Using Demand Transfer Ratios to Infer Market Impacts of New Goods

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Abstract

This paper introduces a measure we call a "demand transfer ratio" (DTR) that is a useful metric for inferring and communicating important market impacts associated with new product introductions. We show that the sign and magnitude of the demand transfer ratio can be used to infer whether the presence of new goods expanded aggregate demand in the relevant market and/or have a demand-cannibalizing effect on pre-existing products. In principle, our unit free DTR metric can be computed for the introduction and presence of new products across a wide cross section of industries for the purpose of comparing the demand transference impacts of various technology innovations and further studying what measurable attributes, strategies, and/or policies are associated with the most impactful innovations in an economy.

Keywords: Demand transfer ratios; New product introduction; Aggregate demand expansionary effect; Demand-cannibalizing effect; Innovation and Technological Change; Environmental Policy

JEL Classification Codes: L13; D11; M31; Q55; Q58; O33

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1. Introduction

In many differentiated products markets, firms periodically invest in developing new products, a practice that is particularly prevalent in the fast-moving consumer-packaged goods (CPGs) sectors as well as industries with frequent innovation or technological upgrades, such as electronics, software, and telecommunications. New product launches in many CPGs industries, for instance, are evidenced to be one of the most important marketing strategies (Sorescu and Spanjol, 2008). According to Mintel Global New Products Database, the number of new product launches in the U.S. CPGs industries has been growing substantially, from around 170,000 in 2005 to 450,000 in 2019, representing an approximate 165% growth in new product introductions (Haas et al., 2020).[1]

The literature in new product introductions has extensively focused on the pricing and welfare effects of the new products (Hausman, 1999; Hausman and Leonard, 2002; Petrin, 2002; Goolsbee and Petrin, 2004). In this paper, we introduce a measure we call a "demand transfer ratio" that is useful for capturing, summarizing, and conveying important demand impacts driven by the presence of new goods in differentiated products markets. We show how this measure can be constructed and applied in a real-world setting using estimates obtained from analytical tools that are popular and now standard in the Industrial Organization (IO) literature.

Based on a discrete choice demand model framework, the demand transfer ratio measures the change in quantity demand of the outside good as a proportion of the actual aggregate quantity purchased of new product(s) that is (are) counterfactually eliminated from the market, an exercise that mirrors Petrin (2002). Products offered before the market presence of new products are classified as "pre-existing" products. Depending on which of three mutually exclusive ranges of values that the demand transfer ratio, denoted DTR, may fall into, one can infer whether introduction of the new product: (*i*) expanded aggregate demand (i.e., generated larger aggregate quantity purchases) in the relevant market as well as increased quantity purchases of pre-existing products, outcomes that correspond to $DTR > 1$; (*ii*) expanded aggregate demand in the relevant market, but cannibalized demand (i.e., decreased quantity purchases) of pre-existing products, outcomes that correspond to $0 < DTR < 1$; and (*iii*) shrank aggregate demand in the relevant market with fewer aggregate quantity purchases as well as cannibalized demand for pre-existing

[1] The growth rate is calculated using Mintel Global New Products Data presented in Exhibit 2.

products, outcomes that correspond to $DTR < 0$. Note that in each of the three mutually exclusive ranges of values listed above, the single *DTR* metric simultaneously conveys information on two distinct demand outcomes caused by the market presence of the new product: (1) the outcome of whether aggregate demand expanded; and (2) the outcome of whether demand for pre-existing products were cannibalized.

In addition, as is easily verified from the definition above and the DTR expression described in a subsequent section, the demand transfer ratio captures the magnitude of transference of demand that resulted from the presence of new goods and, importantly, the measure is unitless. In other words, whatever unit quantity is measured in, units are canceled out in the calculation, which makes it possible to compare the relative size of demand transference across different new products. As such, in principle our DTR metric can be computed for the introduction and presence of new products across a wide cross section of industries for the purpose of comparing the demand transference impacts of various technology innovations and further studying what measurable attributes, strategies, and/or policies are associated with the most impactful innovations in an economy.

To apply the demand transfer ratio analysis in real-world settings, we consider two distinct sectors: (*i*) packaged ground coffee products; and (*ii*) electric vehicles (EV). Our application to the packaged ground coffee sector intends to provide a practical illustration of how our *DTR* measure is computed and used. In contrast, our application to the EV sector intends to illustrate the broad usefulness of our *DTR* measure, which include evaluating the efficacy of environmental policy.

