



University of Oxford Research

The future of automated real estate valuations (AVMs)



Preface

This report aims to bring a deeper understanding of automated valuation models (AVMs) and to speculate about the likely future development of AVMs in real estate valuations.

In PropTech 3.0: The Future of Real Estate? (Baum, 2017), we suggested that in most developed markets, where debt is used in the majority of house purchases, the bank or lending party commissions a valuation by a qualified professional. This inevitably takes time – form filling by the buyer, processing of the application by the lender, commissioning of the valuation, setting up the inspection, preparing, writing and returning the valuation and processing the information received – which can eat into a large proportion of the 100 days.

Uncertainty over the value of the property can also delay the initial sale process, risking gazumping and a long drawn out negotiation. The HouseCanary (an AVM developer) proprietors believed that they can develop intelligent AI algorithms which can be accurate for the vast majority of US homes to within a 2% error range. If this thesis were to be accepted by market participants and lenders, perhaps half of the 100-day lag can be taken out of the process.

So we can imagine a world in which prospective house buyers can go to one site where all houses on the market are listed, with an independent and public valuation discoverable by the seller, the buyer and lenders. The transaction process would be faster, and the liquidity of this huge asset class would greatly improve.

In this report, we present a brief review of traditional valuations and criticisms of this process. We introduce mass appraisal and AVMs, and discuss the development of AI driven AVMs. We offer a discussion on the benefits and limitations of AVMs. We conducted interviews with various industry and government practitioners to gather their valuable opinions on AVMs based on their daily experiences with the valuations. Among all the issues, reliability and transparency seem to be on the minds of many in the industry, especially the AI AVMs.

We undertook a review of AI algorithms and conducted a case study comparing an AI AVM with a statistical AVM to illustrate the technical differences and to demonstrate the clear advantages of the AI model.

Finally, we offer our insights on the future development of AVMs in the specific context of the criticisms of the traditional valuation process. Will AVMs be a step forward? It seems inevitable that (i) AVMs will have wide applications and (ii) thanks to AI, we will see continually improving AVMs which will become essential for the modern real estate sector and the whole economy. The AI-driven AVM is a significant step forward from the hedonic pricing-based mass appraisal techniques of the 1980s.

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1. Introduction

The international definition of market value set out in the valuation standards of the International Valuation Standards Council (IVSC), commonly known as ‘the White Book’, also adopted by the Royal Institution of Chartered Surveyors (RICS) ‘Red Book’, is as follows:

‘the estimated amount for which an asset or liability should exchange on the valuation date between a willing buyer and a willing seller in an arm’s length transaction after proper marketing and where the parties had each acted knowledgeably, prudently, and without compulsion’ (IVSC 2019, RICS 2020c).

Note the use of the word ‘should’ in this definition. This places valuation in the arena of normative economics, focussing attention on the absence of an alternative (positive) approach. This is lacking because real estate markets (especially commercial property markets) are characterised by heterogeneous assets, and because there are typically too few transactions in order for a positive market value estimate to be made with confidence.

While publicly traded securities have a known price in real time, quoted by market makers and capable of being executed, there is no equivalent in real estate (and other private markets). Instead, valuations are commissioned in order that the most likely or most probable selling price can be estimated. Such ‘market valuations’ are used as proxy for trading prices in the measurement of real estate performance, when assembling a balance sheet, and in other situations.

The difference between a positive, data-based, valuation approach and the normative or rules-based approach we are familiar with is significant. It has led to charges of bias, client interference (for a summary, see Baum, Crosby and Devaney, 2021), smoothing (conservatism) and subjectivity. In the context of the fourth industrial revolution, it is inevitable that we will at some point face the question – why not use larger datasets, massively enhanced computing power and even artificial intelligence (AI) to model prices?

Automated Valuation Models (AVMs) are already widely used to support mortgage lending and mortgage-backed security risk assessments. These methods were developed in the 1980s and have been constantly improved. AVMs and AVM-related innovations have also been deployed on projects seeking to automate

the process of acquiring real estate (such as iBuyers). In the recent decade in particular, there has been a rapid development of data digitalisation, data scraping, artificial intelligence, and their application to AVMs. This development has not been geographically consistent. The digitalisation, reliability and availability of data, for instance, is more developed in the United States than it is in many other parts of the world.

In their IVS Agenda Consultation 2020 Invitation to Comment, the International Valuation Standards Council (IVSC) define an AVM as ‘[a] system that provides an indication of value of a specified asset at a specified date, using calculation techniques in an automated manner’. ‘Automated’ is emphasised by organisations such as the European AVM Alliance (EAA), which offers the definition of a ‘hybrid’ or ‘semi-automated’ model which includes human judgement in its output (IVSC, 2020).

In this report, we examine the potential for a new generation of AVM models to be applied to real estate valuation. The report has three main parts.

First, we offer an overview of real estate valuation methods deployed by chartered surveyors. We discuss in particular the direct capital comparison method, which is closely linked to methods deployed by AVMs, and introduce the concept of mass appraisal. We then review the key criticisms of real estate valuation from both the literature and interviews conducted with industry stakeholders. This is followed by an outline of the current applications of AVMs (reviewing the current state of development of AVMs across different countries), an examination of their potential to address key criticisms of human real estate valuations, and their limitations.

We then discuss the opportunities and challenges of marrying AI with AVMs. What are the current technical limitations we are likely to encounter when doing this? What are the current limits to industry application? We compare statistical AVMs and AI algorithms that allow us to expose the black box effect of AI, and we also conduct an empirical exercise comparing AI and traditional AVMs through a London-based case study.

Finally, we provide our outlook concerning the likely future of AI AVMs and real estate valuation in general and the potential for improved accuracy and timeliness.

2. Real estate valuation: a brief review

2.1 Real estate valuation methods

Over time, three general real estate valuation methods have been developed. These are:

- Direct capital comparison (also known as the sales comparison method)
- The cost approach
- The income approach¹

Direct capital comparison is the foundation of most AVMs, but this has hitherto been an intuitive non-scientific process performed by an experienced human being. If large quantities of relevant data are available, a wholly scientific process using computer-estimated equations relating property characteristics and prices becomes conceivable. This approach is known as hedonic pricing, using multiple regression analysis, or (increasingly) automated valuation modelling (AVM).

The direct capital comparison method of real estate appraisal involves comparing the property which is prospectively for sale with properties with similar characteristics that have recently been sold. This method takes into account the impact that different property characteristics have on the value of a specific property. These characteristics include:

- The size of the property and the land it sits on
- Location and neighbourhood (proximity to schools, highways, recreational facilities)
- Features of the property (the number of bedrooms, bathrooms, or garages)

2.2 Appraisal standards

There are a few institutions that publish appraisal and mass appraisal standards. Their standards are implicitly focussed on the human approach to valuation. These institutions include:

The International Association of Assessing Officers: in the late-1970s, the IAAO was one of the first institutions to publish mass appraisal standards; since then it has published multiple updates and revisions. The most recent version was published in 2017. Their

standard is often known as the Standard of Mass Appraisal of Real Property (SMARP).

The Royal Institution of Chartered Surveyors: RICS Valuation – Global Standards (The Red Book) published by RICS dates back to 1983. The most recent update of the RICS Red Book was in January 2020.

The International Valuations Standards Council: since the early 1990s, the IVSC began publishing its International Valuation Standards. The latest version was published in 2017.

The Appraisal Foundation: since 1987, the Appraisal Foundation has also published mass appraisal standards. The latest version – Uniform Standards of Professional Appraisal Practice (USPAP) – was updated in 2020.

The human approach works for individual properties or at a smaller scale. However, this approach encounters critical issues when the number of valuations required scale up to thousands and millions. For instance, thousands of experienced surveyors cannot be hired at a moment's notice to appraise each home in a mortgage lending portfolio whenever a loan book is being sold or an updated valuation is required.

To meet this need, it is essential to have a model that can quickly incorporate all the information available and deliver up-to-date valuations or appraisals. Such comparison-based mass appraisals are ideal for AVMs; applications based on the income approach are also being promoted, but are harder to deliver successfully due to the heterogeneous nature of most investment properties, in particular the lease agreements driving the net operating income.

Traditionally, valuation is labour intensive and time consuming, so it can be cost-inefficient to conduct large-scale valuations or 'mass appraisal' (the process of valuing a large group of properties at a given date using common data and a standardised method, which lends itself to statistical testing). Hence, the drivers of the development of automated valuation models are the potential to provide (i) low cost (ii) accurate valuations of (iii) large volumes of properties at (iv) high frequency.

2.3 Criticisms of real estate valuation

There has been a lot of published work dealing with the valuation process and valuation accuracy over recent decades – for a comprehensive review, see, for example, Gallimore, Baum, Crosby, McAllister and Gray, 2003. Klammer, Bakker and Gruis (2017) offer a review of the valuation judgement literature – highlighting interpersonal valuer judgement studies (client influence), as well as intrapersonal valuer judgement studies (data deficiencies, anchoring bias, stereotyping, availability heuristics, and process inconsistency). In this section, we will review the literature which details these criticisms, as well as offering insights from stakeholder interviews conducted for this study.

Accuracy and variation

The accuracy and variation of real estate valuations has been widely observed in the literature. Boyd and Irons (2002) offer definitions such as ‘valuation accuracy’ (the difference between a valuation and sale price); ‘valuation variation’ (the difference between two or more valuations of the same property); ‘valuation uncertainty’ (inability to determine a single value due to the subjective nature of valuation); and ‘valuation error’ (a mistake made). In the case of commercial property investment, Baum, et al. (2000) highlight the role valuations play in price negotiations, meaning that price and valuation are not independent of one another. This complicates attempts to define or measure valuation accuracy. Although residential valuations generally do not take place until after the contract of sale has been signed and the purchaser applies for finance, informal valuations (such as a sales agent’s price estimate) offer a similar complication.

To test valuation accuracy and variation, we were provided with the valuation history of a recently constructed apartment development in Melbourne, Australia. Of the 148 units within the development, 66 unit valuation histories were available, of which 27 were yet to be valued. The remaining 38 had been valued between May and June 2021 with a standard deviation from asking price of 12.84%. Six were valued at the purchase price, three were valued above the purchase price and 29 were valued below the purchase price. Of the 29 valuations below purchase price, 5 had been revalued. The revaluations varied from a further \$10,000 reduction in value to a \$65,000 increase in value. The \$65,000 uplift represented a 16.25% premium on the previous valuation. There was also an example provided of a one bed apartment being valued 11.43% lower than a duplicate apartment one level below. Several interview participants offered their perspective of why valuations can vary so much for residential purchases. The subjective nature of purchaser decisions in the residential market emerged

as a theme, particularly in the case of owner occupiers and less sophisticated investors.

