WENYING LI

wenying.li25@uga.edu | University of Georgia | Athens, GA 30602

https://sites.google.com/view/wenying

Sep 18th, 2019

Dear Dr. Mark L. Waller and Members of the Search Committee:
The Department of Agricultural Economics
Texas A&M University

In response to your job announcement, I would like to apply for the Assistant Professor position in Agricultural Marketing and Quantitative Analysis.

I am a Ph.D. candidate in Agricultural and Applied Economics at the University of Georgia. My research specializes in food policy/marketing, applied econometrics, and innovative statistical methods. Specifically, I develop and estimate large demand systems and household collective models using big data such as retail and household scanner datasets which are high dimensional datasets consisting of millions of observations. I believe my research direction will largely contribute to the research scope and diversity of the department.

In the past two years, three of my papers were accepted and published in Food Policy, Journal of Agricultural and Applied Economics, and American Journal of Clinical Nutrition. At the University of Georgia, I was the instructor and teaching assistant for two undergraduate-level econometrics classes. I believe that the intense academic training I received, my research experiences, as well as my passion in teaching present an excellent fit and great potential for this position.

Please find enclosed supporting materials for my application. I would appreciate the opportunity to meet you and talk about the opportunities at Texas A&M University.

Sincerely,

Wenying. Li

Wenying Li

WENYING LI

wenying.li25@uga.edu | University of Georgia | Athens, GA 30602

https://sites.google.com/view/wenying

EDUCATION

Ph.D.	Agricultural and Applied Economics, University of Georgia	8/2015 –2020 (Expected)
M.S.	Financial Statistics, London School of Economics and Political Science (LSE)	9/2013 – 8/2014
B.S.	Finance, Renmin University of China	9/2009 - 6/2013

FIELDS OF SPECIALIZATION

Food Policy; Applied Microeconomics; Applied Econometrics; Economics of Nutrition and Healthy Eating; Innovative Statistical Methods and Practice

JOB MARKET PAPERS

- **Two simple strategies for reducing aggregation bias in large demand systems**.
- Specialized Fields: Econometrics, Big Data Analytics, Microeconomics
- Abstract: The increasing availability of detailed scanner data has allowed researchers to study consumer demand at disaggregated levels. However, some degree of aggregation is still necessary for flexible functional form models because of the large number of parameters. Aggregation bias occurs in an inconsistently aggregated demand because the omitted relative prices of elementary products cause the demand residual to be correlated with the aggregate prices. In this paper, we propose two simple strategies for aggregation bias reduction. The first strategy uses the relative prices of elementary products as control variables in the aggregate demand. The second uses a residual-based instrumental variable method to achieve independence between the instrument and the residual. In an application to fruit and vegetable demand estimation, the preferred strategy cut aggregation bias by up to 91% in own-price elasticities and 57% in cross-price elasticities. These simple bias-reduction approaches are broadly applicable to situations where research needs and available computing resources dictate a particular aggregation scheme not supported by aggregation tests.
- **Intended and unintended consequences of salient nutrition labels**. *under review,* Journal of Health Economics
- Specialized Fields: Health Economics, Food Policy
- Abstract: Policy makers are increasingly considering front-of-package labels as a means to improve diet quality. However, evidence on the effectiveness of labels has proven difficult to quantify. We take advantage of a "natural experiment" (an update of the scoring algorithm) to estimate the effects of NuVal, a label that scores foods on a 100-point scale. Using a triple differences approach and focusing on yogurts, which have a large range of scores, we find that an increase in NuVal scores increases diet quality. However, suppliers respond to the increase by raising prices, thus offsetting some of the direct effects of labelling. We also show that a profit maximizing supplier could increase profits by bringing to market very unhealthy products, even if these products are never purchased. If so, this would further weaken the beneficial effects of labelling.

PEER-REVIEWED PUBLICATIONS

- **Li, W**., & Dorfman, J. H. (2019). The implications of heterogeneous habit in consumer beverage purchases on soda and sin taxes. Food Policy, 84, 111-120.
- **Li, W**., Li, Y., & Dorfman, J. (2019). Dynamically Changing Cattle Market Linkages with Supply-Side-Controlled Transitions. Journal of Agricultural and Applied Economics, 51(3), 472-484.
- Finkelstein, E. A., **Li, W**., Melo, G., Strombotne, K., & Zhen, C. (2018). Identifying the effect of shelf nutrition labels on consumer purchases: results of a natural experiment and consumer survey. The American Journal of Clinical Nutrition, 107(4), 647-651 (2019 Impact Factor: 6.77).

WORKING PAPERS

- **Li, W**., Zhen, C., & Dorfman, J. H. Beauty burst during economic decline: an empirical test of the lipstick effect. *under review*, Applied Economics.
- **Li, W.**, & Zhen, C. Estimating consumption economies of scales and household sharing in the U.S.: A collective model approach.
- **Li, W**. Resource sharing and scale economies in families with children in the U.S.

CONFERENCE PROCEEDINGS

- **Li, W**., Li, Y., and J. H. Dorfman. "Examining Dynamically Changing Cattle Market Linkages with Inventory-Controlled Transitions." NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management (2017).

RESEARCH GRANTS

- **Participant,** Building A Public-Use Small Area Panel Price Index Database Using Scanner Data, USDA National Institute of Food and Agriculture, PI: Chen Zhen, $499,991, 2019-2022.
- **Participant,** Promising Strategies for Promoting Healthier Food Purchases Among SNAP Households, USDA National Institute of Food and Agriculture, PI: Chen Zhen, $499,630, 2017–2020.

CONFERENCE PRESENTATIONS

- **Li, W**., and Dorfman, J. H. "Habit Formation with Smooth Transitions: Estimating Demand for US Carbonated-Sweetened Beverages and Beer." Paper presented at the Agricultural and Applied Economics Association Meeting, Washington DC, August 7, 2018
- **Li, W**., and Zhen, C. "A Reassessment of Product Aggregation Bias in Demand Analysis: An Application to the U.S. Meat Market" Paper presented at the Agricultural and Applied Economics Association Meeting, Chicago, IL, August 1, 2017
- **Li, W**., Li, Y., and Dorfman, J. H. "Examining Dynamically Changing Cattle Market Linkages with Inventory-Controlled Transitions." Paper presented at the Agricultural and Applied Economics Association Meeting, Chicago, IL, August 1
- **Li, W**., Zhen, C., and Finkelstein, E. A. "Identifying the Effect of Shelf Nutrition Labels on Yogurt Sales Using a Natural Experiment" Paper presented at the Agricultural and Applied Economics Association Meeting, Chicago, IL, July 31, 2017
- **Li, W**., Li, Y., and Dorfman, J. H. "Examining Dynamically Changing Cattle Market Linkages with Inventory-Controlled Transitions." Paper presented at the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, St. Louis, April 2017

TEACHING EXPERIENCE

- **Instructor**, University of Georgia — Summer 2019

  AAEC 3020: Analytical and Computational Tools for Applied Economics
- **Teaching Assistant** (for Dr. Chen Zhen), University of Georgia — Fall 2016 - 2018

  AAEC 4610: Applied Econometrics & Computation Labs
- **Mathematics Competition Coach**, Athens Academy — Fall 2018

  Coaching for high-school Mathematical Olympiad, American Mathematics Competitions and Mathematical Contest in Modelling

SELECTED HONORS AND AWARDS

- University of Georgia Graduate Teaching/Research Assistantship 2015-2020
- University of Georgia Doctoral Student Travel and Research Grants 2018
- Senior Statistician, Royal Statistical Society, UK 2015
- First Prize in the U.S. Mathematical Contest in Modeling 2013
- Renmin University Chancellor's Scholarship (Highest Honor) 2012
- Renmin University Chancellor's Scholarship (Highest Honor) 2011

PREVIOUS EMPLOYMENT

- University of Georgia, Athens, Georgia, U.S. 2015-2019
  Graduate Assistant (Research and Teaching)
- Citics Security, Beijing, China 2013-2014
  Intern, Investment Banking Department, Real Estate Investment Group

LANGUAGES FLUENCY

- Fluent in English speaking and writing; native in Mandarin
- Proficient in SAS, STATA, R, MATLAB, Python, MySQL and Database Administration.

REFERENCES

- **Dr. Chen Zhen (Ph.D. Committee Chair)**
  Associate Professor, University of Georgia
  Email: czhen@uga.edu Phone: 706-542-0766
- **Dr. Jeffrey H. Dorfman**
  State Fiscal Economist
  Professor, University of Georgia
  Email: jdorfman@uga.edu Phone: 706-542-0754
- **Dr. Octavio Ramirez**
  Professor and Head of Department of Agricultural and Applied Economics, University of Georgia
  Email: oramirez@uga.edu Phone: 706-542-2481

811610777 Wenying Li
Jul 31, 2019 12:13 pm

Unofficial Transcript

This is not an official transcript. Courses which are in progress may also be included on this transcript. Please refer all other transcript needs to the Office of the Registrar.

The “PASSED HOURS” column should be ignored. It is used for calculations by the Board of Regents. Students should view “EARNED HOURS” instead.

If you received a grade of “NG", your instructor did not report your grade. Please contact the instructor of the course for assistance.

A grade of “I” (or "I*" for a course graded S/U) means incomplete. No more than 3 semesters may be allowed to complete the work of the course. If a grade of “I” is not satisfactorily removed after three semesters, the “I” grade will be converted to an “F” (or “U” for a course graded S/U) by the Office of the Registrar.

Transfer credit may not appear in chronological order. The order in which transfer credit is posted is determined by the order in which it is received by UGA Undergraduate Admissions.

Transcripts will include all college level coursework from previously attended institutions regardless of whether UGA awarded transfer credit.

Please contact the Office of the Registrar at 706-542-4040 with any questions. Please note that federal privacy laws prevent discussion of the specific content of your transcript over the telephone.

Institution Credit Transcript Totals Courses in Progress

Transcript Data

STUDENT INFORMATION

Name : Wenying Li

Birth Date: 25-APR

Curriculum Information

Program

Doctor of Philosophy

College: College of Agr and Env Science

Major and Department: Agricultural and Applied Econ, Agricultural and Applied Econ

***Transcript type:Unofficial Web is NOT Official ***

INSTITUTION CREDIT -Top-

Term: Fall 2015

Academic Standing: Good Standing

Subject	Course	Level	Title	Grade	Credit Hours	Quality Points	R
AAEC	6580	DR	Micro/App I	A	4.000	16.00	
AAEC	6610	DR	Quant Tech Ag Econ	A	3.000	12.00	
AAEC	6610L	DR	Quant Methods Lab	A	1.000	4.00	
AAEC	7000	DR	Master's Research	W	6.000	0.00	
AAEC	7000	DR	Master's Research	S	6.000	0.00	
AAEC	8010	DR	Seminar Ag App Econ	S	1.000	0.00	I
AAEC	8210	DR	Macro Issues Ag/Res	A	3.000	12.00	

	Attempt Hours	Passed Hours	Earned Hours	GPA Hours	Quality Points	GPA
Current Term:	24.000	18.000	18.000	11.000	44.00	4.00
Cumulative:	24.000	18.000	18.000	11.000	44.00	4.00

Unofficial Transcript

Term: Spring 2016

Academic Standing: Good Standing

Subject	Course	Level	Title	Grade	Credit Hours	Quality Points	R
AAEC	9000	DR	Doctoral Research	S	8.000	0.00	E

	Attempt Hours	Passed Hours	Earned Hours	GPA Hours	Quality Points	GPA
Current Term:	8.000	0.000	0.000	0.000	0.00	0.00
Cumulative:	32.000	18.000	18.000	11.000	44.00	4.00

Unofficial Transcript

Term: Summer 2016

Academic Standing: Good Standing

Subject	Course	Level	Title	Grade	Credit Hours	Quality Points	R
AAEC	9000	DR	Doctoral Research	S	9.000	0.00	E
AAEC	9300	DR	Doct Dissertation	S	9.000	0.00	E

	Attempt Hours	Passed Hours	Earned Hours	GPA Hours	Quality Points	GPA
Current Term:	18.000	0.000	0.000	0.000	0.00	0.00

Cumulative:	50.000	18.000	18.000	11.000	44.00	4.00

Unofficial Transcript

Term: Fall 2016

Academic Standing: Good Standing

Subject	Course	Level	Title	Grade	Credit Hours	Quality Points	R
AAEC	8010	DR	Seminar Ag App Econ	S	1.000	0.00	I
AAEC	8020	DR	Ag and App Econ Topic	A	3.000	12.00	I
AAEC	8610	DR	Advanced Econometric Apps	A-	3.000	11.10	
AAEC	9000	DR	Doctoral Research	S	5.000	0.00	E
ECON	8110	DR	Econometrics I	A	3.000	12.00	

	Attempt Hours	Passed Hours	Earned Hours	GPA Hours	Quality Points	GPA
Current Term:	15.000	10.000	10.000	9.000	35.10	3.90
Cumulative:	65.000	28.000	28.000	20.000	79.10	3.95

