Online Appendix A:

Benchmark Model with Independent Sales Channels.

Here we consider the scenario in which bidders do not have access to the seller's offline retail channel. Hence, all bidders bid up to their valuation and the auction price might end up higher than the retail channel's list price. Though in reality the seller's information is often only a click away, it is interesting to study this benchmark case and then consider whether the visibility of the list price to bidders impacts the relationship between characteristics of the demand in the retail sales channel and the auction channel outcomes.

The expected profit in this case is given by Equation 2 from the manuscript. The auction channel outcomes are given by Equations 6-8, but we replace $G[p]$ by 1 in Equations 6-8, regardless of the value of p, because bidders do not have access to the list price. In addition, the upper bound of the integral in the expression for EP_A should be set to H regardless of the value of p.

Tables A1 and A2 display the results of the numerical investigation when bidders do not have access to the list price. We see from Table A1 that for 20.44% of the parameter combinations examined it was optimal for the seller to conduct only auctions. That is, the list price was set high enough so that none of the retail-channel's customers would find it optimal to buy the item. In all these cases we had β<1, so that the support set of valuations in the auction channel dominated the support set in the retail channel. It is important to note however that for many parameter combinations with β<1 it was optimal to use both channels. We also see from Table A1 that only for 4.58% of the cases it was optimal to use only the retail channel, and in all these cases we had β>1 and a low discounting rate. Since we are interested in studying how the demand in the retail channel impacts the auction channel outcomes, for Table A2 we considered only the setups for which we determined that it is indeed optimal for the seller to use both channels (i.e., optimal to set prices so that there is positive probability of sale in each of the channels).

In Table A2 we see that the AS and IS probabilities were strictly decreasing in β for all parameter combinations for which it was optimal to utilize both channels. We also see that the optimal auction reserve price and the expected auction sale price increase with β in 99.9% of the cases in which it is optimal for the seller to utilize both channels. Examination of the 94 cases in which the seller utilizes both channels but the reserve price does not increase in β revealed that all these cases happen when the optimal reserve price is not an interior value, that is R_A^*=L. Finally, in 100% of cases the optimal list price in the retail channel increases in β.

Considering the traffic in the retail channel (λ), we see that the AS and IS probabilities were strictly decreasing in λ for all parameter combinations for which it was optimal to utilize both channels. The optimal auction reserve price and expected auction price were increasing in λ in 97.45% of the cases in which it is optimal to utilize both channels. Examination of the 2,296 cases in which the reserve price and auction price were constant in λ showed that in 313 of these cases the reason was that the optimal reserve price was set to the lower bound of bidders valuations (i.e., $R_A^*=L$). In the remaining 1,983 cases we had $\beta<1$ and $p^*>\beta H$-1.5, so that the probability of sale in the retail channel was very small (these cases were borderline of using only auctions) and hence a marginal change in the traffic in the retail channel did not impact the optimal auction reserve price. Finally, in all cases in which the list price was constant in λ (2,248 cases), we had $\beta<1$ and βH-1.5 $<p^*<\beta H$. Only in 15 cases both the auction reserve price and the list price were constant in λ. We conclude that only when the support of valuations in the auction channel dominates the support of valuations in the retail channel, and the optimal list price approaches the upper bound of valuations in the retail channel, it might be optimal to keep one of the prices fixed as traffic in the retail channel increases.

Table A1. Results of Numerical Investigation: Optimal Choice of Channels when Bidders Do Not Have Access to the List Price

Description of Strategy	**# (%) of cases that falls in this category**	**Characteristic of cases within each category**
Only auctions: $p=\beta H$, $R_A<H$	24,530 (20.44 %)	$\beta<1$
Two channels: $p<\beta H$, $R_A<H$	89,970 (74.98%)	None
Only retail channel: $p<\beta H$, $R_A=H$	5,500 (4.58%)	$\beta>1$, $\rho\leq 0.1$

Table A2. Results when Both Channels are being Used and Bidders Don't have Access to the List Price

	Positive	**Negative**	**Zero**
$\Delta AS(\beta)$, $\Delta IS(\beta)$	0	89,970 (**100**%)	0
$\Delta R_A^*(\beta)$, $\Delta EP_A(\beta)$	89,876 (**99.90%**)	0	94 (**0.1%**)[1]
$\Delta p^*(\beta)$	89,970 (**100%**)	0	0
$\Delta AS(\lambda)$, $\Delta IS(\lambda)$	0	89,970 (**100**%)	0
$\Delta R_A^*(\lambda)$, $\Delta EP_A(\lambda)$	87,674 (**97.45%**)	0	2,296 (**2.55%**)[2]
$\Delta p^*(\lambda)$	87,772 (**97.50%**)	0	2,248 (**2.5%**)

Note. The percentages are out of the total number of cases in which it is optimal to use both channels

[1] In all these cases the optimal auction reserve price is L (the lower bound on bidders valuations), L=80, and $N \leq 2$.