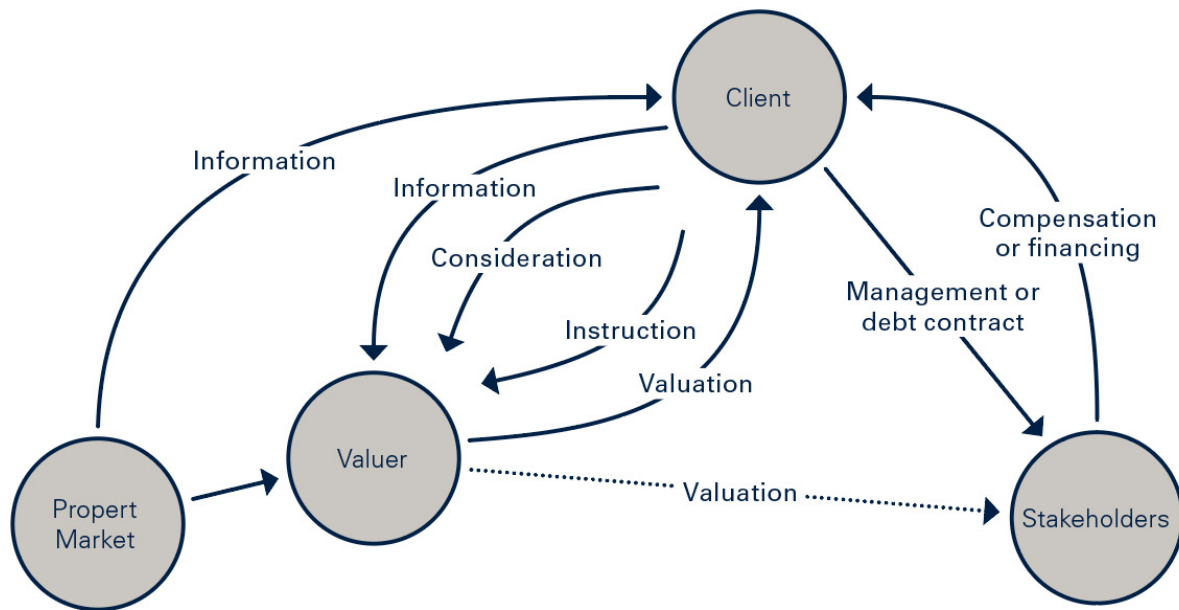
Description	Purchase price	First valuation (premium)	Second valuation (premium)	Third valuation (premium)
1 bed, 1 bath (level 4)	\$380,000	\$390,000 (2.63%)	N/A	N/A
1 bed, 1 bath, 1 car (level 5)	\$468,000	\$470,000 (0.43%)	N/A	N/A
1 bed, 1 bath, 1 car (level 6)	\$486,000	\$490,000 (0.82%)	N/A	N/A
1 bed, 1 bath (level 1)	\$367,000	\$367,000 (0.00%)	N/A	N/A
1 bed, 1 bath, 1 car (level 2)	\$452,000	\$452,000 (0.00%)	N/A	N/A
1 bed, 1 bath, 1 car (level 7)	\$485,000	\$485,000 (0.00%)	N/A	N/A
1 bed, 1 bath, 1 car (level 4)	\$464,000	\$400,000 (-13.79%)	\$465,000 (0.22%)	N/A
2 bed, 2 bath, 1 car (level 7)	\$570,000	\$490,000 (-14.04%)	\$500,000 (-12.28%)	\$570,000 (0.00%)
2 bed, 2 bath, 1 car (level 7)	\$671,000	\$550,000 (-18.03%)	N/A	N/A

Table 1: Melbourne development - sample of May-June 2021 valuations

Client influence

Human valuers may be placed under undue influence to produce a certain, preferred or required valuation. This could be due to the valuer being in close proximity to those affected by the valuation (such as the seller or purchaser in a property transaction), the looming threat of litigation during downward markets, or the need to cooperate with vested interests in order to continue winning contracts. The current solution to these challenges includes attempts to create psychological distance between the valuer and stakeholders of the transaction they’re working on, but this has practical limitations.

Levy and Schuck (2005) offer a nuanced assessment of clients’ influence on valuations. The regulatory obligation to provide independent and informed opinions of value conflicting with the valuer’s interest in satisfying clients in order to precipitate repeat business is referred to as a ‘principal and agent problem.’ Influence is said to be affected by four main factors: the valuer and valuation firm; external characteristics;



Stakeholders = lenders, equity holder etc.

Figure 1: Levy and Schuck (1999)

client characteristics; and the valuation. In the case of client characteristics, influence from a sophisticated client could be in the form of expert or informational influence, where a less sophisticated client tends to use more coercive influence tactics. The flows of information and compensation between valuation stakeholders are graphically represented in the above figure 1 by Levy and Schuck (1999).

Anchoring

According to Tversky and Kahneman (1974), humans are prone to yield an answer by first starting from an initial value. In the case of real estate valuation, reference points such as previous value estimates, the price paid or a pending sale price may influence a valuer's appraisal (Diaz, 1999; Gallimore, 1994 in Klammer, et al. 2017). The sales comparison method constitutes a form of anchoring, as does the choice of capitalisation rate via the income approach. In the case of securities, Siddiq (2018) found that 'adjusting the CAPM for anchoring provides a unified theoretical framework for understanding key asset pricing anomalies.'

Shie (2020) offers a brief history of the anchoring effect in real estate literature. Northcraft and Neale (1987) identify the application of anchoring in the context of the purchase of residential real estate – where 'fair market value (FMV) of the piece of property is not objectively determinable.' Their findings argue that the seller's asking price serves as an anchor for both amateur and expert subjects, and identify limited

support for their hypothesis that the impact of the anchor value (asking price) will be diminished as it becomes a less credible estimate of fair market value. Unveren and Baycar (2019) identify anchoring bias in the 1875 Ottoman cadastral survey of Istanbul, whereby homes were found to be valued higher than an identical home if its door number was higher – indicative of 'incidental anchoring'.

Smoothing

McAllister, et al. (2003) assumes smoothing in the context of property appraisals to refer to 'an under-measurement of 'true' variance' – and links the issue to valuation anchoring by reducing the deviation of value from one period to the next. In the absence of transaction data, valuations inform property performance indexes, as well as portfolio performance reporting. Smoothing issues are therefore particularly relevant to these areas.

According to Edelstein and Quan (2006), an artificially smooth series 'will underestimate the riskiness of the real estate asset class, and may distort its correlations with returns of other assets.' They found that '[t]he variance of appraisal based return indexes is substantially understated'. Cho, Hwang and Lee (2014) found that smoothing increased significantly between the 1990s and 2010, and that smoothing increased when uncertainty increased. Lai and Wang (1998) offer a defence for smoothing, gesturing to the 'unique characteristics of real estate markets as possible explanations for the seemingly low variance observed in appraisal-based (or transaction-based) return indexes.'

Demographic biases

During an interview, we were informed of research conducted in the US on the issue of valuation professionals undervaluing homes and neighbourhoods when the occupants fit particular demographic profiles. In May 2021, Business Insider and the Indianapolis Star reported a case of a valuation increasing twofold when a black homeowner had a white acquaintance stand in for them. In recent years, wider neighbourhood studies have been conducted by Redfin, 2021 and Perry, Rothwell and Harshbarger for the Brookings Institute (2018). Howell and Korver-Glenn (2018) highlight racial disparities in home values at the neighbourhood level in a US city and suggest remedying the issue by using an automated process to present comparable sales evidence from other neighbourhoods to the valuer.

2.4 Statistical AVMs

The sales comparison approach relies on finding many comparable sales to an accurate assessment of value. It makes sense to employ statistical models to develop this approach further. These can be categorised as hedonic models or artificial intelligence models.

Most of the traditional AVMs fall into the hedonic model category. Following Rosen (1974), hedonic pricing models are widely applied in the real estate sector by assuming that the property value is derived from basic property attributes such as construction year, size, the extent of capital improvements, locational characteristics and amenities. This type of modelling has been subject to constant development, in particular by introducing spatial and time correlation. In the later section of our empirical exercise, we present a hedonic pricing model with such spatial and temporal correlations.

AI models are based on the advent of machine learning and big data analysis. Machine learning algorithms such as decision tree models, artificial neural network models and clustering algorithms can be employed. We offer an extensive review on AI-driven AVMs in a later section.

We will later present two examples in detail in the case study section: we present one statistical AVM and two AI AVMs in order to draw a comparison between the two.

The main difficulty shared by any type of modelling in predicting the most likely selling price of a property is the backward-looking nature of any statistical inference method. For instance, the hedonic pricing model is designed to explain historic house prices and to show how much people are willing to pay for the features

of the house compared with the market average. However, such a model will have difficulty in predicting future house prices as this requires the model to be dynamic (the relationships between prices and the explanatory variables will change over time).

House price indices (the Nationwide and Halifax UK indices, for example) are often constructed using hedonic pricing models. The hedonic pricing model is run every quarter and applied to a fixed stock of representative houses, showing dynamic shifts in preferences in certain housing markets. However, one cannot observe the parameter updates before the houses are sold. To predict prices using a hedonic approach, one needs to assume that house attributes will be priced similarly in the near future and that the price of the representative stock of houses will remain the same.

The characteristics of the homes (size, number of rooms, age of the building, energy efficiency, etc) and the amenities (green space, convenience of transportation) may be priced differently in different locations. Green space is a more valuable amenity feature for a house in the city centre than for a house in the countryside. Moreover, the willingness of buyers to pay for certain attributes can vary through time. For instance, as household wealth increases in a particular region, occupants are more willing to pay for certain attributes such as a green space or public park. In the context of hedonic model panel regressions, regional and time fixed effects are often introduced to account for spatial heterogeneity and the dynamic nature of the willingness to pay for house attributes.

These difficulties cannot be entirely mitigated by the AI AVM, which is still a statistical inference model at its core. However, AI AVMs, having more flexibility in their functional forms, are good at mitigating many issues with statistical models for within-sample predictions.

¹ Certain property types require the use of a different way of estimating rent as an input into the income approach. This is known as the profits method.

3. Applications of AVMs

The increasingly widespread use of AVMs is attributable to the scalability of the technology, facilitating faster and more cost-effective underwriting of residential mortgages, as well as real estate portfolio valuation and other applications. AVM exponents argue that the technology fills a gap that cannot be achieved by humans, particularly in such cases where multibillion dollar real estate portfolios need to be valued within a reasonable degree of accuracy on a periodic basis; or when the supply of chartered surveyors does not meet the demand for valuations that arise from transactions. According to RICS (2020a), there are 1,415 registered residential property surveying firms in the United Kingdom. With a 10-year average of 61,720 transactions per month across the UK (Bank of England 2020), this implies an average of 43.62 valuations for residential mortgages per firm per month without the use of AVMs. In 2016, EAA estimated that approximately 30 percent of mortgage originations were facilitated by AVMs in the UK (with new purchases utilising them less than refinancing). From the interviews conducted for this project, it is estimated that between 30 and 70 percent of mortgages are now underwritten by AVMs in developed economies.

When residential lenders are making use of AVMs, they are generally doing so to facilitate lower-risk transactions. Examples of factors that can determine whether an AVM is used include loan-to-value ratio, dwelling characteristics, market risk and borrower characteristics. For instance, it is unlikely that a lender would seek the services of an AVM to underwrite a newly constructed home for a first-time buyer at a 95 percent loan-to-value ratio. The reluctance to use AVMs to facilitate higher risk transactions stems from the error distribution (quantified in the industry as 'forecast standard deviation'), as well as the question of accountability to a set of professional standards which apply to chartered surveyors. In addition, some jurisdictions implicitly prohibit the use of AVMs in some cases by requiring a formal valuation (by a chartered surveyor or similar) to be conducted. This will be discussed in more depth in section 4.

3.1 Conventional applications

The applications of AVMs have been growing in significance, although this appears to have been relatively unnoticed in the real estate and finance sector. We briefly present a few examples and cases where AVMs have been applied or are likely to be applied in the near future.

Mortgage lending

Mortgage lending is an area where AVMs are well established. Banks and other lenders need a quick and effective way to decide whether the collateral value of any potential mortgage contract is sufficient at the time of mortgage issuance. This is a critical step for effective risk management for banks and other lenders, as well as their insurers. Without AVMs, banks would have to hire professional surveyors to conduct a manual valuation of each property, which can be fairly costly. Given the improved accuracy of AVMs, and the common application of conservative loan to value ratios by banks which reduces the importance of valuation accuracy, many of these transactions can now be underwritten by an AVM without increasing risk as claimed by many AVM providers in the UK such as Hometrack and Corelogic.²

Mortgage backed securities

Once a mortgage is issued, it is often bundled with other mortgages and sold in the secondary market. The resultant product is known as a mortgage backed security (MBS). MBS investors use AVMs to assess the risk exposure of their investments. They also use AVMs to conduct mass appraisals to update the valuation of their portfolios.³

Property tax

In many jurisdictions, taxes are applied to households in proportion to the value of their home. In the UK and other countries, households are charged a council tax in proportion to their home's value as determined by a government valuation agency (in the UK, the Valuation Office Agency or VOA). In order to ensure each household is charged the appropriate amount of council tax, periodic valuations of all housing stock within a jurisdiction need to be conducted.

