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Introducing AutoCycle Australia

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Introduction

This white paper lays out AutoCycle Australia, a forecasting methodology able to generate used-vehicle prices under a wide array of macroeconomic conditions. The core capabilities of our model capture ageing and usage effects and illustrate the material implications for vehicle valuation of different macroeconomic scenarios such as recessions and oil price spikes. AutoCycle Australia is applicable to managing residual risk, forecasting the value of lease portfolios, and pricing individual lease contracts for new or used cars. The modeling process uses a purely quantitative approach that allows users and validators to fully evaluate the model and conduct detailed and transparent sensitivity analyses.

Introducing AutoCycle Australia

TONY HUGHES, MICHAEL BRISSON AND LOC QUACH

This white paper lays out AutoCycle Australia, a forecasting methodology able to generate used-vehicle prices under a wide array of macroeconomic conditions. The core capabilities of our model capture ageing and usage effects and illustrate the material implications for vehicle valuation of different macroeconomic scenarios such as recessions and oil price spikes. AutoCycle Australia is applicable to managing residual risk, forecasting the value of lease portfolios, and pricing individual lease contracts for new or used cars. The modeling process uses a purely quantitative approach that allows users and validators to fully evaluate the model and conduct detailed and transparent sensitivity analyses.

Accurate auto residual price forecasts are more important than ever. While new-car sales have declined over the last two years, the market for new vehicles has trended up since the financial crisis. At the same time, worries about the vehicle's retention of value weigh on the portfolio manager's mind as global growth begins to slow. The key risks associated with financing vehicle purchases are invariably realized when cars are sold into the secondary auto market. Anyone with a pecuniary interest in the value of large numbers of vehicles would be wise to understand the dynamics of such markets and fully assess the variety of risks faced by such portfolios.

In this paper, we introduce a new tool for quantitatively analyzing these dynamics. Our modeling methodology produces used-vehicle price forecasts over horizons of up to 10 years. The model is able to produce price forecasts under baseline and stressed macroeconomic scenarios for used vehicles sold through wholesale channels. Our unique methodology, driven largely by macroeconomic cycles, captures differential effects of supply- and demand-side drivers and fuel prices on observed vehicle values. Additionally, our hedonic controls allow us to accurately differentiate, for example, between two cars of the same type that differ only in terms of their observed mileage. Our model projects the likely performance of new vintages of vehicles based strictly on the past evolution of observed prices within the brand. Further, we are able to differentiate between vehicles that are presented for sale at a variety of quality or condition levels, after controlling for vehicle characteristics, as well as the vehicle's observed age and mileage.

For example, we can project the likely wholesale price of a black 2014 Toyota Hilux, which currently has 55,000 kilometres on the clock[1], which is expected to be driven at the rate of 12,000 kilometres per year, that ultimately presents in a condition that is better than 90% of vehicles with precisely the same traits. Not only can we provide a baseline forecast for this vehicle, we can also forecast the impacts on price from a dire recession, a surge in oil prices, a liquidity crisis in financial markets, or the effects of any combination of these events occurring simultaneously.

Growth in the Australian auto market from 2015 through 2017 occurred at the same time as increased preference for leasing in the Australian market. Novated leases have come to dominate some market segments and Guaranteed Future Value financing arrangements are growing in popularity. As recently as 2016, one in five of all new cars sold in Australia originated under a novated lease agreement. Lessors of new vehicles could benefit greatly from purely quantitative assessments of car value. Making matters more attractive is the fact that vehicles that are subject to lease agreements are usually well-established brands with reams of data on likely resale prices.

Providing customers with a range of options for their end-of-lease arrangements carries risk for the financier. If vehicle values fall unexpectedly, perhaps due to a recession, customers may choose to return vehicles at a high rate, leaving finance companies to liquidate the collateral to recover their exposed funds. In recent years, banks around the world have increasingly used stressed projections to enumerate these risks. It is felt that Australian financiers, as well as other players in the vehicle industry, will find these projections indispensable for purposes of risk management.

Many auto industry insiders focus heavily on the effect of brand makeovers and rede-

1 We use the term "mileage" to describe the distance the vehicle has travelled through its lifetime, while recognizing that these distances are typically measured in kilometres in Australia.

signs. Their position is that these changes make inference from one model year to the next very difficult. We disagree. Sometimes these redesigns, if implemented especially well or especially poorly, can have a profound impact on residual value, but such situations are really quite rare. In cases where the redesign is truly revolutionary—the first hybrid or the first self-driving car—it will be difficult to objectively assess the impact of the innovation on future residuals. More commonly, redesigns represent manufacturers attempting to keep abreast of the market by progressively adding features offered by their rivals. Manufacturers with static offerings tend to lose market share to their competitors.

Finally, redesigns are not always for the better. Customers can and have reacted badly to design changes of beloved models. Occasionally a manufacturer will accidentally or intentionally switch a model to an adjacent sector and as a result lose market position. In part, these changes in design will be reflected in higher (or lower) sticker prices without really affecting the rate at which depreciation subsequently occurs. Ultimately, this is an empirical question, and forecasts from our model can be compared for specific vehicles to show how their prices ultimately evolve. While we take quantitative steps to control for the past pattern of vehicle redesigns, we do not view speculation regarding the success of new upgrades to be useful in predicting future depreciation patterns.

For lessors of new vehicles, the objectivity of a strictly data-based approach will bring significant utility to users of the forecasts. Those managing their businesses under a regulatory spotlight—such as large banks—need analytical solutions where any managerial overlay can be isolated and separately reported. Models used in the risk assessment process must be amenable to validation and back-testing, and sensitivity to changes in input variables must be assessable. This requirement holds as much for challenger models, which are used by banks to encourage improvements in in-house champion models, as it does to the champion models themselves.

Unregulated users will also benefit from these features. We recognize candidly that industry insiders often track brand-specific trends and production data far more closely than we ever would be able to. Nevertheless, in a competitive marketplace like the auto industry, market forces and other macroeconomic supply- and demand-side drivers will still play a dominant role in determining the behavior of prices for individual vehicles or vehicle segments. We envisage that users will employ our purely quantitative forecasts and stress scenarios as the starting point for appropriate, partially subjective forecasts produced by their own in-house teams.

