), SNAP (Supplemental Nutrition Assistance Program), and WIC (Special Supplemental Nutrition Assistance Program for Women, Infants and Children) to pay the bills. θ is a vector of coefficients (τ_1, τ_2, τ_3, τ_4 and τ_5) to be estimated. ε is the random error that has mean zero

The estimates of the coefficients, ω_3 and τ_3 are presented in Table 2.3 in Panel C and D (Column 2). The coefficient of the association between food insecurity and financial liquidity constraint of the black households is statistically insignificant (ω_3 = -0.101) when their participation for SNAP program varied. According to the literature of usage of credit card of the black households (Ruetschlin and Muhammad 2013), about 42 percent of the black households use their credit cards to pay for their basic expenditures that include groceries, utilities, mortgage payments, rent, insurance as they lack adequate money. The role played by the credit in the financial securities of the black households is substantiated by the previous studies. However, our insignificant coefficient of the interaction term of liquidity constrained and payment of grocery bills using credit card (τ_3 =0.178) indicates that the use of credit card does not influence the association between food insecurity and liquidity constrained. Our estimations also suggest that there are other factors which might influence the association between food insecurity and financial liquidity constraint of the black households. We explore this association based on the other factors that include shopping behavior and the availability of low-priced food items.

Influence of the shopping behavior of black households and choice of grocery stores

The characteristics of shopping behavior are number of shop visits in month (i.e., the shopping frequency), use of their own vehicle to reach grocery stores, and distance of the groceries from their households. Limited accessibility may deter the frequencies of shopping for the black households, leading to an impact on their food securities. Thus, we investigate the relation between financial constraint on food insecurity of black households based on the number of visits to the grocery stores.

6) $Pr(food\ insecurity|x, visits, Z, T, \theta) = \alpha + \sigma_1 x + \sigma_2 visits + \sigma_3 x * visits + \sigma_4 Z + \sigma_5 T + \varepsilon$

Here, variable $visits$ is coded as one if the respondents of our survey visit the grocery stores at least once in a week and once in every two weeks and zero if the respondents visit the stores once in a month and less than once in a month. The other variables remain the same as model 1.σ_1 and σ_3 are the coefficients of interest measuring the effect of liquidity constraint on the food insecurity relative to their shop visits. θ is a vector of coefficients (σ_1, σ_2, σ_3, σ_4 and σ_5) to be estimated. ε is the random error that has mean zero.

One of the factors of shopping behavior is access to own transportation. The absence of transport is a structural barrier to food access (Valliant et al. 2021). Now, we investigate how food insecurities are impacted due to change in the liquidity constrained households through the interaction of their modes of transportation and preferences of for low priced food items through two different models.

7) $Pr(food\ insecurity|x, transport, Z, T, \theta) = \alpha + \vartheta_1 x + \vartheta_2 transport + \vartheta_3 x * transport + \vartheta_4 Z + \vartheta_5 T + \varepsilon$

Here, in model (8) the variable travel is constructed as a binary variable, equal to one if the respondents use their family cars, own cars, curb side pick-ups using own cars for their groceries and equal to zero if they get them delivered, get rides from others. The other variables remain the same as model 1. ϑ_1 and ϑ_3 are the coefficients of interest measuring the effect of liquidity constraint on the food insecurity based on how they reach the grocery stores. θ is a vector of coefficients (ϑ_1, ϑ_2, ϑ_3, ϑ_4 and ϑ_5) to be estimated. ε is the random error that has mean zero.

As we also investigate the impact of liquidity constraint on the food insecurity of the black households, contingent on the distance of the grocery shops, the model is:

8) $Pr(food\ insecurity|x, distance, Z, T, \theta) = \alpha + \mu_1 x + \mu_2 distance + \mu_3 x * distance + \mu_4 Z + \mu_5 T + \varepsilon$

In equation (8), the variable, distance is constructed as a binary variable, equal to one if the grocery stores are in the proximity of either less than 5 minutes or between 5 to 10 minutes of their houses, and equal to zero if the stores are located more than 10 minutes from their houses. Other variables remain the same as model 1. μ_1 and μ_3 are the coefficients of interest measuring the effect of liquidity constraint on the food insecurity based on the location of the grocery stores. θ is a vector of coefficients (μ_1, μ_2, μ_3, μ_4 and μ_5) to be estimated. ε is the random error that has mean zero.

We investigate the association of liquidity constraint and food insecurity of the black households depending on the choice of grocery stores because of availability of low-priced items. We build the model in which liquidity constraint interacts with the accessibility of low-priced grocery items:

9) $Pr(food\ insecurity|x, availability, Z, T, \theta) = \alpha + \rho_1 x + \rho_2 availability + \rho_3 x * availability + \rho_4 Z + \rho_5 T + \varepsilon$

The variable, availability is equal to one if the respondents choose grocery stores if they have the access to low priced or good quality products, and equal to zero if they lack the access to low priced or good quality products. Here also, the other variables remain the same as model 1. ρ_1 and ρ_5 are the coefficients of interest measuring the association between liquidity constraint and food insecurity of the black households varying the accessibility of the low priced and good quality grocery items. θ is a vector of coefficients (ρ_1, ρ_2, ρ_3, ρ_4 and ρ_5) to be estimated. ε is the random error that has mean zero.

The equations 6, 7, 8 and 9 are treated as LPM. We present the coefficients of the frequency of visits to grocery stores, mode of transportation to avail grocery stores, the distance between the grocery stores from the places of the black households, and the availability of low-priced grocery items are presented in the Table 2.4, Panels A, B, D and C. Though the coefficients of the association of food insecurity and financial liquidity constraint of the households varying on the shopping behaviors are insignificant (δ_3=0.176, ϑ_3= 0.115, μ_3=0.152), the availability of low-priced food items are found to be significant (ρ_3= 0.286, Table 2.4, Panel C). Our estimates suggest that the choice of grocery stores due to availability of low-priced food items and the prices do play a significant role in the association of food insecurity and financial liquidity constraint of the black households. When the low-priced food items are available, the black households are 33 percent more likely to be food insecure. On the contrary, when the low-priced food items are not available in the grocery stores which the black households are 4.5 percent more likely to be food insecure if they are liquidity constrained. In the situation of liquidity constrained, our estimates present a significant difference in the marginal effects. The large difference in the total effects indicate that the likelihood of considering availability and price of food items depend as a perceived barrier to food access (Chenarides et al. 2020), and the barrier considered that is whether the respondents live on the areas where the grocery shops are located, and also the method of controlling unobserved heterogeneity. From the p value of the f test, we reject the null hypothesis. Even if the black households visit the grocery stores less frequently, they mostly depend on fast food, that are cheap and nutritionally inferior (Crowe et al. 2018), their preferences play an important role. Ample literature indicate that price is one of the important determinants that motivate the decisions for food shopping (Alkon et al. 2013; Hillier et al. 2011; Hendrickson et al. 2006). Preferences for low priced grocery items play an important role for food insecurity. Price also influences the shoppers to select their stores for shopping. However, our estimates do not unequivocally support that role of availability or price is significant to explain the association of food insecurity and financially liquidity constraint.

Conclusion

We focus on how the inadequate cash in hand affects the food insecurity of the black households. Our estimates suggest that there is no significant association between food insecurity and liquidity constraints. Black households have a higher elasticity of consumption compared to white households (Ganong et al. 2020); thus, the welfare gain of eliminating transitory income shocks is more for the black households than their white counterparts. The liquidity constrained households can combat food insecurity if they are able to borrow money from informal sources. Moreover, price is one of the important determinants that motivate the decisions for food shopping (Alkon et al. 2013; Hillier et al. 2011; Hendrickson et al. 2006).

Our data has some limitations. Having cash on hand contributes to financially stability and diminishes food insecurity. The welfare gains for protecting a household from a temporary income shock, is much greater than black households than those of white households because their income elasticities are quite high. Do these welfare gains remain same in poor states? Do the welfare gains impact mitigate food insecurity? These two questions have potential for research and policy further.

Though our survey did not capture proper utilization of SNAP during the time of unemployment will be beneficial to maintain the consumption even if the household is financial liquidity constrained irrespective of race. Rational savings is also responsible to combat the transitory income shock and maintain the previous consumption pattern prior to the income disruption. Policies encouraging savings or different savings scheme may be helpful to maintain cash on hand during emergency to combat food insecurity. In addition to this, the prevalence of wealth inequality and the accessibility to SNAP benefits especially during the time of unemployment have potentials to contribute to future research in the literature of food security.

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Table 2.1. Summary Statistics

Variables	Liquidity Unconstrained	Liquidity Constrained	Total
Food Insecurity	0.497 (0.501)	0.669 (0.472)	0.574 (0.495)
Gender	0.346 (0.477)	0.177 (0.383)	0.271 (0.445)
Relationship	0.298 (0.458)	0.201 (0.402)	0.255 (0.436)
Household with Children	0.459 (0.499)	0.421 (0.495)	0.442 (0.497)
Household Size	2.917 (1.697)	3.061 (1.634)	2.981 (1.669)
Education	0.966 (0.182)	0.890 (0.314)	0.932 (0.252)
Employment	0.649 (0.479)	0.457 (0.500)	0.564 (0.497)
Age (Young, Mid-aged & old)	1.980 (0.995)	1.762 (0.850)	1.883 (0.938)
Poverty Ratio	2.507 (1.776)	1.604 (1.430)	2.106 (1.690)
Specific financial shocks	0.456 (0.499)	0.449 (0.499)	0.453 (0.498)
Amount	0.659 (0.475)	0.341 (0.476)	0.518 (0.500)
Paycheck Time	0.234 (0.425)	0.195 (0.398)	0.217 (0.413)
Informal Borrowing	0.688 (0.465)	0.701 (0.459)	0.694 (0.462)
SNAP Participation	0.266 (0.443)	0.327 (0.471)	0.292 (0.456)
Credit card for grocery bills	0.296 (0.457)	0.177 (0.383)	0.244 (0.430)

Frequency of visit to grocery stores	0.800 (0.401)	0.726 (0.448)	0.767 (0.423)
Distance of the grocery stores	0.571 (0.496)	0.622 (0.486)	0.593 (0.492)
Mode of transport to grocery stores	0.756 (0.430)	0.695 (0.462)	0.729 (0.445)
Availability of low-priced food items	0.203 (0.403)	0.221 (0.417)	0.211 (0.409)

Note: The standard deviations are in parenthesis. Food insecurity is an outcome variable which is binary, equal to one if the households are food insecure and zero if they are food secure. Households are categorized based on their affirmative responses of the situations: "The food that we bought just didn't last and we didn't have money to get more"; and "We couldn't afford to eat balanced meals". The affirmative responses of the households, "often true" and "sometimes true" categorized them as food insecure households. On the other hand, the households responding "never true" are classified as food secure households. Only black households is considered for the sample and is summarized according to the liquidity constrained of the respondents of the survey. Shopping behavior includes frequency of visits to the grocery stores, distance of the grocery stores from the households and the mode of transportation, own vehicle or family vehicle used to reach the grocery stores. Informal borrowing refers to the ability to borrow money from informal sources that include family, friends or partners.

Table 2.2. Association of food insecurity and liquidity constraints (Baseline Model)

Variables	Marginal Effects
Sample with Black Households	
Liquidity Constrained	**0.0591** **(0.97)**
Sample	314

Note: T statistics are in parenthesis. *, **, *** indicate statistical significance at 5%, 1% and 10% level. Other coefficients are omitted for brevity. A full set of results containing the controls is presented in appendix Table A2.1. The dependent variable food insecurity is binary, equal to one if the households are food insecure and zero if they are food secure. Coefficients are the marginal effects of LPM estimated by OLS.