2. The Model

2.1 Demand

We construct the demand transfer ratio measure using a random coefficients logit demand model.[2] In market m at time t, consumer i obtains utility, U_{ijmt}, from consuming product j among J_{mt} distinct product alternatives and an outside option/good $j = 0$. Indirect utility, U_{ijmt}, is a function of consumer $i's$ tastes for a vector of product $j's$ observed non-price attributes, x_{jmt}, its price, p_{jmt}, unobserved (to researchers) attributes aggregated into ξ_{jmt}, and a mean-zero

[2] See Nevo (2000) for a comprehensive description of the random coefficients logit demand model.

stochastic error, ε_{ijmt}. The well-known model-predicted market share function for product j that is derived from assumed utility maximizing discrete choice behavior of consumers is the following:

$$s_{jmt}\left(x_{jmt}, p_{jmt}, \xi_{jmt}; \Theta\right) = \int \frac{e^{\delta_{jmt}+\mu_{ijmt}}}{1+\sum_{l=1}^{J_{mt}} e^{\delta_{lmt}+\mu_{ilmt}}} d\widehat{F(D)} dF(v), \tag{1}$$

where δ_{jmt} is the mean utility (across consumers); μ_{ijmt} is a consumer-specific deviation from the mean utility from consuming product j; and Θ is a vector of demand parameters to be estimated. The outside option yields mean utility that is normalized to be zero. $\widehat{F(D)}$ and $F(v)$ are population distribution functions for consumer demographics (D_i) and random taste shocks (v_i) assumed to be independently and identically distributed.

2.2 Supply

On the supply-side, we assume each manufacturer f offers a set of differentiated products in market m at time t, B_{fmt}. The manufacturers non-cooperatively and simultaneously set their product prices to maximize variable profits, respectively:

$$\max_{p_{jmt} \forall j \in B_{fmt}} VP_{fmt} = \max_{p_{jmt} \forall j \in B_{fmt}} \sum_{j \in B_{fmt}} \left(p_{jmt} - mc_{jmt}\right) q_{jmt}, \qquad \forall f \tag{2}$$

where in equilibrium product $j's$ quantity sold, q_{jmt}, equals to the market demand of this product, i.e., $q_{jmt} = d_{jmt} = M_{mt} \times s_{jmt}\left(x_{jmt}, p_{jmt}, \xi_{jmt}; \Theta\right)$; M_{mt} is a measure of the potential market size; and mc_{jmt} is the marginal cost of providing product j.

2.3 Counterfactual Experiment

We counterfactually remove the new products from consumers' choice set in each market. Let PRE_{mt} denote the set of pre-existing products and NEW_{mt} the set of new products offered in market m at time t, i.e, $J_{mt} = PRE_{mt} \cup NEW_{mt}$. The new equilibrium price vector, $\boldsymbol{p}^*$, of the pre-existing products is obtained by numerically searching for the vector of prices that satisfy the set of $J_{mt} \backslash NEW_{mt}$ first-order equations generated from the firms' optimization problem described in equation (2) above.

The predicted product shares are given by:

$$s_{jmt}(\boldsymbol{p}; \widehat{\Theta}) = \frac{1}{ns} \sum_{i=1}^{ns} \left(\frac{e^{\delta_{jmt}(p_{jmt})+\mu_{ijmt}(p_{jmt})}}{1+\sum_{l \in PRE_{mt}} e^{\delta_{lt}(p_{lmt})+\mu_{ilmt}(p_{lmt})} + \sum_{l \in NEW_{mt}} e^{\delta_{lmt}(p_{lmt})+\mu_{ilmt}(p_{lmt})}} \right) \tag{3}$$

$$s_{0mt}(\boldsymbol{p}; \widehat{\Theta}) = \frac{1}{ns} \sum_{i=1}^{ns} \left(\frac{1}{1+\sum_{l \in PRE_{mt}} e^{\delta_{lmt}(p_{lmt})+\mu_{ilmt}(p_{lmt})} + \sum_{l \in NEW_{mt}} e^{\delta_{lmt}(p_{lmt})+\mu_{ilmt}(p_{lmt})}} \right) \tag{4}$$

where ns is the number of individual draws used for the numerical approximation of the product share function. Conditional on the estimated demand parameters in vector $\widehat{\Theta}$, equations (3) and (4) yield the model-predicted share for product j and the outside good evaluated at the vector of actual prices, respectively. Using the estimated new equilibrium price vector, $\boldsymbol{p}^*$, the counterfactual model-predicted share functions are:

$$s_{jmt}(\boldsymbol{p}^*;\widehat{\Theta}) = \frac{1}{ns}\sum_{i=1}^{ns}\left(\frac{e^{\delta_{jmt}(p^*_{jmt})+\mu_{ijmt}(p^*_{jmt})}}{1+\sum_{l\in PRE_{mt}} e^{\delta_{lmt}(p^*_{lmt})+\mu_{ilmt}(p^*_{lmt})}}\right) \tag{5}$$

$$s_{0mt}(\boldsymbol{p}^*;\widehat{\Theta}) = \frac{1}{ns}\sum_{i=1}^{ns}\left(\frac{1}{1+\sum_{l\in PRE_{mt}} e^{\delta_{lmt}(p^*_{lmt})+\mu_{ilmt}(p^*_{lmt})}}\right) \tag{6}$$

3. Demand Transfer Ratios

The "demand transfer ratio" measures the proportion of counterfactually removed new product demand that is diverted to the outside option and is computed as:

$$DTR_{mt} = \frac{d^*_{0mt}-d_{0mt}}{\sum_{j\in NEW_{mt}} d_{jmt}} = \frac{s_{0mt}(\boldsymbol{p}^*;\widehat{\Theta})-s_{0mt}(\boldsymbol{p};\widehat{\Theta})}{\sum_{j\in NEW_{mt}} s_{jmt}(\boldsymbol{p};\widehat{\Theta})} \tag{7}$$

The relative size of the outside good shares in the factual and counterfactual environments determines the sign of DTR_{mt}, and thus provides evidence of whether the presence of new products had an expansionary or a shrinking effect on aggregate demand in the relevant market. We summarize in Table 1 various scenarios with corresponding demand transfer ratios that may occur in the counterfactual results.

Table 1: Using Demand Transfer Ratio, DTR, to Interpret Counterfactual Outcomes

Scenarios	DTR: Predicted Quantity Change in Outside Option divided by Quantity of the New Products Eliminated	Aggregate Demand Expansionary Effect	Aggregate Demand Shrinking Effect	Demand-increasing Effect on Pre-existing Products	Demand-cannibalizing Effect on Pre-existing Products
1	$DTR > 1$	✓	✕	✓	✕
2	$DTR = 1$	✓	✕	✕	✕
3	$0 < DTR < 1$	✓	✕	✕	✓
4	$DTR = 0$	✕	✕	✕	✓
5	$DTR < 0$	✕	✓	✕	✓

Notes: Symbol ✓ indicates the presence of the effect described in the column, while symbol ✕ indicates absence of the effect.

3.1 Aggregate Demand Expansionary vs. Aggregate Demand Shrinking Effects

Table 1 shows that evidence of an aggregate demand expansionary effect is inferred from obtaining a positive demand transfer ratio, i.e., $DTR > 0$. Distinct Scenarios 1 through 3 all exhibit an aggregate demand expansionary effect since quantity demand for the outside option is predicted to increase with the counterfactual elimination of the new products in each scenario. This also implies that the presence of the new products causes quantity demand for the outside good to be smaller than it would be otherwise. In contrast, demand transfer ratios that are either equal to zero (Scenario 4), or negative (Scenario 5), are not consistent with an aggregate demand expansionary effect. Scenario 4 implies the market presence of the new products does not influence quantity demand for the outside option; whereas Scenario 5 implies the aggregate demand shrinks due to the newly introduced products, as the predicted quantity demand for the outside option declines with the counterfactual elimination of the new products.

3.2 Demand-Increasing vs. Demand-Cannibalizing Effects on Pre-existing Products

The expanded product demand is shared by both new and pre-existing products in Scenario 1, but not in Scenarios 2 and 3. Specifically, for markets satisfying Scenario 1, our model predicts that all the eliminated new product demand, and a portion of the pre-existing product demand, transfer to the outside option. The portion of pre-existing product demand transferred to the outside option is a measure of the demand-increasing impact that the presence of new products has on the pre-existing products.

In Scenario 2, the quantity demand for the outside good increases by an amount exactly equal to the new product demand removed from the market. This implies the presence of new products expands the total market demand by the exact amount of the new product demand without any positive spillover demand effects to the pre-existing products. Both Scenarios 1 and 2 suggest no cannibalizing effect exists, as all the new product demand is transferred to the outside option.