Unofficial Transcript

Term: Spring 2017

Academic Standing: Good Standing

Subject	Course	Level	Title	Grade	Credit Hours	Quality Points	R
AAEC	8010	DR	Seminar Ag App Econ	S	1.000	0.00	I
AAEC	8020	DR	Ag and App Econ Topic	A	3.000	12.00	I
AAEC	8350	DR	Res and Prof Dev	A	1.000	4.00	
AAEC	9000	DR	Doctoral Research	S	9.000	0.00	E
STAT	8260	DR	Linear Models	W	3.000	0.00	

	Attempt Hours	Passed Hours	Earned Hours	GPA Hours	Quality Points	GPA
Current Term:	17.000	5.000	5.000	4.000	16.00	4.00
Cumulative:	82.000	33.000	33.000	24.000	95.10	3.96

Unofficial Transcript

Term: Summer 2017

Academic Standing: Good Standing

Subject	Course	Level	Title	Grade	Credit	Quality	R

					Hours	Points	
AAEC	9000	DR	Doctoral Research	S	9.000	0.00	E
AAEC	9300	DR	Doct Dissertation	S	8.000	0.00	E

	Attempt Hours	Passed Hours	Earned Hours	GPA Hours	Quality Points	GPA
Current Term:	17.000	0.000	0.000	0.000	0.00	0.00
Cumulative:	99.000	33.000	33.000	24.000	95.10	3.96

Unofficial Transcript

Term: Fall 2017

Academic Standing: Good Standing

Subject	Course	Level	Title	Grade	Credit Hours	Quality Points	R
AAEC	8140	DR	Consumer Dem Thy	A	3.000	12.00	
AAEC	9000	DR	Doctoral Research	S	9.000	0.00	E
AAEC	9300	DR	Doct Dissertation	S	3.000	0.00	E
ECON	8040	DR	Macroeconomics I	A-	3.000	11.10	

	Attempt Hours	Passed Hours	Earned Hours	GPA Hours	Quality Points	GPA
Current Term:	18.000	6.000	6.000	6.000	23.10	3.85
Cumulative:	117.000	39.000	39.000	30.000	118.20	3.94

Unofficial Transcript

Term: Spring 2018

Academic Standing: Good Standing

Subject	Course	Level	Title	Grade	Credit Hours	Quality Points	R
AAEC	8100	DR	Nonmrkt Econ Val	A-	3.000	11.10	
AAEC	9000	DR	Doctoral Research	S	7.000	0.00	I
AAEC	9300	DR	Doct Dissertation	S	8.000	0.00	I

	Attempt Hours	Passed Hours	Earned Hours	GPA Hours	Quality Points	GPA
Current Term:	18.000	18.000	18.000	3.000	11.10	3.70
Cumulative:	135.000	57.000	57.000	33.000	129.30	3.91

Unofficial Transcript

Term: Summer 2018

Academic Standing: Good Standing

Subject	Course	Level	Title	Grade	Credit Hours	Quality Points	R
AAEC	9000	DR	Doctoral Research	S	9.000	0.00	I
AAEC	9300	DR	Doct Dissertation	S	9.000	0.00	I

	Attempt Hours	Passed Hours	Earned Hours	GPA Hours	Quality Points	GPA
Current Term:	18.000	18.000	18.000	0.000	0.00	0.00
Cumulative:	153.000	75.000	75.000	33.000	129.30	3.91

Unofficial Transcript

Term: Fall 2018

Academic Standing: Good Standing

Subject	Course	Level	Title	Grade	Credit Hours	Quality Points	R
AAEC	9000	DR	Doctoral Research	S	9.000	0.00	I
AAEC	9300	DR	Doct Dissertation	S	9.000	0.00	I

	Attempt Hours	Passed Hours	Earned Hours	GPA Hours	Quality Points	GPA
Current Term:	18.000	18.000	18.000	0.000	0.00	0.00
Cumulative:	171.000	93.000	93.000	33.000	129.30	3.91

Unofficial Transcript

Term: Spring 2019

Academic Standing: Good Standing

Subject	Course	Level	Title	Grade	Credit Hours	Quality Points	R
AAEC	9000	DR	Doctoral Research	S	9.000	0.00	I
AAEC	9300	DR	Doct Dissertation	S	9.000	0.00	I

	Attempt Hours	Passed Hours	Earned Hours	GPA Hours	Quality Points	GPA
Current Term:	18.000	18.000	18.000	0.000	0.00	0.00
Cumulative:	189.000	111.000	111.000	33.000	129.30	3.91

Unofficial Transcript

TRANSCRIPT TOTALS (DOCTORAL) -Top-

	Attempt Hours	Passed Hours	Earned Hours	GPA Hours	Quality Points	GPA
Total Institution:	189.000	111.000	111.000	33.000	129.30	3.91
Total Transfer:	0.000	0.000	0.000	0.000	0.00	0.00
Overall:	189.000	111.000	111.000	33.000	129.30	3.91

Unofficial Transcript

COURSES IN PROGRESS -Top-

Term: Summer 2019

Subject	Course	Level	Title	Credit Hours
AAEC	9000	DR	Doctoral Research	6.000
AAEC	9300	DR	Doct Dissertation	6.000

Unofficial Transcript

Term: Fall 2019

Subject	Course	Level	Title	Credit Hours
AAEC	9000	DR	Doctoral Research	9.000
AAEC	9300	DR	Doct Dissertation	9.000

Unofficial Transcript

The University of Georgia
Department of Agricultural & Applied Economics
Athens, GA 30602-7509

Prof. Jeffrey H. Dorfman
312 Conner Hall
ph: 706.542.0754
email: jdorfman@uga.edu

September 25, 2019

Department of Agricultural Economics
Texas A&M University
College Station, TX

Dear Search Committee Members:

I am writing to provide my recommendation for Wenying Li for your assistant professor position. I am very confident he will make an excellent professor and colleague.

Wenying is already a polished researcher, even though he is still finishing his Ph.D. I am not his major professor, but have co-authored three papers with him (two already forthcoming) in the past two years, while he is also busy writing his dissertation. The best part of our collaboration is that Wenying brings the ideas. He read one of my papers and has found new applications of a model I used that have allowed us to empirically investigate very different situations in a robust manner.

In particular, Wenying realized that smooth transition models could be used as an infinite mixture model that allowed the modeling of consumer behavior to incorporate heterogeneity in a simple, understandable, and empirically tractable way. This led to our forthcoming paper in *Food Policy* in which we show that consumer demand models that impose homogeneity overestimate the efficacy of sin tax policies like soda taxes. Because the heaviest consumers tend to be the most habitual and, thus, have the most price inelastic demand, aggregate changes in consumption from such a policy will be smaller than forecast by a model that does not account for that heterogeneity and the public health benefits will be vastly overstated.

Mr. Li's dissertation research is focused on issues related to aggregation and scanner data from consumer grocery purchases. Wenying is establishing conditions when it is, or is not, okay to collapse lots of precisely specified products into more common categories such as beef, chicken, or pork. This work combines quite advanced microeconomic theory with some serious econometric and statistics. Plus, thanks to the size of the data sets involved, Wenying is getting a lot of practical experience in handling big data.

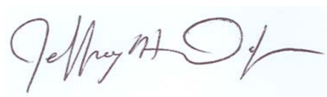
I am completely confident that our paper in *Food Policy* will not be a one-off and that Wenying will be capable of regularly publishing at that *Food Policy/AJAE* level with some general economics journals included from time to time. His work is definitely that high quality.

While Wenying is from China, between his time getting a master's degree at London School of Economics and his time in Georgia for his Ph.D. his English is nearly flawless. His writing is very good and he will be easy for students to understand in a classroom. I have seen him give presentations several times and have no doubt that he will make a good teacher.

Mr. Li is a highly motivated researcher, has his own ideas, works well with others (our three papers have three, two, and three authors), and carries them through to completion. These are skills not all faculty members have, let along Ph.D. students. Because Wenying is already such a polished researcher, with no shortage of future research ideas, his transition to assistant professor should be pretty seamless. I have no doubt he will be a highly successful researcher.

When you put together his research productivity with his apparent aptitude at teaching, Wenying Li is going to be a great professor somewhere. I encourage you to hire him; you will be glad you did.

Sincerely,



Jeffrey H. Dorfman
Professor and
State Fiscal Economist of Georgia

Octavio Ramirez
301 Conner Hall
Athens, Georgia 30602
TEL 706-542-0738 | FAX 706-542-0739
oramirez@uga.edu

College of Agricultural and Environmental Sciences
Agricultural and Applied Economics Department

September 18, 2019

Mark L. Waller
Department of Agricultural Economics
Texas A&M University
2124 TAMU
College Station, TX 77843-2124

Dear Dr. Waller:

It is my pleasure to recommend Wenying Li, an expected 2020 Ph.D. graduate from the Agricultural and Applied Economics Department at the University of Georgia, for the Assistant Professor position in the Agricultural and Applied Economics department at Texas A&M University. I have had the pleasure of having Mr. Li in my Quantitative Techniques in Agricultural Economics class, and he has proven to be a creative and productive economic modeler and researcher. Though I have not personally worked with him beyond my class, his performance in that class was excellent, ranking him in the top 5 of more than 500 students I have taught throughout my career, and his work with other faculty members in the department has been outstanding. I believe he would be an ideal fit for your faculty position.

In the first two years of Mr. Li's Ph.D. studies, he worked with Dr. Chen Zhen as a research assistant and statistician, dealing with retail and household scanner data. This project gave Mr. Li the first-hand experience in data management and cleaning techniques necessary to collaborate extensively with colleagues in agricultural economics, enabling him to extend the research scope of his department.

Mr. Li has three peer-reviewed publications from his time at UGA and is currently working on another four, including his job market paper which is currently under review at the *Journal of Health Economics*. Clearly, he has the motivation and dedication to be an outstanding and productive researcher and agricultural economist. His interests lie in incorporating heterogeneity in demand estimations, enabling economists to estimate effects on individuals as opposed to whole populations. He is a creative economic modeler who uses state-of-the-art methods to understand public policies and their impacts, and his background in both statistics and economics will allow him to collaborate on projects across multiple fields.

Additionally, Mr. Li has already participated on two projects, with Dr. Chen Zhen, funded by the USDA National Institute of Food and Agriculture, as well as presented four different papers at five different conferences since

2017. Since 2016, he has been Dr. Zhen's teaching assistant, even teaching his own section of AAEC 3020, Analytical and Computational Tools for Applied Economics, in the summer of 2019.

In short, Wenying Li is an excellent and productive researcher with a unique background and a unique approach to his research. He is able to collaborate and work well with other researchers, as well as teach his methods and big data and machine learning techniques to students, making him an outstanding overall candidate for the Assistant Professor position in your department. I am confident he would be a fine addition to the faculty at Texas A&M. If you have any further questions, please do not hesitate to ask.

Sincerely,

Octavio Ramirez
Department Head and Professor

UNIVERSITY OF GEORGIA
College of Agricultural & Environmental Sciences
Department of Agricultural and Applied Economics

September 24, 2019

Dear Dr. Waller and Members of the Search Committee:

It is my great pleasure to write a letter of recommendation in support of Mr. Wenying Li's application to the assistant professor of agricultural marketing and quantitative analysis position at Texas A&M. I have had the enjoyable experience working with Wenying for over four years. He is my first PhD student ever. As his dissertation advisor and funder of his research assistantship over the entire period, I am able to comment on all aspects of his professional life with confidence. I work with Wenying in the following three areas:

1. nutrition labels,
2. consistent aggregation of food products for demand analysis, and
3. equivalence scale and identification of intrahousehold sharing.

All three are his dissertation research and he has made critical intellectual contributions to each topic that I will discuss in the space below. Overall, I place Wenying at the top **1%** of the ag and applied econ graduate students enrolled since 2015, which is the year I joined UGA after working at RTI for nine years.

Wenying started planning his research agenda as soon as he arrived at UGA. One of his areas of interest is "big data" and applied econometrics. This comes as natural because he already had a master's degree in statistics from LSE. I told him that I work almost exclusively with scanner data that tend to be very "big" and I always need talented and aspiring research assistants for my funded research. This is how he came onboard.

Wenying's first line of research concerns the role of shelf nutrition label in food purchasing decisions. This research started in 2015 when I received a Healthy Eating Research grant from the Robert Wood Johnson Foundation to examine the impact of NuVal labels on food sales. NuVal, now defunct, was a numeric score ranging from 1 (least healthy) to 100 (most healthy) affixed to the price tag at participating retailers. The difference between NuVal and traditional nutrition facts labels is that NuVal was interpretive in that it provided consumers a summary assessment, done by a team of nutrition experts convened by NuVal, of a product's healthfulness. For economists, the pitfall of evaluating a voluntary labeling program has always been the selection bias. That is, retailers with more nutrition-oriented customers may self-select into the program. In the work with Wenying, we (including Dr. Eric Finkelstein at Duke-NUS Medical School) exploited a natural experiment in which NuVal revised its nutrient profiling algorithm such that the majority of food products received substantially lower scores while others received higher new scores. We used retail scanner data before and after the update from a NuVal participating retailer to test the effect of the score changes on sales. We found a 1-point decrease in NuVal score reduced yogurt sales by 0.49%. This was published in the *American Journal of Clinical Nutrition* (Finkelstein, Li, Melo, Strombotne and Zhen 2018; alphabetical order), which is a top journal in nutrition (impact factor 6.6).

