The Next Generation of AVMs

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Property valuation is an integral part of the housing industry that is long overdue for improvement in various ways. Although much could be said on the topic of automated valuation models (AVMs) in this article, I explore the current state of the commercially available (i.e., private sector) AVM market, discuss how current AVMs fall short of meeting customers' expectations, and, last, propose a direction for the AVM industry to meet future customer demands.

An in-depth discussion of the various flavors of residential automated valuation models or AVMs (e.g. distressed, contemporaneous, lender-grade, marketing-grade, and so on), the difference between AVMs and computer-assisted mass appraisal (CAMA) systems, and various ways to estimate "value" (e.g., broker price opinions [BPOs], appraiser-assisted AVMs, form appraisals) are important related topics that are beyond the scope of this particular article.

AVM reports can be used by a wide variety of individuals, both in professional applications and for general research. Real estate lenders can use AVMs to provide support in loan applications and underwriting, while real estate professionals use AVMs to determine listing price, to negotiate between buyers and sellers, and to support an appraiser. Government agencies may use AVMs to assist with land use and planning decisions, valuation accuracy, and right-of-way value estimates.

AVMs are beneficial to individual researchers for listing price and offering price support in estate estimates, divorce settlements, and general real estate decision-making. Continued improvements in AVM data compilation and reconciliation, coupled with more universal standards, make the uses of AVM reports boundless in the valuation industry as well as in private research.

What Is the Current State of the AVM Market?

The current state of the AVM market is quite competitive. In the lending world, AVM estimates obtained via 1 of the approximately 20 commercially available AVMs range from $1.50 per property (for a high volume of properties) to more than $12 per property (for one-at-a-time valuations). In the lead generation world (e.g., online lead engines that underlie web-based home loans, car loans, and the like), AVM estimates are generated for pennies, literally, depending on the client and the intended use.

With such a wide range of AVM pricing strategies, the opportunity exists for new competitors to enter the market in an innovative way by differentiating themselves not only on pricing but also on the data returned to customers for each property valued using an AVM. In this article, I discuss ways in which this disruption of the industry can be achieved.

Why Do Current AVMs Fall Short?

Current AVMs fall short in multiple ways. First, some customers request AVM estimates only, whereas other customers request AVM reports. The return of AVM estimates often includes simply the AVM value for the subject property, but potentially an error statistic (the most common being the forecast standard deviation or FSD) and sometimes a range of possible values for the subject. These AVM estimates can be used for estimating homeowners' equity in their home (e.g., current home value minus current balance on the loan[s]). Obviously, reports contain much more detail on the subject property as well as data on the *best* comparable properties, the neighborhood where the subject is located, and (sometimes) the region where the subject is located. These outputs returned to customers have been fairly standard for the last 20 years, and as far as I can tell, no real innovation in the outputs delivered to customers has occurred.

Second, current AVMs possibly fall short in the data used to generate the AVM estimates. From others in the industry, I have learned that some attempts at incorporating different data sources have occurred. In an attempt to mirror contemporary sale price trends, some AVMs use listing data from multiple listing services (MLSs) in generating their estimates, while others continue to use only historical comparable sales transactions. Some AVMs use tax assessed value (TAV), which is often updated yearly, in their algorithms as a proxy for other unobservable variables. The point is that as long as data verification and quality control are not addressed in systematic ways through workflow documentation, then AVM estimates may be viewed as suspect.

Currently, AVMs can be enhanced with assistance from local appraisers. Products that incorporate these enhancements are called appraiser-assisted AVMs. Appraiser-assisted AVMs are particularly valuable in more remote, rural areas where property data may not be as consistent, as frequently available (i.e., fewer transactions in total), and as accurate as in larger metropolitan areas. Local appraisers may also be more familiar with the idiosyncrasies in a particular area where fully automated models may fall short.