The rest of this paper proceeds as follows. Section 2 lays out the AutoCycle Australia model methodology. Section 3 describes the data. Section 4 lays out the results, with model validation in Section 4.1, an illustration of ageing and usage effects in Section 4.2, and a discussion of macroeconomic scenario-driven price forecasts in Section 4.3.

2. Methodology

In this section, we describe the Australian AutoCycle model set-up and specifications. Validation exercises of model performance are reported in Section 4.

AutoCycle Australia

AutoCycle Australia is an econometric model used to capture the relationship of residual vehicle values to vehicle features and the macroeconomic environment. The dependent variable for the model is a logit transformation of the vehicle's sale price as a fraction of its manufacturer suggested retail price, or MSRP. A logit transformation restricts the price-to-MSRP forecasts to the interval (0,1). The independent, or right-hand-side, variables of the model include time invariant vehicle features, time varying mileage-per-year (MPY) and vehicle age variables, month-of-year dummies to capture seasonal effects, and macroeconomic variables.

We use the mileage-per-year determinant of car value, rather than a direct mileage variable, for two reasons: Mileage has a time trend that renders the variable nonstationary in levels, and measuring mileage in this way would conflate overall miles driven with the car's age. Using mileage-per-year as the car usage variable solves both of these problems. Since both age and mileage-per-year are considered, we can easily reconstruct projections for vehicles with any observed mileage at any point in time.

Regarding macro drivers of car value, we include drivers that allow us to capture the divergent behaviors often displayed by different cars during periods of economic stress. Some of these economic variables, such as the change in unemployment rate since year of production, are meant to capture demand for vehicles, and others such as the growth of new-vehicle registrations as a percent of the population are meant to gauge the supply of vehicles in the market at the time of sale. A representation of the model, which is a reduced form capturing underlying supply and demand conditions, can be seen in Equation (1) below.

AutoCycle Australia Model Equation

$$
\begin{aligned}
(1)\ & ln(y_{it}/(1-y_{it})) \\
&= \alpha + \vec{\beta}_1' \overrightarrow{Feat_{it}} + \vec{\beta}_2' \overrightarrow{TimeFeat_{it}} \\
&+ \vec{\beta}_3' \overrightarrow{Macro_{it}} \\
&+ \vec{\beta}_4' Fueltype_i \overrightarrow{Gassdeflate_{it}} \\
&+ \vec{\beta}_5' Seg_{it} \overrightarrow{Age_{it}} + \vec{\beta}_6' Age_{it} \overrightarrow{Mileage_{it}} \\
&+ \varepsilon_{it}
\end{aligned}
$$

Here y_{it} is the vehicle's price-to-MSRP, where the subscript i indexes the individual sale records of particular vehicles and t is the month that the sale record takes place. On the right-hand-side of the equation, a is a constant term. Of the explanatory variables, $\overrightarrow{Feat}$ is a vector of time invariant vehicle features including vehicle induction type, exterior color, body type, sale type, sale location, make, and vehicle sub-segments; $\overrightarrow{TimeFeat}$ is a vector of variables that move with time, including age, age-squared, seasonality indicators, and mileage per year splines; $\overrightarrow{Macro}$ is a vector of macroeconomic variables, including the year-over-year percentage in Australian gross domestic product, the change in the Australian unemployment rate over the past 12 months, the number of new vehicles sold as a percent of the total population between ages 15 and 64 in year of production, and the percentage change in the

Datium-Moody's price index since model production year. $Fueltype_{it}$ is a vector of categorical variables that give the energy source the vehicles uses. $\overrightarrow{Gassdeflate_{it}}$ is a macroeconomic variable of fuel price inflation over the rate of inflation for the economy as a whole. *Seg* represents the sub-segment of vehicles; $\overrightarrow{Age}$ is a vector of age variables interacted with sub-segment that includes age, and age squared; *Age* represents the age of the vehicle as an integer; $\overrightarrow{Mileage}$ is a vector of mileage splines interacted with the vehicle age; and ε_{it} is an assumed i.i.d. Gaussian error term indexed by transaction and time.

Model calibration

One of the toughest challenges in residual value forecasting is heterogeneity between vehicle types. Each vehicle contains its own design idiosyncrasies, supply dynamics, and popularity levels. Moreover, many other factors influence residual values, including mileage, vehicle age, seasonality and economic conditions. At a more aggregated level such as in a price index, the effects of these minutiae largely cancel out and a clean signal of market fundamentals can be used for forecasting future price trends. However, to be most effective, residual value forecasts for lease and loan risk management and pricing must capture variance at the individual vehicle level. Modelers must therefore consider as much granularity as possible.

In light of these considerations, the main regression equation was developed to balance the aforementioned trade-offs in a parsimonious yet statistically rigorous manner. In doing so the framework was chosen to be a pooled ordinary least squares model using cross-sectional dynamics to the make/sub-segment/characteristic level, combined with macroeconomic cyclicality. This approach has consistently proven to adequately balance out-of-sample accuracy, granularity, the reasonableness of macroeconomic stress, and transparency in accord with the modeler's initial goals.

The absence of vehicle-model control variables in the regression model means that the conditional average forecasts will differ from the true population average if a particular vehicle model performs significantly differently from its make/sub-segment average, all else equal. In general, we find that vehicle-model dynamics are similar to their make-sub-segment estimates, and that pooled least squared regression adequately performs its core function without their consideration. However, there are indeed some vehicle models with unique idiosyncrasies, and the regression predictions may underperform on portfolios with large concentrations of such vehicles. In response, a model calibration algorithm is employed to adjust forecasts by vehicle model in a purely quantitative, theoretically sound, and transparent manner.

The model calibration for a given make-model-model year MMY sold in month m can be described mathematically as:

$$calib_{MMY,m} = \overline{logit\_xprice}_{MMY} - \overline{flogit\_xprice}_{MMY}$$

Where:

$\overline{logit\_xprice}_{MMY,m}$ is the average logit-transformed[2] price-to-MSRP ratio of all VINs of type MMY sold at auction in every month up until month m.

$\overline{flogit\_xprice}_{MMY,m}$ is the average in-sample predicted logit-transformed price-to-MSRP ratio of all VINs of type MMY sold at auction in every month up until month m.