The Finkelstein et al. study was a step forward compared to studies (e.g., Nikolova and Inman 2015; Melo, Zhen, Colson, 2019; Zheng and Zhen 2019) using pre- and post-label data. However, it lacked a control group so that secular sales trends may be confounded with the true effect of the score change. To confront this issue, Wenying took the initiative of obtaining a number of control stores from the Nielsen Scantrack data at the Kilts Center for Marketing. In the new manuscript, we used triple-difference to control for a number of confounders. We found that not only the score changes impacted sales, but also the NuVal retailer realized the sales loss and reacted with price cuts on products that received lower scores after the update. We argue that the price cuts had two potential unintended consequences. First, when a market is consisted of a variety of consumer types, the more price-responsive but less nutrition-oriented consumers may lower the nutritional quality of their purchases. Second, the lower prices and lower margins help explain the eventual demise of NuVal not long after the update. Wenying's significant contributions to this work **earned him the first authorship** on the manuscript (Li, Finkelstein, and Zhen 2019), which is under review at *Journal of Health Economics*.

Wenying's second line of research, funded by ERS, concerns the consistent product aggregation in consumer demand models. As a practical matter, it is necessary to aggregate elementary products into groups before estimating a demand system at the group level. For decades, aggregation decisions are driven by the specific needs of the research. For example, if the interest is in soda tax, it is customary to aggregate all sugary drinks into one or a few groups. However, if the aggregation is not theoretically consistent, bias may occur. There are three alternative theories to justify an aggregation scheme: separability, Hick's composite commodity theorem, and Lewbel's (AER 1996) generalized composite commodity theorem (GCCT). GCCT has the most empirically plausible requirements for consistent aggregation. However, even with these mild requirements, it is not a routine for demand studies to test their aggregation scheme for consistency with the GCCT. There are several reasons for this. First, the time-series unit root tests and cointegration tests required by the GCCT have low power. Second, and especially for scanner data applications with numerous elementary products at the barcode level, there is a large number of alternative aggregation schemes. This makes testing GCCT a time consuming and tedious process. It would be useful if there is a method to reduce or even eliminate aggregation bias in an *inconsistently* aggregated demand system. It is with this in mind that Wenying set out to search for the answer.

With much hard work and a little serendipity, Wenying discovered that we can use the relative (to the group) prices of elementary products as control variables in group demand systems to reduce aggregation bias. This was the same procedure Lewbel had used to test for separability. However, no one recognized its role as a bias-reduction technique until now. Wenying also made the interesting observation that although inconsistent aggregation a la Lewbel is an omitted variable (OV) problem, unlike the standard OV cases, standard instrumental variables are of no help. However, it is possible to construct instruments that are orthogonal to the aggregation bias. The importance of these findings can hardly be overstated. This is because practitioners finally have a simple method to reduce aggregation bias in the demand estimates from an aggregation scheme most convenient, although may be inconsistent with the GCCT, for answering the research questions. In the application to fruit and vegetable demand, Wenying found that up to 90% of the aggregation bias in price elasticities is removed by the simple method. The manuscript (Li and Zhen 2019) is being fine-tuned for submission to a top applied economics journal. **I**

would like to emphasize that Wenying made these discoveries mostly on his own. My role as an advisor is to point him to the right literature and help him recognize the significance of the issue and his discoveries.

The third line of Wenying's research aims at making empirical advances in equivalence scale and intrahousehold sharing. The recent theoretical contributions of Lewbel, Pendakur, Browning and others on these topics have provided new tools for applied econometricians to investigate such policy-relevant issues such as setting the poverty threshold, and determining the Supplemental Nutrition Assistance Program and other safety net program benefit levels across households of vary sizes and composition. Wenying aims to achieve identification of intrahousehold resource sharing through observations on the share of purchases that is exclusively for the wife's (or husband's) consumption (e.g., feminine products). Conventional budget surveys either do not have information on these assignable products or lack price information. Wenying is bridging this gap between theory and empirics by using the Nielsen Homescan household scanner data. While virtually all of the few frontier applications of recent intrahousehold sharing and equivalence scale theories are focused on developing economies, **Wenying's work will be one of the first applications of the recent theoretical developments to US households**.

In my four years of advising, supervising and collaborating with Wenying on the above research topics, I have found him to be an intelligent, curious, loyal, dashing and hardworking researcher. He is honest and has very good work ethics. My expertise is consumer demand models and nutrition policies. Besides mostly high-level guidance on research directions, Wenying demonstrated great independence in his ability to frame the research questions and solving highly technical problems. With the above three areas of research well underway and a number of collaborative work with other faculty, he has an amazing pipeline of manuscripts publishable in high caliber ag, applied and health econ journals. His extensive experience with the Nielsen and IRI scanner data will be a tremendous resource for his future colleagues and employer. I will continue to collaborate with Wenying on several projects and look forward to exploring new funding opportunities with him for the exciting line of research he has developed.

In closing, I have complete confidence in Wenying research aspiration and capability. I am confident he will exceed all expectations held for this position. Thank you for your time and consideration.

Sincerely,

ChenZhen

Dr. Chen Zhen
Associate Professor & UGA Athletic Foundation Professorship in Food Choice, Obesity, and Health Economics
Department of Agricultural and Applied Economics
University of Georgia
Athens, GA 30602
Email: czhen@uga.edu

Two Simple Strategies for Reducing Aggregation Bias in Demand System Models

Wenying Li
wenying.li25@uga.edu
University of Georgia

Chen Zhen
czhen@uga.edu
University of Georgia

Abstract

The increasing availability of detailed scanner data has allowed researchers to study consumer demand at more disaggregated levels than previously possible. However, some degree of aggregation is still necessary for flexible functional form models because of the large number of parameters. Aggregation, if done consistently, avoids the curse of dimensionality by reducing the number of simultaneous demand equations to a manageable level. Among those that formally tested for consistent aggregation, many found that products could be consistently aggregated into broad categories. We argue that the low rates of rejection are likely due to the low power of time-series unit root tests. Using fruit and vegetables as an example, we found that most products cannot be consistently aggregated when examined by the more powerful panel unit root tests. Aggregation bias occurs in an inconsistently aggregated demand because the omitted relative prices of elementary products cause the demand residual to be correlated with the aggregate prices. We propose two alternative strategies for bias reduction. The first strategy uses the relative prices of elementary products as control variables in the aggregate demand. The second uses a residual-based instrumental variable method to achieve independence between the instrument and the residual. In our example application, the preferred strategy cut aggregation bias by up to 91% in own-price elasticities and 57% in cross-price elasticities. This simple bias-reduction approach is broadly applicable to situations where research needs and available computing resources dictate a particular aggregation scheme not supported by aggregation tests.

Financial support from U.S. Department of Agriculture (USDA) Economic Research Service (ERS) Cooperative Agreement 58-5000-5-0009 is gratefully acknowledged. Access to IRI InfoScan data is made possible through a Third-Party Agreement. The findings and conclusions reported here do not necessarily represent the views of the USDA ERS.

In recent years, measuring the price elasticities of food demand—a traditional area of research for agricultural economists—is of growing interest to the broader community of public policy. The newfound interest in food demand is a response to the ever-increasing policy calls for using price (dis)incentives to improve diet and reduce obesity and nutrition-related noncommunicable diseases in the United States and globally. Many of the policy scenarios concern taxes or subsidies that target finely defined food and beverage categories differentiated by nutrient contents (e.g., sugary vs. diet beverages). The need for predicting and comparing outcomes of these policy alternatives fuels the drive toward estimating highly disaggregated food demand systems.

Thanks to greater accessibility of scanner data, researchers now have the liberty of disaggregating demand to a level as detailed as the barcode (Broda and Weinstein 2010). However, unless one is willing to use restrictive functional forms such as the constant elasticity of substitution demand, a degree of product aggregation is necessary to make estimation practical. This is especially true for flexible functional form systems where there are at least as many price variables per equation as the number of goods in the system. Even if we impose the symmetry, homogeneity and adding up restrictions, the number of parameters would still be too high to estimate them for a large system. Aggregating to fewer product categories would reduce the dimension of the parameter space but at the potential cost of creating bias if aggregation is inconsistent. From an economist's perspective, an aggregation scheme is consistent if the aggregated categories maximize a utility function given aggregate price indexes and income.

The canonical approach to reducing aggregation bias is to test the sufficient conditions for consistent aggregation. There are two alternative types of conditions. The first is a set of equality restrictions on product-level price and income elasticities implied by separable utility (Blackorby, Primont, and Russell 1977; Blackorby, Davidson, and Schworm 1991; Moschini, Moro, and Green 1994). This requires first estimating the product-level demand system and then determining if certain products can be aggregated into separable groups based on tests of the equality constraints. As prices of similar products tend to be highly collinear, thereby producing imprecise coefficient estimates, test of separability may have low power. Moreover, if a product-level demand system can be estimated to credibly test the separability restrictions, it obviates the need for aggregating products into fewer groups. The alternative condition for consistent aggregation concerns movement of product prices in the same group. The Hicks-Leontief composite commodity theorem states that products whose prices are perfectly correlated can be consistently aggregated into a group. This requires within-group product prices to move in perfect synchronization, which is empirically unlikely.

In a seminal paper, Lewbel (1996) extended the Hicks-Leontief theorem into an empirically more plausible generalized composite commodity theorem (GCCT) that only requires the deviation of product prices from its group price be independent of the group price. The significance of Lewbel's GCCT is that its mild restrictions on price variation rationalize some of the common product groupings that were previously untested or rejected by separability tests (e.g., Davis, Lin, and Shumway 2000; Reed, Levedahl, and Hallahan 2005; Schulz, Schroeder, and Xia 2012; Heng, House, and Kim 2018). Indeed, Shumway and Davis (2001) found that GCCT tests had the lowest frequency of rejection among all types of aggregation tests in a survey of 22 peer-reviewed studies. There is a concern, however, that the low rejection rates may be an artifact of size distortions and power problems associated with time-series unit root and cointegration tests in small samples (Davis 2003).

Although multiple aggregation tests are available, most demand studies do not test for consistent aggregation. Rather, aggregation decisions are guided by research questions, constrained by data availability, and often follow convention, intuition or even convenience. For example, the literature on sugar-sweetened beverage taxes has either aggregated all sugary drinks into a single category (Lin et al. 2011; Allcott, Lockwood and Taubinsky 2019) or up to three product types (Dharmasena and Capps 2012; Zhen et al. 2014). One factor in the infrequent deployment of aggregation tests in demand analysis may be time. Testing an exhaustive list of potential cointegrating relationships under the GCCT framework can be time-consuming even with a large number of elementary products.[1] Given that aggregation decisions are not formally tested in most studies, it will be useful to develop a practical approach that reduces bias when the chosen aggregation schemes violate the GCCT.

The objective of this study is to propose two alternative strategies for reducing aggregation bias. The first strategy uses the log relative (to the group) product prices as control

[1] The time-consuming aspect of the GCCT test arises from the fact that there are a large number of alternatives to combine elementary products into groups. The combinations with at least two nonstationary product-level prices need to be tested for cointegrating relationships. The final aggregation scheme can be especially difficult to choose if some unit root and cointegration test results are indeterminate.

variables in the group demand equations. Although Lewbel (1996) had used essentially the same procedure as a test for separability in a *consistently aggregated* demand system, its ability in reducing bias from inconsistent aggregation was not previously recognized. The second strategy uses linear regression to project each log group price onto the log relative prices of elementary products and a residual. The residual is then used as an instrument for the group price. Both the control variables method and the residual-based instrumental variables method are simple enough for use in any flexible demand systems where bias from inconsistent aggregation is of concern. To address the issue of low power in time-series unit root tests, we conduct the GCCT tests in a panel data setting. This is the first application of panel unit root tests to the GCCT. In an example application to fruit and vegetable demand, the more powerful panel tests rejected aggregation schemes at a much higher rate than time-series tests. The preferred bias-reduction method reduced aggregation bias in elasticity estimates by up to 67% for fruit and 91% for vegetables.

The next section briefly reviews the GCCT, where we motivate bias from inconsistent aggregation as a special case of the omitted variable problem. We then discuss using the panel unit root tests to examine the GCCT with more power. This is followed by an empirical illustration of the proposed methods using retail scanner data on fruit and vegetable from 72 US markets over the 2008–2012 period. The final section summarizes and discusses an extension of the methods.

Composite Commodity Theorems

For ease of exposition, we discuss Lewbel's GCCT in the context of a linear approximate almost ideal demand system. All results apply to other functional forms. Let the product-level demand system be

(1) $w_i = \alpha_i + \sum_{j=1}^{n} \beta_{ij} \ln p_j + \theta_i \ln y + \varepsilon_i$

where elementary products are indexed by $i \in D = \{1,2,\dots,n\}$, w_i is the budget share of product i, p_j is the price of product j, y is total expenditure in real terms, α, β, and θ are parameters, and ε_i is the orthogonal residual term. We suppress the time and market subscripts to simplify notation in this section. They are introduced in later sections to properly denote variables in panel setting.

