VANDERBILT UNIVERSITY

# Used Car Pricing Algorithm

*Model Development and Business Application*

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## Executive Summary

Our used car pricing algorithm offers businesses a competitive edge in predicting the final retail transaction price of vehicles, enabling better decision-making, inventory calibration, and avoidance of costly errors. By leveraging our proprietary dataset that combines private transaction prices from state title registrations, extensive dealer listings, in-depth vehicle specifications, and external economic data, our model identifies complex pricing patterns. In addition, we target multiple price quantiles to provide a spread of potential retail selling prices with less susceptibility to outliers. Our approach allows the user to make informed decisions and pricing adjustments as needed at any stage of the acquisition, reconditioning, and sales processes.

GitHub Repo: github.com/sheacon/used_car_pricing

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## Introduction

In the used car market, determining the final retail transaction price of vehicles is crucial for businesses to make informed decisions about which cars to acquire and at what price. At auction or trade-in, a business must be able to price many vehicles in a timely manner to keep profitable inventory stocked.

However, used cars are an idiosyncratic asset - no two are alike. Pricing them is a challenge, especially at scale. Although pricing algorithms are a common data science problem[1], our project introduces a unique approach that results in a far more useful product. Our model is differentiated by several key factors.

Most importantly, instead of using list price as the prediction target, we acquired true final transaction prices from the department of motor vehicles of several states. When a car is purchased, the new owner must register for a title with their county or state government. The registration form requires disclosure of the sales price.

Predicting the price at which the vehicle sold after private negotiation is much more valuable than the prices listed online. Listing price is a poor analog for the true market value of the vehicle. In fact, listing data itself won't indicate whether the vehicle sold at all.

Extensive data collection resulted in a massive training set exclusive to this project. Our data partner MarketCheck provided dealer listings[2] for a five-year timespan for several states and allowed us to make academic use of what is normally a commercial product. This data included updates as a listing changed over time.

MarketCheck also supplemented these listings with greater detail about each vehicle. This

[1] Kaggle Used Car Price Projects

[2] MarketCheck Automotive Data

additional data included trim-level and vehicle-specific standardized features and add-ons. We were able to identify which features each vehicle had and whether it was included with its trim or optionally added.

With a more comprehensive dataset across several years and multiple states, we were able to identify deeper pricing patterns in modeling. While using a dataset that spanned time and location has advantages for scale, it required appending local and macro economic features to control for these differences. These features also enable the model to generalize to new locations and changing market conditions over time.

While utilizing this comprehensive dataset with accurate pricing gave our used car pricing algorithm a competitive edge, we also implemented asymmetric tilted loss functions to target our model to arbitrary quantiles. Instead of predicting the mean, we produced models for the 30th, 40th, 50th (median), 60th, and 70th quantiles. For any vehicle, multiple price points are provided, giving the user an idea of the spread of possible retail selling prices. Targeting quantiles instead of the mean also made our model less susceptible to outliers in the training data.

## Data Collection

*Transaction Price Data*

Cars are an expensive purchase for consumers, and used cars have no agreed-upon valuation. The final transaction price at a used car dealership is usually the result of a private negotiation and unavailable. However, our project exploited the fact that sales price must be included on motor vehicle title registrations, and title registrations are public records, available upon request. Official request forms and persistence are required to gain access to these records, but it is possible. See Appendix A for examples of state title registrations forms.

We prioritized the five states with the most automobile registrations[3] - California, Texas, Florida, New York, and Ohio - for data collection to maximize return on time spent. We also included Tennessee, as the location of Vanderbilt University, for good measure. Freedom of Information Act style legislation in each state allowed for requests of these public records.

We requested all motor vehicle title registrations statewide from 2018 to 2022. Texas, Ohio, and Tennessee responded positively. An industry expert[4] also highlighted Texas and Ohio as states with especially reliable DMV pricing data. We deduplicated records by industry-standard vehicle identification number (VIN), keeping the most recent. The number of unique VINs for used vehicles was 17.6m in Texas, 10.6m in Ohio, and 5.7m in Tennessee.

*Car Detail Data Collection*

We put equal effort into acquiring quality features that described the vehicles. Title registrations rarely include more than make, model, year, and mileage. Therefore, we partnered with MarketCheck[5], a market-wide online aggregator of dealership listings.

MarketCheck made available a five-year dataset for each of the three states where we had registrations. This listings data was 2.1Tb and 245m records. Since MarketCheck data is a comprehensive history of listing changes, there were many deduplicates by VIN. The unique VIN record count was 18.3m.

The records included information found on online listings from car dealerships, appended with known vehicle specifications based on VIN[6] as well as proprietary features developed by MarketCheck.

## Data Analysis

*Deduplication and Matching*

Due to this research project's limitations in big data processing infrastructure, we took a simplified approach for deduplication. We deduplicated VINs by keeping the latest record.