[2] In 313 of these cases $Ra^*=L$ =80. In the remaining 1,983 cases βH-1.5 $< p^* < \beta H$ and $\beta<1$.

Online Appendix B:

Dealer's Website Functionalities Used to Determine the Dealers Electronic Commerce Capabilities (ECC_{WEB})

1. Lists price on website.
2. Lists options on website.
3. Lists photo on website.
4. Links to independent sites.
5. Tool for credit application.
6. Price quotes request form.
7. Tools to order parts.
8. Tools to schedule service appointments.

Online Appendix C. The Heckman Results

Variables	Sale Price[1]	Sale Price[1]	Sale Price[2]	Sale Price[2]
ln(AHI)	0.526*	6.374	0.525*	6.415
$\ln(AHI)^2$		-0.671		-0.676
ln(TP)	0.112*	1.652*	0.112*	1.655*
$\ln(TP)^2$		-0.061 $^{\Psi}$		-0.061 $^{\Psi}$
ECC_{WEB}	0.108***	0.108***	0.107***	0.107***
$\ln(ECC_{SOW})$	0.425***	0.424***	0.423***	0.421***
Vehicle supply	-0.016***	-0.016***	-0.016***	-0.016***
ln(Miles)	-2.779***	-2.776***	-2.779***	-2.775***
Certified	0.397	0.438	0.393	0.432
Inspected	0.270**	0.294**	0.271**	0.296**
Warranty	0.648***	0.641***	0.646***	0.639***
ln(Positive feedback)	-0.017	-0.022	-0.015	-0.020
ln(Negative feedback)	-0.156**	-0.147**	-0.158**	-0.150**
ln(Number of bids)	0.221**	0.214**	0.222**	0.216**
Auction length	0.059**	0.062**	0.056*	0.058*
Starting bid	0.042***	0.041***	0.042***	0.041***
Ended on weekend	-0.038	-0.037	-0.037	-0.036
Time	0.012	0.012	0.012	0.012
ln(Auction count)	-0.065	-0.060	-0.067	-0.062
Ended in Buy-It-Now	0.765***	0.773***	0.766***	0.774***
Nonselection			-0.030	-0.041
Observations	5,081	5,081	5,081	5,081
Adj R^2	0.971	0.971	0.971	0.971

Table A3. Results of a two-stage Heckit procedure for *sale price* alongside results from simple OLS regression using only auctions that ended in a sale.

Notes: *** p<0.001, ** p<0.01, * p<0.05, $^{\Psi}$ p<0.10;
Dummy variables for *vehicle model* (1391), *vehicle year* (6), and *vehicle color* (7) are not shown. [1]Original OLS Results. [2]Results with *nonselection* variable based on Heckit procedure.

Online Appendix D. Hazard Ratio Results

Variables	Item-sale (Base Model)	Item-sale (Linear)	Hazard (Nonlinear)
ln(AHI)		0.714***	0.010 $^{\Psi}$
$\ln(AHI)^2$			1.630 $^{\Psi}$
ln(TP)		0.951**	0.201***
$\ln(TP)^2$			1.063***
ECC_{WEB}	0.962***	0.969***	0.970***
$\ln(ECC_{SOW})$	0.782***	0.780***	0.776***
Vehicle supply	0.995***	0.995***	0.995***
ln(Miles)	1.072**	1.085***	1.080**
Certified	0.789	0.788	0.743
Inspected	1.027	1.044	1.02
Warranty	0.861***	0.832***	0.833***
ln(Positive feedback)	1.197***	1.196***	1.205***
ln(Negative feedback)	0.828***	0.824***	0.819***
ln(Number of bids)	1.043	1.049 $^{\Psi}$	1.048 $^{\Psi}$
Auction length	0.635***	0.639***	0.635***
Starting bid	1.012***	1.011***	1.012***
Ended on weekend	1.145**	1.149**	1.155**
Observations	21,234	21,234	21,234
Chi^2 / Adj R^2	3,813	3,978	4,019
Log-likelihood	-46,926	-46,844	-46,823

Notes: *** p<0.001, ** p<0.01, * p<0.05, $^{\Psi}$ p<0.10;