To aggregate the n products into N groups, define an aggregate indexing set $I = \{I_r\}_{r=1}^{N}$, where $I_r \subseteq D$ for any $r = 1, \dots, N < n$. Let the aggregate price index for group r be P_r. The log ratio of p_j to P_r is calculated as

(2) $\ln(p_j/P_r) = \rho_j \text{ , } j \in I_r$

where the relative price ρ_j measures the deviation of the log product price from its group price index and can be considered as an aggregation error. Replacing $\ln p_j$ in Eq. (1) with $\ln P_r$ and ρ_j yields

(3) $w_i = \alpha_i + \sum_{r=1}^{N} \psi_{ir} \ln P_r + \sum_{j \notin I} \beta_{ij} \ln p_j + \theta_i \ln y + \sum_{j \in I} \beta_{ij} \rho_j + \varepsilon_i \text{ ,}$

where $\psi_{ir} = \sum_{j \in I_r} \beta_{ij}$. Aggregating Eq. (3) of products $i \in I$ into N group share equations yields the following demand system:

(4a) $W_s = \mathrm{A}_s + \sum_{r=1}^{N} \Psi_{sr} \ln P_r + \sum_{j \notin I} \mathrm{B}_{sj} \ln p_j + \Theta_s \ln y + \sum_{j \in I} \mathrm{B}_{sj} \rho_j + \mathrm{E}_s \text{ , } \ s = 1,2, \dots, N$

(4b) $w_k = \alpha_k + \sum_{r=1}^{N} \psi_{kr} \ln P_r + \sum_{j \notin I} \beta_{kj} \ln p_j + \theta_k \ln y + \sum_{j \in I} \beta_{kj} \rho_j + \varepsilon_k \text{ , } \ k \notin I$

where W_s is the aggregate budget share of group s, w_k is the budget share of product k not aggregated into one of the N groups, $A_s = \sum_{i \in I_s} \alpha_i$, $\Psi_{sr} = \sum_{i \in I_s} \psi_{ir}$, $\mathrm{B}_{sj} = \sum_{i \in I_s} \beta_{ij}$, $\Theta_s = \sum_{i \in I_s} \theta_i$, and $E_s = \sum_{i \in I_s} \varepsilon_i$. If all n products are allocated into the N groups, the system (4a-b) reduces to Eq. (4a).

The Hicks-Leontief composite commodity theorem states that products can be consistently aggregated into groups if product prices within each group r are *perfectly* correlated, that is, ρ_j being constant over time for $\forall\, j \in I_r$. This allows $\sum_{j \in I} \mathrm{B}_{sj} \rho_j$ in (4a) and $\sum_{j \in I} \beta_{kj} \rho_j$ in (4b) be combined with A_s and α_k, respectively, to form the new intercepts for the system (4a-b). Independence of the residuals E_s and ε_k from P_r ($r = 1, \dots, N$) and p_k ($k \notin I$) ensures consistent estimation of Ψ_{sr}, B_{sj} ($j \notin I$), and Θ_s in (4a) and ψ_{kr}, β_{kj} ($j \notin I$), and θ_k in (4b). Unfortunately, the Hicks-Leontief theorem does not hold empirically because it requires prices of all products within a group move in absolute synchronization.

Lewbel's key insight is that consistent estimation of the slope coefficients in the system (4a-b) does not actually require constancy of ρ_j, only that the distribution of ρ_j be independent of P_r and p_k $\forall j, r, k$. To see this, without loss of generality, let ρ_j be a zero-mean random variable. This would be the case if both p_j and P_r, $j \in I_r$, are indexes normalized to 1 at the base, which is set to the sample mean of each variable. Then the new composite residuals of (4a) and

(4b) are $\sum_{j \in I} \mathrm{B}_{sj}\rho_j + \mathrm{E}_s$ and $\sum_{j \in I} \beta_{kj}\rho_j + \varepsilon_k$, respectively. Both would have an expected value of 0 and are independent of P_r and p_k if the GCCT holds. The GCCT relaxes the empirically untenable Hicks-Leontief theorem into a more plausible requirement on how product prices move within a group. Lewbel (1996, p. 526-527) showed that, under the GCCT if the adding up, symmetry and homogeneity conditions hold for the product-level Eq. (1), then the aggregate system (4a-b) would also possess these properties. In addition, elasticities derived from the system (4a-b) are the best unbiased estimates of group demand elasticities that would be obtained from estimation of Eq. (1) using disaggregate data (Lewbel 1996, p. 528).

As noted earlier, in most cases, aggregation into groups is driven by the specific needs of the analysis as opposed to the GCCT test results. If the selected aggregation scheme violates the GCCT, omission of the relative prices ρ_j from the system (4a-b) will cause the composite residuals to be correlated with the group prices P_r and, thereby, bias the coefficient estimates on group prices. This can be seen as a special case of the omitted variable problem in two aspects. First, unlike a standard case of omitted variables,[2] conventional instrumental variables will not help reduce the endogeneity bias attributed to inconsistent aggregation. Given that ρ_j is inversely related to P_r, it will be difficult to identify a naturally-occurring instrument that is strongly correlated with P_r but independent of ρ_j except in the trivial case of ρ_j being independent of P_r. Second, unlike endogeneity bias due to unobserved heterogeneity, the relative prices are perfectly observed by the econometrician. The latter distinction leads to two surprisingly simple strategies for reducing bias in the group price coefficients Ψ_{sr} and ψ_{kr} in an inconsistently aggregated system.

The first strategy uses the relative prices $\rho_j\ \forall j \in I$ as control variables in the system (4a-b). The second, called residual-based instrumental variables, is implemented by regressing each group price on all relative prices and using the residual as instruments for group prices in the aggregate demand. By design, the residual-based instrument is orthogonal to the relative prices and produces consistent estimates of the group price coefficients.

[2] Many standard sources of endogeneity bias are fundamentally an omitted variable problem. For example, classical demand-supply simultaneity bias in demand analysis is caused by unobservable (to the econometrician) demand shocks that are omitted from the demand regression. In the absence of direct measures of the unobserved demand shocks, supply-side variables are often used as instruments for the endogenous prices.

Panel GCCT Tests

Aggregation according to the GCCT entails testing the independence between the ρ's and the P's. If prices are nonstationary, as they often appear to be, ordinary covariances and correlations cannot be used to test independence. There are a few complications associated with detecting nonstationarity and testing for independence among nonstationary prices. Unit root tests, such as the augmented Dickey-Fuller (ADF) test (Dickey and Fuller 1979), are problematic in that they are not very powerful in distinguishing highly persistent stationary processes from nonstationary processes, especially in short time series. Schwert (1987) and Lo and MacKinlay (1989) documented that tests for a unit root (the null) have low power in finite samples against the local alternative of a root close to but below unity. Cochrane (1991) decomposed a unit root process into a stationary and a random walk component. He argued that because the random walk component can have arbitrarily small variance, a test of the null hypothesis of a unit root has arbitrarily low power against the alternative of trend stationarity in finite samples. To address the power issue in unit root tests, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al. 1992) switched the null to trend stationarity against the alternative of a unit root. However, Caner and Kilian (2001) showed that the use of conventional asymptotic critical values for stationarity tests may cause extreme size distortions, if the model under the null hypothesis is highly persistent. In essence, the size distortion of stationarity tests is the mirror image of the low power of unit root tests. If prices are indeed nonstationary, multivariate cointegration tests are necessary to determine independence. However, studies (Haug 1996; Ho and Sørensen 1996) have shown that the Engle and Granger (1987) cointegration test has power problems similar to those of the unit root tests. To confront these issues, Davis (2003) proposed modified Bonferroni procedures to strengthen the time series GCCT test. Davis et al. (2000) provided additional strategies to more powerfully test the GCCT using time series data.

Inspired by the increasing availability of scanner panels, we take a different approach to strengthening the GCCT test. Testing unit roots using panel data is driven by the desire to gain power over tests for single time series (Levin et al. 2002; Im et al. 2003; Breitung 2000). Since the low power problem is most severe in small samples, one can increase the sample size by pooling time series data across the cross-sectional units. That said, it is important to account for cross-sectional dependence when conducting panel unit root tests. Neglecting this common feature of panel data is shown to lead to severe power reduction and size distortion (O'Connell

1998). For this reason, we chose Pesaran's (2007) cross-sectionally augmented Im-Pesaran-Shin (CIPS) test to test for panel nonstationarity.

An Application

We illustrate the two bias reduction strategies with an example of fruit and vegetable demand that is of continuing interest to agricultural economists. Estimates of fruit and vegetable elasticities have been used to explain the farm-retail price spread (Wohlgenant 1989), understand the role of farm policy in the obesity epidemic (Okrent and Alston 2012), and predict the effects of prices on food waste (Hamilton and Richards 2019), among other applications. We selected 15 fruits and 15 vegetables for analysis (see table 1 for a list). These tend to be the most commonly available fruit and vegetables at retail. We call each fruit or vegetable a product. The GCCT tests are used to determine whether these products may be consistently aggregated into fewer groups. We compare test results from the time series unit root tests with those from the panel tests to highlight the differences in aggregation scheme suggested by each type of tests. The demand system with GCCT-consistent aggregation scheme is treated as the benchmark model. We evaluate the performance of the bias reduction methods in a GCCT-inconsistent aggregate system by comparing the bias-adjusted estimates with the benchmark estimates.

The Demand Model

We choose the quadratic almost ideal demand (QUAID) (Banks et al. 1997) as the functional form. Compared with the almost ideal demand, QUAID has more flexible Engel curves but retains exact aggregation over consumers. The group-level budget share equation for group s is

$$(5) \quad W_{mst} = A_{mst} + \sum_r \Psi_{sr} \ln P_{mrt} + \Theta_{1s} \ln \left[\frac{x_{mt}}{a(P_{mt})}\right] + \frac{\Theta_{2s}}{b(P_{mt})} \left\{\ln \left[\frac{x_{mt}}{a(P_{mt})}\right]\right\}^2 + \mathrm{e}_{mst}$$

where the subscripts m and t denote the cross-sectional unit and time period, respectively; x_{mt} is total nominal income; $\ln a(P_{mt}) = A_0 + \sum_s A_{s0} \ln P_{mst} + 0.5 \sum_s \sum_r \Psi_{sr} \ln P_{mst} \ln P_{mrt}$; $b(P_{mt}) = \prod_s P_{mst}^{\Theta_{1s}}$; e_{mst} is the residual; and the A's, Ψ's, and Θ's are parameters. The intercept A_{mst} is specified as $A_{mst} = A_{s0} + \mathbf{z}_{mst}\boldsymbol{\delta}_s$, where $\mathbf{z}_{mst}$ is a row vector of control variables and $\boldsymbol{\delta}_s$ is the corresponding column vector of parameters.

Eq. (5) is the quadratic counterpart of group-level demand in Eq. (4a). To avoid notational clutter, we have assumed all products are aggregated into some groups so that Eq. (4b) drops out. This is a harmless assumption because if group r consists of a single product then the group price P_{mrt} and budget share W_{mrt} equal those of the product.

Data and Variable Construction

Information on fruit and vegetable sales comes from the IRI InfoScan retail scanner data that the USDA Economic Research Service acquired to support food market and policy research. Our sample covers 65 quadweeks (i.e., 4-weekly periods) between January 6, 2008 and December 29, 2012. In InfoScan, there are 65 markets and 8 standard whitespaces (i.e., remaining Areas of the contiguous United States). We dropped the Green Bay, WI market from the sample due to insufficient retail data for the study period. This gives a balanced panel with 4,680 market-quadweek observations. Some InfoScan-participating retailers provided data at the store level but others only at the retail marketing area (RMA) level (Muth et al. 2016). The geographical coverage of RMA varies across retailers, but a typical RMA contains a cluster of counties. We aggregated store-level data to the IRI market level. For RMA-only retailers, IRI reports the number of stores and addresses in each RMA. To estimate IRI market-level sales for these retailers, we divided RMA-level sales by store number to get average sales per store and allocate RMA sales to each IRI market based on the number of stores the retailer has in each IRI market.

Compared to traditional budget surveys, the detailed product information in scanner data allows the researcher to better control for the unit value bias. A unit-value price is calculated as the expenditure on a good divided by its purchase quantity. Bias may arise if the construct of the demand model is abstract from the quality decision while the unit-value price encompasses both the quality and quantity dimensions of consumer choice (Deaton 1988; Cox and Wohlgenant 1986). To differentiate quality among varieties within a fruit or vegetable, we define variety at the type (up to two types per fruit/vegetable, e.g., romaine vs. leafy lettuce), brand (name brand, no brand, private label), organic (organic, nonorganic), and form (fresh, frozen, canned) level. This yields up to 36 unique varieties per product.[3] We then constructed the superlative Fisher Ideal price index for fruit or vegetable product j as follows

$$(6) \quad p_{mjt} = \sqrt{\left(\frac{\sum_k (p_{mt}^k q_0^k)}{\sum_k (p_0^k q_0^k)}\right)\left(\frac{\sum_k (p_{mt}^k q_{mt}^k)}{\sum_k (p_0^k q_{mt}^k)}\right)}$$

where the subscripts m and t index market and period, respectively; p_{mt}^k and q_{mt}^k are the price and volume sales of variety k, respectively, and p_0^k and q_0^k are the base price and volume of

[3] Our maintained hypothesis is that the ≤36 varieties can be consistently aggregated into a single fruit or vegetable.

variety k set at their sample means. The Fisher Ideal price index is superlative because it approximates the true cost of living index for a class of expenditure function (Diewert 1976). It allows the researcher to account for within-product substitution without estimating a variety-level demand system. Davis (1997) developed a test for unit value bias and found important differences in estimates and policy implications between a demand model using superlative price indexes and a model using unit-value prices.