[3] Highway Statistics Series, Table MV-1 (2020); US Department of Transportation

[4] A vehicle transaction data broker at Cross-Sell LLC

[5] MarketCheck.com

[6] VIN Decoder Data

Since the data spans a five-year period, this process likely discarded information from multiple sales of the same vehicle. After this step, we matched MarketCheck vehicle listings to title registrations by VIN with a 71% match rate, leaving 13.1m records.

*Data Cleaning and Subsetting*

In this project, we removed data for three reasons. First, features critical to modeling were unreliable or unavailable (e.g. errant price data entry, mileage reporting exemption, and missing make/model). Second, the vehicle did not apply well to the business use case of the project. And third, matching between listing and registration records was not possible or inaccurate. These record removals finally resulted in 6.4m vehicles with high quality data.

We made business case exclusions to focus the model on priority pricing targets. We removed records that were not consumer cars or trucks, such as passenger vans or chassis cabs (trucks with no factory-installed bed). Vehicles more than twenty years old are considered vintage and can be licensed as an antique in many states[7]. We excluded these.

Prices over $100,000 are not in the price range of most used car dealerships, so we dropped them. Low prices were not dropped because vehicles must be priced on the low end to avoid overpricing of junk cars. Losing an auction for bidding too low is a much smaller problem than winning an auction by bidding too high.

Specialty or extreme-luxury vehicles are not within the scope of this project. Therefore, we excluded make/model/trim combinations with fewer than 1,000 observations in the dataset. As a side effect, that makes each excluded make/model/trim incompatible with our algorithm, but it also avoids model fitting towards outlier vehicle types. Examples of exotic vehicles that are incompatible with our algorithm include: Ferrari LaFerrari Base, Maserati Gransport Victory 2, and Aston Martin Rapide AMR.

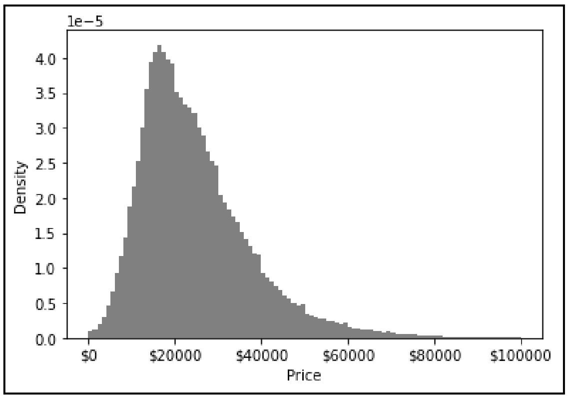



**Figure 1:** Vehicle Prices
Vehicle prices show an expected right skew. Mean and median prices are $24,798 and $22,200 respectively.

*Exploratory Data Analysis*

We reviewed key explanatory variables included in the listings data, such as model year, mileage, engine specifications, and fuel efficiency in univariate analysis for distribution sanity and outliers. We also conducted bivariate analyses to compare how the variables interacted.

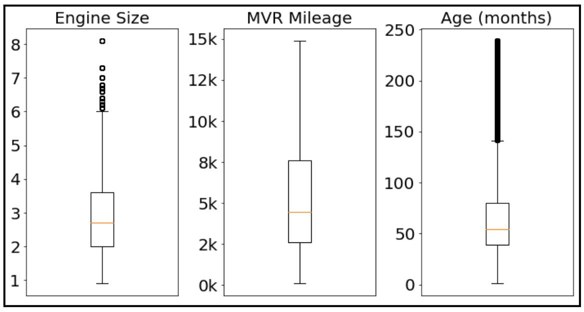



**Figure 2:** Core Feature Distributions
A selection of core features and their distributions.

*Missing Data*

We addressed missing data in various ways appropriate to the variable concerned. For simple flags, such as vehicle certification, we assumed a negative for missing values. For numeric variables, we imputed the median based on appropriate groupings, such as make/model. For categorical variables, we imputed the mode by similar groupings. We took care to avoid data leakage in imputation between the training set and validation or test sets.

7 [Wikipedia: Antique Vehicle Registration]

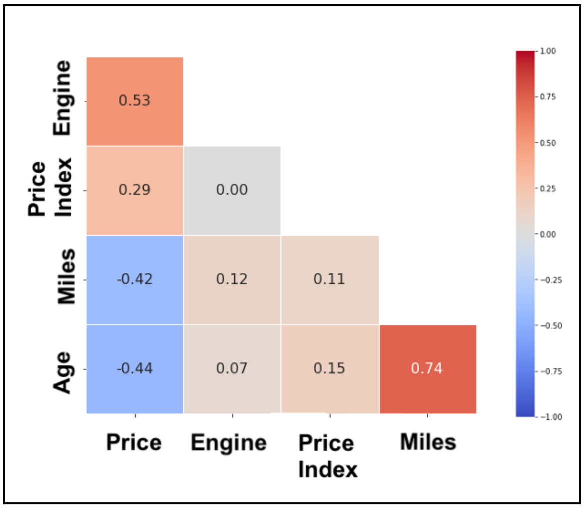



**Figure 3:** Correlation Plot
This plot shows correlations among important numeric features.

## Feature Engineering

Feature engineering is the process of creating new features or transforming existing ones to better represent the underlying patterns in a dataset and improve the performance of our algorithm. By carefully crafting features, we captured more meaningful information from the data and built a more accurate and robust model. Good feature engineering also requires domain knowledge for considering supplemental data.