According to the Office for National Statistics, there were approximately 27.79 million households in the UK in 2020. Manually valuing each of these dwellings is impractical, prompting the argument for using accurate, automated alternatives. While this leap has not yet been made in England and Wales, some jurisdictions are already employing AVMs as the benchmark for property taxation. For instance, the Northern Ireland Valuation and Lands Agency (NIVLA) and the Rating and Valuation Department for the Hong Kong SAR Government (RVDHK) have used AVMs for property tax purposes. Tretton (2007) documents in detail the practice of AVMs for tax purposes.⁴

Commercial real estate

Given the low frequency of commercial property transactions, it is unrealistic to assume that a hedonic pricing model-based AVM would perform as well in commercial real estate as it does for residential property. In most cases, there simply are not enough data points to support such a method in commercial real estate, be it based on AI or a statistical approach.

3.2 Innovative applications

Opendoor

Some of the innovative users of AVMs are new players like Opendoor, which is categorised as an iBuyer.⁵ In effect, Opendoor acts as a real estate agent – buying homes from homeowners and later selling them for a premium. This is achieved by deploying AVM technology and a quick turnaround to make commission and to benefit from potential price disparities.

The major benefit of homeowners dealing with iBuyers such as Opendoor is the speed and convenience of the transaction. Opendoor's self-assessment is the following:

'iBuyers use technology to quickly make an offer on your home. If you accept, they assume the risk and holding costs of finding a buyer so you can have a simpler, more convenient, and more certain sale. This represents a dramatic shift in the way people are buying and selling homes, offering an alternative to the pain points of the traditional process.'

The success of such business models relies on the accuracy of their internal valuations. Their most profitable deals are cases where the seller is under pressure to sell immediately, or under-valued assets. A high performing AVM could identify under-valued properties.

According to interview responses, iBuyers are much more active players in the US due to the availability of data and technology. Moreover, it was also highlighted that the service and housing stock iBuyers provide is relatively homogenous.

Invitation Homes

By taking one step further than the conventional iBuyer model, some property management firms retain the acquired properties for rental income. Companies such as Invitation Homes buy single family housing across a region or even a country, then lease them out – offering a maintenance service for steady rental cash flow from the tenants. This is a fundamentally different business model but can still benefit from an accurate AVM.

Rental and capital valuations are critical in developing the single family rental market. For a rental income-driven property company, a low-yielding property is an underperforming asset. Replacing them with high rent, low price property would improve the overall return of their portfolio. Moreover, selling overpriced assets will deliver capital gains. Accurate AVMs that offer up-to-date valuations of the properties within the portfolio are vital and sit at the heart of this proposition.

Zillow Offers

In 2018, Zillow announced plans to get into the house flipping business. Algorithms would help it find under-valued properties. The company would buy the homes and resell them for a quick profit. But in 2021 Zillow shut down the iBuyer business, laid off a quarter of its staff and made a writedown of over \$500m because Zillow's algorithm was unable to predict the future pricing of the homes it was targeting.⁶

3.3 AVMs in different countries

The Americas

The United States, as one of the two or three largest real estate markets in the world, is likely to be the region with the most active AVM adoption. There are numerous providers of AVM services from industry leaders to emerging entities. We briefly introduce a few well-established AVMs to showcase the application in the US.

- Zillow Zestimate

Zillow claims to be the most visited real estate website in the United States. The group includes a number of brands that facilitate selling, buying, renting and financing homes in the United States. Zestimate is

Zillow's estimate market value for a home, integrating data from public sources and users.

- Trulia AVM

Trulia is a home and neighborhood site for buyers and renters to find homes and neighborhoods across the United States through recommendations, local insights, and map overlays that offer details on commute times, reported crime, schools, and nearby businesses (Crunchbase, 2021). In 2014, Zillow announced that it had entered into an agreement to acquire Trulia. Trulia is now owned and operated by Zillow, but the companies do not produce the same AVM outputs.

- HouseCanary

HouseCanary was founded in 2013 and provides services in valuations, forecasts and transaction support. It is considered one of the leading AVM providers in the US. According to HouseCanary, their clients use them to drive acquisition, underwriting, portfolio management and more. HouseCanary uses artificial intelligence and image recognition technology to drive their real time automated valuation process (Baum, 2017).

There are many other AVM providers in the US. Several other notable providers include:

- Realtor.com AVM
- CoreLogic Real AVM
- Realtor Property Resource (RPR) RVM
- Homesnap
- Freddie Mac Home Value Explorer

Europe, Middle East and Africa (EMEA)

EMEA is another active region for AVMs thanks to the well regulated market and good data availability. However, the activity is mostly concentrated in European states, among which the UK is probably the most active in applying AVMs for various uses, followed by Germany and other eurozone countries. Examples of EMEA-based AVM providers include:

- CoreLogic UK

'IntelliVal is a next generation automated valuation model (AVM) from CoreLogic that has been deployed across three international markets prior to being developed for the UK property financial services industry. IntelliVal capitalises on Artificial Intelligence to deliver a powerful AVM solution that more effectively predicts and responds to market conditions. The ability for IntelliVal to process complex correlations and market trends, combined with continuous learning from historic outputs provides lenders with better quality information to validate property estimates and assess risk.'⁷

- Hometrack/Zoopla UK

'After Zoopla purchased Hometrack, the Hometrack Automated Valuation Model (AVM) has been the UK market leader. In fact, 13 of the top 15 UK mortgage lenders use our AVM as an integral part of their processes. Hometrack's AVM has been used in over 50 Residential Mortgage Backed Securities (RMBS) and was the first model accredited by all of the major ratings agencies.'

- Immoscout24 Immobilienbewertung Germany/Austria

'Immobilienscout24 is the largest online property listing platform (in Germany). They also offer property valuation to the users of the website using AVM. ImmoScout24 has the great advantage in this as they are data aggregator themselves too, which allows them to be very timely in training the AVM. The bare minimum information they need for valuation are: postcode, size and number of rooms, construction year, and special equipment.'⁸

- On-Geo Germany/Austria

'On-Geo GmbH has been supplying data, software and services for property valuation for over 19 years. Dr. Klaus Wiegel, founded in 2002, started with a web-based research data platform for the real estate industry. Today on-geo GmbH is the market leader in Germany with the LORA® real estate valuation solution, the geoport webshop and its network of experts for viewing and appraising real estate. On-geo GmbH currently has 160 employees from its Munich, Erfurt and Vienna locations – and the trend is rising – now throughout Europe.'⁹

- EffiCity and Iad, France

Those are two examples of active AVM providers in France, which offer similar services to customers for free. Both of them are also offer real estate agency services.

- Lightstone – South Africa

'Lightstone is a South African company founded in 2005. They provide information, valuations and market intelligence on all properties in South Africa. Their AVM was designed to estimate residential property values across South Africa and claims to be the 'only one regularly reviewed by international rating agencies and bank credit committees' (Lightstone, 2021).

Here is a list of AVMs used in other European countries:

- HouseVault, Rightmove AVM, Homeflow AVM – UK
- Calcasa – the Netherlands
- CRIF and Arc Real Estate – Italy
- Eiendomsverdi – Norway
- Tinsa – Spain
- Värderingsdata – Sweden

² <https://www.hometrack.com/uk/products/valuations/automated-valuation-model/>; <https://www.corelogic.com/wp-content/uploads/sites/4/downloadable-docs/about-automated-valuation-models.pdf>

³ <https://pubsonline.informs.org/doi/10.1287/mnsc.2019.3569>

⁴ <https://www.emerald.com/insight/content/doi/10.1108/14635780710776684/full/html?skipTracking=true>

⁵ <https://www.opendoor.com/w/guides/what-is-an-ibuyer>

⁶ Financial Times (2021): Zillow's flip-flop shows limits for Big Data in property - <https://www.ft.com/content/c4338149-59b3-4a4b-ae19-f9e45ff1a3d2?accessToken=zwAAAX1cjSYwkdPEM4>

⁷ <https://www.corelogic.uk/products/intellival/>

⁸ <https://www.immobilienscout24.de/anbieter/avm-immobilien-herbert-m-hoerl/a9e0ed10f01ad38403a09a7>

⁹ <https://www.on-geo.de/ueber-uns/>

4. Current limitations and challenges of AVMs

4.1 Process transparency and the black box

Like any other prescriptive model, an AVM can be broken down into three constituent parts: inputs, process, and output. Inputs are datasets, which could comprise comparable sales data, property features, economic data, location features and a wide range of others.

The process can be one of many currently deployed by AVMs which can fall within or outside the definition of artificial intelligence. Combined, inputs and process are the most tightly held secrets of an AVM, which contrasts with a valuation conducted by a human professional. This concealment is referred to as the ‘black box’—seen by AVM developers as intellectual property vital to their competitiveness and by valuation practitioners as a likely deviation from prevailing valuation methodology.

Inputs	Process	Outputs
The inputs and their relative significance in the respective model are kept private.	Key component of intellectual property and the most heavily guarded.	Shared with end users and clients, therefore can be used to measure performance.

Figure 1: inputs, process, and output

Since the output (valuation) is the most transparent part of an AVM, this has been the area of most focus for quality control. For instance, when conducting periodic assessments of the quality of an AVM, mortgage lenders will have the model conduct a retrospective valuation and compare the output to a professional’s valuation. Output is also an area of focus for organisations aiming to set and uphold professional standards for the technology, such as the European AVM Alliance (EAA).

The transparency of data inputs and processing algorithms can also be of concern for many potential adopters of AVMs. For instance, if we were to apply

AVMs to taxation, the algorithm and data input transparency are both critical, as they are essential in helping to convince the public that the valuation has been produced in a fair and just way. However, the need for better transparency does not mean that AVM practitioners, who often rely on proprietary data and algorithms to stand out from the competition, will be happy to go along with this. Higher levels of transparency would level the playground for all and may lead to many AVM producers losing their competitive edge or even going out of business. For now, there does not seem to exist a clear way out of such a conflict.

In the interviews we conducted, perspectives on AVM transparency varied. Those comfortable with current levels of transparency suggested that not too long ago valuers were collecting their own data in silos, black boxes in all but name. It was also pointed out that statistical valuation methods such as hedonic pricing models have also been known to conceal inputs and processes. Are AVMs all that different to their predecessors?

‘What’s actually in the black box? This doesn’t inspire much confidence. But in saying that, it wasn’t too long ago that the valuation profession was reluctant to share data and calculations. This was practically the same as the black box we see in today’s AVMs. Just as valuers are much more transparent as to valuation calculations with their clients, AVMs need to show exactly how the calculations work’ (Nick Knight, CBRE)

Those expressing concerns about AVM transparency usually focussed on the role of the chartered valuation professional. In some instances, interviewees expressed skepticism over models which were developed through technical or statistical prowess in the absence of oversight from experienced and qualified valuation professionals and accepted valuation methodology. Some argued that this was a key differentiator for AVMs developed by leading real estate firms which are also able to offer users traditional desktop and more labour-intensive human valuations.

Overall, transparency issues seem the most pressing concern if AVMs are to be widely adopted across

sectors. People are genuinely uncomfortable with the unknown and uncertain. Some of the issues regarding transparency can be resolved by more and more people learning how AI works and how statistical models function.