To construct the price index for the numéraire good, we multiplied annual Regional Price Parities for 2008-2009 from the Bureau of Economic Analysis with monthly Consumer Price Index from the Bureau of Labor Statistics to obtain a panel of the cost-of-living index for metropolitan statistical areas. The index numbers were then weighted by county population to construct the numéraire price index at the IRI market level.

Price endogeneity is a concern, even with consistent aggregation, because of demand-supply simultaneity and unobserved heterogeneity. We created a Hausman-type (Hausman et al. 1997) instrument p_{-mjt} for each fruit or vegetable price p_{mjt}, where p_{-mjt} is the average price of j in the five IRI markets closest to market m in distance. Identification of the price coefficients in the demand model relies on 1) there be common supply shocks across nearby markets, and 2) the restriction that unobserved demand shocks be uncorrelated across markets after accounting for market, year and seasonal fixed effects in the $\mathbf{z}_{mst}$ vector. Using the nearest markets is designed to increase the strength of p_{-mjt} in explaining the variations in p_{mjt}. We used the same approach to create instruments for group prices.

For the residual-based instrumental variables method, we use the following linear regression to generate the instrument

(7) $\ln P_{-mrt} = a_r + \sum_{j \in I} b_{rj} \rho_{mjt} + u_{mrt}, \qquad r \in I$

where P_{-mrt} is the Hausman instrument for group price P_{mrt} of group r, the a's and b's are parameters, and u_{mrt} is the residual. The fitted residual $\hat{u}_{mrt}$ serves as the residual-based instrument for group price P_{mrt}.

Aggregation Scheme

We take a food-group based approach to aggregating the 30 fruits and vegetables into groups. Because much of the recent food demand literature has a nutrition policy focus, we follow the food categorization scheme used in MyPlate—the current USDA nutrition guide based on the recommendations of the *Dietary Guidelines for Americans*. According to MyPlate, the 15 fruits are categorized into three groups: berries, melons, and other fruits. Similarly, the 15 vegetables are categorized into four groups: dark-green vegetables, red and orange vegetables, starchy vegetables, and other vegetables. Table 1 presents the composition of each group.

Consistent product aggregation requires the relative product price ρ_j to be independent of the group price P_r. Therefore, testing whether an aggregation scheme is consistent with the GCCT is equivalent to testing whether ρ_j and P_r are independent of each other. Tests depend on the time series properties of the data. The procedure consists of two steps: (1) determine the stationarity of each ρ_j and P_r using unit root tests and (2) based on the results of step 1, test independence between ρ_j and P_r. There are three alternative scenarios in step 2. First, if both ρ_j and P_r are stationary, a correlation test is appropriate. Second, if ρ_j and P_r are both nonstationary, a cointegration test should be conducted. Third, if ρ_j is stationary but P_r is nonstationary or vice versa, then no test of independence is necessary because the two series cannot be cointegrated, which is evidence for independence (Lewbel 1996, p. 532).

Davis (2003) correctly pointed out that the GCCT require testing independence of each ρ_i from all of the P_r's, not just price of the group comprising product i as was done in Lewbel (1996) and virtually all published work on GCCT. One reason for limiting the scope of the independence test is the power and size problems of multivariate cointegration tests. Additionally, given evidence for cointegration vectors, exclusion restriction tests are required to determine whether the cointegration is between ρ_i and the P_r's, or among the P_r's (Davis 2003, p. 479). The test workload can quickly become unwieldy as the number of elementary products and aggregation schemes increases. For these reasons, we confine the independence test to between ρ_j and its own group price P_r ($j \in I_r$), which is most likely to correlated or cointegrated with ρ_j among all group prices.

Time Series Test Results

We conducted the ADF and KPSS tests on the relative product prices and group prices. The null hypothesis of the ADF test is the presence of a unit root, while the null of the KPSS is stationarity. Reversing the null and alternative hypotheses is designed to manage the power issue of time series GCCT tests (Davis et al. 2000). When results from the two tests are conflicted, inferences based on the joint confirmation hypothesis (JCH) of a unit root are used (Carrion-i-Silvestre et al. 2001). If the group price P_r and relative price ρ_j are both nonstationary, we used the Engle-Granger test to examine the null hypothesis of no cointegration between the two series. The Spearman's rank test is used to test for correlation when the two series are stationary, with a null hypothesis that the two series are not correlated.

Table 1 reports the test results on fruit and vegetable grouping. The price indices of all groups, bar dark-green vegetables, are nonstationary, and so are 7 of the 30 relative prices. Of the 5 nonstationary relative prices whose group indexes are also nonstationary, the Engle-Granger test failed to reject the null of no cointegration between each relative price and its group price. This confirms independence of the 30 relative prices from their corresponding group prices and consistent aggregation of these products into seven fruit and vegetable groups. This finding is consistent with previous time-series tests of the GCCT that found low rates of rejection of the proposed aggregation schemes (Shumway and Davis 2001).

Panel Test Results

We hypothesize that rejection of consistent aggregation is more frequent in panel-based tests because of the increased power of panel unit roots tests. The null hypothesis of the CIPS panel unit root test is that all units of the panel contain unit roots. The alternative hypothesis is that at least some units are stationary. In contrast to the time-series results that found unit roots in all but one group prices, the panel test (table 2) indicates that only the group prices of berries and starchy vegetables contain unit roots. Tests of independence found that the relative prices of 21 fruits and vegetables are significantly correlated with their group prices and, hence, cannot be consistently aggregated into the MyPlate-based groups.[4] Berries and starchy vegetables, each containing two elementary products, are the only GCCT-consistent groups. Thus, without a bias-reduction method, the researcher has to estimate the remaining 13 fruits and 13 vegetables as individual goods in a demand system to avoid inferential errors due to inconsistent aggregation.

Demand Specifications and Results

To evaluate the empirical performance of the two bias-reduction strategies, we estimate the following four versions of the demand system Eq. (5) separately for fruit and for vegetables:

- **Model 1** uses the consistent aggregation schemes suggested by the panel test results. The demand estimates are set as the benchmark.

[4] A cointegration test is not applicable here because there is not a single case where the relative price and its group price are both nonstationary. Otherwise, we could use Westerlund's (2007) test, which accounts for cross-sectional dependence, to examine panel cointegration.

- **Model 2** follows MyPlate grouping which is not fully supported by the panel test. The differences between Model 2 and Model 1 estimates measure the degree of bias attributable to inconsistent aggregation.
- **Model 3** follows the same grouping as Model 2 but includes the relative prices as control variables in the **z** vector so that the inconsistently aggregated group prices remain orthogonal to the error term e in Eq. (5). Comparing the differences in elasticity estimates between Model 3 and Model 1 with those between Model 2 and Model 1 provides empirical evidence on the efficacy of the control variable method.
- **Model 4** again follows the same grouping as Model 2 but uses the residual-based price instruments. We expect Model 4 to produce bias reduction comparable to Model 3 in magnitude.

We estimated each model using full information maximum likelihood (FIML). Models 1-3 use the Hausman-type instruments to control for price endogeneity. Model 4 uses the residual-based instruments to control for both price endogeneity and aggregation bias. The budget share equation for the numéraire was not estimated. Instead, we recovered its parameters using estimates from the fruit and vegetable budget share equations through the parametric restrictions implied by the adding up, homogeneity, and symmetry conditions. We calculated elasticities at the sample mean. The standard error for each point estimate is generated by taking 100 random draws from a multivariate normal distribution of the model parameters with the mean and covariance set to their estimated values (Krinsky and Robb 1990). These are the more policy-relevant unconditional elasticities because they are not conditional on total fruit and vegetable expenditures that are likely endogenous with prices.

Tables 3a and 3b present the Marshallian price elasticities of fruit and vegetable demand, respectively. All own-price elasticities are negative and statistically significant. Lemons/limes, tomatoes, and onions are the least price elastic with own-price elasticities at around −0.3. Many cross-price effects are consistent with a priori expectations. For example, we found statistically significant substitution between romaine/leafy lettuce and iceberg lettuce, between grapefruit, tangerines and oranges, and between cherries and the berries group. Using the individual fruit and vegetable elasticities, we simulated the aggregate demand elasticity for group s with respect to the aggregate price of group r by changing the prices of all products in r by the same percentage. The resulting group demand elasticities, shown in tables 4a and 4b, are the *benchmark* because they derive from the Model 1 estimates that are GCCT-consistent.

Table 5a presents group demand elasticities estimated by the group demand Model 2, 3, and 4 for fruit. Comparing tables 4a and 5a indicates that the fruit cross-price elasticities of Model 2 and 3 agree in sign but differ from the benchmark in sign between berries and other fruits. By contrast, Model 4, which used the residual-based instruments, correctly estimated the substitutive relationship between berries and other fruits.

Turning now to comparing the vegetable results in table 5b with the benchmark in table 4b. Model 3 and 4 correctly estimated the complementarity between dark-green vegetables and red and orange vegetables, while Model 2 incorrectly suggested substitution. Meanwhile, the substitution between starchy vegetables and red and orange vegetables is correctly predicted by Model 2 and 3 but not by Model 4. Finally, Model 4 is the only aggregate demand that estimated substitution between starchy vegetables and other vegetables.

Table 6 summarizes these comparisons. In terms of the magnitude of the bias, Model 3 and 4 performed better than Model 2, as expected, with the exception of the (unweighted) average own-price elasticity of Model 4 that is more biased than that of Model 2. This is entirely driven by the larger difference in own-price elasticity for berries, which account for 9% of total pound purchased. After weighting the bias by purchase quantity, Model 4 performs 67% better than Model 2 in terms of own-price elasticities. In general, the degree of bias reduction achieved by Model 3 is smaller than that of Model 4, and we observe a more significant bias reduction in own-price elasticities than in cross-price elasticities, and in vegetable demand than in fruit demand.

Conclusion

Users of flexible demand systems usually aggregate many elementary products into fewer groups and estimate consumer preferences at the group level. This is done for practical reasons of avoiding the curse of dimensionality and customizing the analysis to answer specific research questions. The chosen aggregation scheme is frequently justified by tests of the GCCT—the most empirically plausible aggregation theorem of all. Using more powerful panel unit root tests, we showed that the low rejection rates of GCCT-consistent aggregation schemes in past studies are likely caused by the low power of time-series unit root tests. Rejection of a proposed aggregation scheme can be inconvenient because estimation at a more disaggregated level may not be practical due to multicollinearity and constraint on computing resources.[5] With these in mind, it is of significant practical value to develop an approach that reduces bias in an inconsistently aggregated demand system. This would allow practitioners to continue using the aggregation schemes best suited for addressing their specific research questions.

Our approach is motivated by noting a simple fact: the relative prices of elementary products, whose correlation with the group prices is the root cause for aggregation bias, are observable to the econometrician. One strategy is to include these relative prices as control variables in the aggregate demand model such that the group prices are no longer correlated with the regression error. Another strategy is to regress each group price on all relative prices and use the residual, which is free from correlation with the relative prices, as instrumental variables for the group prices in the aggregate demand.[6] We call the latter strategy the residual-based instrumental variable method.

Theory predicts that both strategies produce a similar degree of bias reduction. However, in the application to fruit and vegetable demand, we found the residual-based instrumental variable method to outperform the control variable method. In practice, there may be other reasons to prefer the former method to the latter. For example, when there is a large number of elementary relative product prices, it may not be practical to include all as control variables in the aggregate demand system, especially if the system is nonlinear. The stepwise nature of the residual-based instrumental variable method means that it can be implemented with ease regardless how many elementary products are aggregated into groups. This method is even more appealing in situations where the researcher is already planning to use instrumental variables to account for, in addition to aggregation bias, conventional sources of price endogeneity such as supply-demand simultaneity and unobserved heterogeneity.

Finally, although we illustrated the approach using market-level data, the methodology is equally applicable to demand system estimated on household-level data. For micro data

[5] In our experience estimating large demand systems, the highest consumption of computer memory lies in imposing the cross-equation parametric restrictions of homogeneity and symmetry.

[6] As shown in our empirical illustration, if unobserved demand shocks and heterogeneity exist, one can regress a conventional price instrument on all relative prices and use the residual as the instrument in the aggregate demand.

applications of demand systems, another key motivation for product aggregation is to reduce the number of zeros. Accounting for these corner solutions introduces additional nonlinearity and, hence, complexity to the estimation. It will be straightforward to integrate the residual-based instrumental variable method into, for example, the extended Amemiya generalized least squares estimator for censored micro demand systems (Zhen et al. 2014) to correct for both aggregation bias and conventional price endogeneity.