*Simple Transformations*
Some features were simple transformations or comparisons of existing variables. We computed vehicle age as the difference between model year and purchase date. We created monthly mileage to highlight the difference between vehicles that are driven a lot in a short period from those that are driven more sparingly but are older.

*High Cardinality of Make / Model / Trim*
The identification of the make, model, and trim of a vehicle includes a lot of information relevant to the consumer. Car makes (e.g. Ford, BMW, Toyota), models (e.g. Focus, 5 Series, Camry), and trims (e.g. SE, 540i, XLE) also come in many combinations. After discarding "rare" combinations, our dataset still included 1,229 unique make/model/trims.

Most algorithms do not perform well with high cardinality variables like this. After considering several approaches, we used target encoding to capture the information inherent in make/model/trim and convert it to a numeric value. Target encoding replaces each category with the mean value of the target for that category. For example, the encoding of a Ford Focus SE would be the average price for all Ford Focus SE's in the dataset.

The breadth of our dataset allowed us to apply target encoding reliably to a large number of make/model/trims. Once encoded, the other features of the dataset can be thought of as adjustments to this mean price.

*Dimensionality of High Value Features (HVF)*
One of the benefits of MarketCheck's proprietary dataset was the inclusion of their standardized High Value Features™. For each vehicle, standard and optional vehicle features were specified. See Appendix B for a list of all 82 HVFs. For example, the data indicated whether a vehicle had leather seats and if that comes standard or as an added option.

However, a binary encoding of each of these features introduced the curse of dimensionality to our modeling. Adding this many features to those already present made even our large dataset sparse for some combinations of features. Our solution was to use principal component analysis.

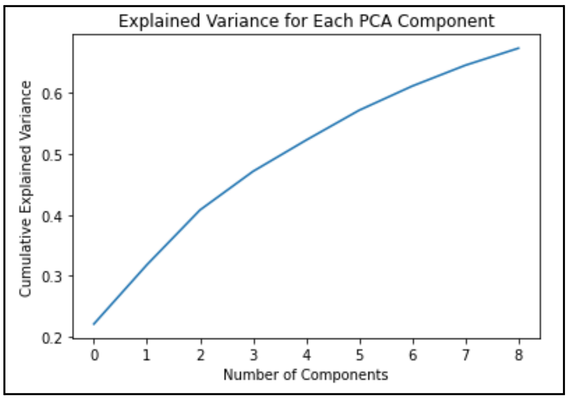



**Figure 4:** Principal Component Analysis
This graph shows the diminishing returns of variance capture for additional components.

Principal component analysis (PCA) is a dimensionality reduction technique that seeks to preserve as much variance of the input variables as possible linearly in a lower dimensional representation. We reduced the 82 binary HVF indicators to 9 features.

*Outside Data Augmentation*
We used data from the Bureau of Labor Statistics and the U.S. Census to incorporate information about the macro economic environment and local demography. We appended these either by year and month or zip code. The statistics included population density, median income, median home value, used car price index, new car price index, gas price index, and consumer sentiment.

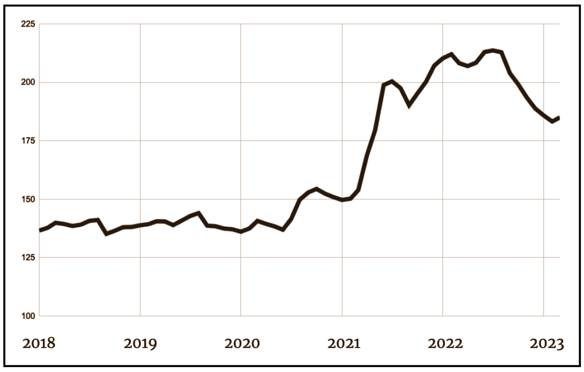



**Figure 5:** BLS Used Car and Truck Price Index
Prices have changed dramatically in recent years due to COVID-19, microchip supply-chain issues, and inflation in raw inputs. Alleviation of some issues is causing another major price shift.

As shown in Figure 5, used car prices have changed dramatically over the timeframe of this data, so having an index to account for price fluctuations for a given set of features was important. This also allows the algorithm to adjust to changing conditions in the future without retraining.

*Unstructured Features*
The dataset included unstructured text features in the listing options and seller comments, but their consideration was beyond the scope of the project. In another iteration of the model, we would like to extract meaningful information here.

## Modeling

*Models*
We trained a baseline linear regression model to provide a floor for model performance. From there, modeling focused on training a gradient boosted tree ensemble from the CatBoost library. This algorithm expands on decision trees by creating an ensemble of trees that iteratively correct the errors of existing trees in the ensemble.

