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## Residual Car Values Forecasting Using AutoCycle™

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**Prepared by**

**Tony Hughes**  
[Tony.Hughes@moodys.com](mailto:Tony.Hughes@moodys.com)  
Managing Director  
Specialized Modeling

**Zhou Liu**  
[Zhou.Liu@moodys.com](mailto:Zhou.Liu@moodys.com)  
Director  
Credit Analytics

**Pedro Castro**  
[Pedro.Castro@moodys.com](mailto:Pedro.Castro@moodys.com)  
Senior Economist  
Credit Analytics

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**Contact Us**

Email  
[help@economy.com](mailto:help@economy.com)

U.S./Canada  
+1.866.275.3266

EMEA (London)  
+44.20.7772.5454  
(Prague)  
+420.224.222.929

Asia/Pacific  
+852.3551.3077

All Others  
+1.610.235.5299

Web  
[www.economy.com](http://www.economy.com)

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**Abstract**

Moody's Analytics has gained substantial expertise in auto finance over the past several decades. Our client base in the area includes a number of captive auto lenders and large banks with considerable exposures to loan and lease portfolios. We have helped our clients forecast their portfolio losses and conduct stress tests both for regulatory compliance and to help managers attempting to enhance the risk profile of their businesses. Ask us what drives auto loan or lease losses, how supply-side dynamics in the market for used cars affect loss given defaults in recessions, or about the payment hierarchy used by distressed consumers, and we will give you a detailed and, we hope, persuasive explanation.

# Residual Car Values Forecasting Using AutoCycle™

BY TONY HUGHES, ZHOU LIU AND PEDRO CASTRO

## 1. Introduction

Moody's Analytics has gained substantial expertise in auto finance over the past several decades. Our client base in the area includes a number of captive auto lenders and large banks with considerable exposures to loan and lease portfolios. We have helped our clients forecast their portfolio losses and conduct stress tests both for regulatory compliance and to help managers attempting to enhance the risk profile of their businesses. Ask us what drives auto loan or lease losses, how supply-side dynamics in the market for used cars affect loss given defaults in recessions, or about the payment hierarchy used by distressed consumers, and we will give you a detailed and, we hope, persuasive explanation.

In the past few years, this expertise has extended to the question of forecasting residual vehicle value. When it comes to the valuation of individual vehicles or fleets of similar vehicles, myriad factors come into play. Whether a purely quantitative, data-driven approach to the problem can defeat a car expert whose job depends on understanding fine differences between competing brands is an empirically verifiable question. In many fields such as medical diagnosis, baseball talent scouting, and loan underwriting, purely quantitative approaches have been found to compete very favorably with expert-driven analysis (often to the chagrin of the experts themselves). On the one hand, a human observer will at least be able to form an opinion about whether the redesigned brake lights on a Dodge Durango will lead to increased sales to 20-something

women. Whether this opinion leads to a more accurate forecast of Durango sales and prices, however, or whether the opinion has economic value that exceeds the cost of obtaining the prediction is an open question. Awareness of some car features, unseen by the statistical model, may well add value. Many will not.

As economists, we would be highly impertinent to try to educate our clients in the auto industry about the value of different vehicle features. Our talents lie in understanding aggregate supply and demand conditions in the economy and in building statistical models that accurately capture and project these effects. Although it is very difficult to identify the effect of macro swings on individual entities (individual borrowers or the price of a specific vehicle, for example), we have developed statistical approaches that rely on share-down procedures from more aggregated specifications that enable us to accurately model and predict such effects. Current approaches to used-vehicle valuation combine statistical modeling with subjective expert overlay; we are unaware of any available car price forecasting tool that is, by contrast, purely quantitative in nature.

The institution of stress-testing has unearthed a need for these kinds of analytics related to used-car valuation. Regulators require banks to be able to model the behavior of their portfolios under a variety of external macroeconomic stress environments. They need to do this with a high level of granularity so that they can potentially identify small pockets of elevated risk. More important, banks are required to do this in a way that

enables the entire process to be externally validated. Models must be carefully assessed and fully understood by internal bank users. Subjective overlays to model projections must be made explicit and, if required, be defended against criticism from senior managers and external assessors. Stress-test processes must be repeatable and fully documented so that the process can survive potential staffing upheavals.

Though purely quantitative models are required for regulatory stress-testing, we believe that such approaches could find broader favor with anyone with an interest in accurate used-car price projections. Even if it is found that expert assessment yields more accurate projections than the "brute force" econometric methodology, access to the model may still provide many benefits. Because the statistical approach boils down to a set of equations describing the process by which forecasts are generated, it is possible for a somewhat math-savvy user to understand exactly how the projection was computed and how forecasts will change given different inputs. This is not possible if the "baseline" projections already include a subjective component.

The pure statistical model gives users a clean canvas upon which they can apply their own subjective overlay. If the canvas already embodies someone else's views, it is more difficult to render the colors correctly. In most cases, users of the model will be car industry experts who know their product (and its competitors) better than anyone else on the planet. Whether these individuals would benefit from the competing opinion of an al-

ternative car industry expert, probably with less insider knowledge, is highly debatable.

Our view is that an industry expert armed with a pure statistical model will do a better job than an expert without a model or a model without an expert.

Other benefits will also accrue to the users of a purely quantitative pricing methodology. Such projections will allow them to benchmark, corroborate or refute existing forecasts. This will be done at relatively low cost and from a distinct methodological vantage point. Users may also gain insight into new sectors of the marketplace—areas where they may lack insider expertise. Users will increase their understanding of macroeconomic drivers and the effect of adverse economic conditions on valuations as well.