The calibration is applied to the forecast to VIN v of type MMY sold in month m by the formula:

$$fxprice\_calib_{v,m} = invlogit^{3}(flogit\_xprice_{v,m} + calib_{MMY,m})$$

In other words, the calibration adjusts the forecast based on the average regression residual for a given make-model-model year since it began being sold. The calibration is calculated according to multiple constraints:

1. The calibration is applied to the transformed dependent variable in order to the linearity assumption of ordinary least squares.
2. The calibration is capped at 1 and -1 to avoid extremes of the logistic function where severe non-linearity can become problematic.
3. The calibration is calculated using sales of vehicles aged 1 year or older before the forecast month due to noisy sales data for vehicles sold in the same year as their model year.
4. The calibration is applied only to models such that there are more than 100 observations to produce the calibration: Estimates obtained using smaller samples are unreliable and harm forecast accuracy.

Make-model-model year combinations with insufficient observations are calibrated using an average across all known model years for a given model.

Vintage quality adjustments

Statistical forecasting models are valuable because of their ability to predict information about unseen observations, whether they exist across time or in a cross-sectional population. In the case of a hedonic asset pricing model this power is derived from the marginal-effect estimates of asset characteristics and conditions at the time of sale. As long as enough observations are used to accurately estimate these parameters, and the data generating process is stable, the conditional mean for out-of-sample observations can be accurately predicted. In all models, this abstraction is constrained by what information about the future observation is measurable and explicitly included in the model.

In the case of used-vehicle prices, the aforementioned constraint is most evident in heterogeneity between vehicle types as described in the model calibration section. However, model calibration is inapplicable to future model years, about which very little is known at the time of forecast about consumer reaction to redesign or quality changes and the impact to residual values.

The problem of forecasting future model year prices on the secondary market is very difficult. A hedonic pricing approach would require an extremely detailed model to un-

2 The logit transformation is the function F(x): $\log\left(\frac{x}{1-x}\right) \rightarrow \mathbb{R}$ for $x \in (0,1)$

3 The inverse logit transformation is the function F(x): $\frac{e^x}{1+e^x} \rightarrow (0,1)$ for $x \in \mathbb{R}$

derstand the valuation of minute vehicle performance and aesthetic components; even then, some model releases flop on the market while others are wildly successful, and it is hard to predict which way fickle consumers will lean. The typical approach to forecasting future model years is editorialization. This technique requires an analyst to judge the likely pricing impact of vehicle design decisions and future segment competition to add-factor a base forecast produced by a quantitative model. Editorialization, however, has a high potential for error because of its subjectivity and interference with rigorous statistical properties produced by a purely quantitative model.

AutoCycle Australia uses a purely quantitative algorithm, herein referred to as the vintage quality adjustment algorithm, to adjust price forecasts of future model years. This algorithm leverages information from the in-sample fitted values to calculate how different vehicle model pricing has evolved with each successive model year change. This trend is forecast for future model year releases and is used to adjust the base forecast output. The primary advantages of the algorithm are that it is robust to subjective bias and it is designed to accord with the statistical properties of the base forecasts.

The vintage quality adjustment algorithm is based on the inductive principle that the past is the best predictor of the future. For instance, if we can observe residual values for a specific make-model combination have been pushed down with each successive model year iteration, then the best prediction is that future model year prices will follow a similar pattern. Of course, original equipment manufacturers can—and do—engineer a redesign to revive popularity in a dying model; but in the majority of cases there is pricing persistence across model year releases because the industry innovates together and consumer preferences change gradually. The goal of the algorithm is to measure this persistence for each vehicle and forecast the trend into the future.

To calculate this adjustment, a series of steps are taken, as outlined below:

1. Calculate the average regression residual (actual price-to-MSRP ratio minus the fitted price-to-MSRP ratio) from the in-sample estimation dataset by make-model-model year, for example, 2010 Honda Civic.
2. Perform sales-weighted first order auto regressions using the averaged regression residuals by make-model in the model year time dimension. A representation is given in the equation below where $\hat{\varepsilon}$ is the averaged regression residual, i denotes the make-model combination, my is the model year, and μ is a Gaussian error term.
$$\hat{\varepsilon}_{imy} = \alpha + \beta_i \hat{\varepsilon}_{imy-1} + \mu_{imy}$$
3. A vintage quality factor for period t is created using the formula:
$$vq_{imy} = \bar{\hat{\varepsilon}}_i - \bar{\hat{\beta}}_i(\hat{\varepsilon}_{imy} - \bar{\hat{\varepsilon}}_i)$$
where $\bar{\hat{\varepsilon}}$ is the mean of the predicted regression residuals over time my_{min} to my_{max} and $\bar{\hat{\beta}}$ is the average of β_i over time my_{min} to my_{max}
4. A mean-reverting vintage quality component is calculated for the next five model year iterations using the following recursive formula:
$$vq_{imy} = \bar{\hat{\varepsilon}}_i - \bar{\hat{\beta}}_i(vq_{imy-1} - \bar{\hat{\varepsilon}}_i)$$

The vintage quality adjustment is therefore a simple auto-regressive forecast of the model calibration applied to previous model year forecasts. The auto regression detects the persistence of the calibration across model years, and the algorithm uses the latest model year calibration as a starting point to forecast future values. Critically, the estimated vintage quality adjustment is made to be mean-reverting so that it is not pushed to extreme values over time.

The vintage quality adjustment is intimately tied to the core model regression. This heteroscedasticity-robust, ordinary least squares regression assumes that there is no serial correlation in the error term. The systematic impact of redesigns and changes in popularity for new model releases violate this assumption. In this context, the vintage quality adjustment can be viewed as a correction to serial correlation within the make-model panel unit in the model year time dimension.

3. Data

The data used to develop and build our AutoCycle Australia model is sourced from Datium Insights. Datium Insights is the analytics division of Pickles, Australia's largest auction house with 23 nationwide locations. The database covers approximately 3% of the Australian used-vehicle market. Transaction-level data cover over 1 million transactions from 1999 through current, including over 1,200 unique models from 93 auto manufacturers. A list of descriptive statistics is available in the appendix. A list of the economic variables used in the model is also available.

The data are extensively cleaned to ensure that the final data used to build the model are of high quality. The most important step of the data cleaning process is to drop observations for necessary variables with values that are missing, unusable, or are likely incorrect entries. For example, an observation is dropped if the sold date is missing. This criterion results in dropping less than 0.1% of total observations. Other instances that led us to drop observations include a zero value for MSRP or sale price, as these are likely data entry errors.