For Scenarios 3 through 5, there exists demand-cannibalizing effect on pre-existing products' demand. The reason is that the demand for new products does not completely transfer to the outside option in the counterfactual world. In other words, either some ($0 < DTR < 1$), or all ($DTR < 0$) of the new product demand switches to consuming pre-existing products in the counterfactual experiment. As such, Scenario 3 through 5 reveal evidence that a portion of pre-existing products demand is displaced by the new products.

4. Application to the Market for Packaged Coffee Products

In this section, we apply the analysis of the demand transfer ratios to Gayle and Lin (2022), which studies the market effects of the introduction of single-cup coffee pods in the retail packaged coffee products sector. The Information Resources Inc. (IRI) retail scanner data used (Bronnenberg et al., 2008) cover sales of traditional auto-drip brew ground coffee and single-cup brew coffee products in a cross section of 6,002 markets over 60 year-month periods from 2008 through 2012.

We specify the consumer utility function to incorporate year-varying consumer-specific preference for the new coffee type:

$$U_{ijmt} = x_{jmt}\beta_i + \alpha_i p_{jmt} + \sum_{y=1}^{5}\left(\phi_{i,y} SingleCupBrew_{jmt} \times a_y\right) + \xi_{jmt} + \varepsilon_{ijmt} \qquad (8)$$

with a zero-one dummy variable, $SingleCupBrew_{jmt}$, to capture the relative preference for the single-cup products versus the pre-existing auto-drip coffee products interacted with the year dummy, a_y. The coefficient estimates on $\phi_{i,y}$ are found to be positive and increase in magnitude over the sample years, suggesting a growing trend of coffee drinkers' valuation of the new products.

Based on these demand estimates along with the assumed supply-side price-setting behavior of firms described in equation (2) above, Gayle and Lin (2022) find that demand for the outside good is predicted to increase over time with the counterfactual removal of single-cup products in each year. Specifically, the new coffee product is estimated to have brought in an additional 0.24% to 2.28% of potential demand for brew-at-home coffee that would otherwise not have resulted in coffee product purchases over the sample years. Furthermore, market presence of the new product is also found to have caused purchases of the pre-existing auto-drip coffee products to fall each year, with the size of the fall growing by almost tenfold from a 1.16% fall in 2008 up to a 11.5% fall in 2012.

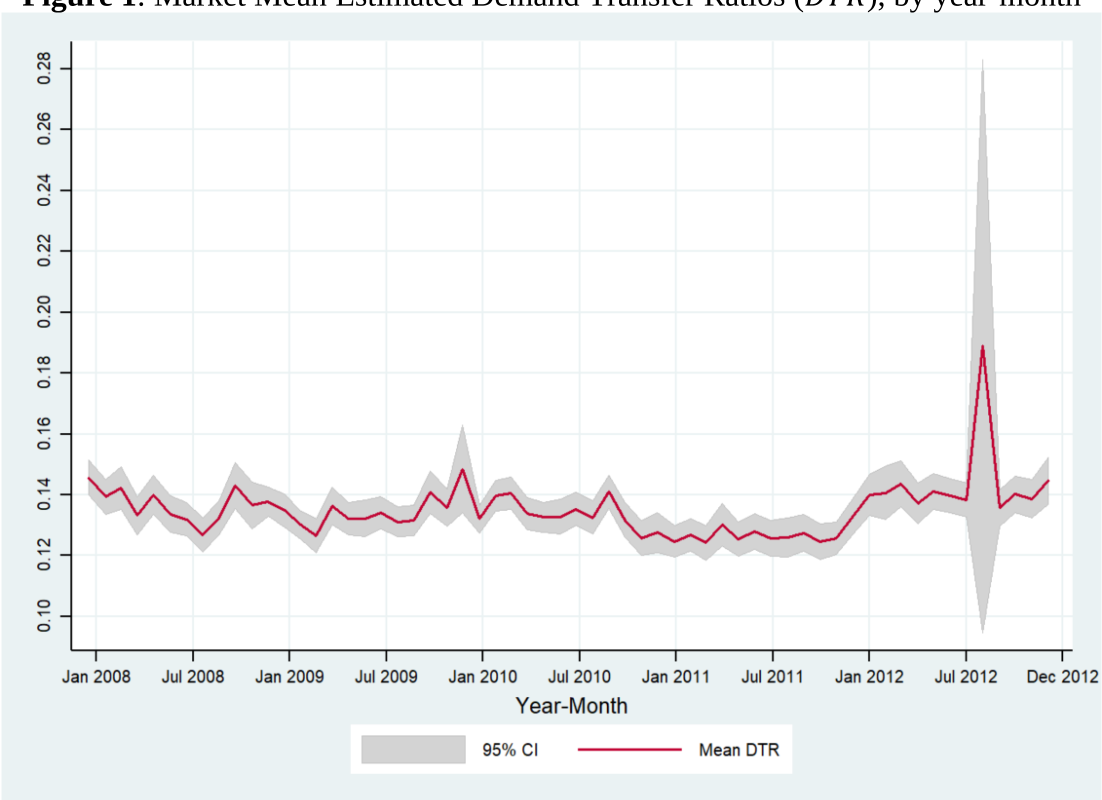
Keeping in view the findings from Gayle and Lin (2022) described above, in the present paper we use the predicted shares obtained from the counterfactual experiment and compute demand transfer ratios using equation (7) and report the estimated market mean DTR estimates in Figure 1. The shaded area around the line plot represents the 95% level of statistical confidence. The line plot shows the mean $DTRs$ vary between 0 and 1 with the average being 0.14. Accordingly, these mean DTR estimates are characterized by Scenario 3 in Table 1 revealing both an aggregate demand expansionary effect and a demand-cannibalizing effect.

