# How Do Adopters Transition Between New AND INCUMBENT CHANNELS? 

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## Appendix

## Altering the Parameters Used to Derive the Typology

Three parameters govern the typology of channel use patterns: the number of states, the number of periods, and the state in the initial period. The typology shown in Table 1 is based on three states (Incumbent, Both, and New) and three periods (periods 1, 2, and 3), with entities in the Incumbent state in the initial period. Here, we describe the effect of adjusting each of the three parameters by (1) adding more time periods and states, and (2) allowing entities to be in a state other than Incumbent in the initial period.

## Adding More Time Periods and States

Adding more periods and permuting across them is possible but, in general, does not yield substantially new patterns, while also causing the number of permutations to grow exponentially. For example, sequences of Inc $\rightarrow$ Inc $\rightarrow$ Inc $\rightarrow$ Both and Inc $\rightarrow$ Both $\rightarrow$ Both $\rightarrow$ Both are both examples of the extension pattern. Also, we suspect that in many empirical contexts, entities reach a stable point where they remain in the same state indefinitely. The typology is effective for capturing patterns that display this type of stability. For example, a pattern of Inc $\rightarrow$ Both $\rightarrow$ Inc $\rightarrow$ Both $\rightarrow$ New $\rightarrow$ New $\rightarrow$ New stabilizes at the end and is approximated by the gradual replacement pattern.

The Both state groups together entities whose percentage of new channel use relative to total use was both very low (but not $0 \%$ ) and very high (but not $100 \%$ ). For empirical applications (such as the one we investigate), it may be beneficial to divide the Both state into multiple substates that reflect different levels of new vis-à-vis incumbent use, such as a Both (Mostly Inc) and a Both (Mostly New) state. The patterns shown in Table 1 remain valid in this case. For example, a pattern of Inc $\rightarrow$ Both (Mostly Inc) $\rightarrow$ Both (Mostly New) $\rightarrow$ New fits the gradual replacement pattern, a pattern of Inc $\rightarrow$ Both (Mostly Inc) $\rightarrow$ Inc fits the discontinuance pattern, and a pattern of Inc $\rightarrow$ Both (Mostly New) $\rightarrow$ Both (Mostly Inc) fits the retrenchment pattern.

It is possible that additional patterns might be derived by adding more time periods and/or states. However, as articulated by Bailey (1994), a good typology must be detailed enough to capture relevant heterogeneity within a population, but not so detailed as to render the classification process moot (i.e., by creating a multiplicity of sparsely populated classes). We submit that the typology as derived strikes that balance. There is support for this in our empirical analysis: there are no major empirical patterns that are not represented by the typology.

## Allowing Entities to Be in a State Other than Incumbent in the Initial Period

The typology shown in Table 1 assumes that entities are in the Incumbent state in time period 1. Table A1 shows versions of Table 1 in which entities are in the Both and New states in period 1. As is the case with adding more states, patterns shown in Table 1 remain evident, including Abrupt Replacement, Retrenchment, and Discontinuance (Extension and Replacement). Additional patterns also become evident, such as when an entity shifts from using both channels to using only the incumbent channel to using only the new channel. We do not focus on these additional patterns for the following reasons. First, cases in which entities are in the "Both" or "New" states in period 1 are quite rare in our empirical context, as noted in the "Empirical Validation of the Typology" section of the main text. Second, this helps us maintain the focus of the paper. Deeper exploration of these additional patterns in other contexts is an opportunity for future research.

Table A1. Typology of New and Incumbent Channel Use Patterns When Entities' Initial State is "Both" or "New"

| State at Period 1 = "Both" |  |  |  |  | State at Period 1 = "New" |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | State at Period 3 |  |  |  |  | State at Period 3 |  |  |
|  |  | Inc ("I") | Both ("B") | New ("N") |  |  | Inc ("I") | Both ("B") | New ("N") |
| \% | I | $\begin{array}{r} 100 \% \\ 0 \% \\ \underset{12}{ }{ }^{2} \end{array}$ | $\begin{array}{r} 100 \% \\ 0 \% \\ \hline 2 \pi \end{array}$ | $\begin{aligned} & 100 \% \\ & 0 \% \underset{123}{ } \end{aligned}$ |  | I | $\begin{array}{cl} 100 \% \\ 0 \% & \underset{1}{2} 3 \\ \hline \end{array}$ | $\begin{array}{r} 100 \% \\ 0 \% \\ 123 \end{array}$ | $\begin{array}{r} 100 \% \\ 0 \% \\ \hline 123 \end{array}$ |
| $\begin{gathered} \bar{\omega} \\ 0 \\ \stackrel{\rightharpoonup}{\pi} \end{gathered}$ | B |  | $\begin{array}{r} 100 \% \\ 0 \% \\ \hline \end{array}$ |  |  | B | $\begin{gathered} 100 \% \\ 0 \% \underset{123}{ } \end{gathered}$ | $\begin{array}{r} 100 \% \\ 0 \% \\ \hline 23 \end{array}$ | 100\% ${ }_{\text {0\% }}$ \} |
|  | N |  |  | $\begin{array}{r} 100 \% \\ 0 \% \\ \hline 123 \end{array}$ |  | N |  | $\begin{array}{r} 100 \% \\ 0 \% \\ \hline 123 \end{array}$ | $\begin{aligned} 100 \% & \square \\ 0 \% & \overline{123} \end{aligned}$ |

Note: See Table 1 of the main text for a further description of this table.