Acknowledging the competing priorities of speed (i.e., appraiser-assisted AVMs are slower than fully automated AVMs) and accuracy (i.e., local knowledge of appraisers may improve AVM accuracy), appraiser-assisted AVMs still have room for further development to meet clients' needs, and more robust data are critical in order to achieve this development.

Another improvement that can be made to commercially available AVMs is through user- or client-added data. This enhancement is created when a user has an opportunity to edit information on a site that generates an AVM. When accessing Zillow, for example, the user is asked whether he or she owns the property located at a given address. With a quick verification of ownership, the home's facts can be edited to correct for any inaccurate information. This process recalibrates Zillow's AVM model that produces its Zestimate and creates a more reliable valuation if users understand the data points being asked for and the range limits of the variables being changed.

Either way, it seems that the time is right for other *big data* and crowd-sourced data to be used in AVMs. In the academic literature, it is becoming more common for Twitter data to be used to predict stock prices (e.g., see Bollen, Mao, and Zeng 2010) and Google data to predict movements in house price indices (e.g., see Kulkarni et al. 2009).

For tax assessors, though, the value added of appraiser-assisted AVMs is in the local knowledge that tax assessors bring to the table and the ability to control for widely varying changes year-to-year in tax assessed values for specific properties. The IAAO *Standard on AVMs* defines this as "statistically based models that provide a range of comparable sales. This process assumes that the appraiser will develop the final estimate of value" (IAAO 2004). Some jurisdictions treat this *fairness* issue very seriously, even capping year-over-year changes in property taxes to a predetermined level.

Other issues that arise for tax assessors are described in Appendix K of the draft IAAO *Standard on AVMs*, which is titled "Mapping Examples Related to AVMs." This appendix uses examples such as residential properties that are assessed in separate taxing districts or counties.

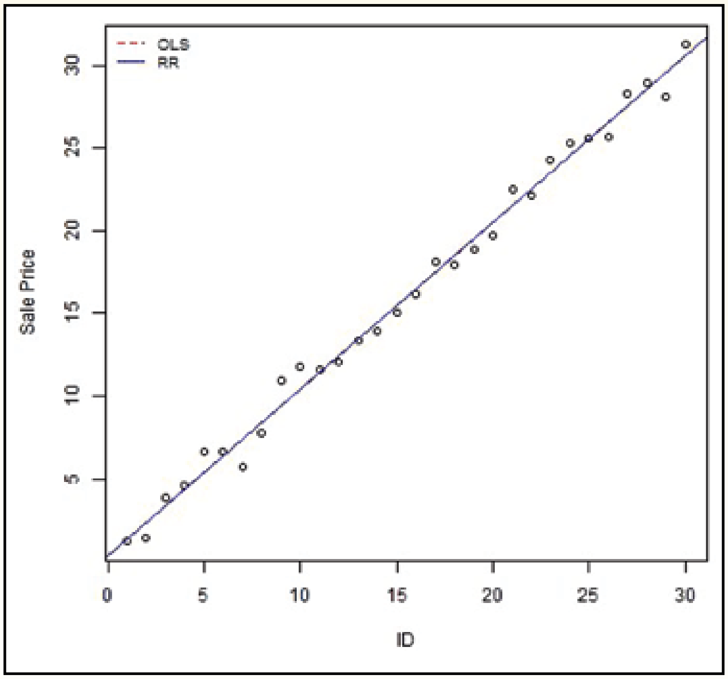
What Else Could AVMs Deliver to Customers?

Reason codes or *variances* are common in some industries. For example, one might find on his or her credit report a reason for a lower credit score (e.g., too recent opening of an account). In AVMs, reason codes can provide reasons for a particular determination or indications for situations in which some variable is "out of tolerance" or outside of a predetermined range of acceptable answers. This would give customers additional insight into the confidence that the AVM provider has in its estimates. One easily computable reason code that would provide additional insight is the number of comparable sales transactions used to produce the valuation estimate for a given subject property. (However, it is my opinion that this information is viewed by some AVM companies as trade secret information and would not be released.)