*Loss Functions*
A loss function quantifies the difference between the predicted output and the actual target values in a model. It serves as a metric for evaluating the performance of the model during the training process, which is designed to minimize loss. For this project, we utilized the lesser known tilted loss function to enhance the applicability of our model to the business use case.

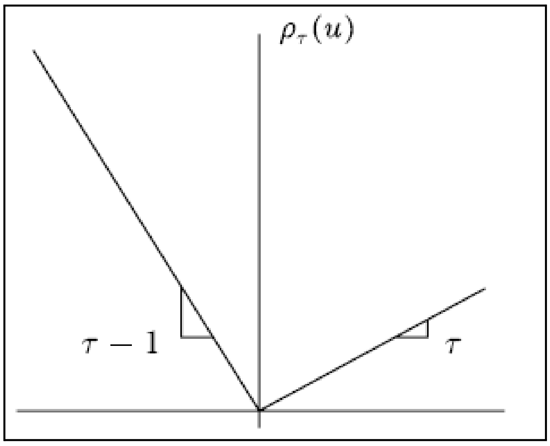



**Figure 6:** Tilted Loss
Titled loss allows for asymmetric targeting in order to model different points in the prediction distribution.

The tilted loss function is asymmetric[8], meaning it penalizes over- and under- predictions differently depending on the chosen parameters. In the context of used car pricing, a tilted loss results in quantiles that can provide a spread of predicted sales prices. This conveys the uncertainty in a prediction for a given set of features and allows the user to calibrate their price expectations.

[8] Quantile loss (y, y_pred) = τ * max(y - y_pred, 0) + (1 - τ) * max(y_pred - y, 0)

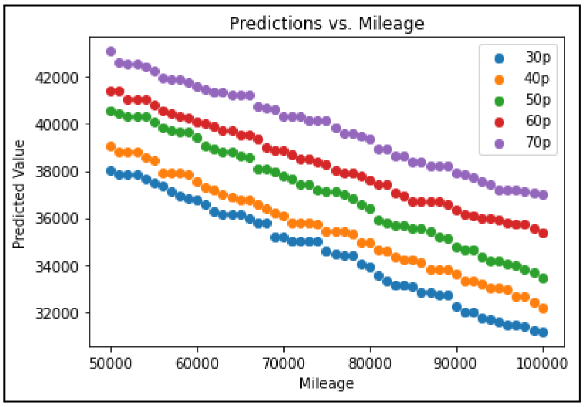



**Figure 7:** Quantile Regression
Training multiple models with different tilted loss functions enables quantile regression. The result is a spread of predicted values across selected quantiles for a given set of features.

## Results

As expected, the gradient boosted tree ensemble algorithm outperformed the baseline linear model. In addition, we trained diagnostic models excluding different engineered features to assess their value.

**Table 1:** Comparison of model results on the validation dataset

| Model | R2 | MAE | MAPE |
|---|---|---|---|
| Linear | 0.842 | $3,511 | 19.6% |
| CatBoost without Target Encoding | 0.69 | $4,749 | 23.2% |
| CatBoost without External Data | 0.871 | $3,208 | 18.1% |
| CatBoost without High Value Features | 0.876 | $3,116 | 17.7% |
| CatBoost Final | 0.894 | $2,838 | 16.8% |

Finally, the CatBoost algorithm was fine-tuned with a hyperparameter grid search for optimal performance. This algorithm was then tested against the "golden holdout" test set. The final model generalized well, showing similar performance from validation to test.

**Table 2:** Final results on test set

| Model | R2 | MAE | MAPE |
|---|---|---|---|
| CatBoost Final | 0.881 | $3,074 | 18.4% |

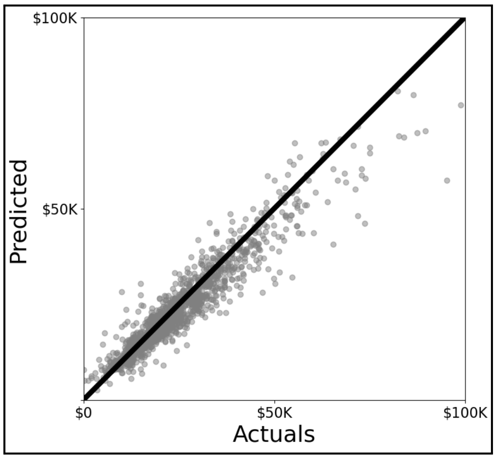



**Figure 5:** Predicted vs Actuals
This graph shows the accuracy of the model. Observations near the black line represent accurate pricing while deviations are less accurate. Below the line is underpricing.

## Discussion

We were pleased with the results and think that this pricing algorithm, trained to target true retail transaction prices, makes a unique contribution to the subject.

When buying used cars at auction, it's essential to balance pricing strategy to minimize overpricing while ensuring enough auction wins to maintain inventory. If the model consistently underprices vehicles, vehicles that could have resulted in a profit are foregone. On the other side, worse, if the model consistently overprices vehicles, acquired vehicles can't be sold at a profit. Having a series of models that produces price quantile predictions provides insight and flexibility to the user.