In this paper, we will introduce the methodology we have applied to the problem of wholesale vehicle valuation. We will describe our approach, the modeling methods used to develop the projections, and the data employed for this purpose, and we will provide case studies showing recent price projections.

## 2. Data Description and Analysis

The data we employ to build our models are sourced from Auction Net, a database maintained by the National Automobile Dealers Association. Information is collected regarding actual results of wholesale vehicle auctions. The data are not provided at the transaction level; rather, they represent averages of transactions occurring in the same month and involving vehicles

that share similar characteristics, such as make, model, vehicle year, vehicle trim, style, fuel type and body type. Among other variables, we observe the number of transactions being aggregated, the standard deviation of the sales prices in those transactions, and the average actual transaction price.

The original dataset classifies the vehicles in 25 segments. Because some segments have thin data, we opted to reclassify the vehicles into 16 categories. For example, the Premium Luxury Large segment was found to have few elements, so we merged the data into a broader Luxury segment. Our view is that, in general, it is reasonable to believe that vehicles within a given segment will generally respond to macroeconomic shocks in a homogeneous manner.

The original dataset contains transactions from January 1995 to December 2014 for vehicles from years 1989 to 2014. Although in principle we thought of using the whole dataset, we used only transactions that occurred no earlier than March 1996 and vehicles from year 1997 or later. This was mainly to make sure we have a full life cycle of transactions for each vehicle-model year pair in our dataset. Also, models from before 1997 become increasingly less relevant, as they are increasingly different from more recent models.

The other important dimension is the make of the vehicle. The original dataset had 44 makes. Several makes with a small number of transactions were aggregated into an "Other" category, and in a few cases two

or more makes were merged into a single category (for example, Dodge and Dodge Truck became only Dodge). After these adjustments, the estimation dataset had 31 makes.

The two final dimensions we should mention are fuel type and

body type. Fuel type can take six different values (gasoline, ethanol, natural gas, hybrid, diesel and electric) and is overwhelmingly represented by gasoline. Despite the small variability of fuel types in the data, we decided to keep this dimension because of its increasing relevance in the auto market and because it is a key dimension to assess the relative prices of vehicles when there is a large variation in fuel prices.

Our final dataset contains observations for transactions corresponding to vehicles and model years over time, where a vehicle is defined as a combination of make, model, fuel type and body type.<sup>1</sup> Examples are 2014 Acura IXL gas sedan or 2012 Honda Accord gas coupe.

## 3. Factors Driving Price Change

To reiterate, the Moody's Analytics methodology to forecast used-car prices stands out among those of competitors as largely quantitative and wholly transparent. More specifically, we build a multivariate econometric model to establish the relationship between used-car prices and various internal and external drivers. The price depreciation process of a new car, in a nutshell, is driven by vehicle-level depreciation and dynamics in used-car markets.

### 3.1. Modeling Age and Mileage

Depreciation at specific vehicle level is mainly driven by wear and tear or physical depreciation and by the fact that the particular model gradually becomes overshadowed by new technology installed in more recent models. Physical depreciation is quantified by mileage, that is, how intensively a car has been driven. Temporal depreciation can be proxied by age or how many years since the model entered the market. Statistically, age and mileage are highly correlated, as older cars are generally associated with higher mileages. We include both variables in the equation nevertheless because conceptually they measure two distinct driving forces behind depreciation. For example, ignoring some antique cars that are bought as a form of investment, a

<sup>1</sup> There are 1,196 different vehicles in our final dataset.

### Chart 1: Auction Prices

2000 Toyota Corolla gas sedan, baseline (spliced), \$



Source: Moody's Analytics

car would devalue over time even if it never hits the road.

It is commonly perceived that new cars depreciate faster than old cars. As an illustration, Chart 1 shows the depreciation curve for a 2000 Toyota Corolla sedan. The graph shows different depreciate rates across the life cycle of the model, with the fastest depreciation taking place in the first few years. More specifically, we typically observe around 20% value loss in the first year, and about 15% annually in the second and third year. After five to six years, the slope becomes less steep. Based on the depreciation curve, we posit that age and mileage affect price change in a nonlinear way.

Because the initial sale date of cars is generally not available in our database, age can be quantified only on an annual basis. Given this constraint, we approximate age as the difference in years between the auction date of a used car and vehicle model year. The measurement in annual frequency implies that the variable takes (integer) values from zero to 18. The small number of distinctive age values renders it possible to assume a different effect for each age. In econometric terms, we model the life cycle simply by including 18 indicator variables, one for each observed age.

Since the mileage variable takes continuous values, we employ a different approach. We use cubic splines to approximate the nonlinear relationship between used-vehicle value and mileage. The cubic spline is a parsimonious yet effective way to capture nonlinear relationships. It is defined to be a continuous smooth function that is linear before the first knot, a piecewise cubic polynomial between adjacent knots, and linear again after the last knot.

Intuitively, not all cars with the same age and mileage depreciate at the same rate. The rates presumably vary across make and model. For example, valuable brands with high demand boast better resale values in the secondary market, holding other factors constant. Some manufacturers opt out of fleet sales, and the strategy might work to their advantage in terms of the retention of values in used-car markets. We further allow for the effects of age and mileage to differ

across make and model. Other characteristics of cars can be reasoned to explain resale value as well. For example, preownership may make a difference in the condition of used cars, as lessees tend not to look after their cars in the same way as those seeking to own their car outright.