The average DTR being 0.14 suggests that, on average, 14% of the demand for the counterfactually eliminated single-cup products is transferred to demand for the outside option;

while the remaining 86% of the demand for single-cup products switched to the closest substitute, pre-existing auto-drip coffee products. Put differently, in the factual world with the market presence of single-cup products, 14% of these new product sales come from consumers who would not otherwise purchase any brew-at-home coffee products, while the remaining 86% of the sales come from consumers who substituted away from purchasing the pre-existing brew-at-home coffee products in favor of the new single-cup brew coffee products.

Therefore, using this DTR measure, on the one hand, we can quickly identify the key market impacts of the introduction of single-cup brew coffee products: an aggregate demand expansionary effect and a demand-cannibalizing effect on the pre-existing auto-drip coffee products as shown and discussed in Gayle and Lin (2022). On the other hand, the measure also effectively conveys the respective magnitude of the demand transference that is attributed to consumers of the pre-existing products as well as to consumers who initially chose not to consume brew-at-home coffee products. In the appendix, we also provide geographic area (county)-specific time-series plots of the mean DTR estimates. The above finding holds in each county, i.e., the presence of single-cup coffee products is predicted to have an aggregate demand expansionary effect as well as a demand-cannibalizing effect on auto-drip coffee products in each county.

Figure 1: Market Mean Estimated Demand Transfer Ratios ($\overline{DTR}$), by year-month



4.1 Robustness Checks

The above-mentioned results were obtained under several assumptions made in Gayle and Lin (2022). Here, we change some of the assumptions to determine the extent to which our demand transfer ratio estimates are robust to these changes. Our robustness checks of the baseline results are performed based on the following types of changes: (i) changes in the definition of potential market size; and (ii) randomly selecting subsets of the "inside" products for re-running the analysis.

The baseline analysis defines potential market size as 170% of the actual coffee quantity sales, i.e., a potential market size factor of 1.7, a definition based on coffee consumption behavior revealed by the National Coffee Association (NCA) annual coffee consumption survey. In the first set of robustness checks, we re-define the potential market size using two assumed potential market size factors of 1.5 and 3, respectively, similar to the robustness exercise and potential market size factors used in Ivaldi and Verboven (2005). In the second type of robustness checks we randomly drop 10% and 30%, respectively, of the "inside" products from each market to create two separate subsamples of the original data.

For each of the assumed changes considered for the purpose of the robustness checks, we re-estimate the demand model and recompute the associated DTR estimates, which are reported in Figure A2 in the appendix. The DTR estimates based on the baseline market definition and factual number of "inside" products are shown in Figure A2 as the solid line plot. Regarding the robustness checks for different potential market size definitions, the dotted line plot represents DTR estimates based on the potential market size factor being 3, a plot that lies entirely above the baseline DTR plot. In contrast, the long-dashed line plot represents DTR estimates based on the potential market size factor being 1.5, a plot that lies entirely below the baseline DTR plot. Accordingly, we can infer from these checks that the magnitudes of the DTR estimates tend to be positively correlated with the size of the potential market. However, note that the key qualitative prediction from the DTR still holds even with using an extremely large potential market size factor of 3, i.e., the DTR estimates associated with each potential market size definition still lie between 0 and 1 implying that the presence of single-cup coffee products is predicted to have an aggregate demand expansionary effect as well as a demand-cannibalizing effect on auto-drip coffee products.