With any model in production use, tracking model performance with new data is necessary. But, between retrainings and adjustments, quantile price predictions do allow for ad hoc changes in strategy for auction bidding and listing price.

## Improvements

Due to processing limitations, we deduplicated and matched records in a less-than-optimal fashion that discarded useful data and possibly introduced errors. In future iterations, we would like to address this concern.

In addition, valuable information was not extracted from the unstructured text features in the data. Arbitrary listed options and seller comments reveal aspects of the vehicle that affect price and should be captured.

## Acknowledgements

I would like to thank my advisor Prof. Jesse Blocher for his valuable insights at each stage of this project, the Campbells at MarketCheck for sharing their data and expertise, state officials in Ohio, Tennessee, and Texas, and lastly my mother for her enduring support.

## References


- Brendan Hasz. *Quantile Regression*. Dec 2018.
- J.P. Morgan Research. *Inflation and the Auto Industry: When Will Car Prices Drop?*. Nov 2022.
- Bureau of Labor Statistics. *Used Car and Trucks in U.S.* Mar 2023.
- Cox Automotive. *2018 Used Car Market Report & Outlook*. March 2018.
- Carfax, CarMax, Edmunds, Kelly Blue Book, and TrueCar Online Pricing Tools

## Appendix A: State Title Registration Forms

OHIO DEPARTMENT OF PUBLIC SAFETY
BUREAU OF MOTOR VEHICLES

**APPLICATION(S) FOR CERTIFICATE OF TITLE TO A MOTOR VEHICLE**

**(Type or Print in Ink)**

CHECK TYPE OF APPLICATION(S) Fee of $5.00 for failure to apply for title within 30 days of assignment.

| | |
|---|---|
| | COUNTY |
| PRIMARY APPLICANT'S NAME | SSN / EIN |
| PRIMARY APPLICANT'S ADDRESS | |
| SECONDARY APPLICANT'S NAME | SSN / EIN |
| SECONDARY APPLICANT'S ADDRESS | |

Hereby declares under penalty of perjury that he / she is the lawful (owner / purchaser / lien holder) of the following described motor vehicle and hereby makes application for the following:

☐ ORIGINAL CERTIFICATE OF TITLE Evidence of ownership ____________
MCO, Previous Title No., Registration, etc.

Applicant acquired said motor vehicle by (state how acquired) ____________

from: Name of Previous Owner ____________ Is Seller a Minor? ☐ Yes ☐ No

Address of Previous Owner ____________

The following is a full statement of all liens on said motor vehicle. If no lien state "none", if more than one lien, attach statement **of all additional liens**.

Lien Holder ____________ /E Code # ____________ Address ____________

☐ DUPLICATE CERTIFICATE OF TITLE

Applicant states that Certificate of Title Number ____________ has been ____________ ;
that said motor vehicle has not been sold or disposed of except as stated below: lost, stolen, destroyed

The vehicle is in the possession of ____________

residing at ____________ and that if said Certificate of Title be hereby recovered by this applicant he will deliver same to the Clerk of Courts for cancellation.

The following is a full statement of all liens on said motor vehicle. If no lien state "none", if more than one lien, attach statement **of all additional liens**.

Lien Holder ____________ /E Code # ____________ Address ____________

☐ REPLACEMENT CERTIFICATE OF TITLE for Certificate of Title Number ____________

☐ ...RANDUM CERTIFICATE OF TITLE for Certificate of Title Number ____________

...FICATE OF TITLE
...e original Certificate of Title Number ____________
...he Clerk of Courts.

BODY TYPE

PURCHASE PRICE
$

TAX PAID
$

VENDOR'S NU...

| | | | |
|---|---|---|---|
| VIN | | MODEL | |
| MAKE | | CONVERSION | |
| TRADE IN ALLOWANCE $ | GROSS TAX DUE $ | VENDOR'S DISCOUNT $ | |
| TAX EXEMPTION ☐ Yes REASON: | | DEALER'S PERMIT NUMBER | |
| CONDITION OF VEHICLE, WATERCRAFT, or OUTBOARD MOTOR (Check only one) ☐ Good ☐ Fair ☐ Poor ☐ Wrecked | | | |

...o state the true selling price. A false statement is in violation of section 2921.13 of the Ohio Revised Code and is punishable by ...ne of up to one thousand dollars or both. All transfers are audited by the Department of Taxation. The seller and buyer must ...sted by the Department of Taxation. The buyer may be assessed any additional tax found to be due.