### 3.2. Macroeconomic Drivers

All vehicle prices fluctuate with dynamics in used-car markets where laws of supply and demand naturally apply. Industry-level market forces, in their turn, are shaped by the broader economy, which can be proxied by various macroeconomic indicators. The question of how we are able to identify the most relevant drivers arises given that there are numerous available indicators of macroeconomic condition. One solution is to rely on an automated variable-selection process. A blanket search can be unjustifiably costly, considering the significant amount of time required to cycle through a large set of variables. More important, testing irrelevant factors needlessly increases the probability of capturing chance relationships. These random relationships cannot be reasonably explained and therefore likely indicate coincidences that will not repeat themselves. Our endeavor to alleviate this confusion manifests itself in our leveraging economic theory at the start of the analysis to filter out variables that are counter or marginally productive for our purposes. The final candidate pool consists of 20 variables. The variables we have identified can be roughly classified to four categories, including indicators for the auto market (both supply and demand), household finances and labor markets, interest rates, and gas prices.

Almost all supply forces can be exclusively identified with the auto market specific variables. An increase in new-car sales will lead to a higher supply of late models in the secondary markets in coming months, and more supply will tend to depress used-car prices. Equally predictable is the inter-temporal relationship between lease originations and market entry of used cars. Lessees can decide whether to return the car at the maturity date of the lease. The vehicles that are returned will find their way into secondary

markets. The impact of lease return can be best evidenced by the outstanding concern in the industry that used-car prices will trend lower in coming quarters on the heels of too many cars coming off lease. Therefore, we posit that lease originations lagged by 36 months, the most popular lease term, might hold greater explanatory power for used-car price changes occurring today.

Moreover, the auto inventory-to-sale ratio and stock of cars presumably move the supply curve, too. Lower turnover indicates slow sales, causing pressure on manufacturers to slash prices or offer incentives on new cars. Cheaper new cars put a brake on the growth in used-car prices, as new and used cars are close substitutes. Besides the substitution effects, there is also an income effect at work between the two markets. For example, if new-car sales are driven by fundamentals, these forces should be mirrored somewhat in associated used-car markets. Strong vehicle sales growth is generally associated with used-car price acceleration.

The Manheim used-car price index is a widely used industry benchmark for used-car prices. Partly because of the fact that the index is based exclusively on sales at Manheim Auto Auctions, it falls short of a universal gauge and is not expected to provide adequate explanatory power, especially for used-car prices auctioned elsewhere. That said, the Manheim is considered to be the most important indicator of used-vehicle dynamics at the industry level.

Demand-side factors manifest themselves through consumer preferences and the overall level of demand in the economy. The condition of labor markets is the bellwether of how consumers are faring. For this reason, the unemployment rate and total employment growth are included in the candidate variable list. The consumer confidence index is another prominent measure, as it gauges the willingness of households to make purchases of durable goods such as vehicles. Variables that describe income and household balance sheets are also important for this reason. We find factors such as the debt service burden and growth of personal disposable income to be important demand-side drivers of behavior.

The third group, also pertaining to the demand side, covers various interest rates. Lower rates mean lower credit and lower interest payments. These forces induce consumers to spend more on big-ticket items requiring financing. On the other hand, lower rates indicate that the Federal Reserve considers that there is a significant amount of slack in the economy. A weak economy is overall a negative factor to car consumption, so we must take pains to ensure that any rate variables used are interpreted carefully.

Gas prices, the final category, play a big role in auto purchase decisions. We view such prices as being the key driver of the relative cost of vehicle ownership. It is well known that as gas prices rise, demand for hybrid vehicles and other fuel-efficient models tends to be well-supported, while light trucks and large SUVs typically take a price hit.

The contemporaneous relationships between macroeconomic environments and used-car prices are readily established because of temporal proximity. For example, a tightening of credit conditions will soon be followed by falling auto purchases. Other than the concurrent relationships, macroeconomic conditions at the time when the particular model enters the market have a bearing on the subsequent price depreciation schedule. When the economy is booming, consumers can better afford expensive add-on equipment, which might not retain much value in secondary markets.

### 3.3. Stress-Testing

An important objective of our model is stress-testing. Given that there is much more perceived volatility in the economy than before the Great Recession, Moody's Analytics produces a number of alternative economic scenarios each month to address our clients' concern of uncertainties. The model is able to stress-test used-car prices by plugging in the respective values of the macroeconomic drivers under alternative scenarios.

As in any other exercise, we develop hypotheses based on economic theory before we perform any empirical analysis to avoid pure data mining. Above all, do we expect used-car prices to rise or fall under recession? Used-car markets, unlike those

for new cars, are countercyclical because of the interplay of income and substitution effect between new and used cars mentioned above. Consumers purchase fewer cars when they are financially strained and not optimistic about their job prospects. On the other hand, when they need to buy a car they are more inclined toward a used one. Whether the used-car markets will receive a net gain from recession depends on which force gains the upper hand. The tension between income and substitution effect is similar to that observed in residential rental markets. A mild recession helps landlords, as those who cannot afford to buy a home turn to rent. However, as recession goes deeper, apartment buildings suffer, too, when people significantly retrench their budget on housing.

### 3.4. Capturing Different Responses Across Cars

Another related issue to contemplate is that cars are not created equal when facing changes in macroeconomic environments. Take as an example the recent plunge in oil prices. Crude oil prices are almost half of what they were one year ago. Lower gas prices provide auto sales with a huge boost as a whole. Within the industry, large cars receive a disproportionately bigger benefit at the expense of small cars. The reverse was true in 2008, when gas prices at one time exceeded \$4 a gallon and demand for trucks took a nosedive. Another example would be so-called performance vehicles such as Jeep Wrangler. Our hypothesis is that these cars should fall more into the discretionary category on consumers' wish lists and, consequently, their sales would suffer a bigger hit when consumers pare back their spending. Recession should drive a similar wedge between economy cars and luxury cars.