Clearly, the key test of the likely acceptability of AVMs will be based on the requirements of any good valuation, plus the ability of the AVM to overcome criticisms of human valuations without introducing new problems.

In section 2, we suggested that a good valuation process will be able to produce low cost, accurate valuations of large volumes of properties at high frequency. We also summarised criticisms of human valuations to include client influence, bias and inconsistency. How do AVMs perform in this context?

4.2 Accuracy

There are a number of definitions associated with the accuracy of AVM outputs. The confidence level, for instance, is defined by EAA (2016) as '[a] predictive measure (usually given on an AVM provider's proprietary scale) expressing the estimated accuracy of each AVM result and as such directly translatable into a Forecast Standard Deviation'. Reliability is also a common term applied across jurisdictions, referring to whether an AVM's output falls within a predetermined range for what would be considered market value - defined by EAA (2016) as 'benchmark value'. This raises the question of how to determine market value. One solution used is for AVM stakeholders to compare an AVM output to a valuation conducted by a chartered valuation professional retrospectively. This follows a precedent set by legal proceedings whereby a challenged valuation is compared to a retrospective one conducted by a disinterested third party. Bias follows the same definition as elsewhere in statistics, being the presence of variation in one direction (e.g. an AVM being inclined to produce undervaluations).

Gayler et. al (2015) offer a perspective on evaluating the strengths and weaknesses of AVMs under conditions related to their use. They define 'hit rates' as '...the average percentage of properties that the AVM claims it can produce a usable valuation for. Claims of approximately 75-80% hit rates seem to be fairly common...'; and 'confidence scores' as '...typically of the form "X% of valuations will be within Y% of sales price.' A key issue raised in this report is the lack of standardisation of performance metrics across AVMs, meaning that the measure of accuracy in one AVM could be different from the measure of accuracy in another.

During the interviews we observed more appetite for a higher proportion of automated valuations to fall within the existing range than there was for that range to tighten (say, from 15 percent to 5 percent). This, however, is indicative of a key limitation of automated valuations, particularly in the case of underwriting residential mortgages. If a lender used an automated valuation to underwrite a higher risk mortgage (e.g. a 95 per cent loan-to-value ratio loan), the lender risks lending a higher amount than the underlying asset's market value. Because of this, AVMs are generally only used to underwrite low-risk mortgages, limiting their scope somewhat. These are referred to as low-intensity valuations.

The required intensity of a valuation is illustrated by a cascade model, whereby the viability of an automated valuation is assessed, followed by a desktop valuation, a kerbside valuation or a physical inspection for more complex cases. In the case of mortgage origination, interviews indicate that this currently limits AVMs to an estimated 60 percent of the Australian market, 50 percent of the U.S. market, and 30 percent of the UK market.

Accuracy becomes less of a problem in the context of portfolio appraisal and mass valuation if the variation is random and can be 'averaged out'. Consequentially, multiple interviewees identified valuation for the purposes of portfolio appraisal and mass valuation as a strength and opportunity for AVMs (also due to the impracticality of humans conducting so many valuations periodically). Alongside other applications, however, they are not immune from bias. This issue emerged during interviews.

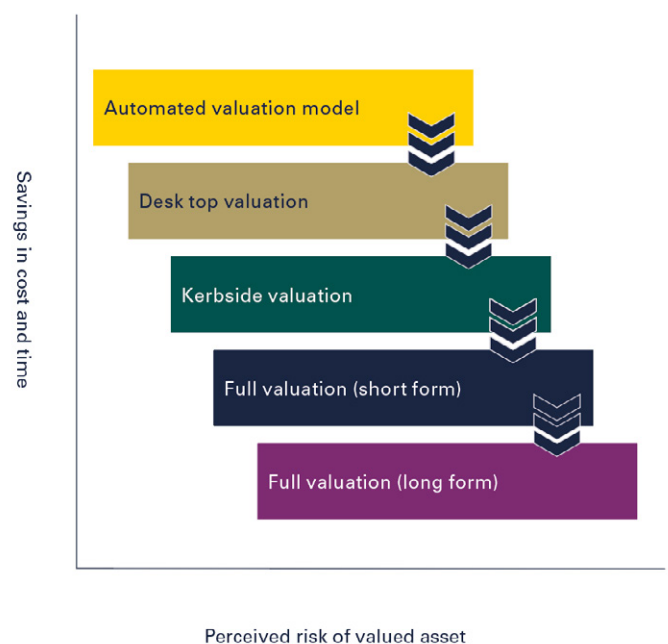


Figure 2: a valuation cascade model, adapted from Gayler, et. al (2015)

A consistent theme during the interviews was an acknowledgement of a valuer's inclination to err on the side of caution when conducting valuations. However, bias within AVMs was also cited. Although people try to eliminate the bias in modelling, some biases simply cannot be circumvented. We have to acknowledge these potential sources of bias regarding AVMs.

Data lag induced bias

A primary cause of this challenge for AVMs is believed to be real estate data lag. In the case of transaction data, there is a question of when a sale price should be reflected in the data (at listing, offer, exchange of contracts or settlement), as well as how long it takes for that data to be released (for instance, it is common for statistical agencies or national land registries to take three or six months for a particular sale to be reflected in their price index and/or other summary statistics). As a consequence of this, various AVMs are perceived as playing catch up during periods of price movement (most recently during the coronavirus pandemic). One such solution to data lag has been to incorporate presale/listing information, but there are varying perceptions of the credibility of this information given its use for marketing purposes.

Data availability bias

Depending on the type of AVM one uses, data availability biases can arise in most cases. For instance, if a regional housing market happens to have zero transactions in the past few quarters, any AVMs relying on comparables to form estimations would suffer greatly and induce bias due to a small sample size. AVMs, like human valuations, rely on recent observations to form predictions. When the number of observations becomes too low, the chance of a bias sample not representing the whole market in a given time period becomes very high. In such cases, professional human judgement could yield results that are superior to an AVM.

Sampling bias

One important question regarding the process of using recent transactions to form valuations is that whether the property on the market reflects the overall stock of the properties at the local residential market. For example, in some periods, the local residential market might have overwhelmingly lower valued properties due to some specific shocks.

'There's a perception of a material lag between what data the AVM uses and what the market is seeing. In my experience, an effective remedy to this has been to incorporate presale data. Given the nature of some presale data points (e.g. distinct views of listings for a property, suburb, etc) the ability of invested parties to influence

unduly is limited. In general, presale data is used to inform the direction and magnitude of forecast market movements at a more macro level which is then input into the AVM, this diversifies away some of the risks associated with individual reporting by agents, etc.' Darren Lawton

4.3 Emulating the human touch

From the stakeholder interviews conducted during our research, a common theme of skepticism toward AVMs emerged especially where there was little-to-no involvement from chartered real estate professionals. This contrasts with the alternative view that an AVM ceases to be so once there is any human interference in the process. A key concern raised was the inability of AVM technology to emulate the human touch. The alternative perspective is that this is a positive thing: subjective human appraisal is controlled for in an automated valuation. Nevertheless, a number of potential shortcomings of AVMs in their current state were highlighted.

- Transformations in the purchasing power of demographic groups, leading to certain features (such as real or perceived safety) having a greater weighting on the value of a dwelling, as well as variation in preference of transport infrastructure.
- Accounting for views, ceiling heights, quality of fixtures, renovations and extensions. In one case, two AVMs were deployed to underwrite a residential mortgage. One returned a higher valuation than the other because it used satellite imagery and had detected an extension to the dwelling.
- Highly subjective and localised features adding value to certain buyers.

In order to test an AVM's capacity to account for some features while holding others constant, comparisons were made between three publicly available AVMs in the UK on two separate pairs of very similar dwellings in south-east London. These comparable properties differed mainly in their aspect (east or west facing).

There was a high variation between AVM outputs for the same dwelling. In some cases, there was also variation between dwellings using the same AVM. In the first example, there was a 52.5 percent (west) and 141.6 percent (east) valuation variation between the lowest and highest output. In the second example, both dwellings returned 104.4 percent valuation variation between the lowest and highest output. These variations are substantially beyond the usual 5-20 percent valuation variation tolerances cited in the literature – see, for example, Crosby, Lavers and Murdoch (1998).



2 Dec 2020	End terrace (west), northerly aspect faces other buildings	End terrace (east), northerly aspect faces Thames and City
JLL	£1,007,400 - £1,231,200 (£1,119,300)	£476,900 - £582,700 (£529,800)
Zoopla	£1.1 - £1.34 million (£1,220,000)	£1,150,000 - £1,410,000 (£1,280,000)
Your Move	£720,000 - £880,000 (£800,000)	£720,000 - £880,000 (£800,000)



3 Dec 2020	No particular noteworthy aspect features, but same floor plate as comparable	Rear of terrace is westerly aspect over park, Thames and city
JLL	£660,600 - £807,400 (£734,000)	£660,600 - £807,400 (£734,000)
Zoopla	£610,000 - £915,000 (£763,000)	£1,000,000 - £1,110,000 (£1,060,000)
Your Move	£1,350,000 - £1,650,000 (£1,500,000)	£1,350,000 - £1,650,000 (£1,500,000)

Figure 3: AVM outputs compared

AVM output variation was defended by several interview participants. It was pointed out that human valuations are also prone to variation (as highlighted in section 2).

'A challenge faced by residential AVMs is the level of subjective human decision making in the market. This is going to be difficult for an AVM to replicate. In saying that, an advantage of AVMs becoming more widely used is controlling for some undesirable subjective human biases, such as undervaluing a property because of the occupant's demographic profile. If implemented correctly AVMs could help solve some of the inequalities that exist in our societies.' Cate Agnew

In other words, the market may be subjective, in which case a valuer needs to account for that (and an AVM will struggle to be able to do so).

4.4 Geographic challenges

A key differentiator of AVM technology is the ability to promptly value assets and/or portfolios in a cost-effective manner. However, AVMs in their present state exhibit geographic constraints at a sub-county or sub-municipality level level (in other words, the model is specified for a particular location, which has to be pre-defined). Attempts to broaden these geographic constraints reportedly lead to 'degradation' of model

outputs. This leads to several implications, such as:

- AVM providers have identified that attempts to expand the geographic boundaries of their models lead to degradation and less reliable outputs.
- Input variables are not necessarily consistent between geographies. In other words, the variables used to determine value in one area are likely to differ entirely to another, even if they are proximate to one another. Input variables within the same geographic area are also known to vary over time. The quantity of observations will also vary between geographic areas due to sales volumes and/or population.
- Geographic constraints can serve as a barrier to entry, serving established providers but obstructing new entrants who are unable to develop the number of models required by clients with the greatest geographic distribution (such as mortgage lenders). For example, a country the size and complexity of the United Kingdom requires approximately 1,000 geographically separate models.
- Lengthy contracts with premium AVM clients (such as mortgage lenders) were reported to be up to a decade in length, which offers a first mover advantage to established AVM providers. This challenge is likely to be more pronounced in markets where lending oligopolies exist.
- Jurisdictional differences within and between countries result in AVM developers having to

contend with different laws, regulations, definitions and datasets in order to scale their product beyond a local market. One example offered was the contrast in the definition of 'book value' within Canada which influences how property is taxed.

'Postcode sectors aren't the best location input for an AVM. It's used by the post office for a reason. Alternative methods of grouping common location characteristics can be more useful, but labour intensive. Manually creating polygons to group broadly similar location factors across a country such as the UK can take up to 7,000 person hours.'