...re X ____________ Is Applicant a Minor? ☐ Yes ☐ No

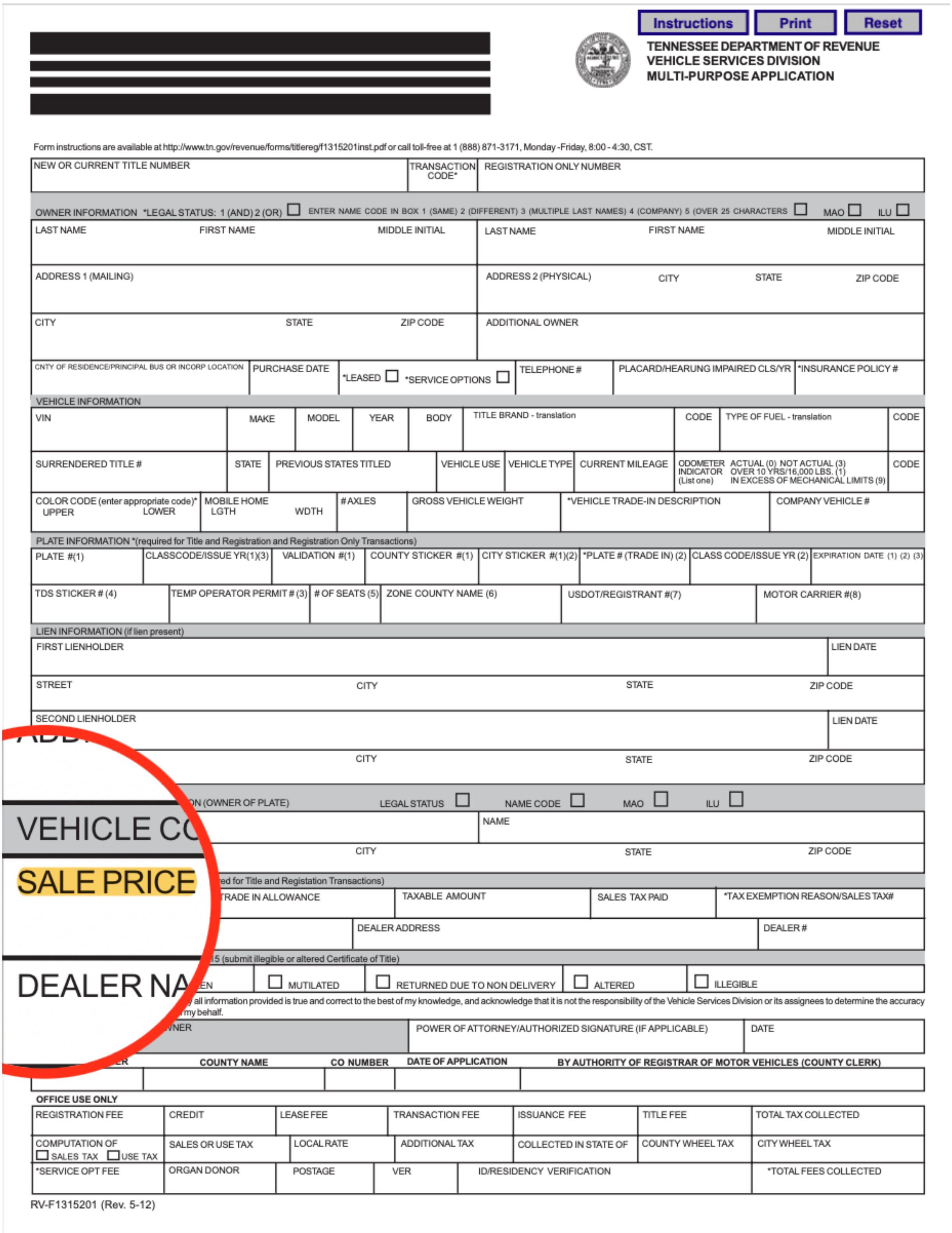
Sworn to and subscribed in my presence this _______ day of____________, 20 ____ in ____________County, State of ____________.

(Notary Seal)

X ____________ My commission expires ____________

Signature of Notary Public or other Authorized Officer by law

BMV 3774 11/21 [17601081]



Instructions | Print | Reset

[redacted]

TENNESSEE DEPARTMENT OF REVENUE
VEHICLE SERVICES DIVISION
MULTI-PURPOSE APPLICATION

Form instructions are available at http://www.tn.gov/revenue/forms/titlereg/f1315201inst.pdf or call toll-free at 1 (888) 871-3171, Monday-Friday, 8:00 - 4:30, CST.

NEW OR CURRENT TITLE NUMBER | TRANSACTION CODE* | REGISTRATION ONLY NUMBER

OWNER INFORMATION *LEGAL STATUS: 1 (AND) 2 (OR) ☐ ENTER NAME CODE IN BOX 1 (SAME) 2 (DIFFERENT) 3 (MULTIPLE LAST NAMES) 4 (COMPANY) 5 (OVER 25 CHARACTERS ☐ MAO ☐ ILU ☐

LAST NAME | FIRST NAME | MIDDLE INITIAL | LAST NAME | FIRST NAME | MIDDLE INITIAL

ADDRESS 1 (MAILING) | ADDRESS 2 (PHYSICAL) | CITY | STATE | ZIP CODE

CITY | STATE | ZIP CODE | ADDITIONAL OWNER

CNTY OF RESIDENCE/PRINCIPAL BUS OR INCORP LOCATION | PURCHASE DATE | *LEASED ☐ *SERVICE OPTIONS ☐ | TELEPHONE # | PLACARD/HEARUNG IMPAIRED CLS/YR | *INSURANCE POLICY #