Our model takes into account different responses by allowing for different sensitivities, or in econometric terms, different slopes on macroeconomic variables across cars. Now the question arises as to what level of heterogeneity in sensitivity the model should capture. At one extreme, we can assume that different responses at a very fine level—say, the 2005 and 2006 Jeep Cherokee—change

with economics in different ways. Intuitively, the assumption is overly strict, as the intersegment heterogeneity is supposedly not significant enough to be worth modeling at the expense of efficiency. Statistically, such granularity would lead to a very complicated and superfluous model, which may well lead to over-fitting.

Our current solution is to assign cars to 16 segments and allow for different sensitivities to macro variables across the segments. They are compact, compact SUV, large car, large pickup, large SUV, large van, luxury, luxury midsize, luxury utility, midsize pickup, midsize SUV, midsize van, midsize car, near-luxury, sports and subcompact.

### 3.5. Consideration of Conflict Between Objectives

There is a tension between the dual purposes of the model, namely, accurate forecasting and plausible stress-testing. For one thing, parsimony is a golden principle of forecasting models. In other words, the model should try to include fewer explanatory variables, given similar model performance. On the other hand, a stress-testing model is only as informative and useful as it is realistic and comprehensive. More specifically, in order to differentiate the impacts of alternative stress scenarios, it is necessary to include multiple variables that capture various segments of the economy where shocks likely come from. Let's visualize two recessions of the same severity in terms of their damage to GDP and employment. One is driven by oil-price shocks and the other by the Federal Reserve's mishandling of its interest rate policies, such as by raising rates too fast and too much. We expect these two stress scenarios have very different implications for used cars and, for that matter, for various subsegments of the markets. The model will not be able to capture the nuances of these scenarios unless we explicitly include gas prices and interest rate variables as drivers of the model. Taking a panoramic view of the economy is critical for sophisticated stress-testing exercises to yield reasonable results, but we need to balance the requirement of inclusiveness with the parsimony principle of accurate forecasting.

#### 4. Model Estimation

The final dataset used for the model estimation has a panel format where the different panel units correspond to vehicles from a specific year. Using our vehicle definition, that means our panel units are identified by unique combinations of make/model/fuel type/body type/model year; for example, 2013 Honda Accord gas sedan and 2010 Jeep Wrangler gas utility are two panel units in our final dataset.

We end up with 6,310 panel units in the estimation dataset. Given that the first vehicle model year we consider is 1997 and the last transaction period we observe is December 2014, we can observe a panel unit for a maximum of 216 periods (12 months per year times 18 years). This means our final dataset is significantly longer in the panel dimension than in the time dimension. Moreover, our panel dataset is unbalanced; as time passes, new model years enter the dataset when new model years come to the market and others leave as transactions for some model years stop being observed. Model years that entered the dataset later will have transaction data available for a smaller number of periods.

Finally, there are different combinations of make/model/fuel type/body type entering and leaving the dataset over time. Two main factors cause this; the first relates to the existence of the vehicle and the second concerns the existence of a transaction that was recorded.

Regarding the first factor, imagine if Toyota decided to stop producing the Camry gas sedan in 2010. That means we would not be able to observe transactions for those vehicles in model years 2011, 2012, 2013 and 2014; they would not exist. Similarly, if Hyundai started to produce a new vehicle X in 2010, then we potentially would be able to observe transactions for the Hyundai X model years 2010, 2011, 2012, 2013 and 2014, but not for any model year prior to 2010, since that vehicle would not have existed before that.

The second factor is similar to the first one but relates to the limitations of our dataset. Although a specific model year may have been produced and sold, in some

cases no transaction was recorded for that model year. For example, we may observe transactions for model year 2010 and 2012 but not for model year 2011. That would be a relatively extreme case. A potentially less problematic (but also more frequent) variation of this problem occurs when we observe transactions for a model year but not continuously over time. For example, we may observe transactions for a vehicle for a given number of months, then we do not for some months and, a few months later, we observe transactions for that vehicle again. Our dataset is very rich and covers approximately 80 million transactions, but we still have to deal with several cases of “missing data.”

We end up with what is known as an unbalanced panel dataset with gaps. The next steps are, in this order, the choice of an estimation method and of a functional form. We discuss the different possibilities available to us in the next paragraphs.

A commonly used technique for panel dataset models is the fixed effects estimator. In principle, explicitly including vehicle-specific effects would be appropriate (remember, each vehicle is defined as a unique combination of make/model/fuel type/body type/model year). There is one big problem, though. We want to forecast “future vehicles,” for example, we want to generate forecasts for the 2017 Hyundai Sonata gas sedan or the 2016 GM Impala gas sedan. Since these vehicles do not exist yet, they are not in our estimation dataset. We would not be able to estimate their fixed effects and, therefore, a fixed effects model would not allow us to forecast their future price. Given that forecasting existing and future vehicles is our main goal, we eliminate the fixed effects estimator from our list of possible choices. Once we decided to not use the fixed effects estimator, we were left with two other commonly used options, the random effects estimator and the pooled ordinary least squares estimator. We chose the latter option; our judgment is that this choice makes the model easier to understand and more accessible to a wider audience. On the downside, we might have some efficiency loss, but we feel that is a cost worth paying. Finally, to address possible concerns about

omitted variables, we add dummy variables to capture make/model/fuel type/body type-specific effects; this would be effects that are time-invariant and common across different model years (for example, ones that are common to Honda Civic gas coupe of different model years).