A second possible output is a statistically derived (bootstrapped) confidence interval around the valuation estimate for each subject property. The bootstrapping literature traces back at least to the work of Stine (1985).

A third possible output is somewhat more complex. AVMs that use regression-based methods typically choose a single

Figure 1. Ordinary least squares and robust regression estimation with no outliers



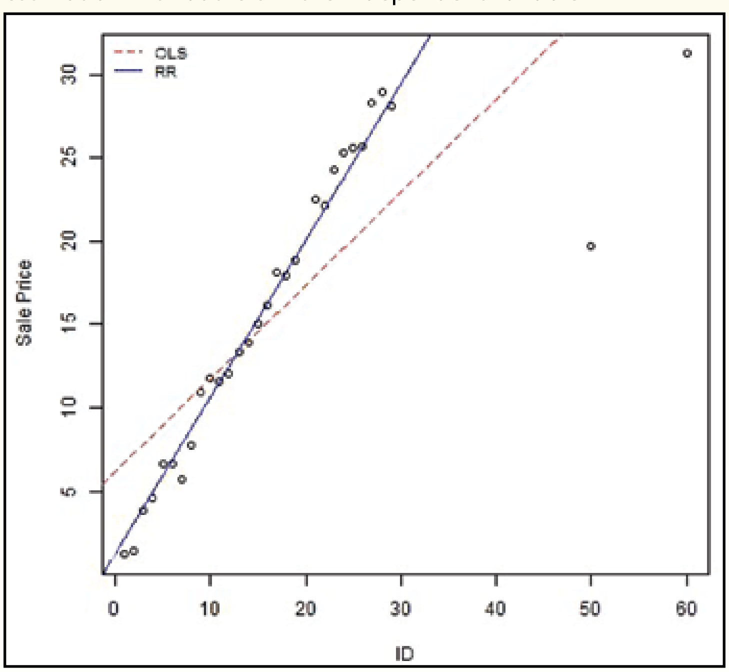
estimator. Alternative regression estimators could be used and the results produced for the end user of the AVM estimates to adjudicate. Two estimators used in AVMs today are the familiar ordinary least squares (OLS) estimator and the robust regression (RR) estimator. In *letting the data speak*, these two estimators treat potential outliers differently. In one case, when there are no outliers in the independent or dependent variables, the *lines of best fit* for the OLS and RR estimators are identical, as shown in the simulation depicted in figure 1.

Then, as a second case, when there are outliers in one of the independent variables in the regression model, the OLS and RR estimators produce different lines of best fit, as shown in figure 2. What is shown is that the line of best fit produced by the RR estimator represents the data better than the OLS estimator (which assigns equal weight to each observation). Mechanically, the RR estimator downweights the outliers and produces a line of best fit that better fits the large majority of data points in figure 2.

As a final example, figure 3 shows the simulated differences in OLS and RR estimators when there are outliers in the dependent variable (sale price). Note that the RR estimator provides a better fit to the large majority of observations than the OLS estimator.

AVMs could also deliver estimates that are based on a reconciliation of multiple data sources in a data warehouse that stores the reconciled property-level data from several sources (ATTOM Data Solutions, http://www.attomdata.com/data).

Figure 2. Ordinary least squares and robust regression estimation with outliers in the independent variable