Mike Brankin

4.5 Human resistance

Jefferies (2017) offers a timeline of the development of real estate investment income valuation models in regions such as Europe, North America and Australasia spanning from the 17th century 'estate management surveyors' of English manors to the present day. Perceptions of value were reshaped by rapid transformations in technology and politics which took place in 18th century England (Featherson, 1975). It is no coincidence this period saw the establishment of The Surveyor's Club, followed by the Royal Institution of Chartered Surveyors (RICS). According to RICS (2020b), 'the requirement for such an organisation was driven by the rapid development and expansion of the industrialised world; as infrastructure, housing and transport links grew, so did the need for more stringent checks and balances'.

Over its existence, the valuation profession has faced real and perceived threats. Jaffe (1986) asked whether there was a future for the profession in the wake of the 'microprocessor revolution'. In particular, the major change forecasted at that time was the 'increased availability of empirical methodologies for valuation, but the future lies in information management and data

analysis'. However, perceived threats of technological progress are not constrained to valuation professionals in recent decades. It can be observed repeatedly over centuries, professions and geographies. Perhaps the most familiar account of technological resistance from the historical record are the 19th century Luddites who have since become synonymous with anti-technology sentiment (Clancy, 2017).

AVMs represent a radical change in the way business is conducted in the valuation profession, as well as the broader real estate industry. Aside from the direct impact on the undertaking of valuations, they could also have an influence on the speed of property transactions and the feasibility of emerging business models (such as iBuyers and online listing platforms), as well as property taxation. This change does not come without challenges. One of the key challenges identified was how AVMs and their developers are received by the valuation profession and wider real estate industry.

Kanter (1995) outlines sources of resistance to change. Some of these are directly relevant to the increased adoption of AVMs. 'Real threats', for instance, exist in the form of the increased adoption of AVMs in areas where valuation professionals would usually be deployed (such as underwriting residential mortgages and commercial real estate valuations). Other sources of resistance should also be considered, such as:

Loss of control: valuation professionals being excluded from the AVMs as tools of a conversation, raising questions about the absence of real estate know-how in AVMs.

Uncertainty: limited communication between stakeholder groups leading to confusion.

Concerns about competence: a lack of awareness of how valuation professionals could use AVMs to their advantage.

A key difference between the perspectives of real estate professionals and AVM developers pertains to the definition and application of AVMs. Valuers who are welcoming of AVM proliferation see it as a tool no different than a slide rule or Parry's tables. From this perspective, AVMs simply serve to refine the valuation profession. Some even argue that valuers will benefit from a lot of the mundane and repetitive work being automated, freeing up their time to focus on more appealing work such as thought leadership. The challenge faced by this theory, however, is the very definition of AVMs (as per the AVM community). Simply put, an AVM ceases to be automated as soon as a human gets involved. Therefore, AVMs as a tool of a valuation professional are likely to better resemble a hybrid AVM. Having clarity in each area of possible

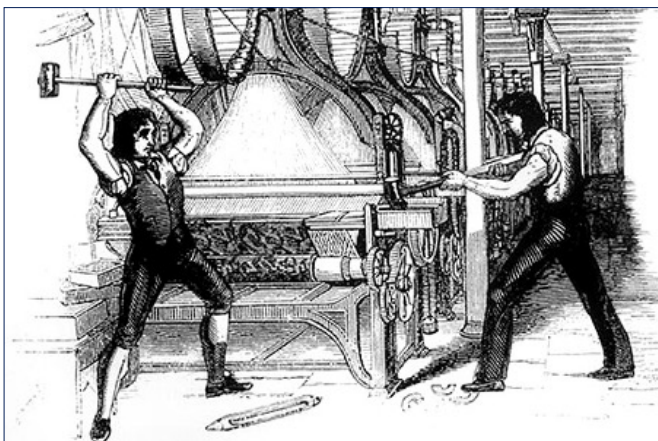


Figure 4: Luddites

resistance will be vital to the successful adoption of the technology across the valuation and wider real estate profession.

As part of the PropTech revolution, AVMs have also faced criticism similar to other PropTech verticals. One was the misalignment some founders have with the real estate industry, namely the inclination to enter the industry with a revolutionary attitude which ceases to gain any traction. These anecdotes suggest that change in the industry continues to be largely incremental - something AVM developers are going to have to contend with.

‘In the case of AVMs, the ‘A’ stands for automated. As soon as you attach a human to it, it becomes what we’d refer to as semi-automated or hybrid. Naturally we recognise and respect the contribution of surveyors and we welcome close collaboration with them on hybrid valuations.’

Dr Andrea Biguzzi, Secretary General of the European AVM Alliance

4.6 Regulatory inertia

Incremental change is reflected in the regulatory landscape of many jurisdictions. Whether for the purposes of self regulation of AVM users or via regulation imposed by government, regulatory inertia is a key obstruction to the use of AVMs. In the US, ‘appraisal waivers’ are required for alternative valuation methods such as AVMs. According to (Neal and Goodman, 2020; Di Martino Booth, 2020) the coronavirus pandemic increased the rate of appraisal waivers for government-sponsored enterprises Fannie May and Freddy Mac. Whether the coronavirus pandemic facilitated a permanent nudge toward a higher proportion of appraisal waivers or a temporary one is yet to be determined.

Inertia can also be observed in valuation for the purposes of taxation. This topic is a politically contentious one, which perhaps explains why there has been no revaluation since 1991 in England and 2005 in Wales. A revaluation planned for 2007 was ‘postponed’ by the sitting government of the time, with media reports claiming a revaluation would impact poorer communities the most by elevating their tax band (Weaver and Siddique, 2010; BBC, 2010). Although unlikely to be changed any time soon, it has been suggested that more frequent valuations at this scale would enable practitioners to distinguish between market movements and valuation anomalies.

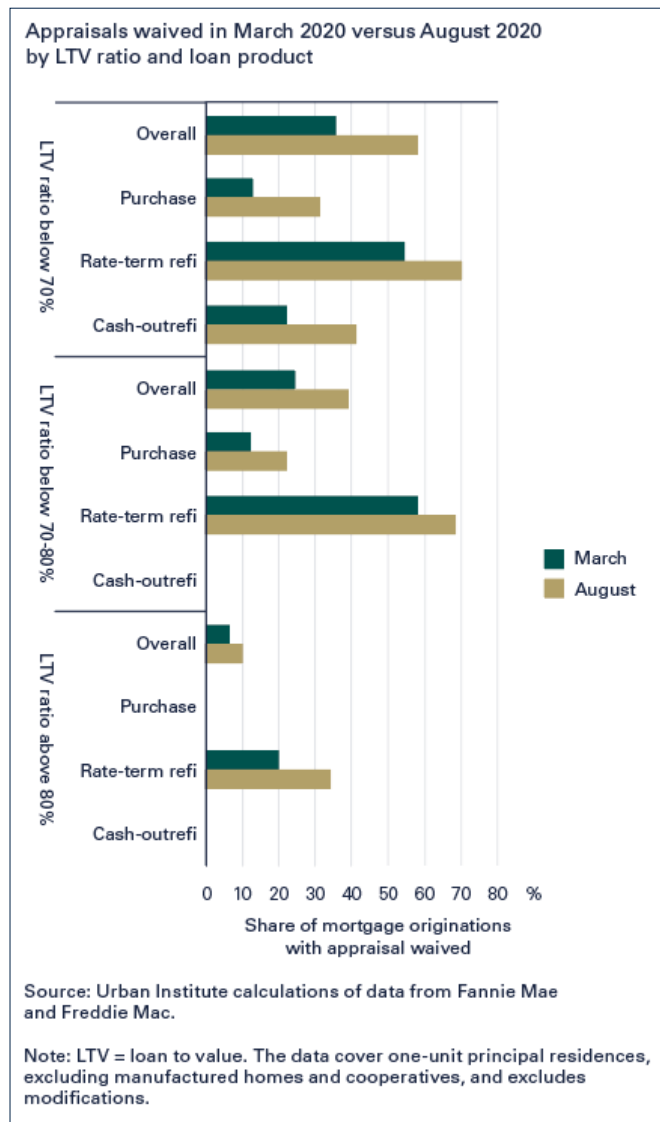


Figure 5: the impact of COVID on valuation waivers

5. A London case study

We take advantage of good data availability in the UK to test two prevalent AVM modelling approaches: AI driven and statistical AVMs.

5.1 Empirical exercise design

In this section, we conduct an empirical comparison between a statistical model (the FoRE model) and an AI-based AVM model (the SAMAI model) to demonstrate the efficacy of both models in terms of estimating house prices. We try to configure the tests as fairly as possible to make sure that both methods are compared on the same basis.

Here are the details of the empirical exercise.

- **Data:** both methods primarily use the Land Registry Price Paid Data for all the transactions in Greater London since 1995, as well as all the available Energy Performance Certificate data in Greater London since 2007. SAMAI also uses some additional data such as local housing market metrics (average sale price within 1 km radius, min and max of sale price within 2 km radius, etc). However, the FoRE method does employ some socio-economic indicators at local authority level, which are not used in the SAMAI model. Overall, when it comes to data usage, the AI AVM certainly has some advantages.
- **Model training:** due to incomplete 2020 data at the time of the empirical test, we decided to use the years prior to 2019 as the training periods for both methods. For the FoRE method, the spatial Durbin dynamic model was run using the data from 1995 to 2018; and the SAMAI model uses the same period to train the algorithm.
- **Test period:** we require that both methods value all properties subject to recorded transactions in Greater London in 2019 without using the observed transaction prices. Notice that all the other information besides price can be used for the valuation, such as number of rooms, size of the property and age of the building.
- **Accuracy measure:** we primarily adopt two important measures to test the efficacy of the methods: average prediction error (APE) and average absolute prediction error (AAPE).

They are defined as follows:

$$APE = \frac{\widehat{P}_{i,j} - P_{i,j}}{P_{i,j}} * 100\% \text{ and } AAPE = \frac{|\widehat{P}_{i,j} - P_{i,j}|}{P_{i,j}} * 100\%.$$

The first measure captures average accuracy with large number of predictions and detects whether it produces any systemic valuation bias. The second measure captures the accuracy of the valuations, which is similar to the standard error metrics. The smaller the AAPE, the more accurate the valuation is likely to be.

5.2 The FoRE hedonic model

This is a hedonic house price model with regional and time fixed effects.

As a first step, we run a hedonic price model over the entire time span of the sample and assume that the parameters for the attributes specific to house characteristics remain the same. We employ time and spatial fixed effects to capture both the time varying and regionally heterogeneous changes in willingness to pay for house attributes. The model can be summarised as follows:

$$\log(p_{\{i,j,t\}}) = \alpha_{\{0,j,t\}} + \alpha_{\{1\}} Z_{\{i,j,t\}} + u_{\{i,j,t\}}$$

where $\alpha_{\{0,j,t\}}$ are the time and regional fixed effects capturing the evolution of house pricing in the region throughout time; and $Z_{\{i,j,t\}}$ are the house characteristics excluding regional amenity features. Therefore, any pricing effect that is regional specific would be included in the time and regional fixed effects, which we denote as the regional house pricing benchmark (RHPB). We can then extract the fixed effects and treat them as the regional house pricing evolution that is uncorrelated with the observable housing characteristics and individual pricing errors. Therefore, for the purpose of prediction, as long as we can provide consistent predictions of the fixed effects in the future period and the house characteristics, we can predict house prices under the assumptions that all the coefficients of the observable house characteristics remain unchanged.

It is relatively easy to estimate the model and obtain the coefficients and fixed effects. However, it is beyond the ability of the house price panel regression to provide dynamic predictions of the future fixed effects. We need a second step to provide the necessary estimates to formulate future regional and time fixed effects.