## Channel Use Patterns for Dealers Who Purchased in Fewer than 25 Quarters

As noted in the main text, we focused on dealers who made purchases in the 25 quarters contained in our data. Here, we consider whether our results are robust to including dealers who purchased in fewer quarters. First, we reran the cluster analysis for dealers who purchased in $x$ quarters in our data, starting with $x=24$ and progressively lowering $x$ to 14 . An issue with the cluster analysis for these dealers is that PctElecPurchases ${ }_{i t}$ is null for the quarters $t$ in which they did not purchase (because its denominator is zero). To account for this, we "closed up" each dealer's PctElecPurchases array by dropping the null values. For example, if the PctElecPurchases array for dealer $i$ was $\{0.2,0.2$, null, and 0.3$\}$ for the four quarters of 2003 , we closed up the array to yield $\{0.2,0.2$, and 0.3$\}$. Figure A1 shows the results of the cluster analysis for the dealers who purchased in $x=24$ quarters. We determined the optimal number of clusters for this analysis to be 9 , using the same procedure as in the main text. The use patterns are similar to those shown in the main text (see Figure 3). One difference is that there are fewer dealers following the extension and retrenchment patterns. This is likely because the dealers in this analysis had relatively low purchase volumes (on average), and the extension and retrenchment patterns are typical of dealers with high purchase volumes. Similar results hold for different values of $x$.

|  | Gradual Replacement | $\rightarrow$ Extension | $\rightarrow$ Retrenchment | $\rightarrow$ Discontinuance |
| :---: | :---: | :---: | :---: | :---: |
| $1^{\text {st }}$ Adopters |  | $\begin{array}{r} 2 \\ \begin{array}{r} 100 \% \\ 50 \% \\ 0 \% \end{array} \end{array}$ |  |  |
| $2^{\text {nd }}$ Adopters |  |  |  |  |
| $3^{\text {rd }}$ Adopters |  |  | $\left.\begin{array}{r} 100 \% \\ 50 \% \\ 0 \% \end{array}\right]_{0}^{\mathrm{R} 3 \text { (223) }}\left[\begin{array}{l} 45 \\ 23 \\ 0 \end{array}\right.$ |  |
| No Adoption |  |  |  | $\left. \underset{0}{45} \begin{array}{l} 23 \\ 0 \end{array}\right]$ |
| Note: See Figure 3 of the main text for a description of the plots. |  |  |  |  |
| Figure A1. New and Incumbent Technology Use Patterns from the k-Means Cluster Analysis for Dealers Who Purchased in 24 Quarters of the Data |  |  |  |  |

The advantages of the closing up procedure are that it preserves the temporal order of each dealer's behavior and it eliminates the need to impute values for observations when PctElecPurchases $_{i t}$ is null. A disadvantage is that if a dealer waits several quarters between purchases, then the closing up procedure will obscure this gap. To explore this, we reran the cluster analysis for each value of $x$ (from $x=14$ to $x=24$ ) for only those dealers with no gaps in their purchasing behavior. Results remain consistent.

## Mixed Logit Results for Dealers Who Purchased in All 25 Quarters of the Sample Period

As noted in the main text, we ran the mixed logit model for only those dealers who purchased in each of the 25 quarters of the sample time period. Table A2 shows the results.