Table 2.3. Influence of employment status, borrowing money from informal sources, participation in SNAP and the use of credit card for paying grocery bills

Variables	Marginal Effects
Panel A: Interaction Model with Employment Status of the households	
Liquidity Constrained	-0.0396 (-0.49)
Employed	-0.0772 (-0.96)
Liquidity Constrained*Employed	0.177 (1.64)
Total Effect at employed situation	0.1378 (p=0.103) (1.63)
Sample	314
Panel B: Interaction Model with borrowing from Informal Sources	
Liquidity Constrained	0.226* (2.21)
Informal Sources	0.200* (2.58)
Liquidity Constraint*Informal Sources	**-0.260*** **(-2.25)**
Total Effect for being able to borrow from informal sources	**-0.034*(p=0.03)** **(2.24)**
Sample	314
Panel C: Interaction Model with SNAP participation	
Liquidity Constrained	0.0865 (1.11)
SNAP	0.0681 (0.75)
Liquidity Constrained*SNAP	-0.101 (-0.85)
Total Effect for participation in SNAP	-0.0145 (p=0.39) (0.84)

Sample	297

Panel D: Interaction Model with payment of grocery bills using credit card

Liquidity Constrained	0.0185 (0.27)
Credit Card	0.00254 (0.03)
Liquidity Constrained*Credit Card	0.178 (1.48)
Total Effect for using Credit Card	0.1965 (p=0.14) (1.48)
Sample	312

Note**:** T statistics are in parenthesis. *, **, *** indicate statistical significance at 5%, 1% and 10% level. Other coefficients are omitted for brevity. A full set of results containing the controls is presented in appendix Table A2.2. The dependent variable food insecurity is binary, equal to one if the households are food insecure and zero if they are food secure. Only black sample is considered for estimation. Informal borrowing refers to the ability to borrow money from informal sources that include family, friends or partners. Coefficients are the marginal effects of LPM estimated by OLS. P values in brackets after coefficients of total effects are generated from the joint F tests.

Table 2.4. Influence of shopping behavior and availability of low-priced food items

Variables	Marginal Effects
Panel A: Interaction Model with Number of visits to the grocery stores	
Liquidity Constrained	-0.0731 (-0.69)
Visits	-0.252** (-2.81)
Liquidity Constrained*Visits	0.176 (1.43)
Total Effect of visiting grocery stores at least once in a week or once in two weeks	0.103 (p=0.15) (1.43)
Sample	314
Panel B: Interaction Model with Distance of the grocery stores	
Liquidity Constrained	-0.00658 (-0.08)
Distance	-0.0680 (-0.92)
Liquidity Constrained*Distance	0.115 (1.08)
Total Effect of grocery stores within less than 5 minutes or 5-10 minutes	0.108 (p=0.28) (1.08)
Sample	314
Panel C: Interaction Model with Availability of low priced food items	
Liquidity Constrained	0.0459 (0.57)
Availability	0.0126 (0.12)
Liquidity Constrained*Availability	**0.286*** **(1.97)**
Total Effect of choosing grocery stores due to availability of low-priced food items	**0.33* (p=0.05)** **(1.97)**

Sample	234

<u>Panel D: Interaction Model with Transportation availed to the grocery stores</u>

Liquidity Constrained	-0.0445 (-0.52)
Transport	-0.281*** (-3.43)
Liquidity Constrained*Transport	0.152 (1.37)
Total Effect of using own car or family car to reach grocery stores	0.1075 (p=0.17) (1.37)
Sample	314

Note: T statistics are in parenthesis. *, **, *** indicate statistical significance at 5%, 1% and 10% level. Other coefficients are omitted for brevity. A full set of results containing the controls is presented in appendix Table A2.3. The dependent variable food insecurity is binary, equal to one if the households are food insecure and zero if they are food secure. Only black sample is considered for estimation. Coefficients are the marginal effects of LPM estimated by OLS. Shopping behavior includes frequency of visits to the grocery stores, distance of the grocery stores from the households and the mode of transportation, own vehicle or family vehicle used to reach the grocery stores. P values in brackets after coefficients of total effects are generated from the joint F tests.

Appendix

Table A2.1. Association of food insecurity and liquidity constraints among black households (Baseline Model)

Variables	Marginal Effects
Liquidity Constrained	0.0591 (0.97)
Male	0.00785 (0.12)
Married	-0.151* (-2.16)
Household with children	0.0679 (0.92)
Household (2 members)	0.0634 (0.68)
Household (3 members)	0.232* (2.44)
Household (4 members)	0.114 (0.95)
Household (5 members)	0.0989 (0.82)
Household (6 members)	0.173 (1.08)
Household (7 members)	0.435** (3.10)
Household (8 members)	0.253* (2.39)
Household (9 members)	-0.451** (-2.90)
Household (10 members)	0.257* (2.21)
Education	-0.0353 (-0.32)
Employment	0.0164 (0.29)

Age (>30 & <=50)	0.0348 (0.55)
Age (>50 & <=65)	-0.0566 (-0.66)
Age (>65)	0.0542 (0.43)
Poverty (>=200% &<300%)	-0.108 (-1.35)
Poverty (>=300% &<400%)	-0.351*** (-3.40)
Poverty (>=400% &<500%)	-0.414*** (-3.63)
Poverty (>=500% &<600%)	-0.538*** (-4.99)
Poverty (>=600% &<700%)	-0.196 (-1.25)
Poverty (>=700% &<800%)	0.325** (3.09)
Poverty (>=800% &<900%)	-0.227 (-0.79)
Poverty (>=900% &<1000%)	-0.338 (-1.23)
Financial shock	0.0335 (0.63)
Amount to obtain	0.0897 (1.66)
Time of paycheck	-0.124 (-1.65)
Constant	0.571*** (3.64)
Sample	314

Note: T statistics are in parenthesis. *, **, *** indicate statistical significance at 5%, 1% and 10% level. Financial shock refers to sudden requirement of money for repairing car. Amount to obtain is ability to obtain either $100 or $3000. Time of payment refers to the beginning of the month when usually respondents receive paychecks.

Table A2.2. Influence of employment status, ability to borrow money from informal sources, participation in SNAP and the use of credit card for paying grocery bills

Variables	(1)	(2)	(3)	(4)
	Marginal Effects			
Liquidity Constrained	-0.0396 (-0.49)	0.226* (2.21)	0.0865 (1.11)	0.0185 (0.27)
Employed	-0.0772 (-0.96)			
Liquidity Constrained*Employed	0.177 (1.64)			
Male	0.0139 (0.22)	-0.00357 (-0.06)	0.00926 (0.14)	0.000840 (0.01)
Married	-0.161* (-2.30)	-0.132 (-1.84)	-0.144* (-1.99)	-0.151* (-2.12)
Household with children	0.0738 (1.02)	0.0623 (0.84)	0.0553 (0.72)	0.0700 (0.94)
Household (2 members)	0.0626 (0.67)	0.0689 (0.75)	0.0997 (1.03)	0.0470 (0.51)
Household (3 members)	0.221* (2.35)	0.238* (2.51)	0.229* (2.31)	0.220* (2.33)
Household (4 members)	0.119 (0.99)	0.120 (1.01)	0.121 (0.96)	0.122 (1.01)
Household (5 members)	0.0974 (0.82)	0.112 (0.93)	0.117 (0.96)	0.112 (0.92)
Household (6 members)	0.161 (1.02)	0.154 (0.96)	0.176 (1.04)	0.156 (0.99)
Household (7 members)	0.423** (2.95)	0.452** (3.02)	0.433** (2.93)	0.402** (2.75)
Household (8 members)	0.227* (2.17)	0.225* (2.19)	0.242* (2.13)	0.263* (2.51)
Household (9 members)	-0.512** (-3.20)	-0.528*** (-3.35)	-0.427** (-2.60)	-0.473** (-2.74)
Household (10 members)	0.290* (2.47)	0.207 (1.85)	0.294* (2.35)	0.270* (2.30)

Education	-0.0438 (-0.40)	-0.0465 (-0.42)	-0.0222 (-0.19)	-0.0543 (-0.49)
Employment		0.0108 (0.19)	0.00826 (0.14)	0.000266 (0.00)
Age (>30 & <=50)	0.0254 (0.40)	0.0522 (0.82)	0.0198 (0.30)	0.0309 (0.48)
Age (>50 & <=65)	-0.0604 (-0.71)	-0.0248 (-0.29)	-0.0661 (-0.72)	-0.0455 (-0.53)
Age (>65)	0.0313 (0.25)	0.0469 (0.39)	0.0361 (0.27)	0.0613 (0.49)
Poverty (>=200% &<300%)	-0.0951 (-1.18)	-0.109 (-1.41)	-0.0935 (-1.12)	-0.0906 (-1.12)
Poverty (>=300% &<400%)	-0.331** (-3.17)	-0.339** (-3.20)	-0.340** (-3.18)	-0.343** (-3.27)
Poverty (>=400% &<500%)	-0.402*** (-3.48)	-0.422*** (-3.65)	-0.434*** (-3.64)	-0.452*** (-3.89)
Poverty (>=500% &<600%)	-0.504*** (-4.63)	-0.509*** (-4.91)	-0.481*** (-3.99)	-0.534*** (-4.94)
Poverty (>=600% &<700%)	-0.187 (-1.22)	-0.181 (-1.21)	-0.209 (-1.33)	-0.189 (-1.18)
Poverty (>=700% &<800%)	0.364*** (3.36)	0.270** (2.66)	0.349** (3.03)	0.340** (3.22)
Poverty (>=800% &<900%)	-0.274 (-0.94)	-0.234 (-0.78)	-0.223 (-0.79)	-0.198 (-0.66)
Poverty (>=900% &<1000%)	-0.323 (-1.24)	-0.344 (-1.24)	-0.306 (-1.11)	-0.367 (-1.51)
Financial shock	0.0289 (0.54)	0.0383 (0.71)	0.0300 (0.55)	0.0289 (0.54)
Amount to obtain	0.0881 (1.64)	0.0875 (1.57)	0.0943 (1.68)	0.0848 (1.55)
Time of Paycheck	-0.115 (-1.53)	-0.123 (-1.62)	-0.127 (-1.62)	-0.109 (-1.45)
Informal Sources		0.200* (2.58)		

Liquidity Constrained*Informal Sources		-0.260* (-2.25)		
SNAP			0.0681 (0.75)	
Liquidity Constrained*SNAP			-0.101 (-0.85)	
Credit Card				0.00254 (0.03)
Liquidity Constrained*Credit Card				0.178 (1.48)
Constant	0.640*** (4.04)	0.440** (2.64)	0.541** (3.22)	0.601*** (3.76)
Sample	314	314	297	312

Note: T statistics are in parenthesis. *, **, *** indicate statistical significance at 5%, 1% and 10% level. Financial shock refers to sudden requirement of money for repairing car. Amount to obtain is ability to obtain either $100 or $3000. Time of payment refers to the beginning of the month when usually respondents receive paychecks. Model (1) represents the influence of employment status. Model (2) presents the influence of ability to borrow money from informal sources. Model (3) is the influence of SNAP participation and Model (4) is the influence of method of payment for grocery bills through credit card.