Second, randomly reducing the number of "inside" products by 30% is predicted to produce a greater magnitude of transference to the outside good, i.e., the DTR estimates represented by the short-dash line is the highest in Figure A2. However, randomly reducing the number of "inside" products by 10% only minimally influenced the DTR estimates, i.e., the dash-dot DTR line in Figure A2 is barely distinguishable from the baseline solid DTR line. In summary, these line plots show that all the estimated $DTRs$ obtained from the robustness checks, though vary in magnitude, still lie between 0 and 1, consistent with our baseline estimates.[3] Therefore, we conclude that the key qualitative prediction of the new coffee product having an aggregate demand expansionary effect as well as a demand-cannibalizing effect on pre-existing coffee products is robust to changing either the potential market size or the actual number of "inside" products.

Notwithstanding robustness of the key qualitative prediction based on the *DTR* metric for the application and data used in this study, it is important for us to acknowledge that changes in either the potential market size or the actual number of "inside" products do matter in affecting the quantitative value of the *DTR* metric. In other words, it can be the case that in other applications and data for which some original *DTR* values are sufficiently "close" to a threshold for deciding a qualitative outcome, e.g., "close" to 0 or to 1, the market size definitional changes may sufficiently influence the quantitative value of the *DTR* metric to also influence the qualitative predictions.

5. Application to the Market for Electric Vehicles (EV)

While in Section 4 we apply our *DTR* metric to study the market impacts of new brew-at-home coffee products, application of our *DTR* metric to other industries may prove informative for the efficacy of environmental policy and more consequential for the wellbeing of current and future generations. In recent years, there has been an increasing push from government agencies to develop and promote products and services that minimize harm to the environment, i.e., eco-friendly commodities.[4] The U.S. Environmental Protection Agency and Department of Energy, for instance, provide detailed guidelines/recommendations to help consumers, federal agencies, institutional purchasers, and manufacturers to promote greener purchasing and selling, and thus a more sustainable marketplace for all. There are many products available for purchase that now have new eco-friendlier substitutes also available for purchase. A specific case of this is gas-fueled vehicles versus eco-friendlier alternate energy technology electric vehicles (EV).

[3] We also run robustness checks at the county-level and plot the county-level mean demand transfer ratio estimates in Figure A3 in the appendix. The baseline results are found to be quite robust even at the county-level.
[4] According to the U.S. Environmental Protection Agency (EPA), environment friendly processes (also referred to as eco-friendly, nature-friendly, and green), are sustainability and marketing terms referring to goods and services, laws, guidelines and policies that claim reduced, minimal, or no harm upon ecosystems or the environment. [see the following URL: https://www.epa.gov/greenerproducts/identifying-greener-cleaning-products]

Given the adverse effects that gas-fueled vehicles have on climate change, there has been a deliberate push from policymakers to incentivize, via various policies, automobile market participants (both manufacturers and consumers) to replace gas-fueled vehicles with new eco-friendlier EVs.[5] The success of these policies is likely to vary across markets for multiple reasons, including the availability of charging stations for EVs that vary across local markets. Our *DTR* measure can provide policymakers and analysts a metric that captures the varying extent to which EVs have, or could have, penetrated a wide cross section of geographically distinct local markets. Furthermore, a secondary empirical analysis that seeks to explain the variation in the *DTR* metric for EVs across local markets may be very helpful for revealing measurable market attributes, e.g., availability of charging stations etc., that are empirically important determinants of consumers' adoption of EVs. Policymakers are likely to find results of the secondary analysis informative for guiding the design of policies most effective for increasing consumers' adoption of EVs.

It is reasonable for the reader to ask: Why not just directly compute actual market penetration rates of EVs from observed unit sales data instead of generating our proposed market specific *DTR* metric for EVs from a structural model? A response to this question is the following. Because the *DTR* measure is generated from a consumer optimization model linked to estimated preference parameters, then the measure affords researchers and analysts the beneficial flexibility of generating its value under various informative counterfactual scenarios, a flexibility not available for market penetration rates directly computed from observed unit sales data.