The second choice we have to make concerns the functional choice we use. Our dependent variable is defined as the ratio of the used-car price to manufacturer’s suggested retail price. As expected, this variable is mostly between 0 and 1; more specifically, it is above 1 for 0.1% of all our observations and never negative. We considered three functional forms—linear, logarithmic and logit—and three main concerns guided our choice. Is the functional form well-defined? Does the functional form generate reasonable forecasts? Is the functional form easy to interpret? We analyze these three points separately.

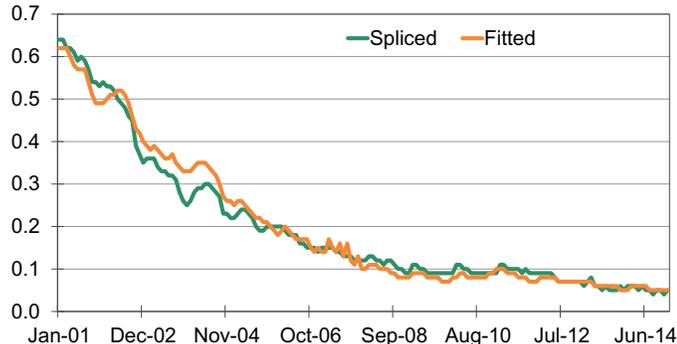
The first concern does not place a significant restriction on our choices; all the three functional forms can handle the values taken by our dependent variables. The logit transformation does not handle values above 1, but we are willing to ignore 0.1% of our observations if it is the best overall.

The second requirement plays a key role in our choice. If we used the linear transformation we could end up with forecasts that are either negative or above 1, something that we definitely want to avoid. If instead we used the log transformation, then we would not get negative forecasts, but we could still get some forecasts above 1. The only functional form that ensures all the forecasts are within the unit interval is the logit regression, so it is clearly the winner here.

Our third concern is about interpretation. The linear regression is easy to interpret, but the linear relationship between the dependent and the independent variables can generate counterintuitive predictions. In particular, it implies that the absolute change in the price-to-MSRP ratio will always be the same given a variation in the independent variables. This can be counterintuitive in some cases. It is arguably a quite different effect if the price-to-MSRP ratio goes down by 0.1 if it is 0.9 or 0.2. The logarithmic trans-

**Chart 2: Price-to-MSRP Ratio**

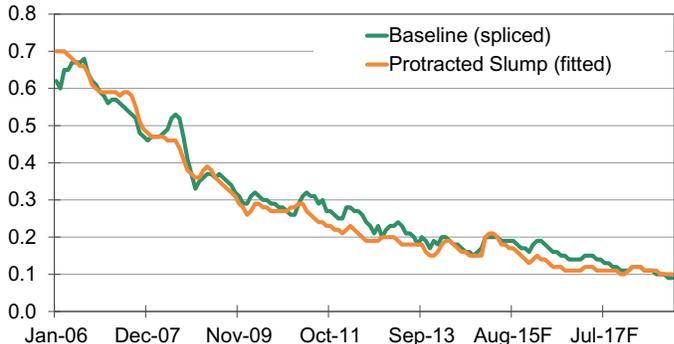
2001 Ford Taurus gas sedan, baseline



Source: Moody's Analytics

**Chart 3: Price-to-MSRP Ratio**

2006 Ford Focus gas sedan



Source: Moody's Analytics

formation is particularly intuitive, since the coefficients are interpreted as the percentage change in the dependent variable for a given change in the independent variables. It is more reasonable to think that the price-to-MSRP ratio will go down by 10%, whether it is initially equal to 0.9 or 0.2, given a change in the explanatory variables. The logit transformation is not as easy to interpret as in the logarithm, but it also shares the nonlinear relationship between the explanatory variables and the price-to-MSRP ratio.

Given the different considerations about the functional options available, we chose the logit transformation; the need to ensure that our forecasts consistently fall within the unit interval was a key element in that decision.

After we chose the estimator and the functional forms, we had to define the appropriate variables to capture the different aspects of the used-car price dynamics. The first set of variables included in the model are intended to capture the age of the car and usage as measured by mileage. We explicitly model the heterogeneity in the relationship between used-car prices and age or mileage for different brands and segments. Moreover, we capture the interaction between mileage and age; in particular, differences in mileage tend to be more important for newer cars. The second set of variables are intended to capture the effect of the macroeconomic environment in used-car prices. Broadly speaking, these variables capture different aspects of supply and demand in the used-car market. For example,

vehicles that originally came to the market during new-car sales booms will tend to have relatively larger supply a few years later and, therefore, lower prices in the used-car market. An important aspect when modeling the effect of the business cycle on used-car prices is to make sure changes in the relative price of the different vehicles are taken into account. For instance, trucks are expected to take a bigger hit than compact cars when oil prices spike. Also, although the purchases of some luxury or exotic vehicles can be classified as discretionary spending, others resemble basic goods. Interaction terms between segments and vehicles-fuel types with macroeconomic variables are then introduced to capture different sensitivities across cars.

### 5. Model Performance

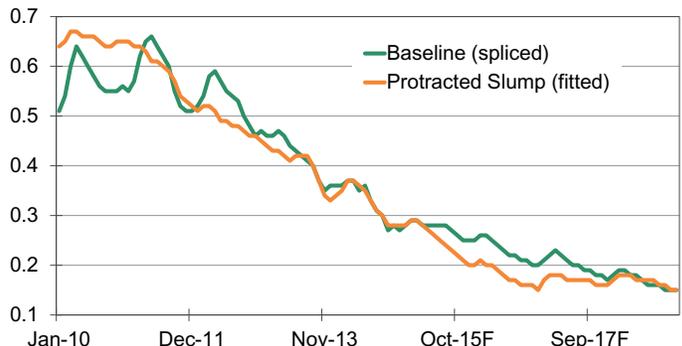
The model produces intuitive forecasts and a very good fit with an adjusted R-square higher than 0.97. As expected, used-vehicle prices are negatively related to age and mileage, capturing the effects of obsolescence and usage. The effect of business cycles is also correctly captured: Used-car prices go down when the economy enters a recession phase. In this section, we illustrate the model performance with some examples.