Table A2.3. Influence of shopping behavior and availability of low-priced food items

Variables	(1)	(2)	(3)	(4)
	Marginal Effects			
Liquidity Constrained	-0.0731 (-0.69)	-0.00658	0.0459	-0.0445
Visits	-0.252^{**} (-2.81)			
Liquidity Constrained* Visits	0.176 (1.43)			
Male	-0.00206 (-0.03)	0.00950 (0.15)	0.0966 (1.26)	0.0193 (0.30)
Married	-0.149^{*} (-2.15)	-0.155^{*} (-2.21)	-0.198^{*} (-2.44)	-0.133 (-1.90)
Household with children	0.0678 (0.93)	0.0723 (0.98)	0.0509 (0.60)	0.0858 (1.16)
Household (2 members)	0.0740 (0.79)	0.0624 (0.66)	0.0652 (0.61)	0.0469 (0.52)
Household (3 members)	0.248^{**} (2.65)	0.225^{*} (2.37)	0.279^{*} (2.50)	0.181 (1.91)
Household (4 members)	0.129 (1.06)	0.109 (0.91)	0.103 (0.73)	0.106 (0.88)
Household (5 members)	0.103 (0.85)	0.0904 (0.75)	0.0390 (0.27)	0.0711 (0.60)
Household (6 members)	0.169 (1.05)	0.162 (1.01)	0.0748 (0.38)	0.122 (0.76)
Household (7 members)	0.423^{**} (2.83)	0.427^{**} (2.96)	0.534^{**} (2.68)	0.369^{*} (2.48)
Household (8 members)	0.246^{*} (2.06)	0.223^{*} (2.03)	0.404^{**} (2.81)	0.130 (1.08)
Household (9 members)	-0.624^{***} (-3.78)	-0.485^{**} (-3.02)	-0.219 (-1.21)	-0.688^{***} (-4.17)
Household (10 members)	0.343^{**} (2.89)	0.215 (1.72)	0.349^{*} (2.28)	0.331^{**} (2.88)

Education	-0.0315 (-0.29)	-0.0356 (-0.32)	0.115 (0.87)	-0.0101 (-0.09)
Employment	0.0328 (0.59)	0.0239 (0.41)	0.0418 (0.66)	0.0303 (0.53)
Age (>30 & <=50)	0.0619 (0.98)	0.0377 (0.60)	0.109 (1.55)	0.0679 (1.10)
Age (>50 & <=65)	-0.0265 (-0.31)	-0.0497 (-0.58)	-0.0294 (-0.28)	0.00147 (0.02)
Age (>65)	0.0716 (0.55)	0.0645 (0.50)	0.169 (0.96)	0.0641 (0.48)
Poverty (>=200% &<300%)	-0.101 (-1.28)	-0.110 (-1.38)	-0.0984 (-1.10)	-0.0872 (-1.11)
Poverty (>=300% &<400%)	-0.341*** (-3.37)	-0.347*** (-3.35)	-0.249* (-2.03)	-0.333** (-3.28)
Poverty (>=400% &<500%)	-0.380*** (-3.40)	-0.417*** (-3.65)	-0.356* (-2.18)	-0.378*** (-3.35)
Poverty (>=500% &<600%)	-0.490*** (-4.44)	-0.533*** (-4.89)	-0.540*** (-4.45)	-0.477*** (-4.37)
Poverty (>=600% &<700%)	-0.188 (-1.27)	-0.203 (-1.27)	-0.334 (-1.89)	-0.183 (-1.18)
Poverty (>=700% &<800%)	0.411*** (3.79)	0.287* (2.57)		0.417*** (3.99)
Poverty (>=800% &<900%)	-0.174 (-0.61)	-0.215 (-0.73)	-0.0116 (-0.03)	-0.184 (-0.67)
Poverty (>=900% &<1000%)	-0.300 (-1.14)	-0.329 (-1.23)	-0.715*** (-4.10)	-0.300 (-1.14)
Financial shock	0.0270 (0.51)	0.0305 (0.57)	-0.0599 (-0.94)	0.0414 (0.79)
Amount to obtain	0.0937 (1.75)	0.0888 (1.64)	0.0843 (1.34)	0.0934 (1.76)
Time of Paycheck	-0.104 (-1.40)	-0.121 (-1.62)	-0.192* (-2.32)	-0.0979 (-1.32)
Distance		-0.0680 (-0.92)		

Liquidity Constrained* Distance		0.115 (1.08)		
Availability			0.0126 (0.12)	
Liquidity Constrained* Availability			0.286* (1.97)	
Travel				-0.281*** (-3.43)
Liquidity Constrained*T ravel				0.152 (1.37)
Constant	0.719*** (4.38)	0.605*** (3.70)	0.406* (2.07)	0.709*** (4.77)
Sample	314	314	234	314

Note: T statistics are in parenthesis. *, **, *** indicate statistical significance at 5%, 1% and 10% level. Financial shock refers to sudden requirement of money for repairing car. Amount to obtain is ability to obtain either \$100 or \$3000. Time of payment refers to the beginning of the month when usually respondents receive paychecks. Model (1) represents the influence of number of visits to the grocery stores. Model (2) presents the influence of distance of grocery stores. Model (3) is the influence of choice of grocery stores and Model (4) is the influence of mode of transportation to reach the grocery stores.

Chapter 3

Estimating the Effects of Generic Advertising on Market Demand: An ADL Approach[1]

Introduction

Farm groups have a long history of supporting generic advertising and other activities designed to strengthen the demand for their products in domestic and foreign markets (Forker and Ward, 1993). Studies designed to estimate the market response to generic advertising can be divided into two groups: those that take a systems approach to demand estimation (e.g., Brown and Lee, 1992; Brester and Schroeder, 1995; Piggott et al., 1996; Kinnucan et al., 1997; Lariviére et al., 2000; Richards and Patterson, 2000; Zheng and Kaiser, 2008; Xie et al., 2009) and those that take a single-equation approach (e.g., Ward and Dixon, 1989; Schmit and Kaiser, 2004; Alston et al., 2005; Williams et al., 2010; Kinnucan and Cai, 2011; Kinnucan and Gong, 2014; Capps et al., 2016; Kaiser, 2016; Williams and Capps, 2020). This study contributes to the latter group. The objective is to evaluate the potential advantages of the autoregressive distributed lag (ADL) approach to estimating the market response to generic advertising in a situation where a single-equation demand model is deemed appropriate or necessary due to data or other limitations. This seems a worthwhile exercise as single-equation models dominate the advertising benefit-cost literature (e.g., see the studies published in Kaiser et al. 2005 and those reviewed by Williams et al. 2018). Advertising dynamics, i.e., accounting for carryover effects, typically are handled in these studies by specifying the advertising variable as a finite distributed lag, by including a lagged dependent variable in the model, or both. The ADL approach nests these approaches and thus is encompassing. Based on their review of long-run demand theory as it applies to food products,

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Tomek and Cochrane (1962, p.720) posit "the adjustment period for most foods is one year or less." This suggests if the data used to estimate the demand relation are of higher frequency than annual distributed lag structures should be specified for prices and income as well as for advertising.

In instances where one or more variables in the demand equation is non-stationary the ADL approach lends itself to testing whether the variables are cointegrated (Pesaran and Shin, 1999; Pesaran et al., 2001). Cointegration is necessary to ensure the estimated long-run effects of the marketing variables are not spurious (Cavaliere and Tassinari, 2001). Recasting the ADL model as an error-correction model (ECM) permits direct estimation of the long-run parameters and their standard errors (Cuddington and Dagher, 2015). Because the error-correction term in the ECM contains the long-run demand relation, there is no need to impose Almon or other restrictions on the coefficients of the distributed lags to obtain precise estimates of the long-run parameters. As noted by Hassler and Wolters (2006, p. 57) "The autoregressive distributive lag model (ADL) is the major workhorse in dynamic single-equation regressions." Yet the ADL approach has not been adopted to any extent in the generic advertising literature.

The next section describes the ADL model and attendant methods to test for cointegration and weak exogeneity. This is followed by an application. A concluding section summarizes key findings.

The ADL Model and Methods

Let the long-run demand relation be defined as follows:

(1) $$q_t = c + \eta_P p_t + \eta_S ps_t + \eta_Y y_t + \eta_A a_t + \epsilon_t$$

where q_t, p_t, ps_t, y_t, and a_t are quantity, own price, substitute price, income, and advertising, respectively, measured over time interval t and expressed in logarithms; the eta coefficients are long-run elasticities; and ϵ_t is a random disturbance term. The corresponding short-run demand relation expressed as an ADL(k, k_1, k_2, k_3, k_4) model is:

(2) $\varphi(L)q_t = c' + \alpha(L)p_t + \beta(L)ps_t + \gamma(L)y_t + \delta(L)a_t + v_t$

where the lag operators are defined as follows:

(2a) $\varphi(L) = 1 - \varphi_1 L - \cdots - \varphi_k L^k \Longrightarrow \varphi(1) = 1 - \varphi_1 - \cdots - \varphi_k$

(2b) $\alpha(L) = \alpha_0 + \alpha_1 L + \cdots + \alpha_{k_1} L^{k_1} \Longrightarrow \alpha(1) = \alpha_0 + \alpha_1 + \cdots + \alpha_{k_1}$

(2c) $\beta(L) = \beta_0 + \beta_1 L + \cdots + \beta_{k_2} L^{k_2} \Longrightarrow \beta(1) = \beta_0 + \beta_1 + \cdots + \beta_{k_2}$

(2d) $\gamma(L) = \gamma_0 + \gamma_1 L + \cdots + \gamma_{k_3} L^{k_3} \Longrightarrow \gamma(1) = \gamma_0 + \gamma_1 + \cdots + \gamma_{k_3}$

(2e) $\delta(L) = \delta_0 + \delta_1 L + \cdots + \delta_{k_4} L^{k_4} \Longrightarrow \delta(1) = \delta_0 + \delta_1 + \cdots + \delta_{k_4}$

where $L^n x_t = x_{t-n}$.

Equations (1) and (2) are linked through their coefficients:

(3a) $\eta_P = \frac{\alpha(1)}{\varphi(1)}$ (LR own-price elasticity)

(3b) $\eta_S = \frac{\beta(1)}{\varphi(1)}$ (LR cross-price elasticity)

(3c) $\eta_Y = \frac{\gamma(1)}{\varphi(1)}$. (LR income elasticity)

(3d) $\eta_A = \frac{\delta(1)}{\varphi(1)}$ (LR advertising elasticity).

Estimation of the long-run elasticities and their standard errors is facilitated by reparameterizing the ADL model as an ECM:[2]

(4) $\Delta q_t = c + \lambda[q_{t-1} - \eta_P\, p_{t-1} - \eta_S ps_{t-1} - \eta_Y y_{t-1} - \eta_A a_{t-1}] + \alpha_0 \Delta p_t + \beta_0 \Delta ps_t + \gamma_0 \Delta y_t + \delta_0 \Delta a_t - \sum_{i=1}^{k-1} \varphi_{i+1} \Delta q_{t-i} - \sum_{i=1}^{k_1-1} \alpha_{i+1} \Delta p_{t-i} - \sum_{i=1}^{k_2-1} \beta_{i+1} \Delta ps_{t-i} - \sum_{i=1}^{k_3-1} \gamma_{i+1} \Delta y_{t-i} - \sum_{i=1}^{k_4-1} \delta_{i+1} \Delta a_{t-i} + v_t.$

where $\Delta = 1 - L$ is the difference operator; $\lambda = -\varphi(1)$ is the speed-of-adjustment parameter; and the expression in brackets is the error-correction term (ECT). If ECT > 0 the observed quantity in the preceding period exceeds its long-run (steady-state) equilibrium quantity, which implies quantity in the current period must fall for equilibrium to be restored, i.e., $\Delta q_t < 0$. The opposite is true if ECT < 0. Consequently, λ is expected to be negative in sign. Since the variables are expressed in log form the speed-of-adjustment parameter indicates adjustment in percentage terms. Thus, for example, if $\hat{\lambda} = -1$ this means 100% of any disequilibrium in the previous period (caused by a random shock to long-run demand in that period) is ‘’corrected’’ in the current period.

The parameters in the ECT are the long-run elasticities defined in equations (3a) – (3d). Their short-run counterparts are the coefficients of the contemporaneous difference terms in equation (4); namely $\eta_P^{SR} = \alpha_0$, $\eta_S^{SR} = \beta_0$, $\eta_Y^{SR} = \gamma_0$, and $\eta_A^{SR} = \delta_0$. In addition to permitting direct estimation of the long-run elasticities and their standard errors, the ECM avoids bias associated with imposing Almon or other restrictions on the distributed lag of the advertising variable.[3] The reason is that the lag distribution $\delta(L)$, which forms the basis for the long-run

[2] For the algebraic steps involved in transforming an ADL model into its equivalent ECM see Appendix I in Cuddington and Dagher’s (2015) paper. This paper provides a useful discussion of the two forms including estimation issues.
[3] Imposing restrictions on the parameters of a lag distribution increases the precision of the estimates, but unless the restrictions are correct the estimates will be biased. For a detailed discussion of this issue in a generic advertising context with particular attention to the appropriateness of the Almon estimator, see Venkateswaran et al. (1993).

advertising elasticity, does not have to be specified as its parameters are embedded in the coefficient of a_{t-1} in the ECT.