References

Allcott, Hunt, Benjamin Lockwood, and Dmitry Taubinsky. "Regressive sin taxes, with an application to the optimal soda tax." Quarterly Journal of Economics 134, no. 3 (2019): 1557-1626.

Banks, James, Richard Blundell, and Arthur Lewbel. "Quadratic Engel curves and consumer demand." Review of Economics and Statistics 79, no. 4 (1997): 527-539.

Blackorby, Charles, Russell Davidson, and William Schworm. "Implicit separability: Characterisation and implications for consumer demands." Journal of Economic Theory 55, no. 2 (1991): 364-399.

Blackorby, Charles, Daniel Primont, and R. Robert Russell. "On testing separability restrictions with flexible functional forms." Journal of Econometrics 5, no. 2 (1977): 195-209.

Breitung, Jörg. "The local power of some unit root tests for panel data." The local power of some unit root tests for panel data. In Baltagi, BH. Ed. Nonstationary panels, panel cointegration and dynamic panels. Elsevier: Amsterdam, 2000: 124-40..

Broda, Christian, and David E. Weinstein. "Product creation and destruction: Evidence and price implications." American Economic Review 100, no. 3 (2010): 691-723.

Caner, Mehmet, and Lutz Kilian. "Size distortions of tests of the null hypothesis of stationarity: evidence and implications for the PPP debate." Journal of International Money and Finance 20, no. 5 (2001): 639-657.

Carrion-i-Silvestre, Josep Lluís, Andreu Sanso-i-Rossello, and Manuel Artís Ortuño. "Unit root and stationarity tests' wedding." Economics Letters 70, no. 1 (2001): 1-8.

Cochrane, John H. "A critique of the application of unit root tests." Journal of Economic Dynamics and Control 15, no. 2 (1991): 275-284.

Cox, Thomas L., and Michael K. Wohlgenant. "Prices and quality effects in cross-sectional demand analysis." American Journal of Agricultural Economics 68, no. 4 (1986): 908-919.

Davis, George C. "Product aggregation bias as a specification error in demand systems." American Journal of Agricultural Economics 79, no. 1 (1997): 100-109.

Davis, George C. "The generalized composite commodity theorem: Stronger support in the presence of data limitations." Review of Economics and Statistics 85, no. 2 (2003): 476-480.

Davis, George C., Ni Lin, and C. Richard Shumway. "Aggregation without separability: Tests of the United States and Mexican agricultural production data." American Journal of Agricultural Economics 82, no. 1 (2000): 214-230.

Deaton, Angus. "Quality, quantity, and spatial variation of price." The American Economic Review (1988): 418-430.

Dharmasena, Senarath, and Oral Capps Jr. "Intended and unintended consequences of a proposed national tax on sugar-sweetened beverages to combat the US obesity problem." Health Economics 21, no. 6 (2012): 669-694.

Dickey, David A., and Wayne A. Fuller. "Distribution of the estimators for autoregressive time series with a unit root." Journal of the American Statistical Association 74, no. 366a (1979): 427-431.

Diewert, W. Erwin. "Exact and superlative index numbers." Journal of Econometrics 4, no. 2 (1976): 115-145.

Engle, Robert F., and Clive WJ Granger. "Co-integration and error correction: representation, estimation, and testing." Econometrica: Journal of the Econometric Society (1987): 251-276.

Hamilton, Stephen F., and Timothy J. Richards. " Food Policy and Household Food Waste." American Journal of Agricultural Economics 101, no. 2 (2019): 600-614.

Haug, Alfred A. "Tests for cointegration a Monte Carlo comparison." Journal of Econometrics 71, no. 1-2 (1996): 89-115.

Hausman, Jerry A., Ariel Pakes, and Gregory L. Rosston. "Valuing the effect of regulation on new services in telecommunications." Brookings Papers on Economic Activity. Microeconomics 1997 (1997): 1-54.

Heng, Yan, Lisa A. House, and Hyeyoung Kim. "The competition of beverage products in current market: A composite demand analysis." Agricultural and Resource Economics Review 47, no. 1 (2018): 118-131.

Ho, Mun S., and Bent E. Sørensen. "Finding cointegration rank in high dimensional systems using the Johansen test: an illustration using data based Monte Carlo simulations." The Review of Economics and Statistics (1996): 726-732.

Krinsky, Itzhak, and A. Leslie Robb. "On approximating the statistical properties of elasticities: a correction." The Review of Economics and Statistics 72, no. 1 (1990): 189-190.

Kwiatkowski, Denis, Peter CB Phillips, Peter Schmidt, and Yongcheol Shin. "Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?" Journal of Econometrics 54, no. 1-3 (1992): 159-178.

Im, Kyung So, M. Hashem Pesaran, and Yongcheol Shin. "Testing for unit roots in heterogeneous panels." Journal of Econometrics 115, no. 1 (2003): 53-74.

Levin, Andrew, Chien-Fu Lin, and Chia-Shang James Chu. "Unit root tests in panel data: asymptotic and finite-sample properties." Journal of Econometrics 108, no. 1 (2002): 1-24.

Lewbel, Arthur. "Aggregation without separability: a generalized composite commodity theorem." The American Economic Review (1996): 524-543.

Lin, Biing-Hwan, Travis A. Smith, Jonq-Ying Lee, and Kevin D. Hall. "Measuring weight outcomes for obesity intervention strategies: the case of a sugar-sweetened beverage tax." Economics & Human Biology 9, no. 4 (2011): 329-341.

Lo, Andrew W., and A. Craig MacKinlay. "The size and power of the variance ratio test in finite samples: A Monte Carlo investigation." Journal of Econometrics 40, no. 2 (1989): 203-238.

Moschini, Giancarlo, Daniele Moro, and Richard D. Green. "Maintaining and testing separability in demand systems." American Journal of Agricultural Economics 76, no. 1 (1994): 61-73.

Muth, Mary K., Megan Sweitzer, Derick Brown, Kristen Capogrossi, Shawn A. Karns, David Levin, Abigail Okrent, Peter Siegel, and Chen Zhen. "Understanding IRI household-based and store-based scanner data." TB-1942, U.S. Department of Agriculture, Economic Research Service. 2016. Available at: https://www.ers.usda.gov/webdocs/publications/47633/57105_tb-1942.pdf?v¼42473

O'Connell, Paul GJ. "The overvaluation of purchasing power parity." Journal of International Economics 44, no. 1 (1998): 1-19.

Okrent, Abigail M., and Julian M. Alston. "The effects of farm commodity and retail food policies on obesity and economic welfare in the United States." American Journal of Agricultural Economics 94, no. 3 (2012): 611-646.

Pesaran, M. Hashem. "A simple panel unit root test in the presence of cross-section dependence." Journal of Applied Econometrics 22, no. 2 (2007): 265-312.

Reed, Albert J., J. William Levedahl, and Charles Hallahan. "The generalized composite commodity theorem and food demand estimation." American Journal of Agricultural

Economics 87, no. 1 (2005): 28-37.

Schulz, Lee L., Ted C. Schroeder, and Tian Xia. "Studying composite demand using scanner data: the case of ground beef in the US." Agricultural Economics 43 (2012): 49-57.

Schwert, G. William. "Effects of model specification on tests for unit roots in macroeconomic data." Journal of Monetary Economics 20, no. 1 (1987): 73-103.

Shumway, C. Richard, and George C. Davis. "Does consistent aggregation really matter?" Australian Journal of Agricultural and Resource Economics 45, no. 2 (2001): 161-194.

Westerlund, Joakim. "Testing for error correction in panel data." Oxford Bulletin of Economics and statistics 69, no. 6 (2007): 709-748.

Wohlgenant, Michael K. "Demand for farm output in a complete system of demand functions." American Journal of Agricultural Economics 71, no. 2 (1989): 241-252.

Zhen, Chen, Eric A. Finkelstein, James M. Nonnemaker, Shawn A. Karns, and Jessica E. Todd. "Predicting the effects of sugar-sweetened beverage taxes on food and beverage demand in a large demand system." American Journal of Agricultural Economics 96, no. 1 (2014): 1-25.

Table 1. Time-Series GCCT Test Results

Group and relative prices	ADF Test H_0: I(1)[a]	KPSS Test H_0: I(0)[b]	I(1) or I(0)[c]	Engle-Granger Test[d]: H_0: Not Cointegrated	Consistent Aggregation (Yes/No)
P (Berries)	-2.23 (10)	0.17*	I(1)		
$\rho_{strawberries}$	-3.09 (7)	0.18*	I(1)	-1.69 (2)	yes
$\rho_{blueberries}$	-3.53 (7)*	0.12	I(0)	n/a	yes
P (Melons)	3.10 (4)	0.17*	I(1)		
$\rho_{watermelon}$	-7.59 (8)*	0.13*	I(0)	n/a	yes
$\rho_{cantaloupe}$	-6.35 (10)*	0.13*	I(0)	n/a	yes
P (Other Fruits)	-1.55 (2)	0.15*	I(1)		
$\rho_{grapefruit}$	-7.76 (5)*	0.12*	I(0) (JCH)	n/a	yes
ρ_{apples}	-4.84 (1)*	0.15*	I(0) (JCH)	n/a	yes
ρ_{grapes}	-5.41 (1)*	0.08	I(0)	n/a	yes
$\rho_{lemons/limes}$	-3.21 (1)*	0.12*	I(1) (JCH)	-1.83 (1)	yes
$\rho_{peaches}$	-5.37 (4)*	0.10	I(0)	n/a	yes
$\rho_{avocado}$	-3.18 (1)*	0.08	I(0)	n/a	yes
ρ_{pears}	-4.96 (1)*	0.14*	I(0) (JCH)	n/a	yes
$\rho_{cherries}$	-6.74 (8)*	0.09	I(0)	n/a	yes
$\rho_{tangerines}$	-5.59 (5)*	0.10	I(0)	n/a	yes
$\rho_{oranges}$	-2.92 (10)	0.14*	I(1)	-1.49 (10)	yes
$\rho_{pineapple}$	-6.02 (2)*	0.10	I(0)	n/a	yes
P (Dark-Green Vegetables)	-3.19 (1)*	0.12	I(0)		
$\rho_{broccoli}$	-3.10 (0)	0.17*	I(1)	n/a	yes
$\rho_{lettuce\ (romaine/leafy)}$	-3.14 (0)	0.16*	I(1)	n/a	yes
P (Red and Orange Vegetables)	-2.93 (1)	0.09	I(1) (JCH)		
$\rho_{tomatoes}$	-5.00 (5)*	0.11	I(0)	n/a	yes
$\rho_{bell\ peppers}$	-4.03 (0)*	0.09	I(0)	n/a	yes
$\rho_{sweet\ potatoes}$	-5.88 (1)*	0.09	I(0)	n/a	yes
$\rho_{carrots}$	-3.39 (1)*	0.09	I(0)	n/a	yes

Table 1. Continued

Group and relative prices	ADF Test H_0: I(1)[a]	KPSS Test H_0: I(0)[b]	I(1) or I(0)[c]	Engle-Granger Test[d]: H_0: Not Cointegrated	Consistent Aggregation (Yes/No)
P (Starchy Vegetables)	-2.07 (0)	0.11	I(1) (JCH)		
ρ_{corn}	-5.68 (3)*	0.12	I(0)	n/a	yes
ρ_{potatoes}	-4.55 (1)*	0.12	I(0)	n/a	yes
P (Other Vegetables)	-2.52 (0)	0.07	I(1) (JCH)		
ρ_{onions}	-2.51 (3)	0.09	I(1) (JCH)	-2.87 (4)	yes
$\rho_{\text{lettuce (iceberg)}}$	-3.41 (3)*	0.07	I(0)	n/a	yes
ρ_{celery}	-5.63 (1)*	0.07	I(0)	n/a	yes
$\rho_{\text{cucumbers}}$	-4.12 (1)*	0.07	I(0)	n/a	yes
$\rho_{\text{mushrooms}}$	-2.66 (0)	0.12	I(1) (JCH)	-2.67 (0)	yes
ρ_{cabbage}	-3.74 (1)*	0.07	I(0)	n/a	yes
$\rho_{\text{green beans}}$	-5.90 (1)*	0.10	I(0)	n/a	yes
10% Critical Value	-3.17	0.12	(–3.64, 0.07)	-3.11	

Notes: * denotes rejection of the null at the 0.10 significance level.

[a] The test statistic of the null hypothesis of I(1) is the augmented Dickey-Fuller (1979) (ADF) t-statistic of the coefficient on the lagged level variable in the regression of the first-difference on a constant, a time trend, the lagged level, and lagged differences of variables appended to the regression. The number of lags of first differences is reported in parentheses and determined by Eviews 10.

[b] The test statistic of the null hypothesis of I(0) is the Kwaitkowski et al. (1992) (KPSS) t-statistic. The t-statistic is the sum of the squared partial sums of residuals divided by an error variance estimator. The residuals are computed from a model in which the series is regressed on a constant and a time trend. For the correction of the error term, a Bartlett window with ten lags was used to ensure the variance matrix was well behaved.