The first example illustrates the model's ability to replicate main trends in used-car prices during the historical period. Chart 2 shows the used-car prices-to-MSRP ratio for a 2001 Ford Taurus gas sedan from 2001 to 2014. As expected, the vehicle price goes down over time at decreasing rates, a pattern that the model successfully replicates.

The second example considers the 2006 Ford Focus gas sedan (see Chart 3). It revisits the model's ability to replicate historical patterns in used-car prices and adds two important elements. First, it shows the predicted values of used-car prices in the coming years, up to December 2018. Second, it shows the forecast of used-car prices under the Moody's S4 Protracted Slump scenario. The model replicates main historical patterns, generates reasonable forecasts under the baseline scenario, and predicts lower used-car prices in the recession scenario.

**Chart 4: Price-to-MSRP Ratio**

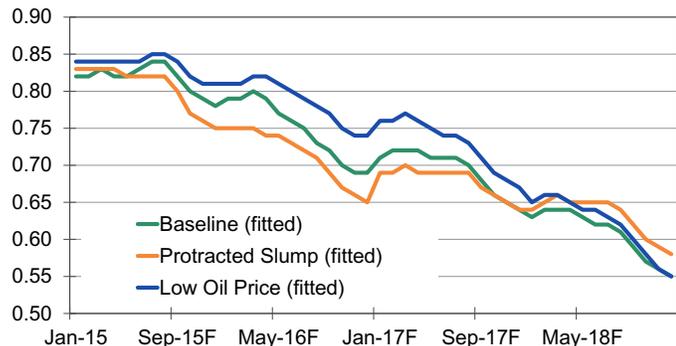
2010 GM Cobalt gas sedan



Source: Moody's Analytics

**Chart 5: Price-to-MSRP Ratio**

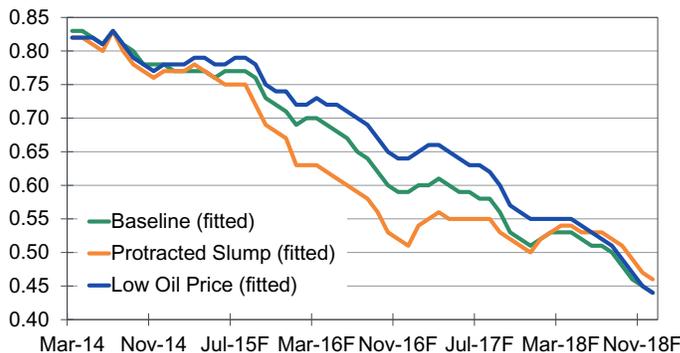
2015 Ford Explorer gas utility



Source: Moody's Analytics

**Chart 6: Price-to-MSRP Ratio**

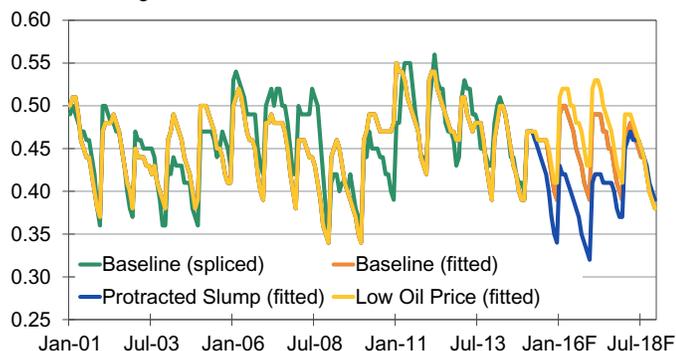
2015 Toyota Camry gas sedan



Source: Moody's Analytics

**Chart 7: Price-to-MSRP Ratio by Fifth Year**

Honda Civic gas sedan



Source: Moody's Analytics

The fourth example considers the 2010 Chevrolet Cobalt gas sedan (see Chart 4). As in the previous example, it shows the capacity of the model to replicate main historical trends, generate reasonable forecasts under a baseline scenario, and successfully predict stressed used-car prices under the Moody's S4 stress scenario.

The fifth and sixth examples consider two different vehicles, the 2015 Ford Explorer gas utility (see Chart 5) and 2015 Toyota Camry gas sedan (see Chart 6), to analyze the model's ability to forecast price dynamics for future vehicles; that is, vehicles for which we did not have transaction data available

when the model was developed. Model forecasts under the Moody's baseline scenario are intuitive, prices monotonically decrease with age, and seasonal patterns in used-cars market are replicated. The sensitivity of the forecasts to alternative scenarios also conforms to economic intuition. Under the Moody's S4 Protracted Slump scenario, prices are lower relative to the baseline forecast because of weaker demand for used cars. Under the Moody's S8 Low Oil Price scenario, prices are higher than under the baseline forecast, reflecting lower gasoline prices.