Therefore, we can remodel and simplify the Dynamic Spatial Panel Model as follows:

$$y_{\{n,t\}} = \eta_{\{0\}} + \gamma y_{\{n,t-1\}} + \rho W_{\{n\}} y_{\{n,t-1\}} + \beta_{\{3\}} X_{\{n,t-1\}} + \beta_{\{4\}} W_{\{n\}} X_{\{n,t-1\}} + \varepsilon_{\{n,t\}}$$

where $y_{\{n,t\}}$ are regional house price benchmarks captured by $\alpha_{\{0,j,t\}}$ in the previous hedonic pricing equation, $x_{\{n,t-1\}}$ are observable neighbourhood specific features and $w_{\{n\}}$ is the geographic distance weighting matrix. This model captures both the autoregressive nature of the housing market and the spatial correlations.

5.3 The SAMAI AVM – AI Model

For the purposes of this report, the authors worked closely with a start-up in the field of residential real estate AVMs. SAMAI was founded in 2018 to specialise in AVMs designed for the UK residential market. Currently their AI valuation service covers the entire UK housing market and is available for free at their website: www.SAMAI.club. Their service provides full array of information regarding a property: an AI valuation, recent transaction records, listing photos and plot boundaries (some of the information is only available at limited capacity).

The developer of SAMAI, David Surkov, is a trained statistician and is experienced in AVMs.¹⁰ In theory, the AI model is a flexible model that tries to search for the best fit of:

$$p_{\{i,j,t\}} = f(Z_{\{i,j,t\}}, \epsilon)$$

No functional assumption or limitation is placed on $f(z)$. The machine learning algorithm thus has the absolute freedom to search all possible fits. This is only made possible thanks to the advancement of computing power. Essentially, the AI model runs millions of regressions with all types of functional assumptions and variable selections. It then presents the one that offers the best solution to a given criterion, which in AVM applications is likely to be prediction accuracy.

Here are a few key elements of the SAMAI AVM method.

(i) The method employs the abundance of data available in the UK market, which includes the same data used in the FoRE statistical model: HM Land Registry price paid data and the EPC data. Additionally, SAMAI also uses other proprietary data to enhance the valuation model.

(ii) The main computation algorithm for the SAMAI method is the boosted random tree machine learning approach. This approach allows a level of freedom for the machine learning process to choose the model that yields the highest predictive power without excessive computation burden. As the algorithm will have to be repeatedly re-run for an up-to-date valuation due to the newly added data and changing economic conditions.

(iii) The valuation model requires that we define or specify the local housing market within which we deem the locational attributes homogenous. To this end, the SAMAI method uses the exact geolocation of the properties to define the local housing market using a fine grid of the UK map such shown in Figure 6.

(iv) With the flexibility of the AI and finely defined local housing market, SAMAI manages to include many regional characteristics in the algorithm such as: max, min, average and median price of the smallest local housing market; maximum, minimum, average and median price of larger local housing market. These are proven to be among the most important attributes along with the size, floor level, building form and number of rooms and so on.

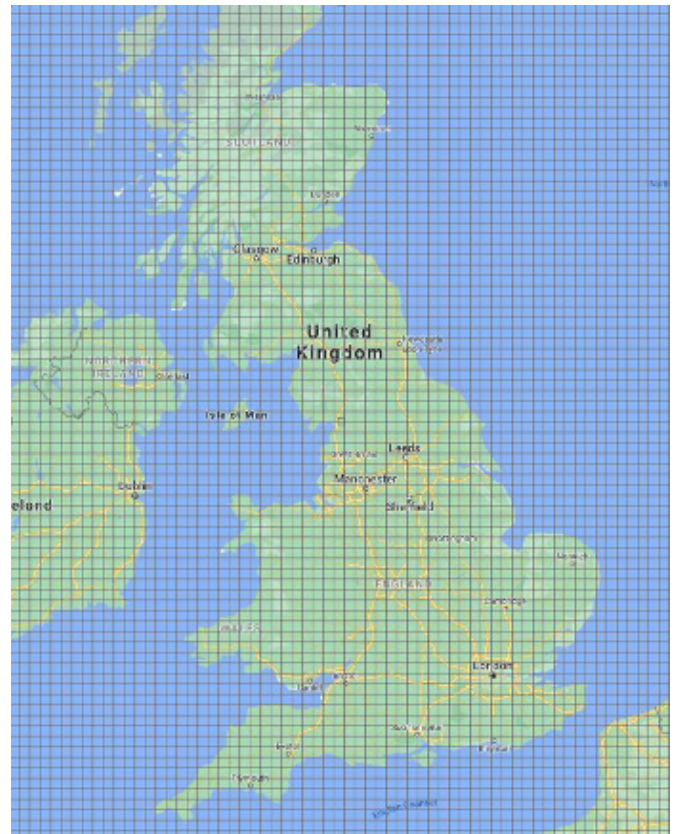


Figure 6: SAMAI local housing market grid

5.4 Test results

In the following two charts, we present the basic summary statistics of the prediction errors. They depict the sharp difference between the SAMAI and FoRE approaches. The SAMAI AVM has a significant advantage when it comes to prediction error, with a mean of 0.0016, which translates to almost no estimation bias. The FoRE AVM also suffers from a systemic underestimation with an average prediction error of -0.073. This is likely because the FoRE AVM performs a strict out-of-sample prediction and requires a time trend estimate for the year 2019 based on previous years.

When performing in-sample predictions, such bias disappears. In addition to the better mean reversion by the SAMAI AVM, it also has a much smaller standard deviation of prediction error, which is only 14.4%. This means that about 67% of the predictions lie within 14% or less of the true underlying value of the properties. This is impressive, considering that we have about 70,000 transactions to estimate. The accuracy result is not as impressive for the FoRE statistical AVM with a standard deviation of prediction error at 37%, which translates to a much wider confidence interval. To summarise, in understanding the comparison, the more important metric to focus on is probably the standard deviation of the prediction errors (shown by the purple lines in Figure 7) instead of the bias (shown by the red lines).

We now break down the prediction accuracy at the postcode district-level in London. Postcode districts in London are smaller than 33 square miles, making them relatively small regions. If we consider those existing boundaries as regional housing markets, then we can evaluate the efficacy of the AVMs at a much smaller scale. This would offer us some insights for the comparison between the two methods.

In Figure 9, we present the average prediction error in all the postcode districts within the Greater London area. As we can see, the majority of districts have small average prediction errors using the SAMAI approach, with $136+59=195$ districts having an average prediction error smaller than 5%. The same number is much lower for the FoRE AVM, which is at $11+56=67$ districts. It is worth pointing out that due to the systemic downward bias, there are 81 districts having an average prediction error between -5% and -10%. Compared with the current industry standard, both methods perform impressively when it comes to the average prediction error. However, it is also evidence that the AI approach has a much lower deviation in a majority of the districts. While AI performs better in most districts, there are still a few districts where the FoRE AVM achieves better results. On close inspection, those are often the ones with a

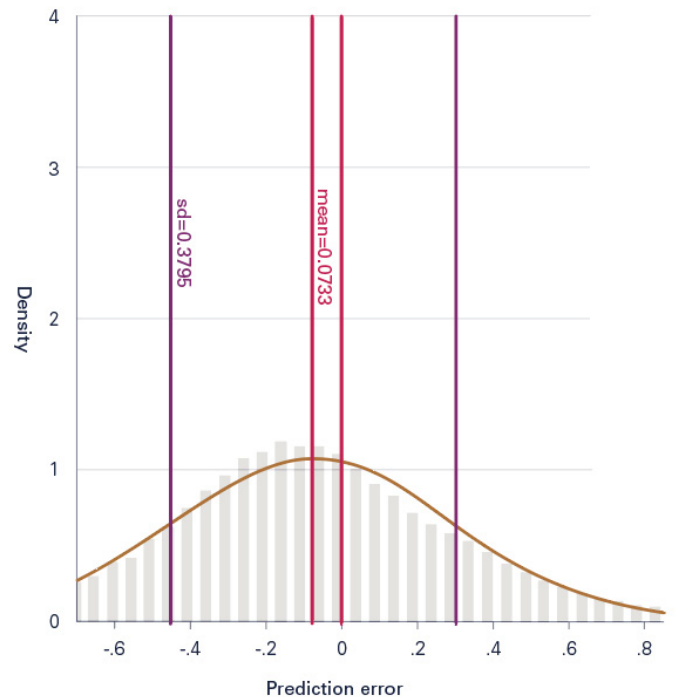


Figure 7: the distribution of prediction error in the FoRE AVM

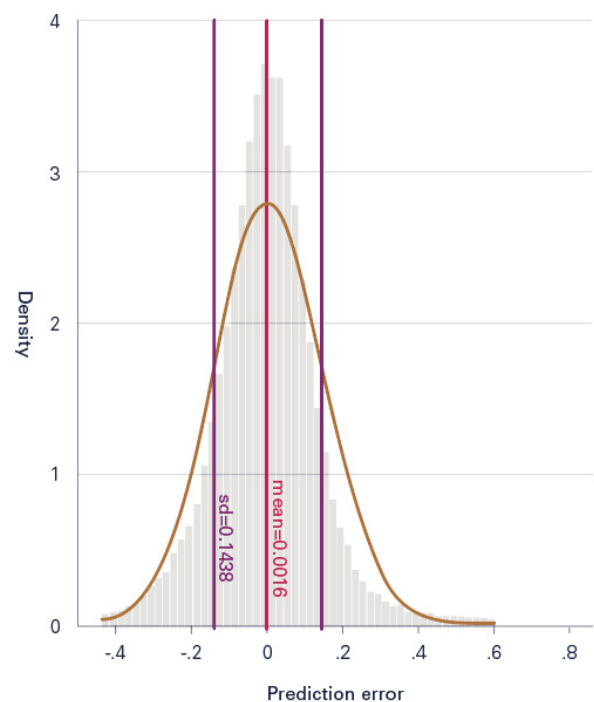


Figure 8: the distribution of prediction error in the FoRE model

higher number of observations in the training period. This goes to show that data availability can significantly improve the performance of a traditional statistical model. However, there does not seem to be a general rule or factor that explains why the FoRE approach outperforms SAMAI in certain districts.

Figure 9 (graphs 3 and 4) also show the difference in average absolute prediction error using two methods. The difference is more evident when inspecting the maps. We can see that the SAMAI AVM outperforms the statistical model in almost all districts by a large margin.

This shows very strong empirical results demonstrating the accuracy improvement of AI models over traditional statistical models.

It is impressive that the AI AVM manages to control the average absolute prediction error to below 15% in 200 out of 241 districts. Such a level of accuracy would not only allow the user to assess the value of large residential real estate portfolios (where errors cancel out) with confidence, but also to value much smaller scale portfolios – even individual properties.

To compare valuation accuracy with one of the industry leaders, Zillow Zestimate, we present the valuation accuracy of top 'MSAs' by Zestimate in the USA in Table 2. We can see that Zestimate's overall performance is only a marginal improvement on the SAMAI AVM, while the FoRE statistical model is easily outperformed by the Zestimate results. We need to account for the fact that Zillow operates in another country with totally different data availability, but it does show that AI driven AVMs can achieve an impressive level of accuracy at a large scale.¹¹

In summary, the empirical exercise shows that the AI AVM does have an advantage over the traditional statistical model in valuation accuracy. Modelling technology has advanced to an unprecedented level, with AI having a distinctive advantage. Such improved accuracy would allow the much wider application of AVMs in areas previously considered to be unsuitable. In practice, this means that the integration of AI in AVMs could offer developers a larger pool of potential clients and a greater return on investment.