[c] Inferences based on the joint confirmation hypothesis (JCH) of a unit root are used when the ADF and KPSS tests are in conflict (Carrion-i-Silvestre et al., 2001). The joint critical values of (–3.60, 0.07) represent the midpoint of critical values for 50 and 100 observations for the ADF and the KPSS (with Bartlett kernel) tests with trend. They are interpreted as follows. If the value of the ADF statistic is less (greater) than –3.60 and the value of the KPSS statistic is less (greater) than 0.07 then the series is considered (at 90% probability of joint confirmation) stationary (nonstationary). Otherwise, the series cannot be confirmed to have a unit root and is therefore considered stationary.

[d] The test statistic is for the Engle-Granger test of the null hypothesis that the kth relative price ρ_k and its group price P_r $(k \in I_r)$ are not cointegrated. The entries are ADF tests of I(1) residuals formed from regressing the relative price on its integrated group price.

The 10% critical values reported for the individual tests are based on 65 observations. The number of lags of the first-differenced residuals in the residual regression is determined by Eviews 10 and reported in parentheses.

Table 2. Panel GCCT Test Results

Group and relative prices	CIPS Test: H_0: I(1)[a]	I(1) or I(0)	Correlation Test[b]: H_0: Not correlated	Consistent Aggregation (Yes/No)
P (Berries)	-2.41	I(1)		
$\rho_{strawberries}$	-5.34*	I(0)	n/a	yes
$\rho_{blueberries}$	-5.32*	I(0)	n/a	yes
P (Melons)	-4.90*	I(0)		
$\rho_{watermelon}$	-5.47*	I(0)	0.71*	no
$\rho_{cantaloupe}$	-5.33*	I(0)	0.74*	no
P (Other Fruits)	-5.03*	I(0)		
$\rho_{grapefruit}$	-5.11*	I(0)	-0.11*	no
ρ_{apples}	-4.84*	I(0)	0.08*	no
ρ_{grapes}	-6.15*	I(0)	-0.07*	no
$\rho_{lemons/limes}$	-4.02*	I(0)	-0.05	yes
$\rho_{peaches}$	-5.07*	I(0)	0.14*	no
$\rho_{avocado}$	-4.43*	I(0)	-0.19*	no
ρ_{pears}	-4.87*	I(0)	0.30*	no
$\rho_{cherries}$	-5.67*	I(0)	0.04	yes
$\rho_{tangerines}$	-5.40*	I(0)	0.34*	no
$\rho_{oranges}$	-2.33	I(1)	n/a	yes
$\rho_{pineapple}$	-4.44*	I(0)	-0.08*	no
P (Dark-Green Vegetables)	-4.40*	I(0)		
$\rho_{broccoli}$	-4.74*	I(0)	0.37*	no
$\rho_{lettuce\ (romaine/leafy)}$	-4.49*	I(0)	-0.36*	no
P (Red and Orange Vegetables)	-4.75*	I(0)		
$\rho_{tomatoes}$	-5.02*	I(0)	-0.28*	no
$\rho_{bell\ peppers}$	-4.61*	I(0)	-0.27*	no
$\rho_{sweet\ potatoes}$	-4.79*	I(0)	0.28*	no
$\rho_{carrots}$	-4.87*	I(0)	0.50*	no

Table 2. Continued

Group and relative prices	CIPS Test: H_0: I(1)[a]	I(1) or I(0)	Correlation Test[b]: H_0: Not correlated	Consistent Aggregation (Yes/No)
P (Starchy Vegetables)	-2.19	I(1)		
ρ_{corn}	-4.86*	I(0)	n/a	yes
ρ_{potatoes}	-4.24*	I(0)	n/a	yes
P (Other Vegetables)	-4.43*	I(0)		
ρ_{onions}	-4.33*	I(0)	-0.34*	no
$\rho_{\text{lettuce (iceberg)}}$	-4.23*	I(0)	-0.22*	no
ρ_{celery}	-4.34*	I(0)	-0.29*	no
$\rho_{\text{cucumbers}}$	-4.53*	I(0)	-0.20*	no
$\rho_{\text{mushrooms}}$	-2.28	I(1)	n/a	yes
ρ_{cabbage}	-4.87*	I(0)	0.03	yes
$\rho_{\text{green beans}}$	-4.24*	I(0)	0.32*	no
10% Critical Value	-2.53			

Notes: * denotes rejection of the null at the 0.10 significance level.

[a] Pesaran (2007)'s cross-sectionally augmented Im-Pesaran-Shin (CIPS) test regresses, for each unit m in the panel, the first difference on a constant, a time trend, the lagged level and its cross-sectional mean, the first difference of the cross-sectional mean and its lags, and the lagged first differences. The CIPS statistic is the cross-sectional average of the t-statistics on the lagged level. The null hypothesis is I(1) for all units. The `xtcips` command in Stata 14 was used to perform the CIPS test. The maximum number of lags included in the model is set to ten for each cross-section.

[b] Spearman's correlation coefficient which can take values from -1 to 1. The closer the test statistic is to zero, the weaker the association between the group price and the relative price. The `spearman` command in Stata 14 was used to perform the test.

Table 3a. Price Elasticities of Fruit Demand (Model 1, aggregation supported by panel GCCT tests)

		With respect to the price of														
			Melons		Other Fruits											
Elasticity of demand for		Berries	Watermelon	Cantaloupe	Grapefruit	Apples	Grapes	Lemons/Limes	Peaches	Avocado	Pears	Cherries	Tangerines	Oranges	Pineapple	Numeraire
	Berries	**-1.836**	0.001	-0.020	0.013	0.061	-0.046	-0.040	0.062	-0.005	0.016	0.121	-0.016	-0.009	-0.030	1.582
		(-30.910)	(-0.077)	(-1.682)	(2.734)	(-1.342)	(-1.216)	(-4.433)	(2.485)	(-0.436)	(0.723)	(3.868)	(-5.349)	(-0.511)	(-1.961)	(9.871)
Melons	Watermelon	0.004	**-1.678**	0.157	-0.022	-0.169	0.095	-0.057	-0.140	-0.005	-0.043	0.046	0.122	-0.062	-0.071	1.779
		(-0.076)	(-23.164)	(-6.019)	(-2.428)	(-2.250)	(1.661)	(-4.029)	(-3.352)	(-0.203)	(-3.568)	(0.717)	(2.673)	(-1.637)	(-2.539)	(5.585)
	Cantaloupe	-0.122	0.286	**-1.743**	0.045	-0.042	-0.048	-0.048	0.178	-0.022	0.023	0.164	0.230	0.021	-0.120	1.543
		(-1.672)	(-5.980)	(-33.256)	(2.856)	(-0.377)	(-0.709)	(-2.363)	(3.182)	(-0.662)	(0.833)	(3.542)	(4.097)	(0.362)	(-2.631)	(5.649)
Other Fruits	Grapefruit	0.200	-0.098	0.113	**-1.290**	0.109	0.026	-0.257	-0.304	0.037	0.328	-0.015	0.044	0.330	0.142	0.441
		(2.762)	(-2.373)	(2.855)	(-23.354)	(1.052)	(0.539)	(-4.737)	(-4.090)	(0.725)	(5.66)	(-0.091)	(0.739)	(5.607)	(2.622)	(2.399)
	Apples	0.051	-0.044	-0.006	0.006	**-0.497**	-0.025	-0.030	-0.034	-0.044	-0.003	-0.021	-0.008	0.048	0.003	0.651
		(-1.295)	(-2.197)	(-0.368)	(1.066)	(-9.983)	(-0.790)	(-3.223)	(-1.360)	(-3.210)	(-0.187)	(-0.820)	(-0.270)	(2.214)	(0.152)	(5.327)
	Grapes	-0.054	0.035	-0.009	0.002	-0.035	**-1.111**	-0.005	0.002	-0.009	0.008	0.125	-0.009	0.050	0.009	0.809
		(-1.196)	(1.687)	(-0.711)	(0.540)	(-0.811)	(-25.018)	(-0.707)	(0.072)	(-0.974)	(1.213)	(4.334)	(-0.240)	(3.124)	(0.772)	(4.811)
	Lemons/Limes	-0.220	-0.096	-0.044	-0.095	-0.194	-0.024	**-0.302**	-0.039	-0.101	-0.024	-0.022	-0.090	0.021	-0.093	1.142
		(-4.409)	(-4.117)	(-2.354)	(-4.778)	(-3.246)	(-0.706)	(-8.876)	(-0.907)	(-4.341)	(-0.85)	(-0.742)	(-2.545)	(0.699)	(-3.143)	(7.928)
	Peaches	0.233	-0.156	0.110	-0.075	-0.145	0.008	-0.026	**-1.650**	-0.105	0.055	-0.187	0.189	0.077	-0.013	1.723
		(2.523)	(-3.35)	(3.168)	(-4.091)	(-1.361)	(0.087)	(-0.899)	(-15.149)	(-2.961)	(2.087)	(-3.908)	(2.870)	(1.386)	(-0.337)	(6.387)
	Avocado	-0.017	-0.005	-0.014	0.009	-0.196	-0.027	-0.070	-0.108	**-0.946**	0.022	-0.082	0.057	-0.191	0.023	1.455
		(-0.404)	(-0.184)	(-0.656)	(0.728)	(-3.232)	(-0.957)	(-4.322)	(-2.997)	(-31.805)	(1.516)	(-2.930)	(1.326)	(-5.643)	(0.641)	(10.539)
	Pears	0.035	-0.077	0.023	0.129	-0.017	0.039	-0.025	0.086	0.035	**-1.511**	0.058	0.072	0.017	0.028	1.092
		(0.769)	(-3.569)	(0.839)	(5.68)	(-0.184)	(1.236)	(-0.844)	(2.101)	(1.521)	(-32.177)	(2.102)	(1.947)	(0.438)	(0.655)	(8.276)
	Cherries	0.508	0.059	0.114	-0.004	-0.104	0.443	-0.017	-0.213	-0.091	0.041	**-2.930**	0.104	0.128	0.076	1.529
		(3.929)	(0.717)	(3.568)	(-0.095)	(-0.844)	(4.172)	(-0.757)	(-3.972)	(-2.946)	(2.091)	(-18.241)	(1.423)	(2.472)	(1.960)	(3.236)
	Tangerines	-0.642	0.173	0.179	0.014	-0.044	-0.037	-0.077	0.240	0.070	0.057	0.116	**-1.932**	0.462	0.143	0.810
		(-5.205)	(2.694)	(3.984)	(0.732)	(-0.289)	(-0.255)	(-2.506)	(2.823)	(1.316)	(1.927)	(1.445)	(-13.373)	(6.479)	(3.145)	(1.891)
	Oranges	-0.028	-0.063	0.012	0.075	0.189	0.142	0.013	0.070	-0.171	0.009	0.104	0.335	**-1.066**	-0.069	0.212
		(-0.5)	(-1.615)	(0.366)	(5.627)	(2.193)	(3.098)	(0.696)	(1.369)	(-5.627)	(0.431)	(2.519)	(6.419)	(-21.803)	(-1.83)	(1.285)
	Pineapple	-0.117	-0.084	-0.077	0.037	0.014	0.031	-0.066	-0.014	0.023	0.019	0.070	0.119	-0.078	**-1.045**	1.049
		(-1.942)	(-2.562)	(-2.635)	(2.605)	(0.149)	(0.778)	(-3.135)	(-0.342)	(0.641)	(0.652)	(1.954)	(3.118)	(-1.832)	(-18.567)	(6.150)
	Numeraire	0.005	0.002	0.001	0.000	-0.002	0.000	0.000	0.001	0.001	0.000	0.001	0.000	-0.001	0.000	**-1.031**
		(6.953)	(4.837)	(3.605)	(-2.185)	(-2.607)	(-0.082)	(2.647)	(3.481)	(4.679)	(0.990)	(2.422)	(0.686)	(-3.588)	(1.119)	(-364.677)

Notes: Elasticities and t-values (in parentheses) calculated at sample mean. Own-price elasticities in bold font.