The Datium Insights dataset includes date sold and the model year of the vehicle. Using these two variables, time-related variables, such as the age of the vehicle, are generated. The age of the vehicle is one of the two most important determinants of the value of a vehicle. All else held equal, a newer vehicle will carry a higher price than an older vehicle. With the age of the vehicle calculated and the number of kilometres on the vehicle provided, we are able to calculate kilometres per year. Kilometres per year is the second most important factor in the resale value of a vehicle.

The number of possible values was reduced for some variables to reduce redundancy and small sample size within buckets. For instance, observations where the make of a vehicle was categorized as "Ford Performance Vehicles" are re-coded to "Ford". Induction type, drive type, and transmission type were also re-categorized in this manner.

Exterior color is consolidated to 13 colors from over 2000 colors. Our approach to categorizing color is as follows. Step 1 is to re-categorize the exterior color into one of the 13 distinct groups if these words exist in the color value. For example, "Kinetic—Blue" is re-categorized as "Blue". Some of the re-coding was less obvious and therefore required a bit of research. For example, a common color is "Blue Grey". It is not exactly clear if the color of the vehicle is closer to blue or to grey. An online search identified this color as more blue than grey. The granular re-categorization process occurs after the sweeping first step, so incorrect categorizations that occurred in the first step would be corrected in the second step. The exhaustive color-coding process was captured in the vast majority of the observations. Unfortunately, it is not possible to capture all colors, as there are obscure color names with few observations and therefore not worth manually categorizing.

The Datium Insights dataset includes additional categorical variables that added predictive power to the model. Vehicle sub-segment (SUV, light passenger, sports car, etc.) and body type (bus, sedan, van, etc.) are variables that could add predictive power to our model if demand ebbs and flows along vehicle segment or body type lines. Induction type (standard, supercharged, turbocharged, etc.) is an important consideration for the segment of the market that wants zippier cars.

Two variables that were promising are warranty years remaining and warranty kilometres remaining. A vehicle with a longer warranty remaining should carry a premium. Surprisingly, these variables were not statistically significant despite numerous attempts at cleaning the data. As a result, we had to leave the warranty variables out of the model.

The macroeconomic variables used in the model development phase are provided by Moody's Analytics and sourced from many different private and government sources. The Moody's Analytics Australia forecast is part of a global macroeconomic model used across the worldwide financial infrastructure, and that includes over 70 of country-specific outlooks. Having a global macroeconomic model instead of a focused Australia macroeconomic model is a strength of AutoCycle. The world's economies are intertwined, so having a macroeconomic model that reflects this allows the Australia macroeconomic forecast, and therefore our used-car price forecasts, to be influenced by the dynamics of the global economy.

The state of the economy is a major determinant of demand for used vehicles. A booming economy lifts all boats, or indeed cars. In such a scenario, credit will be more accessible, income will rise faster, consumer confidence will increase, etc. We used the broadest measure of the economy, GDP, in our model. We also included the unemployment rate as the labor market is the lynchpin of consumer demand and used cars are no exception. Australians are more likely to commit to big purchases, such as a vehicle, when they are employed.

Two important variables in the AutoCycle Australia model are the car-to-population ratio and the Moody's Analytics used-car price index. A high car-to-population ratio suggests a saturated market and therefore less demand for replacement cars. Our used-car price index is created using a weighted hedonic regression on Datium Insights auto data. The appendix includes a table providing a full list of all the macroeconomic variables used and their sources.

All macro variables are rendered stationary before analysis and functional forms are selected carefully to ensure sound model performance.

The left-hand side variable is a logit transformation of the price-to-MSRP ratio. The price-to-MSRP metric allows for a comparison between cars of different MSRPs. The logit transformation restricts the forecast value between 0 and 1. This reflects the fact that vehicles are not likely to be sold at a negative price or at a point above their initial MSRP. This latter condition is possible, especially for specialty vehicles with long waiting lists, but the situation is rare enough that we can safely disregard the phenomenon in building our model.

AutoCycle forecasts are reviewed using a baseline macroeconomic forecast (BL), a protracted slump (S4) scenario, and oil price shock-driven stagflation (S6) alternative economic scenario. Auto resale value is forecast under economic stress scenarios because AutoCycle is most valuable as a risk management tool if it generates realistic forecasts under periods of economic underperformance.

The baseline forecast is the most likely scenario. In this scenario, the unemployment rate holds steady, inflation stays low, and the financial markets largely stay pacified. With the economy largely staying as is, we expect used-car prices to continue on their current trend. The baseline economic scenario does not include a recession in the forecast until the probability of recession reaches above 60%.

In the protracted slump scenario, there is a 96% probability that the Australia economy performs better. In this global slump, credit availability tightens, payrolls contract, and house prices decline. As a result, the economy contracts for an extended period of time. Lower credit availability would make it difficult to fund a car loan. Additionally, many Australians roll their car loans into their mortgages, so declining house prices will further put a car loan out of reach for many. Lastly, rising unemployment would stifle demand for many goods and services, including used vehicles. It is important to note that the impact of an economic slump differs between brands and segments.

In the oil price shock-driven stagflation scenario, there is a 90% probability that the economy performs better. In this scenario, high oil prices lead to high inflation and a stagnant economy. Real wages decline but interest rates spike as the Reserve Bank of Australia raises interest rates to combat inflation. The unsavory combination of high interest rates, a stagnant economy, and high fuel costs weigh on used-car prices. Furthermore, high fuel costs will weigh on large vehicles more than their more fuel-efficient counterparts.