Cointegration

For the estimated long-run relation to have economic meaning the variables in the model must be cointegrated, i.e., the disturbance term in equation (1) must be stationary. A test for whether this condition holds in an ADL context has been developed by Pesaran et al. (2001). Their so-called "bounds test" is applicable irrespective of whether the variables in the model are I(0) (stationary in levels), I(1) (non-stationary in levels but stationary in first differences), or a mixture of I(0) and I(1). However, the variables cannot be I(2) (require to be differenced twice to achieve stationarity), and the data cannot contain seasonal unit roots (Pesaran et al., 2001, p. 291), i.e., any seasonal pattern in the data must be stable over time. Provided these conditions are met the test can be implemented by estimating the following unrestricted or ''conditional'' ECM:

(5) $\Delta q_t = c + \theta q_{t-1} + \omega_1\, p_{t-1} + \omega_2\, ps_{t-1} + \omega_3\, y_{t-1} + \omega_4 a_{t-1} + \alpha_0 \Delta p_t + \beta_0 \Delta ps_t + \gamma_0 \Delta y_t + \delta_0 \Delta a_t - \sum_{i=1}^{k-1} \varphi_{i+1} \Delta q_{t-i} - \sum_{i=1}^{k_1-1} \alpha_{i+1} \Delta p_{t-i} - \sum_{i=1}^{k_2-1} \beta_{i+1} \Delta ps_{t-i} - \sum_{i=1}^{k_3-1} \gamma_{i+1} \Delta y_{t-i} - \sum_{i=1}^{k_4-1} \delta_{i+1} \Delta a_{t-i} + \tilde{v}_t.$

If $\theta \neq 0$ and $\omega_1 = \omega_2 = \omega_3 = \omega_4 \neq 0$ the variables in the long-run demand equation are cointegrated. The appropriate critical values for the *t*- and *F*-statistics under the null hypothesis of no cointegration are provided in Pesaran et al.'s (2001) paper.

Weak Exogeneity

For OLS estimates of the ECM to have the desirable properties the regressors in the cointegrating relationship (the long-run demand relation) must not adjust to past equilibrium deviations (Hassler and Wolton, 2006, p.71). This "weak exogeneity" can be tested by estimating the vector error-correction model (VECM) (Harris 1995, pp. 98-104):

$$(6)\qquad \begin{bmatrix} \Delta q_t \\ \Delta p_t \\ \Delta ps_t \\ \Delta y_t \\ \Delta a_t \end{bmatrix} = \begin{bmatrix} \lambda_q \\ \lambda_p \\ \lambda_{ps} \\ \lambda_y \\ \lambda_a \end{bmatrix} [q_{t-1} - \tilde{\eta}_P\, p_{t-1} - \tilde{\eta}_S ps_{t-1} - \tilde{\eta}_Y y_{t-1} - \tilde{\eta}_A a_{t-1}] + \Gamma_{\mathbf{1}} \Delta \mathbf{z}_{t-1} + \mathbf{v}$$

where $\Delta\mathbf{z}_{t-1} = [\Delta q_{t-1}, \Delta p_{t-1}, \Delta ps_{t-1}, \Delta y_{t-1}, \Delta a_{t-1}]'$ is a vector of all the variables in the model in lagged first differences; $\Gamma_{\mathbf{1}}$ is a matrix of coefficients associated with these variables; and $\mathbf{v}$ is a vector of disturbance terms.[4] The lambda parameters indicate the speed of adjustment of the respective variables to equilibrium deviations in the previous period. Weak exogeneity of the regressors imiplies $\lambda_p = \lambda_{ps} = \lambda_y = \lambda_a = 0$, which can be tested using a likelihood ratio (LR) test.

Application

To evaluate the strengths and weaknesses of the ADL approach as it pertains to generic advertising we apply it to the following equation estimated by Williams and Capps (2020, p. 527, equation (8)):

$$7)\qquad \ln Q_t = a_0 + a_1 \ln Q_{t-1} + a_2 \ln\left(\frac{P_t \cdot XR_t}{API_t}\right) + a_3 \ln\left(\frac{PS_t \cdot XR_t}{API_t}\right) + a_4 \ln\left(\frac{Y_t}{CPI_t}\right) +$$

$$\sum_{i=0}^{2} b_i \ln\left(\frac{A_{t-i} \cdot XR_{t-i}}{CPI_{t-i}}\right) + \mathbf{c}'_{\mathbf{Z}} \mathbf{D}_{\mathbf{Z}} + \mathbf{c}'_{\mathbf{M}} \mathbf{D}_{\mathbf{M}} + e_t$$

where $t = 1, 2, \ldots, 180$ (for monthly observations, 2003-2017); Q_t is the quantity of whitefish exported from Norway; P_t is the unit value of Norway's exports of whitefish expressed in

[4] Equation (6) is predicated on the assumption that all variables enter with a lag length of 2. When the lag length is longer the equation expands in a straightforward manner.

Norwegian kroners (NOK); XR_t is a trade-weighted exchange rate between the kroner and the currencies of the top 10 countries that import whitefish from Norway where $XR = FCU/NOK$ (Foreign Currency Unit/kroner); API_t is a price index for farmed fish developed by the Food and Agricultural Organization; PS_t is the price of Norway's salmon exports expressed in kroners; Y_t is a trade-weighted GDP for the top 10 countries that import whitefish from Norway; CPI_t is a trade-weighted consumer price index for the same countries; A_{t-i} is the seasonally-adjusted expenditure on export promotion of whitefish by the Norwegian Seafood Council in month $t - i$ in kroners; $\mathbf{D_Z}$ is a vector of five dummy variables to indicate shifts in export demand due to weather-related events, the presence of bigger cod, increases in the harvest quota for cod and haddock, financial meltdown, and recesssion; $\mathbf{D_M}$ is a vector of 11 monthly dummy variables to indicate seasonal shifts in export demand; and e_t is a random disturbance term. The coefficients of the distributed lag for the advertising variable (the b_i) were estimated using the Almon procedure. Based on model selection criteria (Akaike Information, Hannan-Quin, and Schwarz) the lag length was set to two and the coefficients were constrained to lie on a second-degree polynomial with endpoint constraints. [5]

The analysis to follow is based on the same data set used by Williams and Capps; the same variables, i.e., $q_t = \ln Q_t$, $p_t = \ln\left(\frac{P_t \cdot XR_t}{API_t}\right)$, $ps_t = \ln\left(\frac{PS_t \cdot XR_t}{API_t}\right)$, $y_t = \ln\left(\frac{Y_t}{CPI_t}\right)$, and $a_t = \ln\left(\frac{A_t \cdot XR_t}{CPI_t}\right)$; and the same deterministic components, i.e., a_0, $\mathbf{D_Z}$ and $\mathbf{D_M}$. However, we do not impose the Almon restrictions. Norway's production of whitefish is constrained by a Total Allowable Catch (TAC) quota. This suggests a price-dependent demand equation might be more

[5] Equation (8) in Williams and Capps' paper defines the income variable as $y = \ln\left(\frac{Y_t \cdot XR_t}{CPI_t}\right)$. In correspondence with the authors we found XR_t is errant; the correct definition is $y = \ln\left(\frac{Y_t}{CPI_t}\right)$.

appropriate than the quantity-dependent equation estimated by Williams and Capps. To check this, we estimated the model in both forms. The long-run demand equations to be estimated are as follows:

(8a) $q_t = b_0 + b_1\, p_t + b_2\, ps_t + b_3\, y_t + b_4\, a_t + \sum_{i=1}^{5} c_i\, D_i + \sum_{i=1}^{11} d_i\, M_i + e_t$

(8b) $p_t = b_0' + b_1' q_t + b_2'\, ps_t + b_3'\, y_t + b_4'\, a_t + \sum_{i=1}^{5} c_i'\, D_i + \sum_{i=1}^{11} d_i'\, M_i + e_t'$

where D_i and M_i are the aforementioned dummy variables. The coefficients b_i' in equation (8b) are flexibilities defined as follows: $b_1' = \partial p/\partial q = 1/\eta_P$; $b_2' = \partial p/\partial ps = -\eta_S/\eta_P$; $b_3' = \partial p/\partial y = -\eta_Y/\eta_P$; and $b_4' = \partial p/\partial a = -\eta_A/\eta_P$. For normal-sloping demand, i.e., $b_1 \equiv \eta_P < 0$, the flexiblities estimated from equation (8b) are expected to have the same sign as the corresponding elasticities estimated from equation (8a).

Model Selection

What is the appropriate dynamic specification for the short-run demand relations corresponding to equations (8a) and (8b)? To decide we conducted a search using the four model selection criteria available in EViews 11 (2020): Akaike Information (AIC), Schwarz (SC), Hannan-Quin (HQ), and Adjusted-R^2. Harris (1995, p. 61) states: ‘’One of the results to emerge from Monte Carlo work is that it is preferable to overparameterise the dynamic model (i.e., a generous lag-length should be chosen) since this reduces any bias when compared to an under-parameterised model, even when the ‘true’ model involves a simple d.g.p. [data generating process] with few dynamic terms.’’ Accordingly, we set the maximum lag length to four. This resulted in an evaluation for each criterion of 2,500 models.

Focusing first on the q-dependent model, four possible dynamic specifications are identified: ADL (4,1,3,3,3), ADL(1,1,3,1,3), ADL(1,1,2,1,1), and ADL(1,1,0,0,0) (Table 3.1). All four criteria are consistent in showing that p_t enters with one lag. Beyond that results diverge, with the Adjusted-R^2 criterion indicating that ps_t, y_t and a_t should enter with three lags and the Schwarz criterion indicating the same variables should enter with no lags. Turning to the *p*-dependent specification a similar pattern emerges in that the most generous dynamic specification ADL (3,4,4,1,3) is selected by the Adjusted R^2 criterion and the least generous specification ADL (1,1,0,0,0) by the Schwarz criterion. For both models (q- and p-dependent) the dynamic specifications selected by the AIC, HQ, and SC criteria are nested in the Adjusted R^2 specification.

Might the more parsimonious specifications suffice to account for the dynamics underlying the long-run demand relation? To address the question we treated the Adjusted R^2 specification as the maintained hypothesis and conducted Wald tests to determine whether the simpler specifications are statistically equivalent. For the q-dependent model we also tested whether the ADL (1,0,0,0,2) specification estimated by Williams and Capps is statistically equivalent.

Focusing first on the q-dependent model, results suggest the dynamics implied by the SC and Williams and Capps' specifications are too restrictive (Table 3.1). Specifically, the null hypotheses that the ADL (1,1,0,0,0) and ADL (1,0,0,0,2) specifications are statistically equivalent to ADL (4,1,3,3,3) are rejected at the p = 0.012 and p = 0.008 levels, respectively. The other specifications, namely ADL (1,1,3,0,3) and ADL (1,1,2,1,1), are not rejected at the p = 0.210 level or higher. Following Occam's razor for the remaining analysis of the q-dependent model we shall focus on the ADL (1,1,2,1,1) specification, hereafter labeled ''Model C.''

Results for the p-dependent model are similar in that the the dynamics implied by the SC specification are too restrictive while the dynamics implied by the AIC and HQ specifications are not (Table 3.1). The null hypothesis that the ADL (1,1,0,0,0) specification is statistically equivalent to the ADL (3,4,4,1,3) specification is rejected at the p = 0.029 level; the ADL

(2,2,0,1,3) and ADL (2,2,0,0,0) specifications are not rejected at p = 0.107 level or higher. Consequently, following Occam's razor for the remaining analysis of the p-dependent model we shall focus on the ADL (2,2,0,0,0) specification, hereafter labeled ''Model C'.''

Following the suggestion of Dorian (2018) the residuals from Models C and C' were subjected to a battery of tests to assess statistical adequacy as shown in Table 3.2. Model C shows no evidence of misspecification. Tests fail to reject the null hypotheses of serially independent and normally-distributed errors, homoscedasticity, and stability of model coefficents. Model C' passes the tests for serial correlation, heteroscedasticity, and non-normal errors. However, the ARCH and RESET tests are less conclusive, which suggests potential mis-specification.

Tests for Cointegraton

For the long-run demand relation to exist the variables in the model must be cointegrated. Our tests for unit roots suggest none of the variables contain seasonal unit roots (Appendix A). In terms of regular unit roots, the tests suggest ps_t is I(0); p_t is I(1); and q_t, y_t and a_t are either I(0) or I(1). The conditions for the bounds test to be valid appear to be met.

The Bounds test for Model C indicate the variables in the long-run demand relation are indeed cointegrated (Table 3.3). The null hypotheses H_1: $\theta = 0$ and H_2: $\omega_1 = \omega_2 = \omega_3 = \omega_4 = 0$ (see equation (5)) are firmly rejected at the 1% level.[6] The ECT in Model C is I(0), which means OLS estimates of the ECM will have the desirable properties provided the regressors are weakly exogenous. For Model C' the nulls H_1: $\theta = 0$ and H_2: $\omega_1 = \omega_2 = \omega_3 = \omega_4 = 0$ are not rejected at even the 10% level. The ECT in Model C' is not stationary, which means OLS estimates of the ECM will not have the desirable properties even if the regressors are weakly exogenous. More to

[6] The dummy variables in equations (8a) and (8b) are included in the test equation (see Appendix B).

the point, the lack of cointegration in the *p*-dependent specification means that the long-run relation implied by this specification does not exist. Consequently, the remaining analsis will focus on Model C.