| State Transitions |  | DistanceClosest Facility ${ }_{\text {it }}{ }^{\text {b }}$ | FitElec_Vehicle Type $_{\text {it }}$ | (Mis)FitElec_ Mileage $_{\text {it }}{ }^{\text {c }}$ | PctElecGeo Neighbors ${ }_{\text {it }}$ | Pct Restricted $_{\text {it }}$ | Purchases ${ }_{\text {it }}{ }^{\text {b }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| From | To |  |  |  |  |  |  |
| Inc | Both (L) | 0.08 (0.01)*** | 2.80 (0.09)*** | -0.74 (0.04)*** | 0.56 (0.13)*** | 0.01 (0.03) | 0.39 (0.01)*** |
|  | Both (H) | 0.19 (0.04)*** | 4.06 (0.35)*** | -1.86 (0.20)*** | 1.23 (0.34)*** | 0.46 (0.09)*** | -0.94 (0.11) |
|  | New | 0.25 (0.07)*** | 6.51 (0.66)*** | -0.76 (0.34)* | 0.00 (0.60) | 0.82 (0.15)*** | -12.72 (0.79)*** |
| Both <br> (L) | Inc | -0.11 (0.02)*** | -2.27 (0.16)*** | 0.09 (0.06) | -0.44 (0.16)** | $0.08(0.04)^{\dagger}$ | -0.43 (0.02)*** |
|  | Both (H) | 0.08 (0.02)** | 2.16 (0.28)*** | -0.32 (0.13)* | 0.54 (0.19)** | 0.52 (0.06)*** | -0.74 (0.04)*** |
|  | New | 0.08 (0.06)** | 4.10 (0.69)*** | -0.47 (0.35) | 0.26 (0.43) | 1.17 (0.13)*** | -9.06 (0.39)*** |
| Both <br> (H) | Inc | -0.03 (0.08) | -1.12 (0.57)* | 0.04 (0.23) | -1.94 (0.59)*** | -0.32 (0.14)* | -5.85 (0.31)*** |
|  | Both (L) | 0.12 (0.04) | -0.72 (0.36)* | -0.13 (0.15) | -1.29 (0.28)*** | $-0.14(0.08)^{\dagger}$ | -0.31 (0.04)*** |
|  | New | 0.11 (0.05)** | 1.63 (0.50)** | -0.67 (0.23)** | 0.13 (0.30) | 0.56 (0.09)*** | -2.25 (0.11)*** |
| New | Inc | -0.21 (0.13)* | -0.81 (0.97) | $1.74(0.42)^{* * *}$ | -0.40 (0.83) | -1.27 (0.22)*** | -3.70 (0.58)*** |
|  | Both (L) | 0.13 (0.08) | -0.72 (0.84) | 1.41 (0.40)*** | -0.75 (0.55) | -0.94 (0.16)*** | 1.39 (0.19)*** |
|  | Both (H) | -0.13 (0.06)* | -1.71 (0.60)** | $0.55(0.30)^{\dagger}$ | 0.11 (0.36) | -0.58 (0.11)*** | $1.87(0.13)^{* * *}$ |

Notes: Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for 23 time
 ChannelHistory ${ }_{i t}$ withheld because it does not vary for dealers in the subsample used for this analysis.
The table includes only those dealers who purchased in each of the 25 quarters in the time span of the study (see the "Model Estimation and Results" section of the main text).

## Potential Heterogeneity in the Buyers Who Purchase Vehicles for Dealer i

In our analysis, the unit of analysis is the dealer/quarter. Used car dealers are typically organizations with multiple employees, one or more of whom purchase vehicles in the wholesale market. Thus, the channel use behaviors of each dealer are determined by the behaviors of one or more employees. This means that some of the variation in channel use between dealers (as well as within a dealer over time) could be driven by the (unobserved) preferences of the employees who make the purchases, to whom we will refer as a dealer's buyers. We do not believe that the possibility of multiple buyers per dealer represents a serious threat to our findings because the channel use behaviors of dealer $i$ 's buyers should be similar. First, buyers do not enjoy complete discretion over which channels to use; some of this is determined at the dealer level. For example, each buyer's ability to use the physical (electronic) channel is constrained by the dealer's travel budget (broadband connectivity). This will engender similarity in channel use by buyers within the same dealer. Second, the explanatory variables that influence a buyer's channel use are consistent across all buyers at dealer $i$; ergo, their channel use behaviors are likely to be consistent. The geographic variables, DistanceClosestFacility $_{i t}$ and PctElec_GeoNeighbors $s_{i t}$, are identical across dealer ' 's buyers. FitElec_VehicleType $_{i t}$ and (Mis)FitElec_Mileagei ${ }_{i t}$ are consistent across dealer $i$ 's buyers because each buyer purchases vehicles that meet the profile of dealer $i$ 's business (in terms of vehicles' make/model, mileage, etc.) Purchases ${ }_{i t}$ and PctRestricted $_{i t}$ are consistent across buyers because they are functions of a dealer's size and relationships with sellers, as opposed to being defined at the buyer level. Despite this, it remains possible that unobserved buyer level characteristics influence a dealer's channel use. However, because these characteristics are aggregated to the dealer-level and distributed across thousands of dealers, they may "wash out" in our analysis.

## Robustness Check: Estimating the Mixed Logit Model Using All Observations in an Omnibus Model and Accounting for Potential Mismeasurement of ChannelHistory ${ }_{\text {it }}$