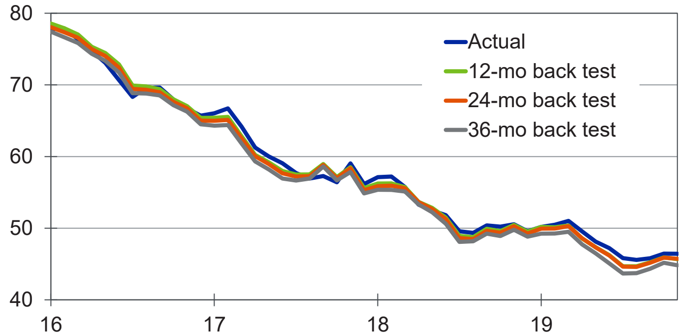
4. Results

In this section of the paper, we will review our AutoCycle model's performance in three ways:

1. Validation: A series of tests and charts are reviewed to test model accuracy both in and out of sample.
2. An analysis of the model's forecast is made across two mileage scenarios: low

Chart 1: 2015 Vehicles Results

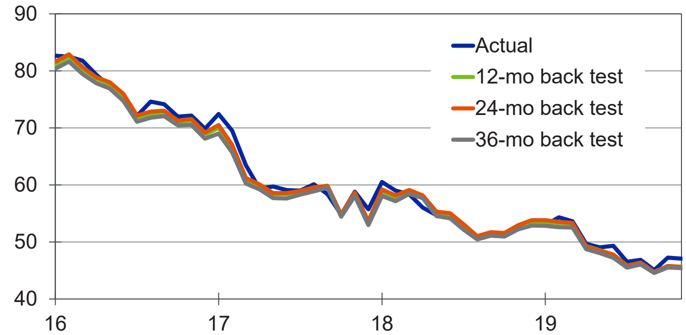
Residual value, % of MSRP, baseline



Sources: Datium Insights, Moody's Analytics

Chart 2: 2015 Medium SUVs

Residual value, % of MSRP, baseline



Sources: Datium Insights, Moody's Analytics

usage and heavy usage. The analysis will also illustrate the effect of age.

3. The forecast is reviewed across three macroeconomic scenarios: the baseline forecast, a protracted slump scenario, and an oil price-driven stagflation scenario.

4.1 Validation

We computed in- and out-of-sample price-to-MSRP forecast performance statistics to validate the AutoCycle Australia model. The in-sample statistics are based on nearly 1 million observations and the out-of-sample statistics are based on 89,516, 192,874, and 282,127 observations. The back test includes only observations from the hold-out period. For example, the 12-month back test ending in November 2019 includes only data from the 12 months ending in November 2019. In generating the baseline and downside macroeconomic scenarios, the model assumes a perfect economic forecast.[4] Table 1 displays the in-sample, 12-, 24- and 36-month out-of-sample R-squared, mean error, mean absolute error, and root mean squared error statistics for the AutoCycle model. Additionally, the table includes the number of observations used to compute these statistics.

Table 1: Australia AutoCycle

	Obs	R-squared	ME	MAE	RMSE
In-sample	991,097	0.8436	0.0004	0.0551	0.0728
12-mo back test	89,516	0.8418	0.0088	0.0605	0.0795
24-mo back test	184,782	0.8415	0.0107	0.0600	0.0793
36-mo back test	282,127	0.8360	0.0162	0.0611	0.0813

Sources: Datium Insights, Moody's Analytics

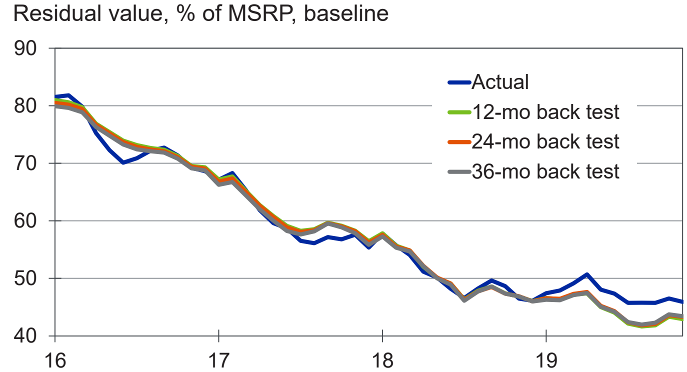
The model's performance statistics make a strong case that it is a good forecasting tool. AutoCycle achieves a 12-month out-of-sample mean error of 0.009, with an R-squared of 0.84. The R-squared of 0.84 means that the variables in the AutoCycle model explain 84% of the variance we see in the resale value. Table 1 shows the model's mean error rises as the out-of-sample period increases as expected. Also evident in this table is that the R-squared and RMSE did not change much with the increasing out-of-sample period. Favorable performance statistics lead us to conclude that the AutoCycle model is a reliable predictor of used-car prices.

Chart 1 compares the price-to-MSRP ratio of model year 2015 vehicles with the results from our 12-, 24- and 36-month back tests. Taking the 12-month back test for an example, the fitted values are slightly lower than actual values with the miss largest in 2017. The biggest miss came in at 2.2% of MSRP, a margin that is pleasantly below what was expected. As anticipated, the miss increases as we hold back more data. In the 36-month back test, the biggest miss was -2.4%.

Chart 2 shows the residual value of 2015 medium SUVs and the results from the

Chart 3: 2015 Small Passenger Vehicles

Residual value, % of MSRP, baseline

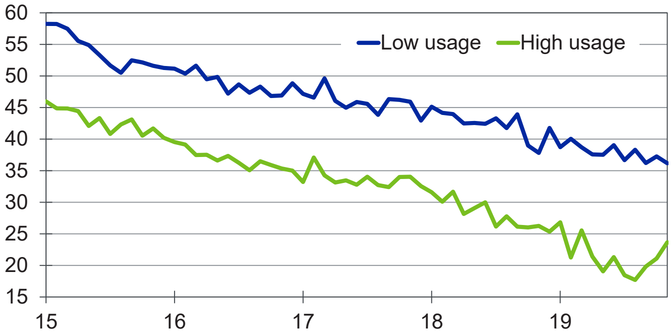


Sources: Datium Insights, Moody's Analytics

4 Macroeconomic forecasts are subject to significant uncertainty. However, assuming a perfect forecast does not detract from the value of AutoCycle Australia. Rather, this assumption allows the test to be solely focused on the error from model specifications rather than the forecast inherent in macroeconomic variable forecasting. Our baseline forecast is based on current economic conditions, is the most likely economic scenario, and is updated on a monthly basis to incorporate the changing dynamics of the economy. Furthermore, accurate models conditional on macroeconomic forecasts highlight the importance of considering a set of stress macroeconomic scenarios and understanding the risk that economic downturns impose on used-car prices.