Tests for Weak Exogeneity

For OLS estimates of an ECM to have the desirable properties the regressors in the "levels equation" must be weakly exogenous. In terms of equation (8a) this means p_t, ps_t, y_t and a_t must not adjust to past equilibrium deviations, i.e., p_t, ps_t, y_t and a_t must be invariant to e_{t-1}. To determine whether this condition holds we estimated a ''full'' VECM, i.e., a VECM that treats all the regressors as endogenous (see equation (6)). We then tested two restricted forms of the full VECM: $\lambda_{ps} = \lambda_y = \lambda_a = 0$ (all regressors except p_t are weakly exogenous), and $\lambda_p = \lambda_{ps} = \lambda_y = \lambda_a = 0$ (all regressors are weakly exogenous). The tests are performed with the lag length in the underlying VAR set to 2, i.e., all endogenous variables enter with two lags. The 16 dummy variables in equation (8a) enter the VECM as exogenous variables. Estimates of the VECMs are provided in Appendix C with results summarized in Table 3.4.

Test results are clear in indicating that ps_t, y_t and a_t are weakly exogenous. The test statistic for $\lambda_{ps} = \lambda_y = \lambda_a = 0$ is 1.787, which is not large enough to reject the restriction at the p = 0.617 level. However, the results with respect to p_t are less clear cut. In the full and partial VECMs that treat p_t as endogenous the estimate for λ_p is positive with a *t*-ratio of 2.2. This implies p_t is responsive to random shocks and thus is not weakly exogenous. However, the hypothesis $\lambda_p = \lambda_{ps} = \lambda_y = \lambda_a = 0$ cannot be rejected at the p = 0.123 level. The joint restriction that all regressors (including own-price) are weakly exogenous cannot be rejected at conventional probability levels.

One reason for the conflicting results may be the relative unimportance of price adjustments in resolving market disequilibria. Focusing on the VECM that treats ps_t, y_t and a_t as weakly exogenous, the estimated values for λ_q and λ_p are respectively (t-ratios in parentheses) -0.773 (-8.06) and 0.142 (2.20). This suggests 77.3% of the disequilibrium caused by a random shock to long-run demand in the previous month is resolved in the current month by an adjustment in quantity; the adjustment in price accounts for only 14.2% of the resolution.[7] Quantity adjustments are 5.5 times more important than price adjustments in restoring dynamic equilibrium to the export market for Norwegian whitefish. The relative importance of quantity adjustments supports the quantity-dependent specification of the demand function. It suggests notwithstanding the TAC the long-run export supply curve for Norway's whitefish is relatively flat.[8] In any event, given that the restriction $\lambda_p = \lambda_{ps} = \lambda_y = \lambda_a = 0$ is not rejected, we proceed under the assumption that the weak exogeneity condition is met.

Elasticity Estimates

Estimates of the elasticities were obtained by estimating the ECM (equation (4)) augmented with the sixteen dummy variables specified in equation (8a). Although Model C is the preferred specification, results for Models D and E are provided as well to assess the extent to which misspecification of the dynamics biases the estimates. Focusing first on Model C, the estimated adjustment coefficient and long-run elasticities all have the correct signs and are significant in the

[7] The total adjustment (= $\hat{\lambda}_p - \hat{\lambda}_q$) is 0.915, i.e., 91.5% of the excess demand caused by a random shock is resolved in one month. This suggests the international market for Norway's whitefish is highly efficient.

[8] Nielsen et al. (2011, pp. 797-798) argue that when the market is supplied from capture fisheries as opposed to farms, as is the case for over 95% of Norway's whitefish (Petersen 2021), the *p*-dependent specification of the demand function is superior to the *q*-dependent specification. However, the authors note that exceptions to the rule may include situations where storage occurs, management of the fisheries is loose, or the level of aggregation is low (e.g., Germany's demand for Norwegian whitefish as opposed to world demand). That cointegration tests showed the *q*-dependent specification in the present study to be superior to the *p*-dependent specification suggests one or more of the exceptions obtain.

sense that none of their 95% confidence intervals goes through zero (Table 3.5). The estimated adjustment cofficient is -0.730 (t-ratio = -12.0). This suggests 73% of the excess demand caused by a random shock to long run demand in the previous month is ‘’corrected’’ in the current month. The 95% confidence interval for this estimate, namely [-0.849, -0.611], brackets the estimates of this parameter obtained from the full and partial VECMs, which lie on the interval $\hat{\lambda}_q \in [-0.783, -0.699]$. Turning to the demand elasticities, results suggest export demand for Norway's whitefish is inelastic. All else equal, a 1% increase in price reduces the quantity demanded by between 0.277% and 0.531%; a 1% increase in salmon price increases demand by between 0.131% and 0.364%; a 1% increase in income increases demand by between 0.118% and 0.431%; and a 1% increase in advertising expenditures increases demand by between 0.034% and 0.135%. According to these 95% confidence intervals export demand is most responsive to changes in own-price and least responsive to changes in advertising expenditures.

Comparing the foregoing estimates with those obtained from Models D and E there is little to choose between them. The point estimates of the elasticities differ in some instances (e.g., the long-advertising elasticity estimated from Model A is 0.0846 compared to 0.0623 and 0.0996 from Models D and E respectively). However, the differences are not significant in that the 95% confidence intervals across the three models overlap. Despite the differences in dynamics implied by the three models, and the fact that Models D and E are rejected when compared with Model A (recall Table 3.1), if interest centers on long run responses any one of the models would serve equally well.

A somewhat different result obtains for the short-run elasticities (Table 3.6). All of the estimated elasticities have the expected sign and their 95% confidence intervals across the three models overlap with one exception, namely income. In this instance, Model C indicates the short-run response might be elastic with $\hat{\eta}_Y^{SR} \in [0.405,1.945]$ while Models D and E indicate a clear inelastic response with $\hat{\eta}_Y^{SR} \in [0.069,0.339]$ for the two models combined. In addition to the estimated income response, Model C differs from Models D and E in that the estimated cross-price effect is not significant, i.e., the 95% confidence interval for $\hat{\eta}_S^{SR}$ from Model C goes through zero. Model D delivers a statistically significant estimate of η_A^{SR} while Model C does not. Combining these results with those obtained for the long-run elasticities would suggest Model D is the superior specification. Might Model D be statistically equivalent to Model C? A Wald test says ''no.'' The computed test statistic $F_{4,151} = 4.020$ is sufficiently large to reject Model D at the p = 0.004 level. The dynamics implied by Model D are too restrictive relative to Model A, but also Model C. Choosing Model D over Model C is innocuous in terms of long-run responses, but not the short-run responses. In the short run (one month) export demand is unresponsive to substitute price and advertising, and an elastic response to income cannot be ruled out.

Concluding Comments

Study results suggest the autoregressive distributed lag (ADL) approach to estimating single-equation demand models and the attendant methods of testing for cointegration provide an improved basis for understanding the market response to generic advertising, but also other variables that affect demand. In the ADL approach all of the variables in the demand specification are permitted to enter with a lag. This expands the scope for identifying the dynamic specification that best fits the data. In instances where the dynamic specification identified by standard model selection criteria such as the Akaike Information, Hannan-Quin and Schwarz differ and the models are nested, Wald tests can be performed to identify the most parsimonious specification compatible with the data. If the selected models are not nested, all of them can be estimated to assess the sensitivity of results to the dynamic specification. Estimating the ADL as an error-correction model (ECM) provides direct estimates of the long-run parameters and their standard errors. If interest centers on the long-run response to advertising, there is no need to impose Almon or other restrictions on the advertising lag structure, as the long-run response (or elasticity) is estimated directly as a by-product of estimating the ECM.

The ADL approach lends itself to testing for cointegration. This proved to be important in the present study as it helped to discriminate between quantity- and price-dependent specifications of the demand equation. As a by-product of estimating the ECM insight is provided as to the relative importance of quantity adjustments in restoring dynamic equilibrium in response to a random shock to long run demand. In the present study, for example, quantity adjustments were found to be 5.5 times more important that price adjustments in resolving dynamic disequilibria in the export demand for Norway's whitefish. This information is not available in the conventional approach to estimating market responses to generic advertising as summarized in the review article by Williams et al. (2018).

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Table 3.1. Lag Orders for the *Q*-Dependent and *P*-Dependent Specifications of the Export Demand Equation for Norway's Whitefish as Determined by Alternative Model Selection Criteria

Criterion	Lag Order[a]	
	q-dependent model	*p*-dependent model
Adjusted R2	A(4,1,3,3,3)	A'(3,4,4,1,3)
Akaike Information (AIC)	B(1,1,3,1,3)	B'(2,2,0,1,3)
Hannan-Quin (HQ)	C(1,1,2,1,1)	C'(2,2,0,0,0)
Schwarz (SC)	D(1,1,0,0,0)	D'(1,1,0,0,0)
WC's specification	E(1,0,0,0,2)	NA
F-tests of alternative dynamic specifications:		
A vs. B	$F_{(5,141)} = 1.049$ ($p = 0.392$)	Fail to reject B
A vs. C	$F_{(8,141)} = 1.380$ ($p = 0.210$)	Fail to reject C
A vs. D	$F_{(12,141)} = 2.260$ ($p = 0.012$)	Reject D
A vs. E	$F_{(11,141)} = 2.464$ ($p = 0.008$)	Reject E
A' vs. B'	$F_{(7,140)} = 1.332$ ($p = 0.239$)	Fail to reject B'
A' vs. C'	$F_{(11,140)} = 1.594$ ($p = 0.107$)	Fail to reject C'
A' vs. D'	$F_{(13,140)} = 1.958$ ($p = 0.029$)	Reject D'

[a]The ordering of the variables in the q-dependent specification is $(q_t, p_t, ps_t, y_t, a_t)$ and in the p-dependent is $(p_t, q_t, ps_t, y_t, a_t)$. See text for details.

Table 3.2. Tests for the Statistical Adequacy of Models C and C’

Item	Test	*p*-values for:[a]	
		Model C	Model C’
Autocorrelation	Breusch-Godfrey test. H_N: no AR up to 4 lags.	0.6431 $[\sim F(2, 149)]$ 0.4102 $[\sim F(3, 148)]$ 0.1390 $[\sim F(4, 147)]$	0.2274 $[\sim F(2, 151)]$ 0.3988 $[\sim F(3, 150)]$ 0.4199 $[\sim F(4, 149)]$
Heteroscedasticity	Breusch-Pagan-Godfrey test. H_N: Homoscedasticity.	0.5672 $[\sim F(26, 151]$	0.7604 $[\sim F(24,153)]$
ARCH	F-test. H_N: Homoscedasticity up to three lags	0.8216 $[\sim F(1,175)]$ 0.9369 $[\sim F(2,173)]$ 0.8799 $[\sim F(3,171)]$	0.013 $[\sim F(1,175)]$ 0.0467 $[\sim F(2,173)]$ 0.1013 $[\sim F(3,171)]$
Non-normality	Bera-Jarque test. H_N: Residuals are normally distributed.	0.4756 $[\sim \chi^2(2)]$	0.597 $[\sim \chi^2(2)]$
RESET	A test for the stability of model coefficients. H_N: Coefficients are stable up to two fitted terms.	0.3649 $[\sim F(1,150)]$ 0.6613 $[\sim F(2,149)]$	0.0611 $[\sim F(1,152)]$ 0.1719 $[\sim F(2,151)]$

[a]Model C is the *q*-dependent specification with lag order (1,1,2,1,1); Model C’ is the *p*-dependent specification with lag order (2,2,0,0,0). Theses specifications are statistically equivalent to the larger Models A and A’ in Table 3.1 and thus, based on Occam’s razor, are deemed the preferred models.