In our focal approach, we estimated the mixed logit model in stages that correspond to the dealer's state at time $t$ - 1 . We also estimated an omnibus model in which we included all of a dealer's observations (regardless of his state at time $t-1$ ). By including all of a dealer's observations in a single model, we can better account for dealers' unobserved channel preferences, which we model via the normally distributed random intercepts for each state $\left(\alpha_{i s}\right)$. Another potential issue is mismeasurement of ChannelHistory ${ }_{i t}$. Because our earliest observations are from Q1-2003, we code all dealers who purchased in Q1-2003 as having the same channel history. However, some of these dealers' channel histories could go back several years, whereas others could go back only a few quarters. To account for this, we identified the subset of dealers whose first observed purchase occurred in 2004 or later. This provides at least a one year buffer to ensure that dealers were not using the
channels before we observe them to. We addressed these two issues simultaneously by estimating the omnibus model using this subset of dealers. We did this for the following reason. To account for state dependence in the omnibus model, we interacted each of the explanatory variables with a dummy variable representing the dealer's state in the prior period. This increased the model's dimensionality considerably, making convergence difficult, particularly given the large number of observations. By using the subset of dealers whose first observed purchased occurred after 2003, we limited the number of observations to include in the model, facilitating model convergence. (We also ran the omnibus model on a $12 \%$ random sample of the full data, achieving similar results.) Furthermore, given the large number of explanatory variables in the omnibus model (due primarily to all of the interactions), we did not include the (numerous) time indicator variables in the model. Instead, we used a linear time variable, which allowed us to control for effects due to the passage of time (e.g., improvements to the functionality and reliability of the electronic channel) without substantially increasing the model's dimensionality. Results are shown in Table A3. They are similar to those reported in the main text, although some of the coefficient estimates that are statistically significant in the focal model are insignificant in the omnibus model, perhaps due to the smaller sample size. In the main text, we focus on the results from separate stage models because they are based on the full data set and we are able to model time using yearly indicator variables, which is more flexible (and we believe more correct) than modeling time as a linear variable.

| State Transitions |  | Channel History ${ }_{i t}{ }^{\text {a }}$ | DistanceClosest Facility ${ }_{\text {it }}{ }^{\text {b }}$ | FitElec VehicleType ${ }_{\text {it }}$ | (Mis)FitElec_ Mileage ${ }_{i t}{ }^{\text {c }}$ | PctElecGeo Neighbors ${ }_{\text {it }}$ | Pct Restricted ${ }_{\text {it }}$ | Purchases ${ }_{\text {it }}{ }^{\text {b }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| From | To |  |  |  |  |  |  |  |
| Inc | Both (Mostly Inc) | -0.04 (0.02) ${ }^{\dagger}$ | 0.06 (0.02)** | 1.36 (0.08)*** | -1.06 (0.03)*** | 1.30 (0.16) ${ }^{* * *}$ | -0.07 (0.05) | 1.09 (0.03)*** |
|  | Both (Mostly New) | -0.18 (0.07)** | 0.03 (0.04) | 0.63 (0.18)*** | -2.08 (0.09)*** | 2.47 (0.36) ${ }^{* * *}$ | 0.79 (0.10)*** | 0.24 (0.11)* |
|  | New | -0.05 (0.05) | 0.14 (0.02) ${ }^{* * * *}$ | $1.11(0.13)^{* * *}$ | -2.18 (0.07)*** | 2.57 (0.24)*** | 1.07 (0.07)*** | -16.58 (0.55)*** |
| Both <br> (Mostly Inc) | Inc | 0.03 (0.04) | -0.06 (0.03) ${ }^{\dagger}$ | -4.11 (0.12)*** | -0.58 (0.05)*** | -0.42 (0.25) ${ }^{\dagger}$ | 0.19 (0.08)* | -1.09 (0.05)*** |
|  | Both (Mostly New) | 0.04 (0.06) | 0.06 (0.04)*** | $0.32(0.19)^{\dagger}$ | -0.32 (0.08)** | 0.73 (0.33)* | 0.68 (0.10)*** | $-0.99(0.07)^{* * *}$ |
|  | New | -0.13 (0.07) ${ }^{\dagger}$ | 0.19 (0.04) | 0.36 (0.24) | -0.68 (0.10)*** | 1.18 (0.40)** | 1.23 (0.12) ${ }^{* * *}$ | -16.71 (0.57) ${ }^{* * *}$ |
| Both <br> (Mostly New) | Inc | 0.32 (0.10)** | -0.05 (0.07) | -4.55 (0.31)*** | $1.00(0.13)^{* * *}$ | -0.67 (0.61) | -0.64 (0.17)*** | $-9.96(0.50)^{* * *}$ |
|  | Both (Mostly Inc) | -0.03 (0.08) | 0.04 (0.05) | -1.42 (0.24)*** | -0.07 (0.07) | -0.32 (0.42) | 0.27 (0.13*) | -0.66 (0.1) ${ }^{* * *}$ |
|  | New | 0.00 (0.07) | 0.11 (0.04)* | -1.00 (0.24)*** | -0.54 (0.10)*** | 0.93 (0.37)* | 0.83 (0.12)*** | -4.09 (0.19)*** |
| New | Inc | 0.46 (0.07) ${ }^{* * *}$ | -0.13 (0.04)** | -3.81 (0.19)*** | -0.09 (0.08) | -1.39 (0.40)*** | -1.0 (0.12) ${ }^{* * *}$ | -3.58 (0.42)*** |
|  | Both (Mostly Inc) | 0.06 (0.08) | -0.06 (0.04) | -1.78 (0.24)*** | 0.25 (0.09)*** | -1.25 (0.43)** | -0.91 (0.13)*** | 3.35 (0.23)*** |
|  | Both (Mostly New) | -0.08 (0.07) | -0.02 (0.03) | $-0.86(0.21)^{* * *}$ | $0.39(0.07)^{* * *}$ | -0.47 (0.32) | -0.66 (0.10)*** | 4.34 (0.19)*** |

Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for linear time trends


## Robustness Check: Potential Reverse Causality

As noted in the main text, we explored potential reverse causality with respect to the fit measures and Purchases $_{i t}$ by estimating the model on the subset of dealers who did not change what and how much they purchased (at least not appreciably) over the time span of our data. For this analysis, we used the dealers who purchased in each of the 25 quarters in the data. By using these dealers, we had enough data points to assess whether each dealer was behaving consistently over time. Also, as shown in Table A2, results for these dealers are similar to those for the full sample. We examined reverse causality with respect to fit by measuring the consistency (or lack thereof) in the types of vehicles purchased by each of these dealers over the 25 quarters in the data. We did this in two ways. First, we identified which make of vehicle (e.g., Ford, Toyota) each dealer $i$ purchased the most of in each quarter $t$, which we labeled ModeMake ${ }_{i t}$, along with the percentage of dealer $i$ 's purchases in quarter $t$ that were of this modal make (ModeMakePercent $t_{i}$ ). There were 2,633 dealers (who purchased 3,335,552 total vehicles) who had the same ModeMake it in at least 24 of the 25 quarters, that is, who consistently purchased a relatively large number of vehicles of the same make each quarter (the average ModeMakePercent ${ }_{i t}$ for these dealers was $71.3 \%$.) We reran the analysis for this subset; results appear in Table A4. ${ }^{1}$

[^0]| State Transitions |  | DistanceClosest Facility ${ }_{\text {it }}{ }^{\text {b }}$ | FitElec VehicleType $_{\text {it }}$ | (Mis)FitElec Mileage ${ }_{i t}{ }^{\text {c }}$ | PctElecGeo Neighbors $_{\text {it }}$ | Pct Restricted ${ }_{\text {it }}$ | Purchase $_{\text {it }}{ }^{\text {b }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| From | To |  |  |  |  |  |  |
| Inc | Both (L) | 0.14 (0.03)*** | 2.08 (0.18)*** | -0.84 (0.11)*** | 1.13 (0.25)*** | -0.07 (0.05) | 0.46 (0.02)*** |
|  | Both (H) | 0.32 (0.09)*** | 3.80 (0.58)*** | -2.11 (0.56)**** | $1.18(0.63)^{\dagger}$ | 0.04 (0.17) | -0.81 (0.18)*** |
|  | New | $0.26(0.15)^{\dagger}$ | 5.73 (1.07)*** | -2.32 (1.17) ${ }^{\dagger}$ | -1.33 (1.29) | 0.40 (0.30) | -11.09 (1.14) ${ }^{* * *}$ |
| Both <br> (L) | Inc | -0.21 (0.04)*** | -1.09 (0.32)** | $0.33(0.17)^{\dagger}$ | -0.78 (0.31)** | -0.07 (0.07) | -0.50 (0.04)*** |
|  | Both (H) | $0.08(0.05)^{\dagger}$ | 0.95 (0.49) ${ }^{\dagger}$ | -0.59 (0.32) | 0.13 (0.34) | 0.52 (0.10)*** | -0.97 (0.07)*** |
|  | New | -0.05 (0.11) | 3.87 (1.26)** | -0.89 (0.91) | 0.78 (0.68) | 1.00 (0.25) *** | -7.79 (0.55)*** |
| $\begin{aligned} & \text { Both } \\ & \text { (H) } \end{aligned}$ | Inc | -0.21 (0.15) | -2.37 (1.15)* | 0.53 (0.63) | -1.92 (1.50) ${ }^{\dagger}$ | -0.44 (0.26) ${ }^{\dagger}$ | -4.97 (0.47)*** |
|  | Both (L) | $0.13(0.07)^{\dagger}$ | 0.41 (0.64) | 0.25 (0.35) | -1.82 (0.49)*** | -0.24 (0.14) ${ }^{\dagger}$ | -0.29 (0.09)** |
|  | New | 0.07 (0.08) | 1.99 (0.86)* | -1.95 (0.59)** | 0.27 (0.51) | 0.46 (0.17)** | -2.45 (0.18)*** |
| New | Inc | -0.75 (0.31)** | -1.54 (2.08) | 1.11 (1.40) | -0.08 (1.85) | -0.66 (0.45) | -3.91(1.04)*** |
|  | Both (L) | 0.16 (0.15) | -1.39 (1.47) | 3.56 (0.90)*** | -1.11 (0.93) | -0.43 (0.29) | 1.26 (0.29)*** |
|  | Both (H) | -0.27 (0.10)** | -1.79 (0.99) ${ }^{\dagger}$ | 0.98 (0.70) | 0.96 (0.55) ${ }^{\dagger}$ | -0.38 (0.19)* | 1.67 (0.19)*** |