Chart 4: Highly Driven Vehicles Cost Less

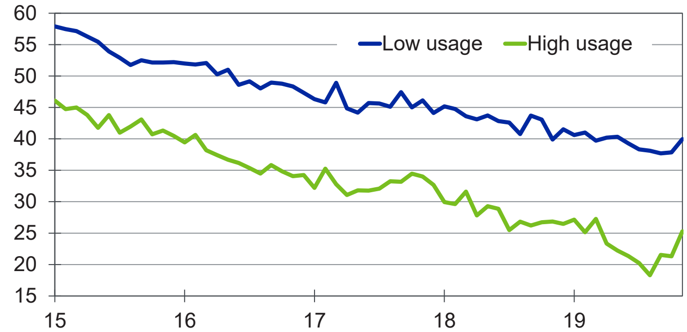
Residual value, % of MSRP, 2012 vehicles



Sources: Datium Insights, Moody's Analytics

Chart 5: Model Accounts for Usage

Residual value, % of MSRP, 2012 vehicles



Sources: Datium Insights, Moody's Analytics

12-, 24- and 36-month back tests. Chart 3 shows the same for small passenger vehicles. In the 12-month and 24-month medium SUV back tests, the model tracked the data well. The model's performance for small passenger vehicles is more nuanced. The model missed on the high side and low side, but importantly, the misses were approximately mean-zero.

4.2 Core functionality: Ageing and mileage effects

Mileage is one of the most important factors in determining a used vehicle's price. While vehicle design has improved over time, parts are still susceptible to wear and tear and will break down with usage. As a result, consumers will pay more for a lightly driven vehicle versus one that has seen more kilometres. Because of this, we have to ensure that the model properly captures the impact of mileage on used-car prices. The analysis will examine the forecast resale value of a heavily driven 2012 model year vehicle and that of a lightly driven vehicle of the same age. The highly driven vehicle is expected to go for a lower price. This is how usage is defined:

1. High Usage: In this usage scenario, the analysis will review the average resale value of 2012 model year vehicles with the kilometre per year value between the 85th percentile and the 95th percentile of the dataset.
2. Low Usage: In this usage scenario, the analysis will review the average resale value of 2012 model year vehicles with a kilometre per year between the 5th and 15th percentiles of the dataset.

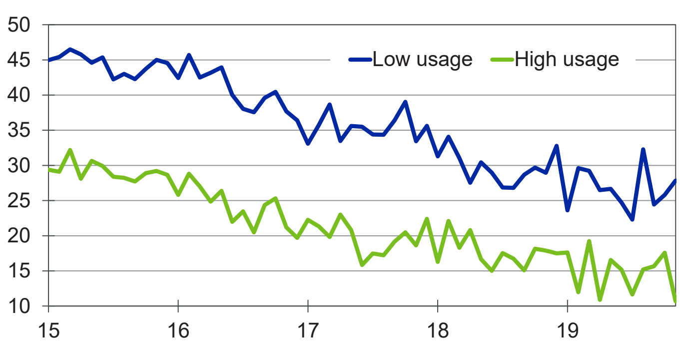
Chart 4 shows the price-to-MSRP ratio, or residual value, for average model year 2012 vehicles under the high usage and low usage scenarios. Overall, vehicles that see more miles are sold at a lower price. By November 2019, the residual value of a high-usage vehicle is two-thirds that of its lightly driven counterpart.

Chart 5 shows the in-sample forecast for average model year 2012 vehicles under the low usage and high usage scenarios. Under the high usage scenario, the model captures the fact that vehicles that have more kilometres on the odometer sell for a lower value. By November 2019, the residual value on the heavily driven vehicle is two-thirds that of the lightly driven vehicle. This difference is in line with actual data.

Chart 6 displays the in-sample forecast for a typical 2010 model year vehicle. As expected, the resale value is lower than that of a typical model year 2012 vehicle. With older vehicles, we see that mileage has a bigger impact on the resale value of used vehicles. By November 2019, the

Chart 6: Mileage More Important With Age

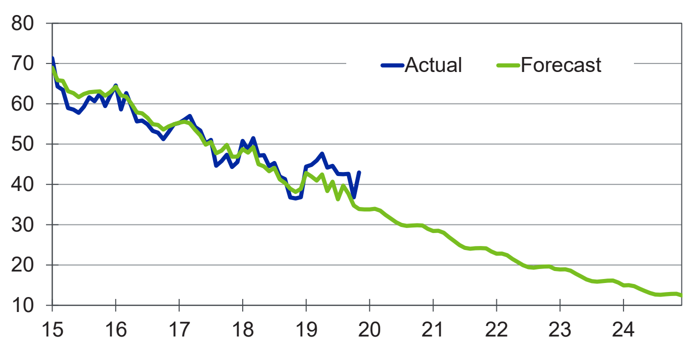
Residual value, % of MSRP, fitted values, 2010 vehicles



Sources: Datium Insights, Moody's Analytics

Chart 7: 2013 Toyota Corolla Forecast

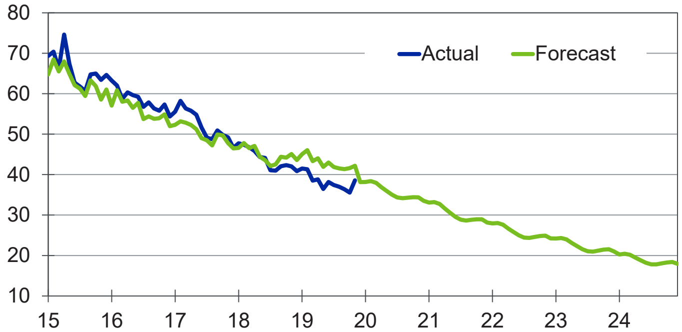
Residual value, % of MSRP, baseline



Sources: Datium Insights, Moody's Analytics

Chart 8: 2013 Ford Ranger Forecast

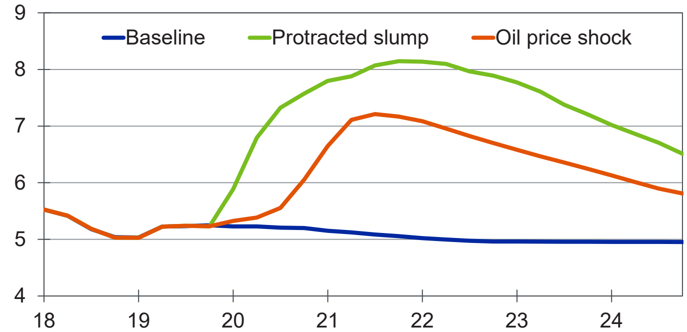
Residual value, % of MSRP, baseline



Sources: Datium Insights, Moody's Analytics

Chart 9: Unemployment Rate Spikes

Unemployment rate forecast, %



Sources: Australian Bureau of Statistics, Moody's Analytics

residual value of a heavily driven model year 2010 vehicle is less than half of a lightly driven one. At 9 years of age, the impact of age has largely played out. However, a lightly driven 9-year-old vehicle is likely to have more life left than a heavily driven 9-year-old vehicle.