Table 3b. Price Elasticities of Vegetable Demand (Model 1, aggregation supported by panel GCCT tests)

		With respect to the price of														
		Dark Greens		Red and Orange Vegetables					Other Vegetables							
Elasticity of demand for		Broccoli	Lettuce (Romaine/ Leafy)	Tomatoes	Bell Peppers	Sweet Potatoes	Carrots	Starchy Vegetables	Onions	Lettuce (Iceberg)	Celery	Cucumbers	Mushrooms	Cabbage	Green Beans	Numeraire
Dark Greens	Broccoli	**-0.952**	0.078	0.141	0.013	-0.055	-0.089	-0.038	0.020	0.139	-0.038	0.046	0.203	-0.198	-0.024	0.650
		(-14.125)	(1.577)	(2.621)	(0.182)	(-1.086)	(-1.192)	(-0.525)	(0.487)	(3.852)	(-1.042)	(1.375)	(2.329)	(-6.555)	(-0.389)	(4.366)
	Lettuce (Romaine/ Leafy)	0.112	**-0.860**	0.055	0.004	-0.085	-0.106	-0.091	0.024	0.121	0.004	0.011	0.379	0.087	-0.048	-0.171
		(1.573)	(-14.290)	(0.851)	(-0.016)	(2.127)	(0.111)	(-1.619)	(0.629)	(3.300)	(0.011)	(0.268)	(3.927)	(2.279)	(-0.818)	(-0.968)
Red and Orange Vegetables	Tomatoes	0.036	0.010	**-0.368**	0.019	-0.012	-0.075	-0.107	-0.158	-0.043	0.009	0.007	-0.057	-0.007	0.019	0.563
		(2.623)	(0.863)	(-7.736)	(0.653)	(-0.429)	(-3.912)	(-2.660)	(-7.330)	(-3.612)	(0.370)	(0.459)	(-1.409)	(-0.882)	(1.098)	(4.497)
	Bell Peppers	0.011	0.002	0.061	**-0.957**	0.099	0.082	-0.107	-0.002	0.043	-0.030	0.003	0.471	0.089	-0.021	-0.025
		(0.176)	(-0.017)	(0.645)	(-12.81)	(2.093)	(1.797)	(-1.291)	(-0.116)	(1.555)	(-0.619)	(0.155)	(4.912)	(3.824)	(-0.583)	(-0.117)
	Sweet Potatoes	-0.106	-0.113	-0.092	0.233	**-2.742**	-0.080	0.462	0.371	0.042	-0.045	-0.059	0.176	0.134	-0.244	1.436
		(-1.089)	(2.139)	(-0.438)	(2.081)	(-22.976)	(-0.781)	(2.810)	(2.594)	(0.891)	(-0.480)	(-0.763)	(0.789)	(2.348)	(-3.205)	(3.727)
	Carrots	-0.075	0.003	-0.247	0.085	-0.035	**-1.155**	0.047	-0.038	-0.079	0.064	0.155	-0.044	-0.174	0.089	1.204
		(-1.195)	(0.113)	(-3.900)	(1.797)	(-0.779)	(-13.051)	(0.764)	(-0.796)	(-2.315)	(1.465)	(3.340)	(-0.302)	(-4.596)	(1.679)	(6.480)
	Starchy Vegetables	-0.005	-0.007	-0.051	-0.016	0.029	0.007	**-0.801**	-0.025	0.016	0.013	-0.004	0.033	0.005	0.000	0.655
		(-0.553)	(-1.614)	(-2.685)	(-1.29)	(2.868)	(0.753)	(-21.188)	(-1.426)	(-3.831)	(2.224)	(-0.413)	(1.722)	(1.537)	(0.012)	(5.322)
Other Vegetables	Onions	0.013	0.011	-0.409	-0.002	0.127	-0.029	-0.137	**-0.330**	-0.028	-0.016	-0.006	0.012	0.031	-0.017	0.574
		(0.480)	(0.633)	(-7.450)	(-0.115)	(2.598)	(-0.797)	(-1.420)	(-4.667)	(-1.334)	(-0.590)	(-0.329)	(0.238)	(1.987)	(-0.647)	(2.503)
	Lettuce (Iceberg)	0.200	0.120	-0.245	0.076	0.032	-0.135	0.188	-0.061	**-0.399**	0.060	0.003	-0.075	0.044	-0.055	0.330
		(3.840)	(3.313)	(-3.636)	(1.557)	(0.896)	(-2.315)	(-3.841)	(-1.338)	(-10.368)	(2.091)	(0.122)	(-0.876)	(1.324)	(-1.087)	(2.197)
	Celery	-0.066	0.004	0.059	-0.063	-0.040	0.133	0.185	-0.041	0.072	**-0.540**	-0.146	-0.056	-0.012	0.047	0.221
		(-1.047)	(0.012)	(0.366)	(-0.618)	(-0.477)	(1.463)	(2.216)	(-0.598)	(2.085)	(-7.565)	(-1.733)	(-0.322)	(-0.342)	(0.623)	(0.834)
	Cucumbers	0.067	0.011	0.039	0.005	-0.045	0.268	-0.046	-0.013	0.003	-0.123	**-0.657**	0.491	0.046	-0.175	-0.197
		(1.369)	(0.270)	(0.450)	(0.154)	(-0.765)	(3.330)	(-0.428)	(-0.331)	(0.121)	(-1.731)	(-8.055)	(3.816)	(1.083)	(-2.831)	(-1.042)
	Mushrooms	0.065	0.084	-0.070	0.185	0.029	-0.017	0.091	0.006	-0.016	-0.010	0.107	**-0.897**	0.070	-0.021	0.294
		(2.329)	(3.904)	(-1.398)	(4.974)	(0.791)	(-0.298)	(1.760)	(0.248)	(-0.864)	(-0.321)	(3.836)	(-9.346)	(3.946)	(-0.735)	(1.632)
	Cabbage	-0.531	0.161	-0.068	0.291	0.186	-0.553	0.112	0.126	0.082	-0.019	0.084	0.587	**-1.527**	0.212	0.773
		(-6.540)	(2.285)	(-0.876)	(3.817)	(2.353)	(-4.609)	(1.571)	(1.986)	(1.326)	(-0.341)	(1.082)	(3.932)	(-18.295)	(2.614)	(4.037)
	Green Beans	-0.026	-0.036	0.082	-0.027	-0.138	0.116	0.004	-0.028	-0.042	0.030	-0.131	-0.073	0.087	**-1.393**	1.547
		(-0.389)	(-0.809)	(1.110)	(-0.572)	(-3.200)	(1.686)	(0.071)	(-0.639)	(-1.081)	(0.626)	(-2.810)	(-0.731)	(2.624)	(-18.503)	(11.325)
	Numeraire	0.000	-0.001	-0.002	-0.002	0.001	0.001	-0.001	-0.001	0.000	-0.001	-0.001	-0.003	0.000	0.001	**-1.024**
		(-1.931)	(-5.939)	(-2.599)	(-4.209)	(2.417)	(2.429)	(-1.095)	(-1.324)	(-2.822)	(-2.743)	(-4.886)	(-4.294)	(-0.797)	(5.119)	(-258.136)

Notes: Elasticities and t-values (in parentheses) calculated at sample mean. Own-price elasticities in bold font.

Table 4a Benchmark Fruit Group Demand Elasticities Derived From Model 1 Estimates

	With respect to the price of			
Elasticity of group demand for	Berries	Melons	Other Fruits	Numeraire
Berries	**-1.836**	-0.019	0.125	1.582
Melons	-0.021	**-1.504**	-0.168	1.731
Other Fruits	0.035	-0.013	**-1.007**	0.900
Numeraire	0.005	0.002	0.001	**-1.031**

Notes: The group demand elasticities are simulated by changing individual fruit prices in Model 1 by the same percentage at the sample mean. Own-price elasticities in bold font.

Table 4b Benchmark Vegetable Group Demand Elasticities Derived from Model 1 Estimates

	With respect to the price of				
Elasticity of group demand for	Dark-Green Vegetables	Red and Orange Vegetables	Starchy Vegetables	Other Vegetables	Numeraire
Dark-Green Vegetables	**-0.773**	-0.104	-0.080	0.492	-0.006
Red and Orange Vegetables	-0.032	**-0.470**	-0.012	-0.019	0.717
Starchy Vegetables	-0.012	-0.031	**-0.801**	0.038	0.655
Other Vegetables	0.081	-0.076	0.022	**-0.502**	0.579
Numeraire	-0.001	-0.002	-0.001	-0.005	**-1.024**

Notes: The group demand elasticities are simulated by changing individual vegetable prices in Model 1 by the same percentage at the sample mean. Own-price elasticities in bold font.

Table 5a Price Elasticities of Fruit Group Demand

	With respect to the price of			
Elasticity of group demand for	Berries	Melons	Other Fruits	Numeraire
	Model 2 (aggregation rejected)			
Berries	**-1.778**	0.072	-0.047	1.356
	(-47.151)	(3.079)	(-0.702)	(13.472)
Melons	0.152	**-1.674**	0.083	1.133
	(3.092)	(-37.489)	(0.726)	(6.756)
Other Fruits	-0.011	0.010	**-0.980**	0.819
	(-0.633)	(0.750)	(-20.612)	(12.539)
Numeraire	0.004	0.001	0.000	**-1.027**
	(8.603)	(2.991)	(-0.227)	(-548.108)
	Model 3 (relative prices used as control variables)			
Berries	**-1.703**	0.062	-0.047	1.317
	(-35.868)	(2.400)	(-0.614)	(11.407)
Melons	0.129	**-1.613**	0.075	1.092
	(2.409)	(-28.135)	(0.641)	(5.755)
Other Fruits	-0.011	0.010	**-1.017**	0.871
	(-0.557)	(0.674)	(-18.006)	(12.385)
Numeraire	0.004	0.001	0.000	**-1.028**
	(6.359)	(2.494)	(0.244)	(-501.682)
	Model 4 (residual-based instruments)			
Berries	**-1.573**	0.062	0.197	0.899
	(-45.933)	(2.642)	(2.847)	(8.950)
Melons	0.130	**-1.493**	-0.160	1.229
	(2.658)	(-33.813)	(-1.209)	(7.209)
Other Fruits	0.052	-0.019	**-0.972**	0.784
	(2.921)	(-1.184)	(-17.449)	(11.093)
Numeraire	0.002	0.001	-0.001	**-1.024**
	(3.617)	(3.532)	(-0.847)	(-525.866)

Notes: Elasticities and t-values (in parentheses) calculated at sample mean. Own-price elasticities in bold font.

Table 5b Price Elasticities of Vegetable Group Demand

	With respect to the price of				
Elasticity of group demand for	Dark-Green Vegetables	Red and Orange Vegetables	Starchy Vegetables	Other Vegetables	Numeraire
	Model 2 (aggregation rejected)				
Dark-Green Vegetables	**-0.812**	0.072	-0.054	0.289	0.328
	(-20.662)	(1.861)	(-1.714)	(4.768)	(3.844)
Red and Orange Vegetables	0.017	**-0.521**	-0.047	-0.203	0.533
	(1.845)	(-14.574)	(-1.695)	(-5.775)	(7.932)
Starchy Vegetables	-0.011	-0.039	**-0.857**	-0.062	0.723
	(-1.751)	(-1.712)	(-28.182)	(-2.588)	(9.692)
Other Vegetables	0.062	-0.177	-0.064	**-0.258**	0.286
	(4.776)	(-5.738)	(-2.533)	(-5.38)	(4.077)
Numeraire	-0.001	-0.003	0.000	-0.008	**-1.021**
	(-6.885)	(-4.145)	(-0.660)	(-9.563)	(-416.958)
	Model 3 (relative prices used as control variables)				
Dark-Green Vegetables	**-0.772**	-0.132	-0.075	0.331	0.517
	(-15.196)	(-2.22)	(-2.148)	(4.268)	(6.046)
Red and Orange Vegetables	-0.033	**-0.544**	-0.059	-0.144	0.601
	(-2.231)	(-10.102)	(-2.09)	(-3.992)	(6.621)
Starchy Vegetables	-0.016	-0.049	**-0.844**	-0.021	0.692
	(-2.193)	(-2.119)	(-24.246)	(-1.178)	(8.109)
Other Vegetables	0.071	-0.125	-0.021	**-0.491**	0.411
	(4.271)	(-3.987)	(-1.13)	(-9.099)	(5.268)
Numeraire	-0.001	-0.003	-0.001	-0.006	**-1.024**
	(-4.224)	(-3.018)	(-0.889)	(-6.105)	(-347.559)
	Model 4 (residual-based instruments)				
Dark-Green Vegetables	**-0.786**	-0.113	-0.043	0.441	0.333
	(-19.811)	(-1.810)	(-1.242)	(6.354)	(3.161)
Red and Orange Vegetables	-0.028	**-0.466**	0.018	-0.046	0.284
	(-1.819)	(-8.164)	(0.851)	(-0.905)	(3.292)
Starchy Vegetables	-0.009	0.014	**-0.782**	0.081	0.435
	(-1.284)	(0.840)	(-21.730)	(2.796)	(4.789)
Other Vegetables	0.095	-0.039	0.087	**-0.515**	0.206
	(6.351)	(-0.889)	(2.836)	(-8.491)	(2.448)
Numeraire	-0.001	-0.006	-0.004	-0.008	**-1.013**
	(-5.405)	(-5.910)	(-4.413)	(-8.228)	(-344.672)

Notes: Elasticities and t-values (in parentheses) calculated at sample mean. Own-price elasticities in bold font.

Table 6 Elasticity Differences between Each Aggregate Demand and the Benchmark

	Average absolute difference						Percent improvement over Model 2			
	Model 2 (a)		Model 3 (b)		Model 4 (c)		Model 3 1-(b)/(a)		Model 4 1-(c)/(a)	
Elasticity	Fruit	Veg	Fruit	Veg	Fruit	Veg	Fruit	Veg	Fruit	Veg
Own-Price										
Unweighted	0.09	0.10	0.08	0.03	0.10	0.01	11%	70%	-11%	90%
weighted[a]	0.09	0.11	0.06	0.03	0.03	0.01	33%	73%	67%	91%
Cross-Price										
Unweighted	0.13	0.08	0.12	0.05	0.06	0.03	8%	38%	54%	63%
weighted[a]	0.11	0.07	0.11	0.04	0.04	0.03	0%	43%	64%	57%

Notes: The group demand elasticities derived from Model 1 estimates are set as the benchmark. The comparisons exclude all numeraire demand and price elasticities. [a]Purchase quantities used as weights.