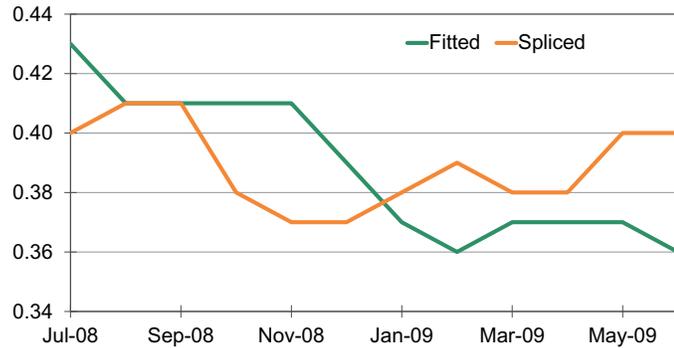
Chart 7 shows the price of a 5-year-old Honda Civic gas sedan over time. Industry players are often more interested in used-car prices of vehicles with approximately the same age than in the forecast of a specific model-year price over time. For example, auto lease finance companies tend to be particularly concerned with prices of used cars that are 2 to 4

years old. Chart 7 shows that the model successfully replicates used-car prices along the constant-age dimension, both in sample and out of sample. In sample, the model accurately replicates the used-car price fluctuations over the business cycle, and out-of-sample used-car prices move up and down across different economic scenarios as expected.

Given that our goal is to forecast used-car prices, we devote a good amount of time analyzing the model's ability to forecast used-car prices out of sample. Here we focus on the 12-month period following June 2008, which includes the most acute phase of the Great Recession, and that following December 2013, which contains the last year in our development dataset. In the first case, we re-estimated the model using data up to June 2008, and in the second we re-estimated the model using data up to December 2013; the model performs well in the backtesting exercises. Charts 8, 9 and 10 illustrate the model performance in the earlier period, while Charts 11, 12 and 13 show the model's out-of-sample predictive ability in 2014. Various statistical measures confirm that the model performs well out of sample; in particular, the mean and median absolute prediction error of the price-to-MSRP ratio in 2014 are 3.1% and 2.1%, respectively.

**Chart 8: Price-to-MSRP Ratio**

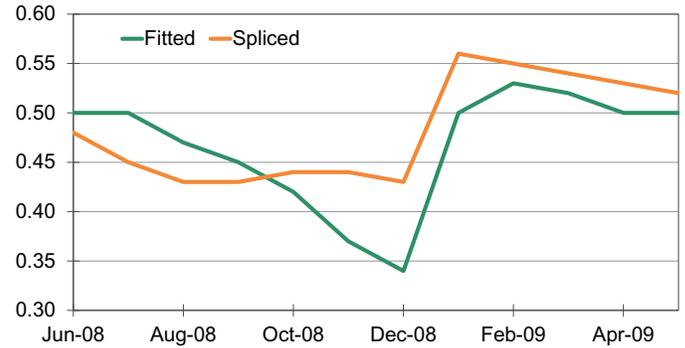
2005 Honda Pilot gas utility, baseline, out of sample, Jun 2008



Source: Moody's Analytics

**Chart 9: Price to MSRP Ratio by Fourth Year**

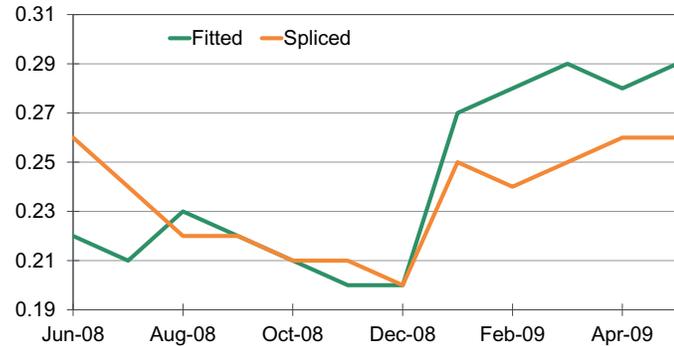
BMW 3 Series gas sedan, baseline, out of sample, Jun 2008



Source: Moody's Analytics

**Chart 10: Price-to-MSRP Ratio by Fourth Year**

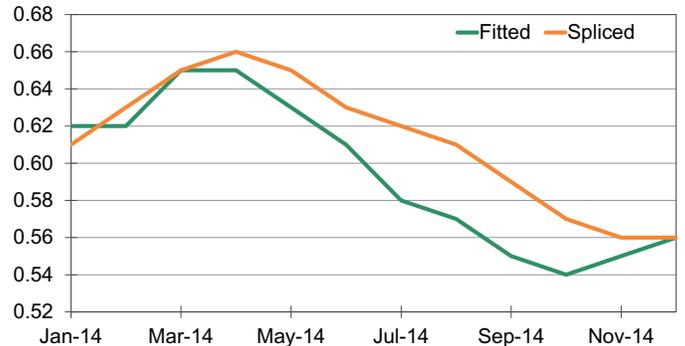
Ford F-150 gas regular cab, baseline, out of sample, Jun 2008



Source: Moody's Analytics

**Chart 11: Price-to-MSRP Ratio**

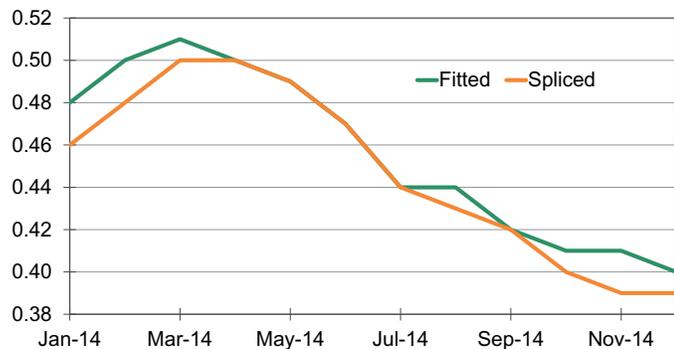
2012 Toyota Camry gas sedan, baseline, out of sample, Dec 2013