Notes: Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for 23 time dummies are not shown. ${ }^{* * *}$, ${ }^{* *}$, *, and ${ }^{\dagger}$ indicate significance at the $0.001,0.01,0.05$, and 0.10 levels. ${ }^{\text {a,b,c }}$ Variables scaled by dividing by 100 (b) and 100,000 (c). ChannelHistory ${ }_{i t}$ withheld because it does not vary for dealers in the subsample used for this analysis
The table includes only those dealers whose ModeMake ${ }_{i t}$ was the same in at least 24 of the 25 quarters.

Second, we computed the standard deviation of (Mis)FitElec_Mileage $e_{i t}$ across the quarters in which dealer $i$ purchased. This allowed us to measure the consistency in the average mileage of the vehicles purchased by each dealer over time. We reran the analysis for the subset of dealers for whom this standard deviation was relatively low (in the bottom tertile); see Table A5.

Table A5. Results of Mixed Logit Model to Examine Dealer Transitions Between States of Electronic and Physical Channel Use

| State Transitions |  | DistanceClosest Facility ${ }_{\text {it }}{ }^{\text {b }}$ | FitElec VehicleType ${ }_{\text {it }}$ | (Mis)FitElec_ Mileage ${ }_{i t}{ }^{\text {c }}$ | PctElecGeo Neighbors $_{\text {it }}$ | Pct Restricted $_{\text {it }}$ | Purchases ${ }_{\text {it }}{ }^{\text {b }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| From | To |  |  |  |  |  |  |
| Inc | Both (L) | 0.15 (0.02)*** | 2.49 (0.15)*** | -0.56 (0.10)*** | 0.46 (0.19)** | -0.12 (0.04)** | 0.23 (0.01)*** |
|  | Both (H) | 0.17 (0.07)* | 3.95 (0.52)*** | -2.79 (0.57)*** | 1.32 (0.51)* | 0.31 (0.14)* | -0.52 (0.13)*** |
|  | New | 0.26 (0.12)* | 3.32 (1.11)** | -2.68 (1.31)* | -2.13 (1.89) | 0.78 (0.30)** | -8.97 (0.99)*** |
| Both <br> (L) | Inc | -0.08 (0.03)** | -1.41 (0.25)*** | 0.60 (0.16) *** | -1.00 (0.22)*** | 0.17 (0.05)** | -0.27 (0.02)*** |
|  | Both (H) | $0.05(0.03)^{\dagger}$ | 2.06 (0.42)*** | -1.71 (0.33)*** | 0.44 (0.25) | 0.41 (0.08)*** | -0.54 (0.05)*** |
|  | New | -0.03 (0.09) | 3.55 (1.14)** | -1.37 (0.92) | 0.05 (0.58) | 1.01 (0.20)*** | -6.88 (0.43)*** |
| Both$(\mathrm{H})$ | Inc | -0.23 (0.13) ${ }^{\dagger}$ | 1.54 (1.11) | 2.21 (0.81)** | -3.10 (0.98)** | 0.12 (0.22) | -4.56 (0.41)*** |
|  | Both (L) | 0.13 (0.05)** | 0.14 (0.58) | 0.20 (0.41) | -1.63 (0.38)*** | -0.18 (0.11) ${ }^{\dagger}$ | -0.28 (0.05)*** |
|  | New | 0.07 (0.06) | 2.97 (0.79)** | $-1.25(0.61)^{*} \mathrm{q}$ | 0.44 (0.41) | 0.66 (0.14)*** | -1.83 (0.13)*** |
| New | Inc | -0.17 (0.22) | -1.67 (1.95) | 1.17 (1.51) | -1.92 (1.48) | -0.97 (0.38)** | -2.98 (0.84)*** |
|  | Both (L) | 0.05 (0.13) | 1.07 (1.53) | 1.53 (1.04) | -0.60 (0.79) | -0.91 (0.25)*** | 1.08 (0.25) ${ }^{* * *}$ |
|  | Both (H) | -0.05 (0.08) | -0.38 (0.95) | -0.99 (0.70) | -0.20 (0.46) | -0.76 (0.16)*** | 1.76 (0.15)*** |

Notes: Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for 23 time dummies are not shown. ${ }^{* * *}$, ${ }^{* *}$, ${ }^{*}$, and ${ }^{\dagger}$ indicate significance at the $0.001,0.01,0.05$, and 0.10 levels. ${ }^{\text {a,b,c }}$ Variables scaled by dividing by 100 (b) and 100,000 (c). ChannelHistory ${ }_{i t}$ withheld because it does not vary for dealers in the subsample used for this analysis.
The table includes only those dealers whose standard deviation of (Mis)FitElec_Mileage ${ }_{i t}$ across the 25 quarters was in the bottom tertile.