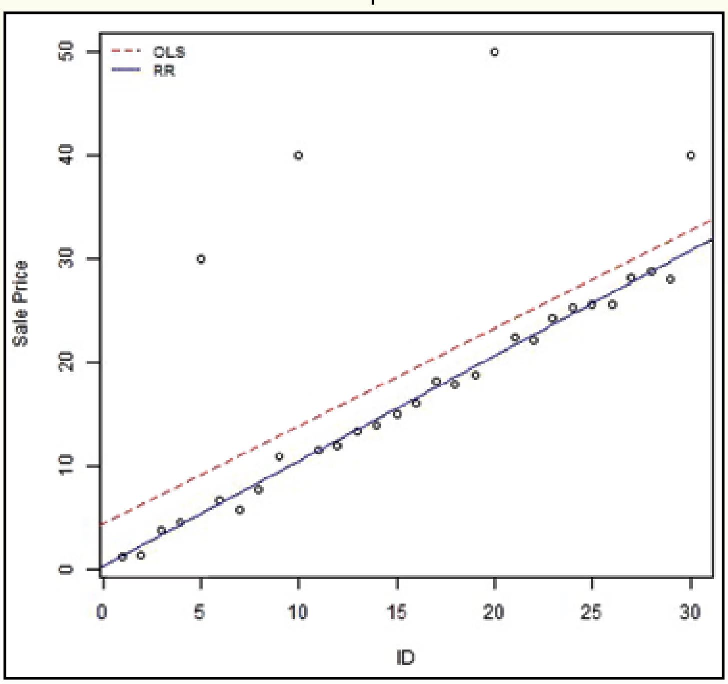
This is important for several reasons. First, when a single data source is used, there may be inherent biases in the raw data and how those data are collected. By using a reconciled database, the opportunity to reconcile differences *at the property level* is presented.

Note that reconciled data sources should be transparent in their use of data from multiple sources or providers and the business rules used to determine when information from one data source takes precedent over another data source.

For example, say that 123 Main Street in Cartersville, Georgia, is listed in one data source (e.g., tax assessor data) as having three bedrooms and two bathrooms. Further assume that a second data source (e.g., a current MLS listing) reports that the same property has four bedrooms and two bathrooms. An important difference here is the contributory value of the fourth bedroom if the MLS listing data are used instead of the tax assessor data; that contributory value could mean the difference in AVM estimate of $15,000 to $20,000 for this property, all else held constant.

My recent research with Krause (2016) describes the importance of documenting the reconciliation of between-source data variation to ensure the *best* valuation possible and replicability by other professionals in the industry.

Figure 3. Ordinary least squares and robust regression estimation with outliers in the dependent variable



Note that reconciled data sources should be transparent in their use of data from multiple sources or providers and the business rules used to determine when information from one data source takes precedent over another data source. This transparency further ensures that the reproducibility of the base dataset used in a CAMA system or an AVM is accurate, providing a clear valuation. The IAAO *Standard on Verification and Adjustment of Sales* (2010) also provides information about sources of sales data, property coding, and verification procedures for assessment purposes.

The question therefore is which data source should be used?

The reconciled data for 123 Main Street used to determine the AVM estimate are from the source that has been deemed most up-to-date, accurate, and reliable for that given jurisdiction *and that given property* based on myriad factors, including timeliness of delivery from the source, percentage of fields consistently populated, and previous performance in producing accurate AVM values.

The best source is often different from one jurisdiction to another, even within the same state, county, city, or ZIP code. The best source may even differ for different fields on the same property (e.g., the best source for number of bedrooms may end up being different from the best source for number of bathrooms). This is important because this process finally fulfills the true promise of multisourcing property data to estimate AVM values—not only for the sake of creating redundancies (which does have some value) but also in creating a new *super set* of synthesized data that is (1) not available from any one source on its own or (2) not available from multiple sources utilized in a binary fashion (i.e., either one source or the other for all properties in a state or county).

Conclusion

In my opinion, the time has come for AVM vendors to start adding more value to the outputs that they provide customers. Standard outputs, such as the AVM point estimate and a measure of confidence in the estimate (often conveyed using the FSD), are just that—standard. Value-added outputs of interest to customers may include reason codes, statistically derived confidence intervals around the AVM point estimate, the number of comparable sales transactions used to value a given subject property, and explanations of the underlying data source used to generate the AVM estimates.

The industries that are catered to by AVM vendors are being heavily regulated; however, the regulatory environment is currently under review in order to streamline and simplify the process while still ensuring consistency with safe and sound banking and valuation practices. See the Additional Resources section at the end of this article for current sources of standards and guidance on the use of AVMs.

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