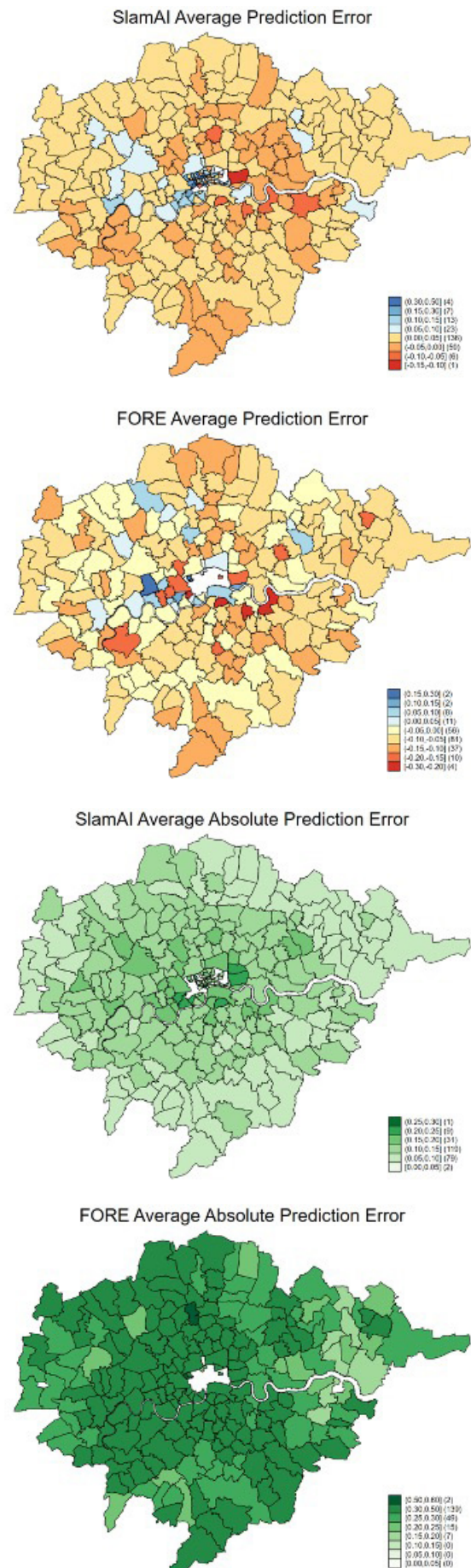


Figure 9: Slam AI and FoRE models, average prediction error

Msa	Median Error	# Homes	Within 5% of Sale Price	Within 10% of Sale Price	Within 20% of Sale Price
Atlanta, GA	7.2%	1.8M	38.3%	61.4%	81.7%
Baltimore, MD	6.7%	833.2K	40.2%	63.6%	82.9%
Boston, MA	7.4%	1.5M	35.9%	61.6%	84.6%
Charlotte, NC	6.7%	778.0K	40.6%	63.7%	83.3%
Chicago, IL	8.1%	2.8M	34.3%	58.1%	81.4%
Cincinnati, OH	8.7%	662.7K	32.3%	54.9%	78.1%
Cleveland, OH	10.0%	651.1K	29.0%	50.0%	74.2%
Denver, CO	5.5%	905.3K	46.4%	72.9%	91.0%
Detroit, MI	8.8%	1.3M	31.9%	54.7%	77.9%
Los Angeles-Long Beach-Anaheim, CA	6.1%	2.9M	43.2%	67.7%	86.8%
Miami-Fort Lauderdale, FL	7.3%	2.2M	37.4%	61.2%	82.6%
Minneapolis-St Paul, MN	6.4%	1.2M	41.2%	66.1%	86.0%
New York, NY	9.5%	5.3M	29.9%	52.1%	76.0%
Orlando, FL	5.9%	797.3K	44.0%	68.6%	87.2%
Philadelphia, PA	8.7%	1.8M	32.7%	54.8%	77.0%
Phoenix, AZ	5.9%	1.5M	44.3%	69.2%	88.0%
Pittsburgh, PA	12.0%	707.3K	24.3%	43.6%	67.5%
Portland, OR	5.8%	752.9K	45.0%	69.6%	88.1%
Riverside, CA	5.5%	1.3M	46.6%	70.1%	87.0%
Sacramento, CA	5.8%	696.0K	45.0%	69.1%	87.1%
San Diego, CA	5.6%	824.3K	45.8%	70.8%	88.8%
San Francisco, CA	7.2%	1.2M	37.8%	62.4%	84.6%
Seattle, WA	6.4%	1.2M	41.6%	67.6%	88.3%
Tampa, FL	8.1%	1.1M	34.9%	57.7%	80.6%
Washington, DC	4.9%	1.8M	51.0%	75.2%	90.9%

¹⁰ Surkov's team entered the Zillow AVM contest and managed to finish within the top 10 of hundreds of participants. We believe that we are therefore employing one of the most advanced AI AVMs for the comparison exercise in this section.

¹¹ We do not have any details of the Zestimate AI algorithm in order to be able to derive any meaningful comparison against the SAMAI algorithm.

Table 2: Zillow Zestimate AVM valuation accuracy of top MSAs in the USA

6. The future likely applications of AVMs

6.1 Residential

Thanks to large transaction volumes and data availability, AVMs have the greatest potential for a much wider application and adoption in the residential sector. As AVM accuracy elevates to a new level, we would expect more substantial impact across residential real estate, from appraisal to mortgage lending, from property funds to taxation. The benefit of the AVM application in residential real estate will be paradigm changing.

Speed of transactions

One of the clear benefits AVMs could bring to residential real estate is to speed up transactions by clearing the bottleneck made possible by time-consuming human valuations. Before the listing, the agent must appraise the property for the seller. Potential buyers have to develop their own assessment of value before making a offer and agreeing a price. Once the price is agreed upon, the mortgage lender conducts a more formal valuation to underwrite the mortgage. If valuations were automated, quick and transparent, negotiation and agreement would be faster.

A modern appraisal profession

The appraisal/valuation/surveying profession may change drastically in the future with the more widespread use of AVMs. Their services may not be required for standardised units such as high rise flats or terraced houses. Instead, modern appraisers would specialise in valuing unorthodox dwellings which produce higher errors for AVMs (and attract higher fees). This would likely reduce the number of appraisers needed, and transform training programs for the profession. Some of our interviewees also mentioned that even without the impact of AVMs, appraisers are dwindling in numbers due to their age distribution and inability to attract new talent for certain property types (such as residential).

Risk management for MBS

Mortgage-backed securities already collect extensive information about the portfolio borrowers and the

underlying properties. It is natural to think that MBS investors could apply AVMs to constantly monitor the value of the collateral of their securities so that they would have a better risk measure. Constant, up-to-date monitoring of an MBS enables an early warning system to prepare for liquidity in the case of a market crash. This could help mitigate financial crises such as the Global Financial Crisis of 2008.

Forecasting prices

Would an AVM have a better chance of picking up an impending fall in prices by marking values down before a human valuer would? There are two possible reasons why this might be the case. First, the speed and potential frequency of an AVM could respond to market signals more quickly than a human valuation. One of the reasons that the global financial crisis broke out in 2008 was that the asset holders of mortgage-backed securities had no idea by how much the value of their collateral had already depreciated. The valuation of the underlying collateral was not updated in a timely way. Automated real time valuations have obvious advantages.

A more speculative potential advantage of an AVM is the possibility that more exogenous variables will be employed to drive its outputs. For example, imagine a situation where an overnight crash in stock prices (or rise in interest rates) precedes a mass valuation. How would the AVM perform relative to a human? A lack of comparable sales since the market shock will inevitably limit the human's ability to respond, while the AVM will automatically mark prices down if there a historic relationship between such a shock and subsequent sale prices.

Active management of residential property funds

When AVMs can accurately and quickly evaluate the market and any property, we will see more and more property companies (such as Invitation Homes) using technology to actively manage residential properties to improve rental and capital returns by the timely identification of under/over performing assets and modifications to the portfolio.

Residential real estate market liquidity

Private market assets such as real estate are said to be illiquid, and returns on such assets are believed to be capable of earning a liquidity premium. This means that prices will generally be lower than they would otherwise be, and that a patient owner timing the sale well can earn a capital gain. This proposition is well illustrated by iBuyers such as OpenDoor (section 3.2), which typically offer to buy residential properties quickly (within a week, rather than the typical 3 months) but at a discount to market value of say 10-15%.

As noted above, if valuations were automated, quick and transparent, negotiation and agreement would be faster, and the iBuyer proposition would be clear, arguably to the benefit of both sides to the transaction. Not only that, but for the first time the liquidity premium (or illiquidity discount) would be capable of precise measurement. The triangular market value (AVM)/agreed price/speed of completion relationship would be quantifiable.

6.2 Government/tax

AVMs could also have a profound impact on property tax practices. As we have discussed in the previous section, property taxes are based on the capital or rental value of the property. Therefore, it stands to reason that the tax levied on a dwelling should reflect an up-to-date or recent value. Property tax is often perceived as a type of progressive tax, because wealthier households usually own higher valued properties.

In reality, property tax is often based on out-dated values. For instance, Council Tax in the UK is levied based on property values estimated in 1991(!). The reasons for such a practice are to do with the high cost of property valuations and subsequent disputes, as well as the political toxicity of mass revaluation initiatives. The high cost can be mitigated by AVMs, as they often have the ability to value millions of properties with the click of a button. The political toxicity, however, may be more difficult to manoeuvre. Adjusting the population to a 'new normal' would require change agents to address concerns surrounding inequality, privacy and other factors.

There are additional caveats to be applied to the future of AVMs in taxation. Transparency and fairness issues are paramount. For AVMs to be adopted for property tax valuations, the process must be transparent and publicly available for constant robustness checks, as this will be the only way that the property taxes remain fair for all property owners. In recent decades,

UK property values have increased divergently, which would mean some households benefit from outdated property values while some relatively overpay. In addition, the 'averaging out' of errors in mass appraisals is a problem for taxation, because errors also result in some households overpaying and others underpaying (even though the 'averaging out' means total tax revenue is approximately what it should be).

Shifting to current market value-based property taxes most likely means that wealthier households will pay more tax, hardly a controversial outcome. However, it is likely that media scrutiny will be applied to increases taxes at the lower end of the housing market. In addition, there might be some equally strong political incentive behind resistance, as regular revaluation will likely increase property tax revenues.

6.3 Digital twins/property passports and data sharing

One of the prerequisites of AVMs is an abundance of data, especially in the case of AI AVMs. Looking into the future of AI driven AVMs, we can expect more and more collection and analysis of data for improved AVM performance. For instance, one of the issues with AVMs is the lack of qualitative amenity data such as the design of the property, the state of the garden or driveway, as well as the condition of the walls and roof. Those are often unavailable in a systemic and organised way, preventing AI AVMs from directly using these inputs for more accurate valuations. However, AI is also advancing rapidly in the domain of image reading and processing. In a few years we can expect that the effort designed to digitalise the amenity/aesthetic features of properties in a codified fashion will increase.

As owners begin to have a vested interest in improved automated valuations¹², we can expect the use of AVMs to encourage the real estate market to be increasingly digitalised, supporting the development of the digital twin of a property. With the abundance of property information, property passports would be a more likely reality when blockchain or other types of encryption technology are applied.

6.4 Commercial real estate

The application of AVMs in commercial real estate will be very different to the way they will be applied in residential real estate. Two of the important differences that cause such a probable divergence are transaction

volumes and simple differences in the universe of properties and the relevant data pool. However, AVMs can contribute to commercial real estate valuations primarily by estimating current market rents, where heterogeneity and data availability is less of an issue.

Commercial real estate valuers and investors typically use the income approach to value properties, and the heterogeneous nature of occupational leases and their impact on rental income is significant in determining differences in value between similar assets.

Maintenance costs, taxes, rent growth, capex and opex are all relevant value drivers, not easily picked up in an AVM.

In summary, AVMs are not likely to be widely applied in directly estimating commercial real estate values due to the limitations of data availability. There is, however, great potential for AVMs to be adopted for rent and rent growth estimation.