We examined reverse causality with respect to purchases by measuring the consistency (or lack thereof) in the number of vehicles purchased by each dealer per quarter. We used an analogous process to identify those dealers for whom the standard deviation of Purchases ${ }_{i t}$ across the quarters in which he purchased was relatively low (in the bottom tertile). The results appear in Table A6. The results are generally consistent with the main result, which supports the direction of causality implied in our main analysis.

| State Transitions |  | DistanceClosest Facility $_{\text {it }}{ }^{\text {b }}$ | FitElec VehicleType ${ }_{\text {it }}$ | (Mis)FitElec_ Mileage ${ }_{i t}{ }^{\text {c }}$ | PctElecGeo Neighbors ${ }_{\text {it }}$ | Pct Restricted ${ }_{\text {it }}$ | Purchases ${ }_{\text {it }}{ }^{\text {b }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| From | To |  |  |  |  |  |  |
| Inc | Both (L) | 0.12 (0.03)*** | 2.90 (0.21)*** | -0.74 (0.09)*** | 0.23 (0.23) | 0.07 (0.06) | 3.84 (0.16)*** |
|  | Both (H) | 0.23 (0.06)*** | 3.28 (0.63)*** | -1.23 (0.32)*** | $1.06(0.56)^{\dagger}$ | 0.63 (0.17)*** | -6.96 (0.85)*** |
|  | New | 0.27 (0.09)** | $6.24(0.96)^{* * *}$ | -0.42 (0.47) | 0.03 (0.94) | 0.81 (0.25)** | -28.60 (2.75) ${ }^{* * *}$ |
| Both <br> (L) | Inc | -0.18 (0.04)** | -1.87 (0.33)*** | 0.32 (0.13)* | -0.61 (0.34) ${ }^{\dagger}$ | 0.29 (0.09)** | -5.49 (0.28)*** |
|  | Both (H) | -0.04 (0.06) | 1.39 (0.56)* | -0.12 (0.24) | 0.61 (0.44) | 0.58 (0.13)*** | -5.90 (0.47)*** |
|  | New | -0.08 (0.12) | 3.10 (1.06)** | 0.04 (0.47) | 1.28 (0.79) | 1.04 (0.24)*** | -23.61 (1.61) ${ }^{* * *}$ |
| Both <br> (H) | Inc | 0.03 (0.14) | -2.29 (0.98)* | 0.71 (0.35)* | -1.54 (0.99) | -0.57 (0.27)* | -14.17 (1.40)*** |
|  | Both (L) | 0.07 (0.09) | -0.88 (0.74) | 0.64 (0.28)* | -1.28 (0.60)* | 0.44 (0.18)** | -0.53 (0.61) |
|  | New | 0.21 (0.10)* | 0.70 (0.91) | -0.75 (0.39) ${ }^{\dagger}$ | 1.50 (0.61)* | 0.81 (0.19)*** | -8.41 (0.80)*** |
| New | Inc | 0.01 (0.22) | -0.68 (1.63) | 2.62 (0.66) ${ }^{* * *}$ | -0.26 (1.39) | -0.98 (0.41)* | -15.03 (2.86)*** |
|  | Both (L) | -0.04 (0.17) | 0.58 (1.57) | 2.37 (0.63)*** | -0.46 (1.06) | -0.88 (0.32)** | 3.81 (1.27)** |
|  | Both (H) | -0.18 (0.11) | -2.45 (1.01)* | 0.60 (0.47) | -0.29 (0.66) | -0.87 (0.20)*** | $6.32(0.78)^{* * *}$ |

Notes: Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for 23 time dummies are not shown. ${ }^{* * *}$, ${ }^{* *}$, ${ }^{*}$, and ${ }^{\dagger}$ indicate significance at the $0.001,0.01,0.05$, and 0.10 levels.
${ }^{\text {a,b, }, ~ v a r i a b l e s ~ s c a l e d ~ b y ~ d i v i d i n g ~ b y ~} 100$ (b) and 100,000 (c). ChannelHistory ${ }_{i t}$ withheld because it does not vary for dealers in the subsample used for this analysis.
The table includes only those dealers whose standard deviation of Purchases $_{i t}$ across the 25 quarters was in the bottom tertile.