Source: Moody's Analytics

**Chart 12: Price-to-MSRP Ratio by Fifth Year**

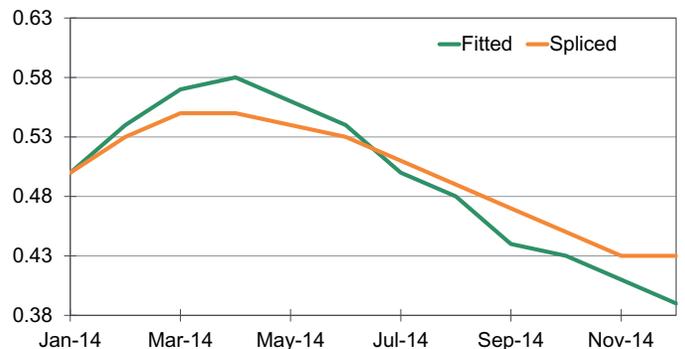
Honda Civic gas sedan, baseline, out of sample, Dec 2013



Source: Moody's Analytics

**Chart 13: Price-to-MSRP Ratio**

2011 Ford Fiesta gas sedan, baseline, out of sample, Dec 2013



Source: Moody's Analytics

# About the Authors

## Tony Hughes

Tony Hughes is a managing director in the Economic & Consumer Credit group at Moody's Analytics. He is the head of a small group of high-caliber modelers, charged with identifying new business opportunities for the company. Prior to this appointment, he led the Consumer Credit Analytics team for eight years from its inception in 2007. His first role after joining the company in 2003 was as lead economist and head of the Sydney office of Moody's Economy.com.

Dr. Hughes helped develop a number of Moody's Analytics products. He proposed the methodology behind CreditCycle and CreditForecast 4.0, developed the pilot version of the Stressed EDF module for CreditEdge, and initiated the construction of the Default, Prepayment and Loss Curves product, which provides forecasts and stress scenarios of collateral performance for asset-backed securities and residential mortgage-backed securities deals worldwide. More recently, he championed the development of the Pre-Provision Net Revenue Factors Library, a tool that provides industry-level projections of key bank balance sheet line items. In the credit field, Dr. Hughes' research has covered all forms of retail lending, large corporate loans, commercial real estate, peer-to-peer, structured finance, and the full range of PPNR elements. He has conducted innovative research in deposit modeling and in the construction of macroeconomic scenarios for use in stress-testing.

Dr. Hughes has managed a wide variety of large projects for major banks and other lending institutions. In addition, he has published widely in industry publications such as American Banker, Nikkei, GARP, and the Journal of Structured Finance as well as papers in peer-reviewed academic journals. He obtained his PhD in econometrics from Monash University in Australia in 1997.

## Zhou Liu

Zhou Liu is a director on the Moody's Analytics Credit Analytics team in West Chester PA. She builds customized models for consumer loans based on clients' proprietary data and conducts stress-testing of portfolio performance. She started her career in the Capital Markets Strategy Department at Fannie Mae analyzing non-agency bonds. She later moved to Fannie's Multi-Family Division to build credit risk models before joining Moody's Analytics in 2010. She has a BA from Peking University, an MA from the University of Chicago, and a PhD from the Kennedy School of Government, Harvard University.

## Pedro Castro

Pedro Castro is a senior economist at Moody's Analytics. As a member of the Credit Analytics team, Dr. Castro provides consulting support to major lending institutions, builds econometric models to analyze credit dynamics, and executes stress tests to monitor portfolio risk. Dr. Castro is actively engaged in explaining the team's research and methodologies to clients and has extensive practice in tailoring the econometric models and risk measures to match different industry needs. He holds a PhD from the University of California, Berkeley, and an MA in economics from the University of Brasilia in Brazil.

# About Moody's Analytics

## Economic & Consumer Credit Analytics

Moody's Analytics helps capital markets and credit risk management professionals worldwide respond to an evolving marketplace with confidence. Through its team of economists, Moody's Analytics is a leading independent provider of data, analysis, modeling and forecasts on national and regional economies, financial markets, and credit risk.

Moody's Analytics tracks and analyzes trends in consumer credit and spending, output and income, mortgage activity, population, central bank behavior, and prices. Our customized models, concise and timely reports, and one of the largest assembled financial, economic and demographic databases support firms and policymakers in strategic planning, product and sales forecasting, credit risk and sensitivity management, and investment research. Our customers include multinational corporations, governments at all levels, central banks and financial regulators, retailers, mutual funds, financial institutions, utilities, residential and commercial real estate firms, insurance companies, and professional investors.

Our web periodicals and special publications cover every U.S. state and metropolitan area; countries throughout Europe, Asia and the Americas; the world's major cities; and the U.S. housing market and other industries. From our offices in the U.S., the United Kingdom, the Czech Republic and Australia, we provide up-to-the-minute reporting and analysis on the world's major economies.

Moody's Analytics added Economy.com to its portfolio in 2005. Now called Economic & Consumer Credit Analytics, this arm is based in West Chester PA, a suburb of Philadelphia, with offices in London, Prague and Sydney. More information is available at [www.economy.com](http://www.economy.com).

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## CONTACT US

For further information contact us at a location below:

### U.S./CANADA

+1.866.275.3266

### EMEA

+44.20.7772.5454 London  
+420.224.222.929 Prague

### ASIA/PACIFIC

+852.3551.3077

### OTHER LOCATIONS

+1.610.235.5299

Email us: [help@economy.com](mailto:help@economy.com)  
Or visit us: [www.economy.com](http://www.economy.com)

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