VEHICLE INFORMATION

VIN | MAKE | MODEL | YEAR | BODY | TITLE BRAND - translation | CODE | TYPE OF FUEL - translation | CODE

SURRENDERED TITLE # | STATE | PREVIOUS STATES TITLED | VEHICLE USE | VEHICLE TYPE | CURRENT MILEAGE | ODOMETER INDICATOR (List one) ACTUAL (0) NOT ACTUAL (3) OVER 10 YRS/16,000 LBS. (1) IN EXCESS OF MECHANICAL LIMITS (9) | CODE

COLOR CODE (enter appropriate code)* UPPER LOWER | MOBILE HOME LGTH WDTH | # AXLES | GROSS VEHICLE WEIGHT | *VEHICLE TRADE-IN DESCRIPTION | COMPANY VEHICLE #

PLATE INFORMATION *(required for Title and Registration and Registration Only Transactions)

PLATE #(1) | CLASSCODE/ISSUE YR(1)(3) | VALIDATION #(1) | COUNTY STICKER #(1) | CITY STICKER #(1)(2) | *PLATE # (TRADE IN) (2) | CLASS CODE/ISSUE YR (2) | EXPIRATION DATE (1) (2) (3)

TDS STICKER # (4) | TEMP OPERATOR PERMIT # (3) | # OF SEATS (5) | ZONE COUNTY NAME (6) | USDOT/REGISTRANT #(7) | MOTOR CARRIER #(8)

LIEN INFORMATION (if lien present)

FIRST LIENHOLDER | LIEN DATE

STREET | CITY | STATE | ZIP CODE

SECOND LIENHOLDER | LIEN DATE

ADD… | CITY | STATE | ZIP CODE

VEHICLE CO…N (OWNER OF PLATE) | LEGAL STATUS ☐ | NAME CODE ☐ | MAO ☐ | ILU ☐

NAME

CITY | STATE | ZIP CODE

SALE PRICE …ed for Title and Registation Transactions)

…TRADE IN ALLOWANCE | TAXABLE AMOUNT | SALES TAX PAID | *TAX EXEMPTION REASON/SALES TAX#

DEALER NA… | DEALER ADDRESS | DEALER #

…5 (submit illegible or altered Certificate of Title)

…EN ☐ MUTILATED ☐ RETURNED DUE TO NON DELIVERY ☐ ALTERED ☐ ILLEGIBLE

…all information provided is true and correct to the best of my knowledge, and acknowledge that it is not the responsibility of the Vehicle Services Division or its assignees to determine the accuracy …my behalf.

…WNER | POWER OF ATTORNEY/AUTHORIZED SIGNATURE (IF APPLICABLE) | DATE

…ER | COUNTY NAME | CO NUMBER | DATE OF APPLICATION | BY AUTHORITY OF REGISTRAR OF MOTOR VEHICLES (COUNTY CLERK)

OFFICE USE ONLY

REGISTRATION FEE | CREDIT | LEASE FEE | TRANSACTION FEE | ISSUANCE FEE | TITLE FEE | TOTAL TAX COLLECTED

COMPUTATION OF ☐ SALES TAX ☐ USE TAX | SALES OR USE TAX | LOCAL RATE | ADDITIONAL TAX | COLLECTED IN STATE OF | COUNTY WHEEL TAX | CITY WHEEL TAX

*SERVICE OPT FEE | ORGAN DONOR | POSTAGE | VER | ID/RESIDENCY VERIFICATION | *TOTAL FEES COLLECTED

RV-F1315201 (Rev. 5-12)

# Application for Texas Title and/or Registration

Applying for (please check one):
☐ Title & Registration ☐ Title Only ☐ Registration Purposes Only ☐ Nontitle Registration

For a corrected title or registration, check reason:
☐ Vehicle Description ☐ Add/Remove Lien ☐ Other:

TAX OFFICE USE ONLY
County:
Doc #:
☐ SPV ☐ Appraisal Value $

1. Vehicle Identification Number | 2. Year | 3. Make | 4. Body Style | 5. Model | 6. Major Color | 7. Minor Color

8. Texas License Plate No. | 9. Odometer Reading (no tenths) | 10. This is the Actual Mileage unless the mileage is: ☐ Not Actual ☐ Exceeds Mechanical Limits ☐ Exempt | 11. Empty Weight | 12. Carrying Capacity (if any)

13. Applicant Type
☐ Individual ☐ Business ☐ Government ☐ Trust ☐ Non-Profit

14. Applicant Photo ID Number or FEIN/EIN

15. ID Type ☐ U.S. Driver License/ID Card (issued by: ) ☐ NATO ID ☐ U.S. Dept. of State ID
☐ Passport (issued by: ) ☐ U.S. Military ID ☐ U.S. Dept. of Homeland Security ID
☐ U.S. Citizenship & Immigration Services/DOJ ID ☐ Other Military Status of Forces Photo ID