4.3 Forecasting car prices under macroeconomic scenarios

The model performs well in the in-sample comparison, but the model is useful only if it could produce high-quality out-of-sample forecasts. Furthermore, a strength of Moody's Analytics is the variety of alternative macroeconomic scenarios that we have, allowing us to generate residual value forecasts under stressed economic conditions. The following examples will show the forecast under three macroeconomic scenarios: a baseline forecast, a protracted economic slump scenario, and an oil price shock-induced stagflation scenario.

It is not uncommon for models to perform well in the in-sample analysis only to generate unrealistic forecasts. To review how the model performs in an out-of-sample context, the analysis will review the retention value of two popular vehicles in Australia: the 2013 Toyota Corolla and the 2013 Ford Ranger. These two vehicles target completely different markets. The Corolla is a passenger vehicle marketed towards young and mid-age adults. The Ford Ranger is a ute designed with outdoor-focused people in mind. If the model generates high-quality residual value forecasts for these two different vehicles, it is reasonable to infer that the model will perform well across a wide swathe of vehicle makes and models.

The forecasts will be judged on three criteria:

1. How well does the model track actual resale value in history?
2. Does the model generate a realistic out-of-sample forecast?
3. How volatile is the forecast? In particular, is there a sudden shift immediately after the historical data end?

The model generated good forecasts in the baseline scenario for both vehicle models. Chart 7 shows that the model fulfills all three criteria for the 2013 Toyota Corolla forecast. The model generated a realistic out-of-sample forecast. The residual value continues to trend downward, reflecting the fact that car depreciation over time is generally monotonic with some seasonal variation. Additionally, the residual-value forecast is stable.

In Chart 8, we see that the model fitted the actual data very well for the 2013 Ford Ranger. The model generated in-sample predictions that tracked actual resale value closely and generated a realistic nonvolatile baseline economic forecast.

In addition to the baseline forecast, the performance of the AutoCycle Australia model will be reviewed under two alternative macroeconomic scenarios: protracted slump and oil price-driven stagflation.

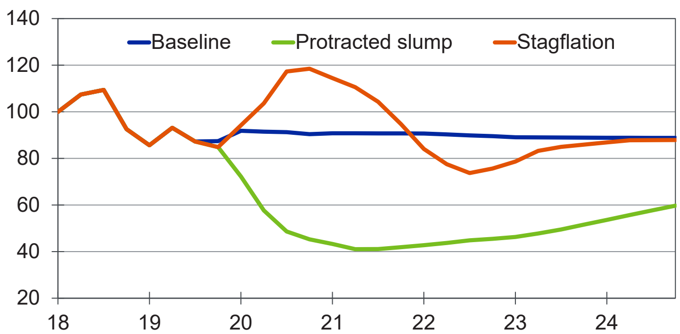
To understand the forecasts under these stressed economic scenarios, it is important to consider the scenarios themselves. The labor market is a major determinant of used-car prices, as most car owners pay for their vehicle with their wage incomes. As Chart 9 shows, the unemployment rate rises rapidly in the protracted slump scenario until 2022 before declining as the economy gradually recovers. In the oil price shock scenario, the unemployment rate rises at a more gradual pace. Neither the protracted slump nor stagflation scenarios' inflation rates converge upon the baseline forecast over the forecast horizon.

Chart 10 shows the inflation-adjusted price of crude oil across the three scenarios. Fuel prices are projected to largely move sideways in the baseline. However, a global economy in recession will demand less oil, driving a noticeable decline in fuel prices under the protracted slump scenario. In the stagflation scenario, the cost of fuel spikes in the near term—the scenario narrative revolves around such an oil price shock. Fuel prices then gradually decline as a slumping global economy inevitably consumes less oil. Eventually, oil prices fall below levels witnessed under the baseline forecast through to the end of the forecast window.

Charts 11 and 12 show the retention value forecast for the 2013 Toyota Corolla and 2013 Ford Ranger in both the baseline and protracted slump scenarios. Under the protracted slump scenario, both vehicles' retention value falls below that of the

Chart 10: Fuel Costs Differ

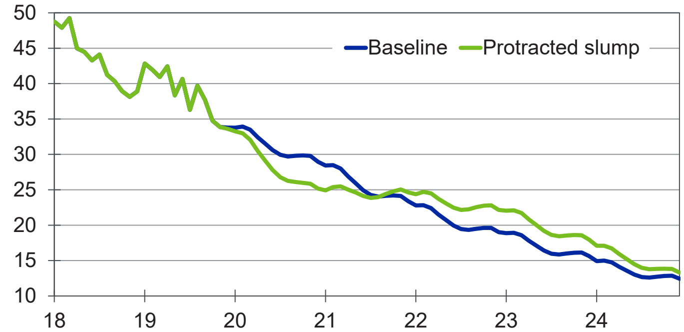
Inflation-adjusted crude oil price forecast, $, 2018Q1=100



Sources: U.S. Energy Information Administration, Moody's Analytics

Chart 11: 2013 Toyota Corolla Forecasts

Residual value, % of MSRP, baseline



Sources: Datium Insights, Moody's Analytics

baseline forecast until late 2021, before rising above. This is intuitive: When a recession hits, demand for cars declines, taking the price of used vehicles down. After the recession, demand for used vehicles returns but fewer used cars are available. During recessions, auto manufacturers cut back on production during times of low demand, leading to a constriction in used-vehicle supply in the years following the downturn. As a result, used-car prices in the protracted slump scenario rise above the baseline forecast during the recovery.