## Robustness Check Regarding Minimum Number of Purchases per Quarter

As noted in the main text, we define the states based on the percentage of electronic purchases. Because this is a percentage, dealer-quarters with low numbers of purchases (the denominator of the percentage) could result in large changes in the percentage with relatively small changes in the numerator. To limit the concern that this could affect the results, we reran the mixed logit model after removing observations in which dealers made fewer than $x$ purchases in quarter $t$ or quarter $t-1$, setting $x=5$ and $x$ $=10$. Results are similar to the focal results and are shown in Tables A7 and A8.
Table A7. Results of Mixed Logit Model to Examine Dealer Transitions Between States of Electronic and
Physical Channel Use

Notes: Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for time indicators are not shown. ***, ${ }^{* *}$, and ${ }^{*}$ indicate significance at the $0.001,0.01$, and 0.05 levels. ${ }^{a, b, c}$ variables scaled by dividing by 10 (a), 100 (b), and 100,000 (c).
The table excludes observations in which dealers made fewer than five purchases in quarter $t$ or quarter $t$

Table A8. Results of Mixed Logit Model to Examine Dealer Transitions Between States of Electronic and Physical Channel Use

| State Transitions |  | Channel History ${ }_{\text {it }}{ }^{\text {a }}$ | DistanceClosest Facility ${ }_{\text {it }}^{\text {b }}$ | FitElec_ VehicleType $_{\text {it }}$ | (Mis)FitElec Mileage ${ }_{\text {it }}{ }^{\text {c }}$ | PctElecGeo Neighbors ${ }_{\text {it }}$ | Pct <br> Restricted $_{\text {it }}$ | Purchases ${ }_{\text {it }}{ }^{\text {b }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| From | To |  |  |  |  |  |  |  |
| Inc | Both (Mostly Inc) | 0.07 (0.02)*** | 0.05 (0.02)** | 3.91 (0.07)*** | -0.74 (0.03)** | 1.53 (0.15)*** | -0.14 (0.03)*** | 0.49 (0.01)*** |
|  | Both (Mostly New) | -0.38 (0.05)*** | 0.13 (0.04)*** | 5.15 (0.22)*** | -1.32 (0.14)*** | 2.35 (0.34)*** | 0.64 (0.08)*** | -0.28 (0.08)*** |
|  | New | -0.23 (0.12) | 0.25 (0.05)*** | 4.93 (0.51)*** | -3.90 (0.49)*** | $2.61(0.51)^{* * *}$ | 0.67 (0.16)*** | -5.02 (0.46)*** |
| Both <br> (Mostly Inc) | Inc | 0.07 (0.02)** | -0.09 (0.02)*** | -2.40 (0.12) *** | 0.27 (0.05)*** | -1.03 (0.18)*** | -0.17 (0.04)*** | -0.36 (0.02)** |
|  | Both (Mostly New) | -0.17 (0.03)*** | 0.06 (0.02)* | 2.36 (0.19)*** | -0.30 (0.09)*** | 0.97 (0.21)*** | 0.86 (0.05)*** | -0.58 (0.04)*** |
|  | New | -0.33 (0.08) ${ }^{* * *}$ | 0.15 (0.04)*** | 4.62 (0.59)*** | -1.05 (0.32)** | 0.75 (0.39) | 1.40 (0.13)*** | -5.30 (0.26) ${ }^{* * *}$ |
| Both <br> (Mostly New) | Inc | 0.48 (0.12)*** | 0.09 (0.08) | -0.97 (0.60) | -0.41 (0.25) | -1.41 (0.67)* | -0.70 (0.16)*** | -3.08 (0.24)*** |
|  | Both (Mostly Inc) | $0.28(0.05)^{* * *}$ | 0.11 (0.04)** | $-0.91(0.29)^{* *}$ | -0.18 (0.12) | -1.15 (0.30)*** | -0.46 (0.08)*** | -0.16 (0.04)*** |
|  | New | -0.13 (0.05)** | 0.18 (0.04)*** | 2.45 (0.36)*** | -0.28 (0.16) | 0.38 (0.28) | 0.81 (0.08)*** | -2.00 (0.10)*** |
| New | Inc | 0.24 (0.19) | 0.20 (0.09)* | -1.82 (1.18) | -0.77 (0.64) | -2.17 (1.02)* | -1.85 (0.27)*** | -0.78 (0.47) |
|  | Both (Mostly Inc) | 0.27 (0.12)* | 0.13 (0.07) | -0.44 (0.82) | 0.81 (0.36)* | -0.62 (0.62) | -1.41 (0.18) ${ }^{* * *}$ | 1.66 (0.22)*** |
|  | Both (Mostly New) | 0.02 (0.06) | -0.03 (0.04) | -0.44 (0.46) | 0.87 (0.21)*** | -0.34 (0.33) | -0.59 (0.09)*** | 2.12 (0.13)*** |

Notes: Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for time indicators are not shown. ***, **, and * indicate significance at the $0.001,0.01$, and 0.05 levels.
a,b,c Variables scaled by dividing by 10 (a), 100 (b) , and 100,000 (c).
The table excludes observations in which dealers made fewer than 10 purchases in quarter $t$ or quarter $t$.


[^0]:    ${ }^{1}$ Conducting the analysis using this subset means that the FitElec_VehicleType ${ }_{i t}$, (Mis)FitElec_Mileage ${ }_{i t}$, and Purchases it $_{\text {_ }}$ coefficients are identified (mostly) based on differences across dealers rather than changes within each dealer over time.