Table 3.3. Bounds Tests for Cointegration of the *Q*- and *P*-Dependent Models[a]

	q-dependent model (Model C)			p-dependent model (Model C')		
Hypothesis:	*t*-statistic	*F*-statistic	Critical Values[b]	*t*-statistic	*F*-statistic	Critical Values[b]
$\theta = 0$	-11.24	--	(-2.57, -3.66)	-1.96	--	(-2.57, -3.66)
			(-2.86, -3.99)			(-2.86, -3.99)
			(-3.43, -4.60)			(-3.43, -4.60)
$\omega_1 = \omega_2 =$	--	28.25	(2.45, 3.52)	--	0.897	(2.45, 3.52)
$\omega_3 = \omega_4$			(2.86, 4.01)			(2.86, 4.01)
$= 0$			(3.74, 5.06)			(3.74, 5.06)

[a]Models C and C' are as defined in Table 3.2. The null hypothesis is no cointegration. The null is rejected if the computed *t*- and *F*-statistics lie above their critical values. If they lie between the critical values, the test is inconclusive; if they lie below the null is not rejected.
[b]Numbers in the first, second, and third rows indicate significance at respectively the 10%, 5%, and 1% levels. Critical values are asymptotic based on a sample size of 1000.

Table 3.4. Tests for Weak Exogeneity of Regressors in Model C

Adjustment parameter	Unrestricted estimates[a]	Restricted estimates[a] $\lambda_{ps} = \lambda_y = \lambda_a = 0$	Restricted estimates[a] $\lambda_p = \lambda_{ps} = \lambda_y = \lambda_a = 0$
λ_q	-0.7836	-0.7728	-0.6992
	(-7.81)	(-8.06)	(-7.83)
λ_p	0.1479	0.1421	--
	(2.24)	(2.20)	
λ_{ps}	-0.0818	--	--
	(-1.28)		
λ_y	0.0078	--	--
	(0.50)		
λ_a	-0.2084	--	--
	(-0.47)		
Hypothesis tests:	χ^2 statistic	Result:	
$H_N^1: \lambda_{ps} = \lambda_{ps} = \lambda_{ps} = 0$	1.787	ps_t, y_t and a_t are weakly exogenous	
	[0.617]		
$H_N^2: \lambda_p = \lambda_{ps} = \lambda_{ps} = \lambda_{ps} = 0$	7.073	All regressors are weakly exogenous	
	[0.132]		

[a]Estimates are based on a VAR(2) model. Lag intervals for the endogenous variables start at 1 and end at 2. Numbers in parentheses are *t*-values; numbers in brackets are probalities of a type 1 error.

Table 3.5. OLS Estimates of the Adjustment Coefficient and Long-Run Demand Elasticities from Alternative Specifications of the Error Correction Model

Elasticity/ Statistic	Model (lag order)[a]		
	C(1,1,2,1,1)	D(1,1,0,0,0)	E(1,0,0,0,2)
Adjustment coef (λ)	-0.730	-0.652	-0.753
	(-12.0)	(-11.2)	(-12.8)
	[-0.849, -0.611]	[-0.766, -0.538]	[-0.868, -0.638]
Own-price (η_P)	-0.404	-0.405	-0.417
	(-6.23)	(-5.43)	(-6.59)
	[-0.277, -0.531]	[-0.295, -0.551]	[-0.293, -0.541]
Cross-price (η_S)	0.247	0.206	0.205
	(4.15)	(3.06)	(3.51)
	[0.131, 0.364]	[0.075, 0.338]	[0.091, 0.319]
Income (η_Y)	0.274	0.298	0.281
	(3.42)	(3.24)	(3.51)
	[0.118, 0.431]	[0.119, 0.478]	[0.125, 0.438]
Advertising (η_A)	0.0846	0.0623	0.0996
	(3.28)	(2.67)	(3.60)
	[0.0343, 0.1352]	[0.0168, 0.1080]	[0.0457, 0.1538]
Adjustment coef (λ)	-0.730	-0.652	-0.753
	(-12.0)	(-11.2)	(-12.8)
Adjusted R^2	0.8475	0.8547	0.8348
D.W. Statistic	1.91	1.92	1.77

[a]Model C is the preferred specification (see text for details). Numbers in parentheses below the point estimates are standard errors; numbers in brackets are 95% confidence intervals.

Table 3.6. OLS Estimates of the Short-Run Elasticities

Elasticity/ Statistic	Model (lag order)[a]		
	C(1,1,2,1,1)	D(1,1,0,0,0)	E(1,0,0,0,2)
Own-price (η_P)	-0.553	-0.547	-0.314
	(-5.05)	(-4.84)	(-5.63)
	[-0.330, -0.768]	[-0.325, -0.769]	[-0.205, -0.423]
Cross-price (η_S)	0.034	0.134	0.154
	(0.28)	(3.06)	(3.50)
	[-0.203, 0.272]	[0.049, 0.220]	[0.068, 0.240]
Income (η_Y)	1.173	0.195	0.212
	(2.98)	(3.02)	(3.28)
	[0.405, 1.945]	[0.069, 0.322]	[0.086, 0.339]
Advertising (η_A)	0.0255	0.0406	0.0198
	(1.48)	(2.54)	(1.07)
	[-0.0081, 0.0593]	[0.0094, 0.0719]	[-0.0163, 0.0561]
Adjusted R^2	0.8475	0.8547	0.8348
D.W. Statistic	1.91	1.92	1.77

[a]Model C is the preferred specification (see text for details). Numbers in parentheses below the point estimates are standard errors; numbers in brackets are 95% confidence intervals.

Appendix A. Tests for Unit Roots

For the bounds test to be valid the variables in the model cannot contain seasonal unit roots and they cannot be I(2), i.e., require more than one differencing to become stationary (Pesaran et al., 2001). We first test for seasonal unit roots using the HEGY test (Hylleberg et al., 1990). We then test for I(2) using both the standard and breakpoint augmented Dickey-Fuller (ADF) tests. The breakpoint test allows for structural breaks in the data, which have been shown to have an important effect on test results (Perron, 1989; Wang and Tomek, 2007). The tests are carried out using EViews 11 (2020).

In an extensive Monte Carlo analysis of the HEGY test Meng and He (2012, p. 11) conclude "unless there are evident signs indicating there are no deterministic seasonality in the series, it is prudent to include [seasonal] dummies in the testing equation." A graph of the data shows clear signs of deterministic seasonality in the q_t, p_t and ps_t series. Accordingly, seasonal dummy variables are considered along with a constant term and linear trend when specifying the deterministic components of the test equation.

The null hypothesis of a seasonal unit root is rejected for y_t and a_t across all seasonal frequencies (Table A3.1). And this is true whether or not seasonal dummies are included in the test equation. For q_t, p_t and ps_t the same result obtains, but only if seasonal dummies are included in the test equation. If they are not included, the null is not rejected at frequencies $2\pi/12$, $4\pi/12$ and $6\pi/12$, i.e., at the annual, semi-annual, and quarterly seasonal cycles. But as noted earlier, research suggests seasonal dummies should be included in the test equation when variables exhibit significant deterministic seasonality, as is true for q_t, p_t and ps_t.

Further evidence is provided in Table A3.2. Here we report the results for three tests: a unit root at zero frequency (HEGY-I), unit roots at all seasonal frequencies combined (HEGY-II), and unit roots at all frequenices inclusive of the zero frequency (HEGY-III). (The zero frequency is interpreted as the "long-run" frequency (Kunst and Franses, 2009, p.13). A test at this frequency is tantamount to a test for a regular unit root.) The HEGY-II and HEGY-III tests both reject the null. The only case in which this is not true is for q_t when a constant and trend but not seasonal dummies are included in the test equation. But since q_t exhibits systematic seasonality test results that exclude seasonal dummies in the test equation can be set aside. Seasonal unit roots appear not to be an issue.

Turning to the tests for regular unit roots, ps_t clearly is I(0) as the null hypothesis that this variable contains a unit root is rejected by both the HEGY-I test and the ADF tests (Table A3.2). By the same criteria q_t, y_t, and a_t are either I(0) or I(1). The only variable that might be I(2) is p_t as the null is not rejected by either the HEGY-I test or the two ADF tests. However, re-running the test on Δp_t rejects the null of non-stationarity in first differences, which suggests p_t is I(1) (Table A3.2, last three rows). The null is not rejected by the standard ADF test when a constant and linear trend are included. This test, however, is biased toward accepting the null when the data are trend stationary with a structural break (Perron, 1989). The null also is not rejected by the HEGY-I test when contant and trend are included in the test equation, but not seasonal dummies. However, as noted seasonal dummies should be included for this variable. Consequently, for the considered sample we conclude that ps_t is I(0), p_t is I(1), and q_t, y_t and a_t are either I(0) or I(1).

Table A3.1. HEGY Tests for Unit Roots at Specific Seasonal Frequencies

Variable	Deterministic Component[a]	Lag Length[b]	Frequency[c] $2\pi/12$	$4\pi/12$	$6\pi/12$	$8\pi/12$	$10\pi/12$	π
q_t	C	0	4.63	3.42	6.85	10.2*	12.6*	-3.11**
	C,T	1	5.32	3.22	6.51	9.24*	10.1*	-2.91**
	C,T,SD	2	12.4**	18.8**	19.9**	12.2**	8.27**	-2.93*
p_t	C	2	1.98	5.84	4.97	15.1*	14.2*	-6.03**
	C,T	2	1.88	6.64	4.77	14.8*	14.3*	-6.06**
	C,T,SD	2	8.58**	9.96**	9.02**	17.6**	17.9**	-5.77**
ps_t	C	1	4.12	8.01	8.21	9.91*	12.9*	-3.76**
	C,T	1	4.25	7.91	8.12	9.71*	12.7*	-3.72**
	C,T,SD	0	10.1**	16.2**	18.8**	16.2**	25.2**	-4.92**
y_t	C	1	28.3*	17.2*	26.8*	25.8*	20.2*	-4.24**
	C,T	1	27.7*	16.3*	26.0*	24.6*	19.6*	-4.19**
	C,T,SD	1	38.4**	28.8**	26.8**	29.1**	21.9**	-4.46**
a_t	C	1	26.2*	17.0*	17.8*	18.9*	14.3*	-4.76**
	C,T	1	26.5*	17.2*	17.7*	18.7*	14.2*	-4.72**
	C,T,SD	2	19.6**	12.0**	15.6**	18.0**	14.1**	-4.89**

[a]C = constant included in the test equation; C,T = constant and linear trend included; C,T,SD = constant, linear trend and seasonal dummy variables included.
[b]Selected according to the AIC criterion.
[c]Single (*) and double asterisk (**) indicate rejection of the null hypothesis of a unit root at the 5% and 1% levels, respectively.

Table A3.2. HEGY Joint Tests for Seasonal Unit Roots and ADF Tests for Regular Unit Roots

	Deterministic	HEGY[b,c]			ADF[c]	
Variable	Component[a]	I	II	III	Standard	Breakpoint
q_t	C	-1.20	9.73*	8.98*	-1.20	-6.48**
	C,T	-2.16	6.95	6.92	-2.04	-8.35**
	C,T,SD	-0.90	14.7**	13.6**	--	--
p_t	C	-1.36	11.0*	10.3*	-1.36	-3.57
	C,T	-2.42	10.9*	10.8*	-2.42	-3.97
	C,T,SD	-1.30	16.4**	15.3**	--	--
ps_t	C	-4.29**	9.36*	12.58*	-4.29**	-5.58**
	C,T	-4.48**	9.27*	12.82*	-4.58**	-5.52**
	C,T,SD	-3.88**	244**	224**	--	--
y_t	C	-3.32*	26.1*	29.2**	-2.32	-4.66*
	C,T	-3.29	24.4*	29.0*	-3.17	-5.16*
	C,T,SD	-2.81	32.0**	35.3**	--	--
a_t	C	-2.75	22.9*	21.7*	-2.82	-8.38**
	C,T	-3.03	23.0*	21.9*	-3.10	-8.60**
	C,T,SD	-2.93	22.4**	21.3**	--	--
Δp_t	C	-3.15*	11.0*	11.7*	-3.15*	-13.3**
	C,T	-3.14	10.9*	11.6*	-3.14	-13.2**
	C,T,SD	-3.04*	16.4**	17.0*	--	--

[a] C = constant included in the test equation; C,T = constant and linear trend included; C,T,SD = constant, linear trend and seasonal dummy variables included.
[b] I = zero frequency, II = all seasonal frequencies, III = all frequencies including zero.
[c] Single (*) and double (**) asterisk indicate rejection of the null hypothesis of a unit root at the 5% and 1% levels, respectively.