Chart 13 shows the price-to-MSRP ratio forecast for the 2013 Toyota Corolla and 2013 Ford Ranger. The chart shows both the baseline forecast and the oil price shock-induced stagflation scenario. The Ford Ranger's residual value declines more than that of the Toyota Corolla in the oil price shock scenario. Consumers tend to shift their preferences in the direction of smaller, more fuel-efficient vehicles at times of high petrol prices. Fuel prices rise rapidly in the mid-2020s in the oil-shock scenario. By August 2020, the price/MSRP difference between the Corolla's oil-shock scenario and baseline scenario reaches 1.1 percentage points compared with the Ford Ranger's 0.8 percentage point.

The AutoCycle Australia model produces intuitive projections under the baseline scenario we reviewed. Just as important, the forecasts across the two economic stress scenarios yield reasonable and intuitive shock properties. Resale value in the protracted slump scenario for both the Toyota Corolla and Ford Ranger decline below those of the baseline forecast before rebounding during the latter stages of recovery. This demonstrates that the model is responding correctly to the lagged effects of supply shifts.

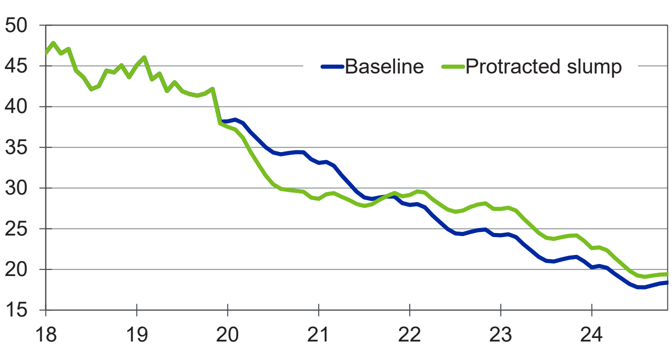
The model also captures the impact of oil price fluctuations well. In the oil shock scenario, the petrol-guzzling Ford Ranger does not retain its value as well as the more fuel-efficient Toyota Corolla.

Conclusion

In this paper, we introduced a new model for forecasting the residual values of cars in the Australian used-vehicle market under a variety of macroeconomic scenarios. We illustrated the model forecasts under varying degrees of vehicle usage over multiple time horizons. We showed that the model produces intuitive stressed scenarios, with an appropriate supply response, following a deep generic recession and also following a severe oil price spike. Finally, we validated the AutoCycle Australia model's forecasts across a variety of holdout periods to demonstrate forecast accuracy. Our model can be used for residual risk management in large lease and auto portfolios, as well as for pricing leases on individual vehicles themselves.

Chart 12: 2013 Ford Ranger Forecasts

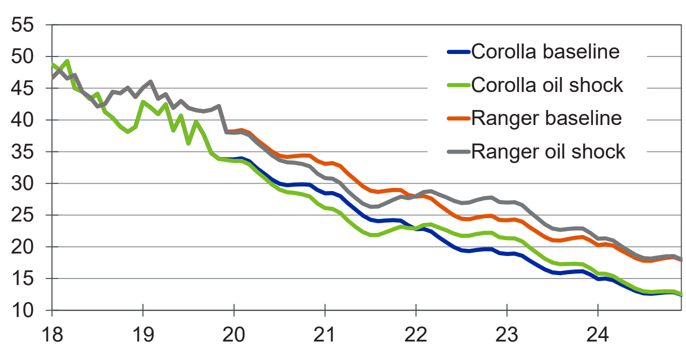
Residual value, % of MSRP, baseline



Sources: Datium Insights, Moody's Analytics

Chart 13: Ford Drops More in Oil Shock

Residual value, % of MSRP



Sources: Datium Insights, Moody's Analytics

Appendix

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Yr	1,217,638	2011.56	5.5245	1999	2019
Age in mos	1,217,638	53.0733	33.1036	0	710
Age in yrs	1,217,638	3.9618	2.7737	0	59
Vin	1,207,265				
Fuel type	1,217,638				
Make	1,216,804				
Model	1,217,435				
Sub-segment	1,217,638				
Region	1,217,638				
Body type	1,217,638				
Sale category	1,217,638				
Induction type	1,217,638				
Exterior color	1,217,638				

Sources: Datium Insights, Moody's Analytics

Table 3: Macroeconomic Variables and Their Sources

Economic variables used in the model

Description	Source
National Accounts: Real gross domestic product	Australian Bureau of Statistics (ABS); Moody's Analytics Forecast
Unemployment rate	Australian Bureau of Statistics (ABS); Moody's Analytics Forecast
New-vehicle sales	Wards Intelligence; Moody's Analytics Forecast
Population: Ages 15-64	Australian Bureau of Statistics (ABS); The World Bank; Moody's Analytics Estimated
Futures price: NYMEX light sweet crude oil - Contract 1	U.S. Energy Information Administration (EIA); Moody's Analytics Forecast
House price: Total - 8 capital cities	Australian Bureau of Statistics (ABS); Moody's Analytics Forecast
Consumer price index	Australian Bureau of Statistics (ABS); Moody's Analytics Forecast

Source: Moody's Analytics

About the Authors

Tony Hughes is a managing director of research at Moody's Analytics. He serves as 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 the company Moody's Economic View.

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 Portfolio Analyzer (ABS) product that provides forecasts and stress scenarios of collateral performance for structured securities worldwide. More recently, he championed and oversaw the development of AutoCycle, a tool that provides forecasts and stress scenarios for used-car prices at the make/model/year level. He has a current development project related to quantifying counterparty network risks that can be applied to the assessment of systemic risk in the financial system.

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 pre-provision net revenue 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 several papers in peer reviewed academic journals. He obtained his PhD in econometrics from Monash University in Australia in 1997.

Michael Brisson is a senior economist and associate director at Moody's Analytics. He is the lead auto economist, working as a member of the Specialized Modeling group in West Chester PA. Mike works developing new empirically driven auto-related products and services. Prior to joining the Specialized Modeling group, Mike built CECL, CCAR, and stress-testing models of consumer loan performance as a member of the Business Analytics team. Additionally, Mike has worked in the Moody's Analytics Research group, where he developed models for state and local government revenue forecasts. Mike holds a PhD in applied economics from Northeastern University.

Loc Quach is an associate economist with the economic research group at Moody's Analytics. He covers state and regional economies. Loc also contributes to the U.S. macroeconomic forecast model. He holds an MS in quantitative economics from California Lutheran University and a BA in economics from California State University, Long Beach.

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