16. Applicant First Name (or Entity Name) | Middle Name | Last Name | Suffix (if any)

17. Additional Applicant First Name (if applicable) | Middle Name | Last Name | Suffix (if any)

18. Applicant Mailing Address | City | State | Zip | 19. Applicant County of Residence

20. Previous Owner Name (or Entity Name) | City | State | 21. Dealer GDN (if applicable) | 22. Unit No. (if applicable)

23. Renewal Recipient First Name (or Entity Name) (if different) | Middle Name | Last Name | Suffix (if any)

24. Renewal Notice Mailing Address (if different) | City | State | Zip

25. Applicant Phone Number (optional) | 26. Email (optional) | 27. Registration Renewal eReminder ☐ Yes (Provide Email in #26) | 28. Communication Impediment? ☐ Yes (Attach Form VTR-216)

29. Vehicle Location Address (if different) | City | State | Zip

30. Multiple (Additional) Liens ☐ Yes (Attach Form VTR-267) | 31. Electronic Title Request ☐ Yes (Cannot check #30) | 32. Certified/eTitle Lienholder ID Number (if any) | 33. First Lien Date (if any)

Mailing Address | City | State | Zip

Yes (Comp

MOTOR VEHICLE TAX STATEMENT

ermit No. and will satisfy the minimum tax liability (V.A.T.S., Tax Code §152.046[c])

ck only if appl

e the Fair Market Value Deduction (V.A.T.S., Tax Code, §152.002[c]). GDN or Lessor Number

Make | Vehicle Identification Number | 37. Additional Trade-In(s) ☐ Yes

SALES AND USE TAX COMPUTATION

) Sales Price ($

) Less Trade-in

) For Dealers

Deducti

s been deducted) $ | ☐ $90 New Resident Tax – (Previous State)
36 above $ ( ) | ☐ $5 Even Trade Tax
r Market Value | ☐ $10 Gift Tax – Attach Comptroller Form 14-317
$ ( ) | ☐ $65 Rebuilt Salvage Fee
b or Item c) $ | ☐ 2.5% Emissions Fee (Diesel Vehicles 1996 and Older > 14,000 lbs.)
tiply Item d by .0625) $ | ☐ 1 % Emissions Fee (Diesel Vehicles 1997 and Newer > 14,000 lbs.)
or ☐ 10% $ | ☐ Exemption claimed under the Motor Vehicle Sales and Use Tax Law because:
(STATE) $
LTY DUE | ☐ $28 or $33 Application Fee for Texas Title
s Item g) $ | (Contact your county tax assessor-collector for the correct fee.)

CERTIFICATION – State law makes falsifying information a third degree felony

I hereby certify all statements in this document are true and correct to the best of my knowledge and belief, and I am eligible for title and/or registration (as applicable).
☐ (Check only if applicable) I certify I am applying for a corrected title and the original Texas Certificate of Title is lost or destroyed.

Signature(s) of Seller(s), Donor(s), or Trader(s) | Printed Name(s) (Same as Signature(s)) | Date

Signature of Applicant/Owner | Printed Name (Same as Signature) | Date

Signature(s) of Additional Applicant(s)/Owner(s) | Printed Name(s) (Same as Signature(s)) | Date

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## Appendix B: MarketCheck High Value Features

3rd Row Seats, 4-Wheel Steering, Adaptive Cruise Control, Android Auto, Anti Collision System, Apple CarPlay, Automatic Transmission, Autonomous Drive Functions, Aux Jack Input, Backup Camera, Biodiesel, Blind Spot System, Bluetooth, Brake Assist, CVT Transmission, Collision/Breakdown Telematics, Coming Home Device, Compressed Natural Gas, Concierge Services, Convertible Roof, Cruise Control, Diesel, Directional Headlights, Dual Rear Wheels, Dynamic Steering, Electric, Fog Lights, Gasoline, HDMI Connection, Hands Free Liftgate, Heads Up Display, Heated Door Locks, Heated Door Mirrors, Heated Seats, Heated/Cooled Seats, Hybrid, Keyless Entry/Locking, Keyless Start/Remote Engine Start, LPG, Lane Keep Assist, Leather Seats, Leatherette Seats, Long Pickup Bed, Manual Transmission, Massage Seats, Memory Mirrors, Memory Seats, Memory Steering Wheel Position, Mirrorlink, Navigation, Panoramic Sun/Moonroof, Parking Assistance, Parking Distance Sensors, Parking Radar, Parking distance system, Phone Integration, Pickup Bed Cover, Pickup Bed Extender, Pickup Bed Liner, Plug-in Hybrid, Power Closing Doors, Power Closing Liftgate, Premium Audio, Premium Cup Holders, Premium Wheels, Rear/Multi-Zone Air Conditioning, Regular Pickup Bed, Satellite Radio, Short Pickup Bed, Steering Wheel Controls, Sun/Moonroof, Touch Screen, Touch Screen Audio, Trailer Assist, Trailer Tow Mirrors, Turbo Boost, USB Connection, Video Entertainment, Voice Recognition, Voice Recognition, WiFi Hotspot, Wireless Charging/Connection