Appendix B. Regression Output for the Bounds Test

Model C (Q-dependent model)

ARDL Long Run Form and Bounds Test
Dependent Variable: D(Q)
Selected Model: ARDL(1, 1, 2, 1, 1)
Case 3: Unrestricted Constant and No Trend
Date: 04/27/21   Time: 11:14
Sample: 2003M01 2017M12
Included observations: 178

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.464912	0.807588	9.243470	0.0000
Q(-1)*	-0.730176	0.064946	-11.24277	0.0000
P(-1)	-0.294739	0.058578	-5.031585	0.0000
PS(-1)	0.180654	0.044308	4.077266	0.0001
Y(-1)	0.199740	0.062230	3.209688	0.0016
A(-1)	0.061792	0.018324	3.372263	0.0009
D(P)	-0.553214	0.109449	-5.054543	0.0000
D(PS)	0.033630	0.120042	0.280154	0.7797
D(PS(-1))	-0.275155	0.122359	-2.248741	0.0260
D(Y)	1.173050	0.393479	2.981227	0.0033
D(A)	0.025476	0.017179	1.482945	0.1402
D1	-0.134372	0.062878	-2.137018	0.0342
D2	0.205730	0.045559	4.515665	0.0000
D3	0.137880	0.062493	2.206311	0.0289
D4	-0.113217	0.059659	-1.897755	0.0596
D5	-0.231119	0.048336	-4.781472	0.0000
M1	0.187539	0.034341	5.461107	0.0000
M2	0.240751	0.031368	7.675071	0.0000
M3	0.275475	0.031535	8.735635	0.0000
M4	0.082112	0.031811	2.581267	0.0108
M5	0.076990	0.031432	2.449401	0.0155
M6	0.009500	0.033752	0.281478	0.7787
M7	-0.029667	0.035534	-0.834890	0.4051
M8	0.023642	0.039927	0.592133	0.5546
M9	0.224191	0.038779	5.781291	0.0000
M10	0.245571	0.032783	7.490791	0.0000
M11	0.130267	0.030890	4.217155	0.0000

* p-value incompatible with t-Bounds distribution.

Levels Equation
Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
P	-0.403655	0.064781	-6.231019	0.0000
PS	0.247412	0.059633	4.148902	0.0001
Y	0.273550	0.080006	3.419116	0.0008
A	0.084627	0.025778	3.282849	0.0013

EC = Q - (-0.4037*P + 0.2474*PS + 0.2736*Y + 0.0846*A)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	**28.25024**	**10%**	**2.45**	**3.52**
K	4	**5%**	**2.86**	**4.01**
		2.5%	3.25	4.49
		1%	**3.74**	**5.06**
			Finite Sample:	
Actual Sample Size	178		n=80	
		10%	2.548	3.644
		5%	3.01	4.216
		1%	4.096	5.512

t-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	**-11.24277**	**10%**	**-2.57**	**-3.66**
		5%	**-2.86**	**-3.99**
		2.5%	-3.13	-4.26
		1%	**-3.43**	**-4.6**

Model C' (P-dependent model)

ARDL Long Run Form and Bounds Test
Dependent Variable: D(P)
Selected Model: ARDL(2, 2, 0, 0, 0)
Case 3: Unrestricted Constant and No Trend
Date: 04/27/21 Time: 11:17
Sample: 2003M01 2017M12
Included observations: 178

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.306826	0.724908	0.423263	0.6727
P(-1)*	-0.083610	0.042963	-1.946080	0.0535
Q(-1)	-0.058718	0.060588	-0.969147	0.3340
PS**	0.029035	0.029266	0.992119	0.3227
Y**	-0.026856	0.044920	-0.597877	0.5508
A**	7.00E-05	0.010604	0.006605	0.9947
D(P(-1))	-0.228683	0.080331	-2.846768	0.0050
D(Q)	-0.236000	0.048506	-4.865327	0.0000
D(Q(-1))	-0.083629	0.043828	-1.908103	0.0583
D1	0.004270	0.043321	0.098573	0.9216
D2	0.019216	0.031872	0.602901	0.5475
D3	0.009753	0.042953	0.227054	0.8207
D4	0.001830	0.040385	0.045322	0.9639
D5	-0.010138	0.034840	-0.290978	0.7715
M1	0.116844	0.022817	5.120893	0.0000
M2	0.108746	0.026394	4.120103	0.0001
M3	0.073862	0.025423	2.905321	0.0042
M4	0.039779	0.021171	1.878934	0.0622
M5	0.042732	0.020469	2.087677	0.0385
M6	0.064135	0.021014	3.052081	0.0027
M7	0.051510	0.022832	2.256018	0.0255
M8	0.144921	0.024480	5.919950	0.0000
M9	0.230938	0.027480	8.403741	0.0000
M10	0.197575	0.027445	7.198935	0.0000
M11	0.085234	0.022217	3.836486	0.0002

* p-value incompatible with t-Bounds distribution.
** Variable interpreted as Z = Z(-1) + D(Z).

Levels Equation
Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.

Q	-0.702290	0.546918	-1.284086	0.2011
PS	0.347272	0.353338	0.982832	0.3272
Y	-0.321212	0.563351	-0.570180	0.5694
A	0.000838	0.126862	0.006604	0.9947

EC = P - (-0.7023*Q + 0.3473*PS -0.3212*Y + 0.0008*A)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	**0.897044**	**10%**	**2.45**	**3.52**
k	4	**5%**	**2.86**	**4.01**
		2.5%	3.25	4.49
		1%	**3.74**	**5.06**
			Finite Sample:	
Actual Sample Size	178		n=80	
		10%	2.548	3.644
		5%	3.01	4.216
		1%	4.096	5.512

t-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	**-1.946080**	**10%**	**-2.57**	**-3.66**
		5%	**-2.86**	**-3.99**
		2.5%	-3.13	-4.26
		1%	**-3.43**	**-4.6**

Appendix C. Tests for Weak Exogeneity

VECM - All Regressors Endogenous

Vector Error Correction Estimates
Date: 04/27/21 Time: 11:27
Sample (adjusted): 2003M04 2017M12
Included observations: 177 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
B(1,1) =1
Convergence achieved after 1 iterations.
Restrictions identify all cointegrating vectors
Restrictions are not binding (LR test not available)

Cointegrating Eq:	CointEq1
Q(-1)	1.000000
P(-1)	0.355799
	(0.06314)
	[5.63510]
PS(-1)	-0.210791
	(0.05784)
	[-3.64413]
Y(-1)	-0.347232
	(0.07904)
	[-4.39321]
A(-1)	-0.078170
	(0.02668)
	[-2.93043]
C	-10.82405

Error Correction:	D(Q)	D(P)	D(PS)	D(Y)	D(A)
CointEq1	**-0.783649**	**0.147935**	**-0.081821**	**0.007802**	**-0.208444**
	(0.10028)	**(0.06591)**	**(0.06415)**	**(0.01565)**	**(0.44196)**
	[-7.81453]	**[2.24449]**	**[-1.27537]**	**[0.49865]**	**[-0.47163]**
D(Q(-1))	0.015063	-0.098269	0.029166	-0.006183	-0.492137
	(0.09145)	(0.06011)	(0.05851)	(0.01427)	(0.40305)
	[0.16471]	[-1.63488]	[0.49851]	[-0.43330]	[-1.22102]

D(Q(-2))	-0.048104	-0.003918	0.025436	-0.003012	-0.598143
	(0.07240)	(0.04759)	(0.04632)	(0.01130)	(0.31910)
	[-0.66439]	[-0.08234]	[0.54914]	[-0.26660]	[-1.87449]
D(P(-1))	0.078862	-0.301527	0.042383	-0.021900	-0.496231
	(0.13633)	(0.08960)	(0.08722)	(0.02127)	(0.60084)
	[0.57846]	[-3.36513]	[0.48595]	[-1.02953]	[-0.82590]
D(P(-2))	0.043383	-0.141334	-0.003099	-0.011010	-1.067044
	(0.13800)	(0.09070)	(0.08829)	(0.02153)	(0.60820)
	[0.31437]	[-1.55822]	[-0.03510]	[-0.51132]	[-1.75442]
D(PS(-1))	-0.219814	0.089113	0.187167	0.017854	-0.108046
	(0.13477)	(0.08858)	(0.08622)	(0.02103)	(0.59394)
	[-1.63108]	[1.00607]	[2.17091]	[0.84905]	[-0.18191]
D(PS(-2))	-0.104974	-0.098408	-0.015956	-0.048419	0.766196
	(0.13220)	(0.08689)	(0.08457)	(0.02063)	(0.58264)
	[-0.79406]	[-1.13257]	[-0.18866]	[-2.34730]	[1.31505]
D(Y(-1))	0.781880	-0.048111	0.646724	0.607711	0.063593
	(0.52031)	(0.34198)	(0.33287)	(0.08119)	(2.29314)
	[1.50271]	[-0.14069]	[1.94288]	[7.48551]	[0.02773]
D(Y(-2))	-0.818174	0.165811	-0.393409	-0.080745	0.922925
	(0.52315)	(0.34385)	(0.33469)	(0.08163)	(2.30566)
	[-1.56392]	[0.48223]	[-1.17545]	[-0.98918]	[0.40029]
D(A(-1))	-0.013564	-0.002586	-0.017893	0.000179	-0.562066
	(0.01970)	(0.01295)	(0.01260)	(0.00307)	(0.08683)
	[-0.68847]	[-0.19970]	[-1.41965]	[0.05834]	[-6.47336]
D(A(-2))	0.020281	0.017236	-0.014946	0.002653	-0.168336
	(0.01903)	(0.01251)	(0.01218)	(0.00297)	(0.08389)
	[1.06547]	[1.37771]	[-1.22739]	[0.89312]	[-2.00662]
C	-0.086965	-0.080544	0.069616	-0.003777	0.002913
	(0.02659)	(0.01748)	(0.01701)	(0.00415)	(0.11719)
	[-3.27042]	[-4.60851]	[4.09226]	[-0.91039]	[0.02486]
D1	-0.162472	0.023810	0.010969	0.002561	0.076625
	(0.06769)	(0.04449)	(0.04330)	(0.01056)	(0.29832)
	[-2.40032]	[0.53520]	[0.25331]	[0.24252]	[0.25686]
D2	0.218440	-0.035909	0.018384	-0.001227	-0.119955
	(0.04960)	(0.03260)	(0.03173)	(0.00774)	(0.21862)

	[4.40367]	[-1.10140]	[0.57932]	[-0.15854]	[-0.54870]
D3	0.160746	-0.037219	0.021291	0.003996	0.297440
	(0.06873)	(0.04517)	(0.04397)	(0.01072)	(0.30289)
	[2.33892]	[-0.82396]	[0.48425]	[0.37265]	[0.98199]
D4	-0.156202	0.003982	0.004397	0.002294	-0.483456
	(0.06433)	(0.04228)	(0.04115)	(0.01004)	(0.28351)
	[-2.42816]	[0.09419]	[0.10684]	[0.22854]	[-1.70523]
D5	-0.269144	0.034238	0.023389	-0.008635	0.026548
	(0.05458)	(0.03587)	(0.03492)	(0.00852)	(0.24054)
	[-4.93122]	[0.95443]	[0.66983]	[-1.01400]	[0.11037]
M1	0.112061	0.085554	-0.066241	-0.004775	-0.302501
	(0.04061)	(0.02669)	(0.02598)	(0.00634)	(0.17899)
	[2.75931]	[3.20519]	[-2.54956]	[-0.75357]	[-1.69009]
M2	0.236300	0.057159	-0.054286	0.018577	0.018672
	(0.04259)	(0.02799)	(0.02725)	(0.00665)	(0.18771)
	[5.54795]	[2.04182]	[-1.99228]	[2.79533]	[0.09947]
M3	0.287834	0.020772	-0.058753	0.008728	0.241199
	(0.03933)	(0.02585)	(0.02516)	(0.00614)	(0.17335)
	[7.31784]	[0.80351]	[-2.33488]	[1.42221]	[1.39140]
M4	0.090675	0.016007	-0.041720	0.005839	0.100743
	(0.03623)	(0.02381)	(0.02318)	(0.00565)	(0.15968)
	[2.50270]	[0.67221]	[-1.79992]	[1.03287]	[0.63091]
M5	0.074253	0.024029	-0.066292	0.001626	-0.077651
	(0.03613)	(0.02375)	(0.02312)	(0.00564)	(0.15925)
	[2.05491]	[1.01177]	[-2.86770]	[0.28846]	[-0.48760]
M6	-0.018973	0.072355	-0.098284	0.006851	-0.240417
	(0.03764)	(0.02474)	(0.02408)	(0.00587)	(0.16589)
	[-0.50404]	[2.92468]	[-4.08149]	[1.16654]	[-1.44925]
M7	-0.052266	0.072469	-0.078229	0.007656	-0.206191
	(0.03844)	(0.02526)	(0.02459)	(0.00600)	(0.16939)
	[-1.35985]	[2.86875]	[-3.18149]	[1.27666]	[-1.21724]
M8	-0.053355	0.164634	-0.114449	0.007676	-0.130378
	(0.04132)	(0.02716)	(0.02643)	(0.00645)	(0.18209)
	[-1.29136]	[6.06260]	[-4.32990]	[1.19069]	[-0.71600]