6. Conclusion

This paper contributes to the new product introduction literature by introducing a measure we call a "demand transfer ratio", that is useful for capturing, summarizing, and conveying important market impacts associated with new product introductions in differentiated products markets. Depending on the sign and size of the demand transfer ratio estimates, one may infer whether the new goods have an aggregate demand expansionary effect and/or a demand-cannibalization effect on substitute pre-existing products. In an application, we use the data from Gayle and Lin (2022) and find demand transfer ratio estimates that support the key empirical

[5] According to data provided by Statista (December 2022), unit sales of EVs have gone up more than thirteen times since 2016. [see the following URL: https://www.statista.com/outlook/mmo/electric-vehicles/united-states#unit-sales].

findings related to the introduction of single-cup coffee products in the retail packaged coffee products sector.

Last, given the unit free feature of our DTR metric, future research may consider computing it for the introduction and presence of new products across a wide cross section of industries for the purpose of comparing the demand transference impacts of various technology innovations and further studying what measurable attributes, strategies, and/or policies are associated with the most impactful innovations in an economy.

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Appendix

Figure A.1: Time-series Plots of Mean Estimated Demand Transfer Ratios by County

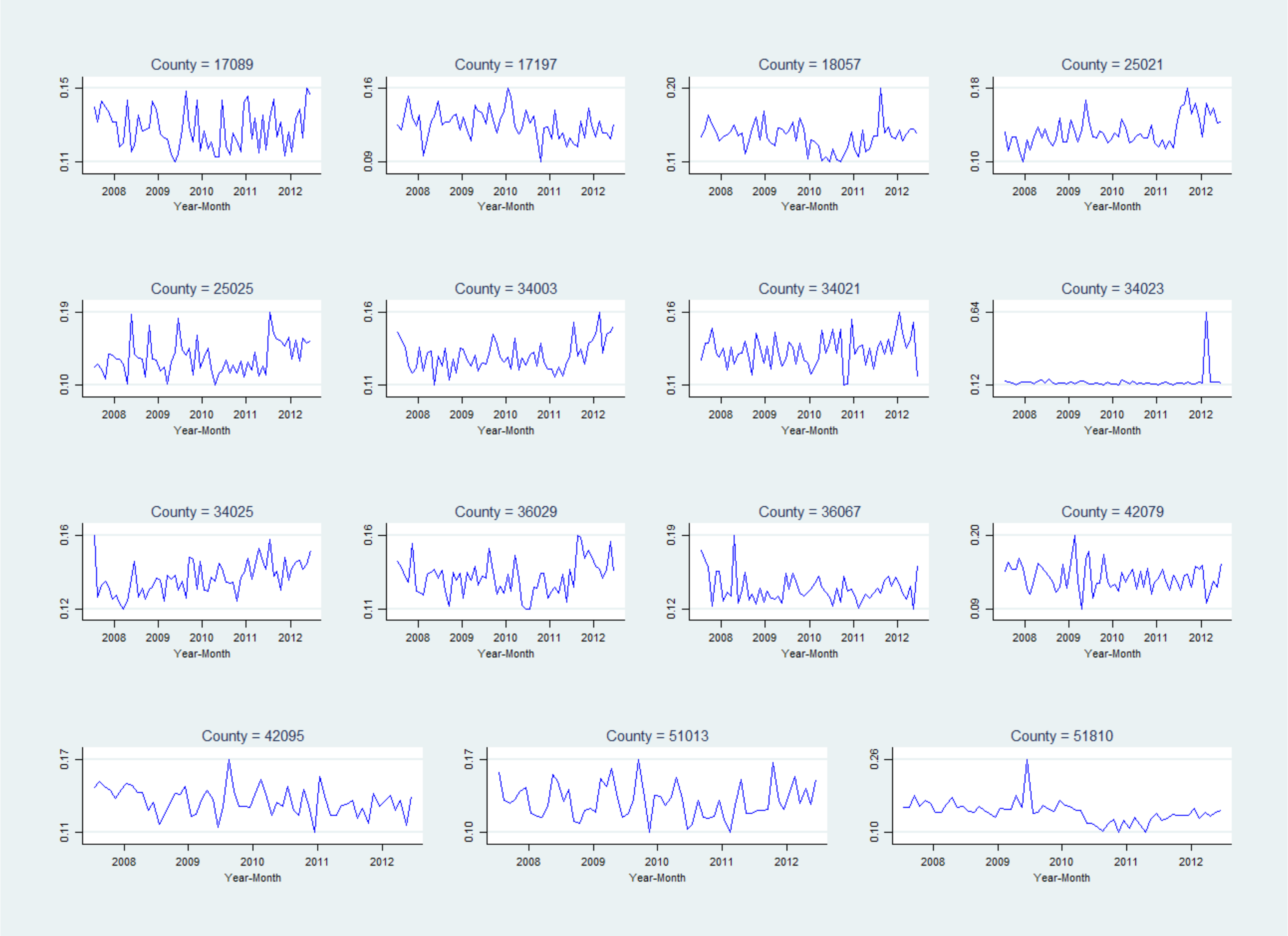

Figure A.2: Robustness Checks of Mean Estimated Demand Transfer Ratios

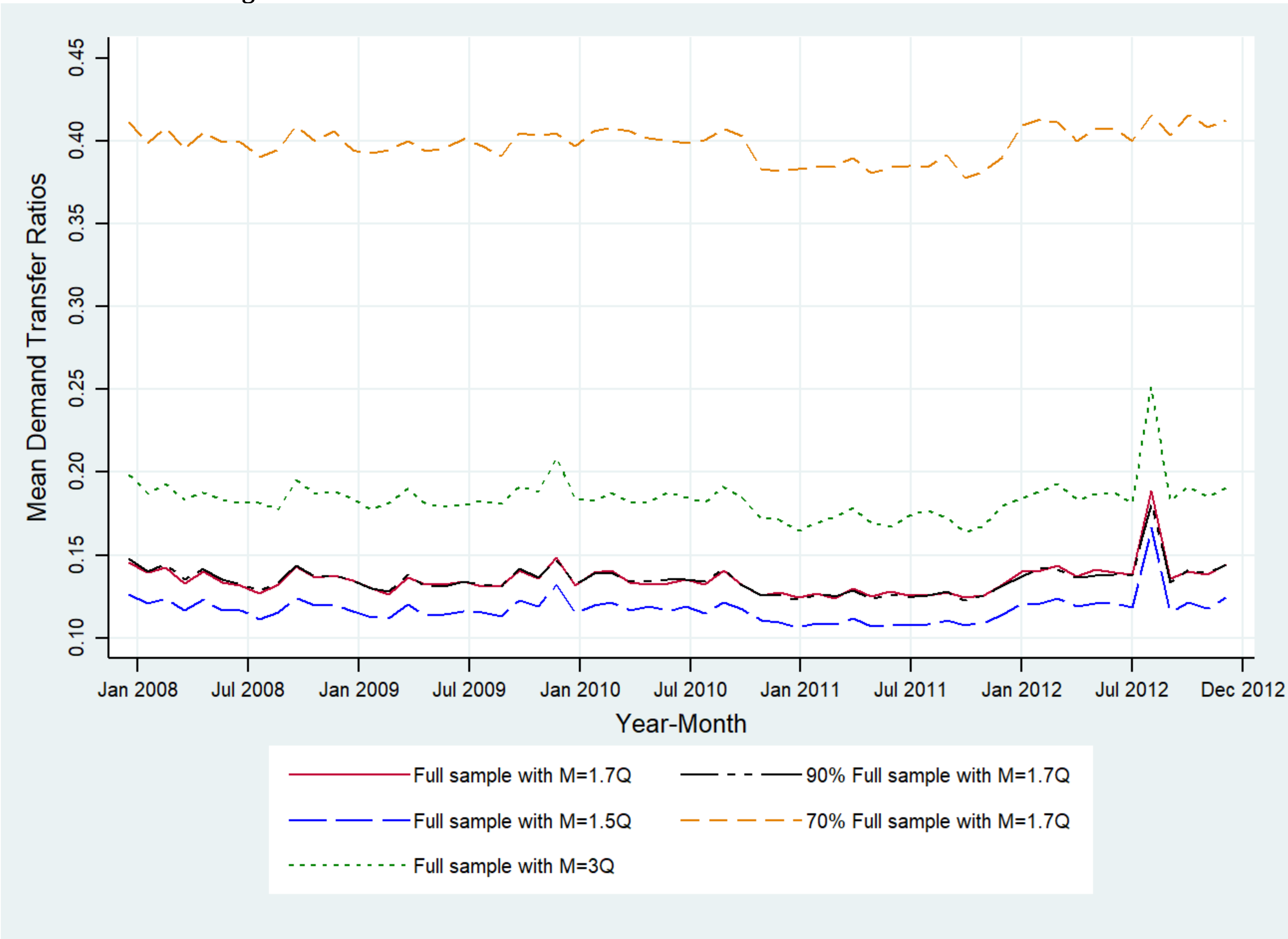

Figure A.3: Robustness Checks of Time-series Plots of Mean Estimated Demand Transfer Ratios by County