¹² This is, of course, subject to the potentially negative effect of AVM-supported property taxes.

6.5 Other potential advantages of AVMs

Besides the relatively direct impact of AVM applications in real estate valuation, AVMs might also help with some potential 'human issues' such as client influence (see section 2), but also fraud and prejudice.

For example, during our interviews some mentioned racial discrimination as one of the potential problems affecting the human appraisal process. Without knowing the occupants of the house or flat, appraisers tend to give lower valuations if the properties have significant ethnically specific decoration styles. The root of such bias in valuation could be very complicated: maybe the appraiser is racially biased; or maybe the local market punishes ethnic decoration styles due to the fact that the majority of potential buyers are of a different ethnicity. In this instance, the lack of soft features in the AVMs could be a positive. As long as we do not train the AVMs to focus on such racial elements, an AVM would never have such a bias. However, there is some evidence that an AI-based AVM trained with racial elements will also turn out to be racially biased.

AVMs should eliminate fraudulent valuations, and are less subject to client influence. This may result in fewer legal disputes and bring a sense of enhanced fairness.

7. Summary and conclusions

This report aims to bring a deeper understanding of the AVMs and to speculate about the likely future development of AVMs in real estate valuations.

First, we present a brief review of traditional valuations and criticisms of this process. Second, we introduce mass appraisal and AVMs, and discuss the development of AI-driven AVMs. Third, we offer a discussion on the benefits and limitations of AVMs. We conducted interviews with various industry and government practitioners to gather their valuable opinions on AVMs based on their daily experiences with the valuations. Among all the issues, reliability and transparency seem to be on the minds of many in the industry, especially the AI AVMs.

We thus added a review of AI algorithms and conducted a case study comparing an AI AVM with a statistical AVM to illustrate the technical differences and to demonstrate the advantages of the AI model.

Finally, we offer our insights on the future development of AVMs in the specific context of the criticisms of the traditional valuation process. Will AVMs be a step forward?

It seems inevitable that (i) AVMs will have wide applications and (ii) thanks to AI, we will see continually improving AVMs which will become essential for the modern real estate sector and the whole economy. The AI-driven AVM is a significant step forward from the hedonic pricing-based mass appraisal techniques of the 1980s.

Human appraisals are categorically more costly than AVMs. The huge cost reduction of replacing appraisals with AVMs will likely cause more clients to lean more heavily toward AVMs, and might change both property tax systems and trading frequency for the better.

AVMs have been improving drastically in the past decade with the introduction of AI and improvement of traditional modelling. In our case study of London, AI showed an impressive advantage over the traditional statistical model in prediction accuracy. However, it is apparent that the 'black box problem' is the key challenge facing AVM developers. We need to be able to demonstrate the improved accuracy of AI-driven AVMs in a more transparent fashion.

There exists an inherent conflict of AVMs when pushing for wider applications in the economy. Different applications of AVMs require different levels of transparency. Currently most AVMs are developed by privately-owned companies offering valuation services, who understandably want to protect their trade secrets. Therefore, they would not make their algorithms and data available for public scrutiny. Such practices are compatible with the use of mortgage lending, risk management and portfolio management.

However, this does not meet the requirements of valuations for taxation or other public interest purposes, which will have to be transparent in a fair and just system. With the significant potential gain of productivity that could be delivered by the use of AVMs in the public sector, it seems inevitable that public AVMs will be a reality, but only if transparency can be guaranteed. Then the question becomes how AVM developers can differentiate themselves from the transparent public systems.

Will AVMs eliminate appraisers as a profession? This issue seems to be on many professionals' minds and was often mentioned in the interviews. Our answer is a resounding 'no'. However, the valuation profession will likely shrink in size and require different training. As stated by the RICS Future of Valuation 2017 report, appraisers should embrace changes and new technologies. AVMs and their hybrid counterparts are already assisting many appraisers to offer quicker and more refined valuation services. There may be fewer valuers in future, but fees for non-standard appraisals will increase.

This report is by no means exhaustive. Many more interesting issues with AVMs will emerge and will need to be studied and discussed. For instance, the issue of privacy and data ownership will become more acute when we start to employ more and more image processing to extract soft features of the property for a better AVM. The future will provide plenty of fuel for further debate.

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Appendix: A review of AI-driven valuation

AVMs have critical and wide application potential in various real estate sectors. Since their introduction in the 1980s, AVMs have undergone continuous review and improvement. More recently, the predominant trend in AVM development is to employ AI in the AVM process to improve accuracy and applicability.

1. Major issues with traditional AVMs

A few critical obstacles stop AVMs from being well trained and tested. First, real estate assets, unlike financial assets, are traded at a low frequency. In Britain, Zoopla (2017) states that the average person moves homes every 22.7 years. This makes the observable 'true value' scarce and results in a lack of data points for the model to achieve accurate estimations.

Second, real estate markets are often highly segregated and heterogeneous across regions. This requires the AVMs to be trained at a local level to reach desirable level of valuation accuracy. But narrowing down the regions from which you can draw transaction records for the AVMs further reduces the data points you can rely on.

Third, real estate assets often have special physical features that can be valued differently depending on the potential buyers. Many of those features are not even recorded in the description of the properties. For instance, the design features of a house and the garden state of a house are usually not detailed in standard property descriptions and are often recorded at random, which makes it very hard for the AVMs to properly incorporate such pricing elements.

Fourth, many of the amenity features of the surrounds of the property are not properly accounted for. For instance, a house next to a park would be more desirable than a house next to traffic lights.

2. What is the future of AVMs?

Thanks to the advent of technology and the effort of more comprehensive data collection in the industry, we are now at the stage of overcoming or mitigating many of the obstacles faced by AVMs. Most importantly,

data is more available now than it was previously in both the volume and the details of each entry.

Online real estate listing platforms are the main repository of such centralised and detailed data collection and presentation. Nowadays, we have several large online listing platforms in all developed countries: Zoopla and Rightmove in the UK, Zillow in the US, Pap and Leboncoin in France, Immobilienscout24 in Germany and so on. Each platform collects and stores millions of data inputs each year, which can be a great resource for training the AVMs.

In the past decade, big data has been a fashionable buzzword and more recently it has been adopted as an interesting concept in the real estate sector. This has led to the development and application of AI to enhance or replace the older models. AI has the distinctive advantage relative to traditional models of dealing with big data, especially unstructured messy data. AI also removes many of the limitations of traditional statistical models such as linear additivity and can optimise and estimate at a higher level of granularity.

3. Critical issues with AI-driven AVMs

AI driven AVMs have received a lot of attention and investment in recent years, as they are likely to be a feature of the future of AVMs in real estate valuation. However, AI has been marketed as the mysterious 'black box algorithm' that supposedly should provide the best real estate valuation. Due to the limited understanding of the public, AI driven AVMs have not been widely trusted by the industry.

4. Hedonic pricing models/multiple regression

A hedonic model examines the relationship between the relevant attributes (building age, area, floor, height, etc.) and the related property value. Through quantitative analysis, the mathematical relationship between the dependent variable and independent variable is calculated. The mass appraisal of real estate

with similar attributes can then be estimated using the known mathematical relationship.

The simplicity of hedonic regression models is its main advantage; users of such models would be able to explain the valuation methods to most of the statistically literate audience. Moreover, the multiple regression models are also very flexible and adaptable, and not bounded by the conventional linear models.

For example, additive nonparametric regression allows the data to determine the shape of the relationship between dependent and independent variables.

5. Artificial neural networks

An artificial neural network (ANN) aims to mimic the functions of biological neurons and the way they communicate using computer simulated neurons, which process knots that connect and pass information to others to form a network of artificial neurons.

The neural network typically consists of an input layer, an output layer and at least one layer of non-linear processing elements, known as the hidden layer.

First, it receives inputs from the other artificial neurons through weighted links; second, it sums and processes these inputs; finally, it outputs the results to other artificial neurons. By feeding into the model more and more inputs with known outputs, we can train the ANN to discover the hitherto unobservable data generating process.

An important advantage of ANNs is the complete independence from any modelling assumptions. By training the ANN using the sample data, the ANN adapts itself to reproduce the required output. The ANN also performs well for modelling non-linear relationships. Due to the fact that ANNs are completely 'model-less', people often refer to the hidden processing layers as a 'black box'.

6. Decision tree based models

Decision tree models sequentially divide the dataset into subsets in order to apply a regression model to each subset. There are two types of decision trees, depending on the type of target variable: classification trees, which are aimed at predicting categorical variables, and regression trees, which predict continuous variables (Breiman et al. [1984]).

Random forest models

A random forest is a kind of ensemble learning to integrate many decision trees into a 'forest'. The model can run efficiently on a large dataset of properties and

deal with input variables without deletion. Antipov and Pokryshevskaya (2012) document the use of the random forest model in mass appraisal for the first time and find it performs the best among other models.

Boosted decision tree models

Boosting is a method of combining many weak learners (trees) into a strong classifier. The main idea is to sequentially iterate decision trees by minimising a loss function. A boosted tree model can achieve higher accuracy and faster running speed. These advantages are urgently needed for a mass appraisal with a large number of data and a time node of appraisal. McCluskey et al. (2014) apply the boosted regression tree for Malaysia's mass appraisal of residential property. They find that the boosted tree is better than the MRA model in terms of the coefficient of dispersion and mean absolute percentage error.

7. Recent AI AVM Innovation – Houzen AI Meta Model

Houzen is a relatively new player in the AI AVM application sector. They started working on AI valuation in the UK real estate market in mid 2020. However, with lack of experience, Houzen's unique meta-analysis approach to AI valuation brings a new perspective as to what could be possible with the development of AI in real estate valuation. Houzen tested a host of different modelling methodologies to perform valuation analysis, such as XGB, LGBM, KNN, random forest, NLP, plain statistics, AutoML, and computer vision. Their methodology consideration includes both traditional statistical models and more recently developed AI models.

Here are the details provided by Houzen as to how they conduct their valuation process.

7.1 Data sourcing/processing

- First, multiple data sources: historical sale price data (Land Registry, Houzen closed properties); real time market data (Zoopla, and LIVE negotiations across Houzen brokerage); Houzen LIVE proprietary data.
- All the data sources are combined to get important details of the properties such as market price which mostly corresponds to asset's monetary worth in the market, number of bedrooms, bathrooms, address, descriptions, location, images, floor plan for each property. Any duplication is removed however the values are kept across all data sources.

- Location feature extractions: Houzen also collects further information on the local amenities and other housing market relevant information.

7.2 Machine learning strategies

- Multiple evaluations are done using different modelling methodologies: K-Nearest Neighbours (KNN), Extreme Gradient Boosting (XGB), Light Gradient Boosting Models, Google AutoML.
- Houzen argues that the meta-analysis approach helps improve valuation accuracy. For instance, they average the nearby market value, rumoured price, and closed deal price with almost the same features from different sources as their valuation output.
- Based on Houzen's internal valuation comparison, AutoML, with its combination of learning models, outperformed XGB, LGBM and KNN on their refined and structured UK property data.

7.3 Optimisation, Improving the model

- The key optimisation of the valuation Houzen conducts is to take the average of all the valuation results from multiple methodologies and sources (including other AI valuation provisions).
- Houzen continuously updates their model on a weekly basis, while also working to expand the geographical scope of their model coverage.
- Two key developments at Houzen include: 1) involving more demographics-based data for real estate pricing, and 2) developing a rent estimation model.

7.4 Summary

Currently, a user can go to www.houzen.co.uk and enter a Zoopla URL of a specific property. This triggers an analysis on that listing and compares the listing's attributes with Houzen's backend database and over 500 analysis factors. Each property goes through the same equations and a simple average of the four valuation methodologies spits out a final valuation.



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