M9	0.133343	0.206775	-0.119996	0.009304	-0.031166
	(0.04412)	(0.02900)	(0.02823)	(0.00688)	(0.19445)
	[3.02226]	[7.13063]	[-4.25130]	[1.35156]	[-0.16028]
M10	0.182600	0.161771	-0.083684	0.009346	0.282142
	(0.04616)	(0.03034)	(0.02953)	(0.00720)	(0.20345)
	[3.95564]	[5.33190]	[-2.83369]	[1.29761]	[1.38681]
M11	0.092440	0.067838	-0.062579	-0.011253	0.366682
	(0.04082)	(0.02683)	(0.02611)	(0.00637)	(0.17989)
	[2.26474]	[2.52869]	[-2.39650]	[-1.76695]	[2.03836]
R-squared	0.763839	0.472425	0.271489	0.488953	0.333152
Adj. R-squared	0.721045	0.376824	0.139477	0.396347	0.212313
Sum sq. resids	1.109943	0.479477	0.454274	0.027022	21.55911
S.E. equation	0.086309	0.056727	0.055216	0.013467	0.380384
F-statistic	17.84909	4.941640	2.056547	5.279930	2.757002
Log likelihood	197.7058	271.9898	276.7686	526.5189	-64.82851
Akaike AIC	-1.917580	-2.756947	-2.810944	-5.632982	1.048910
Schwarz SC	-1.415138	-2.254505	-2.308502	-5.130540	1.551352
Mean dependent	-0.000503	-0.000642	0.000750	0.002252	0.001263
S.D. dependent	0.163414	0.071860	0.059523	0.017333	0.428593

Determinant resid covariance (dof adj.)	1.50E-12
Determinant resid covariance	6.35E-13
Log likelihood	1229.807
Akaike information criterion	-12.25771
Schwarz criterion	-9.655780
Number of coefficients	145

VECM - All Regressors Exogenous

Vector Error Correction Estimates
Date: 04/27/21 Time: 11:29
Sample (adjusted): 2003M04 2017M12
Included observations: 177 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
B(1,1) =1, A(2,1)=0, A(3,1)=0, A(4,1) = 0, A(5,1) = 0
Convergence achieved after 5 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(4)	**7.072558**
Probability	**0.132103**

Cointegrating Eq:	CointEq1
Q(-1)	1.000000
P(-1)	0.386207 (0.06664) [5.79564]
PS(-1)	-0.261283 (0.06105) [-4.27994]
Y(-1)	-0.281656 (0.08342) [-3.37650]
A(-1)	-0.088682 (0.02815) [-3.14999]
C	-10.42215

Error Correction:	D(Q)	D(P)	D(PS)	D(Y)	D(A)
CointEq1	**-0.699256** **(0.08931)** **[-7.82996]**	**0.000000** **(0.00000)** **[NA]**	**0.000000** **(0.00000)** **[NA]**	**0.000000** **(0.00000)** **[NA]**	**0.000000** **(0.00000)** **[NA]**
D(Q(-1))	0.004635 (0.09072) [0.05109]	-0.089001 (0.05972) [-1.49028]	0.012750 (0.05814) [0.21931]	-0.004762 (0.01415) [-0.33665]	-0.554902 (0.39963) [-1.38855]

D(Q(-2))	-0.057848	0.001809	0.016256	-0.002213	-0.632685
	(0.07192)	(0.04735)	(0.04609)	(0.01122)	(0.31683)
	[-0.80431]	[0.03820]	[0.35267]	[-0.19736]	[-1.99693]
D(P(-1))	0.084357	-0.299247	0.035990	-0.021356	-0.522039
	(0.13663)	(0.08994)	(0.08756)	(0.02131)	(0.60186)
	[0.61742]	[-3.32703]	[0.41102]	[-1.00239]	[-0.86737]
D(P(-2))	0.050508	-0.139868	-0.008258	-0.010574	-1.088253
	(0.13831)	(0.09105)	(0.08864)	(0.02157)	(0.60926)
	[0.36519]	[-1.53616]	[-0.09316]	[-0.49027]	[-1.78618]
D(PS(-1))	-0.225067	0.086819	0.193518	0.017313	-0.082439
	(0.13506)	(0.08891)	(0.08655)	(0.02106)	(0.59494)
	[-1.66646]	[0.97649]	[2.23579]	[0.82208]	[-0.13857]
D(PS(-2))	-0.123516	-0.098960	-0.009383	-0.048965	0.794570
	(0.13296)	(0.08753)	(0.08521)	(0.02073)	(0.58571)
	[-0.92895]	[-1.13058]	[-0.11011]	[-2.36165]	[1.35658]
D(Y(-1))	0.803716	-0.045968	0.635848	0.608624	0.017907
	(0.52114)	(0.34307)	(0.33398)	(0.08126)	(2.29566)
	[1.54224]	[-0.13399]	[1.90383]	[7.48955]	[0.00780]
D(Y(-2))	-0.761398	0.160558	-0.398956	-0.080324	0.893114
	(0.52430)	(0.34515)	(0.33601)	(0.08176)	(2.30959)
	[-1.45222]	[0.46518]	[-1.18733]	[-0.98249]	[0.38670]
D(A(-1))	-0.019449	-0.002509	-0.016336	5.14E-05	-0.555133
	(0.02006)	(0.01320)	(0.01285)	(0.00313)	(0.08835)
	[-0.96978]	[-0.19002]	[-1.27100]	[0.01644]	[-6.28360]
D(A(-2))	0.017326	0.017082	-0.013761	0.002554	-0.163275
	(0.01918)	(0.01262)	(0.01229)	(0.00299)	(0.08448)
	[0.90348]	[1.35314]	[-1.11971]	[0.85397]	[-1.93280]
C	-0.083190	-0.080285	0.067971	-0.003640	-0.004065
	(0.02677)	(0.01762)	(0.01716)	(0.00417)	(0.11793)
	[-3.10734]	[-4.55533]	[3.96154]	[-0.87183]	[-0.03447]
D1	-0.168185	0.024283	0.011644	0.002509	0.080084
	(0.06781)	(0.04464)	(0.04346)	(0.01057)	(0.29871)
	[-2.48024]	[0.54397]	[0.26795]	[0.23728]	[0.26810]
D2	0.218372	-0.035599	0.017754	-0.001173	-0.122411
	(0.04965)	(0.03269)	(0.03182)	(0.00774)	(0.21873)

	[4.39788]	[-1.08906]	[0.55791]	[-0.15148]	[-0.55964]
D3	0.158348	-0.035740	0.018886	0.004205	0.288368
	(0.06876)	(0.04526)	(0.04407)	(0.01072)	(0.30289)
	[2.30296]	[-0.78959]	[0.42859]	[0.39220]	[0.95206]
D4	-0.146137	0.002683	0.004187	0.002302	-0.485714
	(0.06449)	(0.04245)	(0.04133)	(0.01006)	(0.28407)
	[-2.26617]	[0.06320]	[0.10131]	[0.22893]	[-1.70985]
D5	-0.262337	0.032957	0.024092	-0.008703	0.028330
	(0.05463)	(0.03596)	(0.03501)	(0.00852)	(0.24064)
	[-4.80223]	[0.91642]	[0.68815]	[-1.02161]	[0.11773]
M1	0.109441	0.085577	-0.065525	-0.004834	-0.299323
	(0.04069)	(0.02678)	(0.02607)	(0.00634)	(0.17923)
	[2.68989]	[3.19507]	[-2.51294]	[-0.76196]	[-1.67008]
rrr					
M2	0.234341	0.056836	-0.053037	0.018472	0.023842
	(0.04267)	(0.02809)	(0.02735)	(0.00665)	(0.18797)
	[5.49169]	[2.02326]	[-1.93937]	[2.77601]	[0.12684]
M3	0.284986	0.020567	-0.057490	0.008623	0.246550
	(0.03943)	(0.02596)	(0.02527)	(0.00615)	(0.17371)
	[7.22704]	[0.79227]	[-2.27486]	[1.40229]	[1.41934]
M4	0.085994	0.017321	-0.043111	0.005963	0.095965
	(0.03620)	(0.02383)	(0.02320)	(0.00565)	(0.15947)
	[2.37540]	[0.72678]	[-1.85815]	[1.05633]	[0.60176]
M5	0.065964	0.025777	-0.067542	0.001742	-0.081360
	(0.03611)	(0.02377)	(0.02314)	(0.00563)	(0.15906)
	[1.82682]	[1.08439]	[-2.91866]	[0.30937]	[-0.51149]
M6	-0.028817	0.073793	-0.098430	0.006873	-0.239582
	(0.03778)	(0.02487)	(0.02421)	(0.00589)	(0.16642)
	[-0.76275]	[2.96706]	[-4.06529]	[1.16674]	[-1.43959]
M7	-0.060066	0.072347	-0.075696	0.007446	-0.195163
	(0.03883)	(0.02556)	(0.02488)	(0.00605)	(0.17105)
	[-1.54692]	[2.83030]	[-3.04184]	[1.22981]	[-1.14099]
M8	-0.061156	0.163504	-0.109798	0.007284	-0.111060
	(0.04192)	(0.02759)	(0.02686)	(0.00654)	(0.18465)
	[-1.45900]	[5.92533]	[-4.08729]	[1.11442]	[-0.60148]

M9	0.129579	0.204685	-0.114507	0.008836	-0.009145
	(0.04446)	(0.02927)	(0.02849)	(0.00693)	(0.19584)
	[2.91463]	[6.99363]	[-4.01890]	[1.27463]	[-0.04670]
M10	0.182876	0.159485	-0.078966	0.008941	0.300572
	(0.04621)	(0.03042)	(0.02962)	(0.00721)	(0.20358)
	[3.95717]	[5.24225]	[-2.66620]	[1.24067]	[1.47646]
M11	0.094098	0.066536	-0.060330	-0.011448	0.375249
	(0.04082)	(0.02687)	(0.02616)	(0.00636)	(0.17981)
	[2.30532]	[2.47615]	[-2.30626]	[-1.79863]	[2.08696]
R-squared	0.763363	0.469659	0.267435	0.488554	0.332447
Adj. R-squared	0.720482	0.373557	0.134688	0.395876	0.211481
Sum sq. resids	1.112182	0.481991	0.456802	0.027043	21.58188
S.E. equation	0.086396	0.056876	0.055370	0.013472	0.380585
F-statistic	17.80205	4.887087	2.014625	5.271509	2.748268
Log likelihood	197.5275	271.5271	276.2774	526.4499	-64.92197
Akaike AIC	-1.915565	-2.751718	-2.805395	-5.632202	1.049966
Schwarz SC	-1.413123	-2.249276	-2.302953	-5.129760	1.552407
Mean dependent	-0.000503	-0.000642	0.000750	0.002252	0.001263
S.D. dependent	0.163414	0.071860	0.059523	0.017333	0.428593

Determinant resid covariance (dof adj.)	1.51E-12
Determinant resid covariance	6.38E-13
Log likelihood	1226.271
Akaike information criterion	-12.21775
Schwarz criterion	-9.615822
Number of coefficients	145